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Regression Techniques for Examining Land Use/Cover Change: A Case Study of a Mediterranean Landscape

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Abstract

In many areas of the northern Mediterranean Basin the abundance of forest and scrubland vegetation is increasing, commensurate with decreases in agricultural land use(s). Much of the land use/cover change (LUCC) in this region is associated with the marginalization of traditional agricultural practices due to ongoing socioeconomic shifts and subsequent ecological change. Regression-based models of LUCC have two purposes: (i) to aid explanation of the processes driving change and/or (ii) spatial projection of the changes themselves. The independent variables contained in the single 'best' regression model (that is, that which minimizes variation in the dependent variable) cannot be inferred as providing the strongest *causal* relationship with the dependent variable. Here, we examine the utility of hierarchical partitioning and multinomial regression models for, respectively, explanation and prediction of LUCC in EU Special Protection Area 56, 'Encinares del río Alberche y Cofio' (SPA 56) near Madrid, Spain. Hierarchical partitioning estimates the contribution of regression model variables, both independently and in conjunction with other variables in a model, to the total variance explained by that model and is a tool to isolate important causal variables. By using hierarchical partitioning we find that the combined effects of factors driving land cover transitions varies with land cover classification, with a coarser classification reducing explained variance in LUCC. We use multinomial logistic regression models solely for projecting change, finding that accuracies of maps produced vary by land cover classification and are influenced by differing spatial resolutions of socioeconomic and biophysical data. When examining LUCC in human-dominated landscapes such as those of the Mediterranean Basin, the availability and analysis of spatial data at scales that match causal processes is vital to the performance of the statistical modelling techniques used here.

Key words: land use/cover change; regression modelling; hierarchical partitioning; land cover classification; Spain.

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Introduction

Landscape Change in the Agricultural Landscapes of the Mediterranean Basin

The high levels of biodiversity that characterize the landscapes of the Mediterranean Basin have been attributed, in part, to high levels of habitat diversity due to biophysical heterogeneity and habitat modification by human activity (Blondel and Aronson 1999). For example, it is widely recognized that the low-intensity, multifunctional farming systems of the Iberian Peninsula (known as *dehesa* in Spain and *montado* in Portugal) support a more diverse range of flora and faunal habitat(s) than do mono-cultural systems (Bignal and McCracken 1996; Rackham 1998; Scarascia-Mugnozza and others 2000; Allen 2001). In *dehesa*-type landscapes, periodic cutting and felling of trees maintains low-density oak woodland (between 40 and 50 trees ha^{-1} of, for example, *Quercus ilex*; see Figure 1). This allows multiple-use farming practices, including cereal cultivation and livestock grazing (sheep, goats, pigs, cattle), between the trees (Joffre and Rambal 1993). Thus, shrub species are prevented from invading into the understorey allowing a rich diversity of native grass and herbaceous species to be maintained. This results in a landscape that provides habitat for endangered animal species including the Spanish Imperial Eagle (*Aquila adalberti*) and the Iberian Lynx (*Lynx pardina*) (Rackham 1998; Grove and Rackham 2001). The importance of human activity in Mediterranean landscapes suggests that future threats to their sustainability and biodiversity are more likely to come from technological and social changes than from climatic ones (Grove and Rackham 2001).

In general, over the last few decades forest cover in the Mediterranean Basin has increased around the northern rim of the Mediterranean Sea and decreased around its southern rim (that is, the Maghreb, Mazzoleni and others 2004a). This increase in forest cover in the northern Mediterranean is often attributed to the abandonment of low-intensity agricultural lands such as those described above (for example, Mazzoleni and others 2004b), and this trend has been discussed in numerous case studies (for example, Pinto-Correia 1993; Gómez-Límon and de Lucío Fernández 1999; Poyatos and others 2003; Coelho-Silva and others 2004; Metailie and Paegelow 2004; Romero-Calcerrada and Perry 2004; Torta 2004). The potential environmental impacts of this land abandonment include soil degradation (Lasanta and others 2000; Dunjo and others 2004) and changes in wildfire occurrence and risk (Mouillot and others 2003; Millington 2005; Mouillot and others 2005). Land abandonment has also been found to affect Mediterranean bird species' abundance negatively, as more densely wooded landscapes provide habitat that other (northern) European species prefer (Preiss and others 1997; Suarez-Seoane and others 2002).

Figure 1. *Dehesa* in the study area. Periodic cutting and felling of trees maintains low density oak species woodland, and allows multiple-use farming practices, including cereal cultivation and livestock grazing, between the trees.

Agri-environmental policies have been implemented recently to address these conservation and land management issues. For example, the EU 'Bird Directive' (79/409/EEC) was passed to prevent pollution in, or deterioration of, habitats of species in danger of extinction, vulnerable to specific changes in their habitat or considered rare because of small population size or limited local distribution. These special protection areas (SPAs) are now an integral part of the Natura 2000 ecological network established by the EU to protect endangered species and habitats. In Spain over 50% of land falling into the Natura 2000 scheme is covered by farmland habitats (EEA 2005). Changes to the structure and function of agricultural landscapes, due to shifts in the nature of human activity in them, pose potential threats to the conservation of biodiversity and survival of endangered species in these protected habitats (for example, Bignal and McCracken 1996; Stoate and others 2001; Regato-Pajares and others 2004; Young and others 2005). Romero-Calcerrada and Perry (2004) described landscape change in SPA 56 'Encinares del río Alberche y Cofio' (SPA 56) over the period 1984–1999, observing increases in scrubland commensurate with decreases in pasture and arable crop land. Romero-Calcerrada and Perry (2004) suggested that the observed, and ongoing, land use/

cover change (LUCC) is driven by socioeconomic changes such as the aging and diminishing of the agricultural population as more of the population as inhabitants become increasingly employed in manufacturing, construction and service sectors.

Empirical Modelling of LUCC

Empirical models of LUCC (for example, regression approaches) derive relationships between observed LUCC (the dependent variable) and the values of physical, economic or social indicators (the predictor variables) such as elevation, annual crop yields, or population density. These techniques can be used for two purposes: (i) to improve explanation of the mechanisms and processes of change (by examining the statistical significance of the influence of predictor variable upon the dependent variable) and/or (ii) prediction of change itself (derived relationships may be used to *project* future land-use/cover from the current values of the independent variable). The distinction between these uses is important but in many studies it is not explicitly recognized—here we highlight this distinction and examine techniques suitable for both purposes. Empirical and process-based models are highly complementary for effectively modelling LUCC (Verburg and others 2006). The implementation of the statistical techniques presented in this paper builds on the empirical work of Romero-Calcerrada and Perry (2004), with the objective of examining the importance of a range of biophysical and socioeconomic factors in driving the observed land-use changes in SPA 56. These statistical models are a component of a wider modelling project, which is assessing potential changes in the land use and cover of SPA 56, and contribute to the development of a process-based simulation model. They also give some indication of the potential state of the study area should observed trends continue in the future.

Because LUCC is usually represented as a discrete change (for example, from agricultural land to scrubland), logistic (both binary and multinomial) regression is an appropriate statistical model to use (Trexler and Travis 1993). Logistic regression has been used in LUCC studies in many different environments, with an emphasis on different types of independent variable, including biophysical (aspect, slope, soil pH, rainfall), social (human population density, human population age, ethnic composition), and economic (agricultural productivity, proximity to nearest urban centre/market, level of farm mechanisation) (for example, Bockstael 1996; Chomitz and Gray 1996; Turner and others 1996; Wear and others 1996; Carmel and others 2001; Schneider and Pontius 2001; Serneels and Lambin 2001; Muller and Zeller 2002; Soares and others 2002; Cheng and Masser 2003; Aspinall 2004; McConnell and others 2004; Munroe and others 2004; Williams and others 2005). For example, Wear and Bolstad (1998) considered land cover dynamics in the southern Appalachians incorporating anthropogenic factors, such as population density, into their model. Although Wear and Bolstad's (1998) models correctly predicted between 68 and 89% of land cover proportions, their results suggested a mismatch in scales between the coarse scale socioeconomic data and fine scale land cover change.

The performance of these 'traditional' multiple regression-type techniques has come under scrutiny in some areas of ecology (for example, Olden and Jackson 2000, 2002). In the context of LUCC modelling, Pontius and others (2004) bemoan the inability of LUCC models to improve prediction beyond the null model of no change in the landscape (that is, simply retaining the original map as a prediction for the future). Recently, Taverna and others (2005) compared the predictive performance of binomial logistic regression models using multiple predictor variables with classification and regression trees (CART) to predict the presence/absence of four forest types in the North Carolina Piedmont, USA. The logistic regression models performed best for one of the four forest types (correctly predicting 65% of the study area) and, although simpler and easier to implement, were unable to represent the relationship of the multiple interacting predictor variables on the response variable (that is, land cover). With these questions about the utility of their use in mind, here we examine the predictive performance (that is, the accuracy of projected maps of change) of multinomial logistic regression modelling of LUCC in a human-dominated Mediterranean landscape (SPA 56). Previous projects examining desertification and land degradation in the Mediterranean Basin have specifically considered the importance of biophysical and socioeconomic drivers of human-driven landscape change in these environments through survey-based studies of local stakeholders (MEDACTION—Juntti and Wilson 2003; for example, DESERTLINKS—Kosmas and Valsamis 2004). As far as we are aware, however, only one study has used logistic regression modelling to explore landscape dynamics in a Mediterranean-type environment. Carmel and others (2001) used multinomial logistic regression to explore vegetation dynamics in an Israeli landscape, focussing on

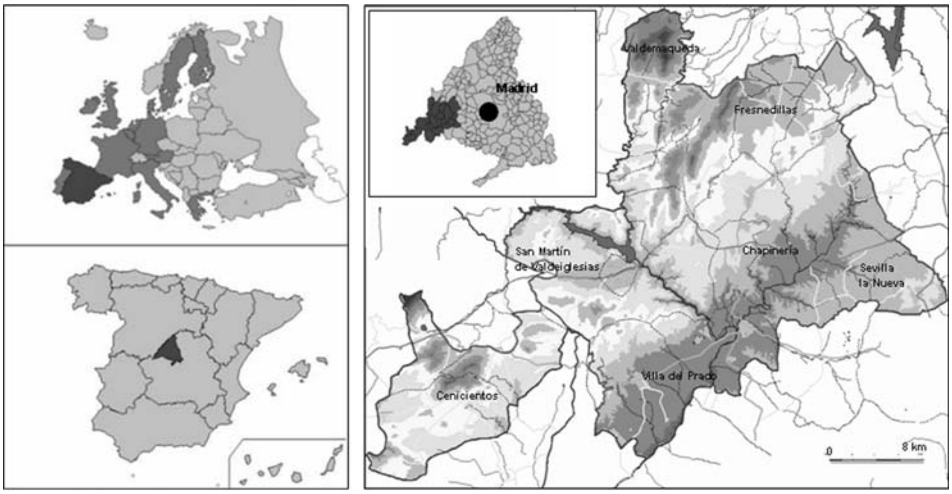

Figure 2. Map of EU special protection area (SPA) number 56 'Encinares del río Alberche y Cofio', central Spain, depicting elevation, and main watercourses, urban centers and roads.

three vegetation types and a single ecological disturbance (grazing of variable intensity) in an area with a very low human population. On a pixel-by-pixel basis for non-calibration data (that is, data independent from that used in model building) their models correctly predicted between 48 and 55% of land cover in the landscape.

Numerous studies have used logistic regression to aid in understanding or explaining the driving mechanisms of LUCC (for example, Aspinall 2004; McConnell and others 2004; Williams and others 2005). However, seeking the single 'best' regression model, that is, the model that minimizes variation in a dependent variable as a function of variation in a set of predictor variables, is not an effective way of finding the predictor variables causing the most variation in the dependent variable (Mac Nally 2000, 2002). The predictor variables contained in this 'best' regression model should not be inferred as having the strongest *causal* relationship(s) with the dependent variable. As Mac Nally (2000) discusses, a variable retained in a single model that provides the best 'fit' may have no influence on the dependent variable if there is multi-collinearity between predictor variables. For example (from Mac Nally 2000), a variable U may happen to be correlated with the actual causal variables, V and W, such that it 'picks up' the explanatory power of V and W, which are omitted from the best model. Recently, hierarchical partitioning has been used in several biological and ecological studies to overcome the potential problems of multi-collinearity between predictor variables (for example, Oliver and others 2000; Radford and Bennett 2004; Banks and others 2005; Heikkinen and others 2005). Here, we assess the potential of hierarchical partitioning for improving assessment of the relative importance of the driving factors of LUCC in the study area, as a complementary approach to the use of multinomial logistic regression to produce maps of projected change.

Any modelling of landscape change in the northern Mediterranean Basin must acknowledge: (i) the inherent complexity of these landscapes, in terms of their composition and configuration, and (ii) the key role of human activities, past and present, in shaping them. We believe this study to be the first use of multinomial regression models in combination with hierarchical partitioning (HP) to examine LUCC in the complex, multi-functional and human-dominated landscapes of the Mediterranean Basin. This paper aims to examine the utility of HP and the performance of multinomial regression models for considering LUCC caused by a combination of inherently different processes and their data (that is, biophysical vs. socioeconomic).

Methods

Study Area

SPA 56 'Encinares del río Alberche y Cofio' encompasses 19 municipalities of the Autonomous Community of Madrid on the southern slopes of the Sierra de Guadarrama and Sierra de Gredos (altitudinal range 600–1300m.a.s.l; see Figure 2). SPA 56 covers 82,980 ha (~830 km^2) and provides a complex mosaic of habitats, in which several endangered bird and mammal species occur (for example, the endemic Spanish Imperial Eagle, *Aquila adalberti*, and the Iberian lynx, *Lynx pardina*). The SPA is characterized by both a Mediterranean-type climate (mean annual rainfall 700 mm and mean annual temperatures ranging from 10 to

Table 1. Data Layers (Maps) Used in This Study and Abbreviations

Variable	Unit of measurement	Year of data	Source
Socioeconomic data			
AGRWK—agricultural workers	Percentage of population	1986, 1991	Instituto de Estadística de la Comunidad de Madrid (see IECM 2005)
FMAGE—mean farmer age	Years	1982, 1989	Instituto Nacional de Estadística (see INE 2005)
MIG—migration	Persons	1988, 1991	Instituto de Estadística de la Comunidad de Madrid (see IECM 2005)
PDENS—population density	Inhabitants/km^2	1985, 1991	Instituto Nacional de Estadística (see INE 2005)
Biophysical data			
ASPECT—aspect	N, NE, E, SE, S, SW, S, NW	1995	Consejería de Política Territorial de la Comunidad de Madrid (see Romero-Calcerrada 2000)
LCAP—land capability	Ranked classification	1997	Romero-Calcerrada (2000)
LC—land cover	Land use	1984, 1991, 1999	Landsat TM (see Romero-Calcerrada and Perry 2004)
TEMP—temperature	Mean annual °C	1965–1995	Instituto Nacional de Meteorología (see Romero-Calcerrada 2000)
Spatial Data			
D_PE—distance to patch edge	Meters	1984, 1991	Derived from land cover maps
D_RIV—distance to river	Meters	1995	Derived from Comunidad de Madrid (1995)
D_ROAD—distance to road	Meters	1995	Derived from Comunidad de Madrid (1995)
D_URB—distance to urban area	Meters	1995	Derived from Comunidad de Madrid (1995)

16°C) and flora (dominated by *Pinus* and *Quercus* species). There are multiple land covers and uses in the SPA including pine (*Pinus pinea* and *P. pinaster*) and oak (predominantly *Quercus ilex*) woodlands, mono-cultural farmland (that is, pasture and arable farmland), multi-functional farmland (*dehesa*), urban areas and, increasingly, recreational areas and abandoned farmland. These land covers are highly fragmented in many parts of the SPA because of a long history of agricultural use and tenure that has favored the growth of small farming units (Simpson 1995). Some areas in SPA 56 dominated by forestry are more homogenous in their composition; more detail regarding SPA 56 may be found in Romero-Calcerrada and Perry (2004).

Data Preparation

Biophysical, socioeconomic and other spatial variables were used in the models considered here (Table 1). From an initial suite of variables, 12 were selected on the basis of their representation of the processes believed to be driving LUCC in the study area (as outlined below). Tests for co-linearity indicated that several of these variables were correlated; mean annual rainfall (with land capability), slope (land capability) and number of persons unemployed (population density) were found to have pairwise (Pearson) correlation coefficients, $r > 0.5$ and so were dropped from the models (the $r > 0.5$ threshold was used as this presented a natural break in values for all variable pairs and removed strongly co-linear variables while retaining a variety of predictor variables, that is, biophysical, socioeconomic, and spatial). Rainfall and slope were discarded as both variables were used to derive the land capability measure (see below).

Four socioeconomic variables were used in the multinomial logistic regression models and HP; agricultural sector employment (*AGRWK*), mean farmer age (*FMAGE*), net migration (*MIG*), and population density (*PDENS*). Population density was favored over number of persons unemployed as the former is an indicator of the labor available to work the land and therefore likely to be a driver of farm-level decision-making, whereas the latter is an indicator of the state of the wider economy. For example, farmers in a similar *montado*-type landscape in Portugal ranked the availability of labor as the second most important influence on their land use decision-making (after availability of irrigation water—Kosmas and Valsamis 2004). The percentage of population employed in the agricultural sector was selected over general unemployment because of the importance of agricultural change in driving LUCC in the study area. The relatively old age of farmers in Spanish agriculture is an important constraint on capital investment (Hoggart and Paniagua 2001), and also influences the ability of a farmer to cultivate extensive areas of land. The population of the study area as a whole has been increasing in recent years but this has not necessarily translated into an increase in farmers or agricultural labor availability. Changes in farm household structure, notably increasing mean farmer age, are occurring as many younger family members now do not want to inherit the farm, preferring to take urban jobs in other sectors (that is, manufacturing and service) (Hoggart and Paniagua 2001). All socioeconomic variables were recorded and aggregated at the municipality level and then converted to raster maps at the same spatial resolution (30 m) as the other maps (see example Figure 3C and as summarized in Table 1).

Three Landsat TM scenes covering the SPA 56 were classified into six categorical maps detailing ten and four classes of land-cover (see Table 2) for the years 1984, 1991 and 1999 at a 30-m resolution (see Romero-Calcerrada and Perry 2004—examples in Figure 3 and see Table 1). By using these two image classifications (derived from the same dataset) the importance of land cover classification, and trade-offs between information and model complexity, can be examined. Recent changes in landscape composition using these two classifications are shown in Figure 4. As the maps are derived from satellite imagery they provide classifications of land cover rather than land use. Land cover is the landscape surface (composed by components such as dense forest, sparse forest, grassland, and so on) and may be documented from direct analysis of remotely sensed imagery whereas land use is an anthropogenic interpretation of this cover (for example, residential, agricultural, and so on) that may be inferred, but not directly derived, from remotely sensed imagery (Brown and Duh 2004). Thus, as *dehesa* is a land use it is not found in the land cover definitions; the cover 'Holm Oak & Pasture' (HOP) corresponds to it most closely. Any

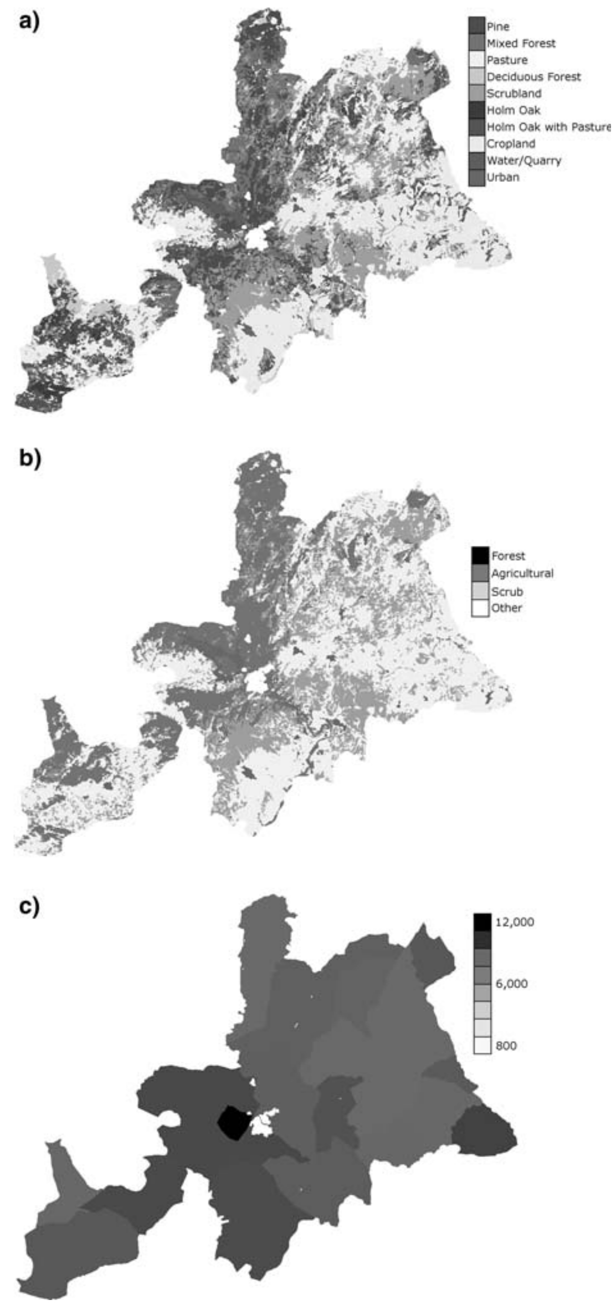

Figure 3. Example land-cover and socioeconomic data maps. **A** 1991 ten-class land cover, **B** 1991 four-class land cover, **C** 1991 population density (person/km^2).

burned areas present in the landscape were removed from the maps (these account for a very small proportion of the landscape). Binary maps of land-cover change (change/no change) were produced for the periods 1984–1991, 1984–1999 and 1991–1999. All maps were subset to identical extents resulting in 884,501 data points (pixels) per map at a spatial resolution of 30 m.

A qualitative land-evaluation technique, based on the MicroLEIS expert system (de la Rosa 1990),

Table 2. Relationship Between Ten- and Four-Class Resolution Land Cover Classifications

Four-class classification	Ten-class classification	Description
Forest	Pine	Primarily *Pinus pinea* and *P. pinaster*
	Transition Forest	Mixed *Pinus, Quercus* and *Juniperus* species
	Deciduous	Primarily chestnut (*Castanea sativa*) and alder (*Alnus glutinosa*) but also *Populus* species
	Holm Oak	*Quercus ilex*
Agrarian	Pasture	Land exclusively reserved for livestock grazing
	Holm Oak with Pasture	Representative of traditional *dehesa* woodland
	Cropland	Cereals, vines, olives, almonds and figs
Scrub	Scrubland	*Cistus, Lavandula* and *Genista* species with *Pinus* and *Quercus* species
Other	Water/Quarry/Urban	–

The ten-class land covers were aggregated into the four classes as shown.

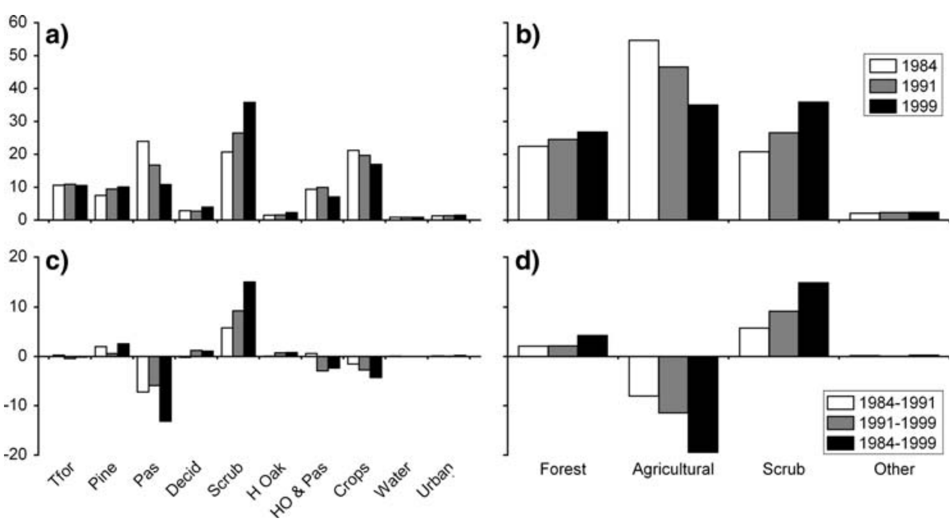

Figure 4. Recent landscape composition and landscape composition change for ten-class (**A** and **C** respectively) and four-class (**B** and **D** respectively) land-cover classifications. Units are percentages of the landscape. Increases in scrubland, commensurate with decreases in agricultural land covers, are observed.

was used to derive 'land capability' from ancillary slope, soil type, erosion risk and climatic data (Romero-Calcerrada 2000). In this context, 'land capability' is an indicator of land 'quality' and provides a measure of the potential of parcels of land for sustainable agricultural development or use. Land capability is considered along a continuum of decreasing resource use (and quality) from arable agriculture, through pastoral agriculture and forestry to 'unusable'.

For each of the six land cover maps, a corresponding map of 'distance to patch edge' was created where map pixels were designated as 'edge' (distance = 0) if at least one of the eight neighboring cells had a different classification to the focal pixel. These maps were derived to examine the importance of landscape structure on LUCC. Maps were also created to quantify the distance from each pixel to the nearest 'urban' pixel, nearest road, and nearest watercourse (both ephemeral and perennial). Maps of distance to urban areas and roads are used as representative of transportation costs (analogous to the von Thünen model of agricultural productivity, Chisholm 1962) and the intensity of human activity (greater activity is more likely nearer these structures); distance to watercourse is a primitive proxy for soil moisture.

Regression Modelling

Generalized linear models (GLMs) are able to model non-normally distributed dependent variables, and thus overcome some of the problems of the assumptions of other linear regression models (Venables and Ripley 2002). Specifically, GLMs can model dependent variables that have distributions from the exponential family (that is, normal, binomial, Poisson, gamma and negative binomial distribution). This is useful for LUCC modelling where the dependent variable is typically a categorical variable. Further, multivariate GLMs may incorporate both continuous and categorical predictor variables (we use the term 'predictor variable' here rather than 'independent variable' to prevent confusion with the term 'independent' in the HP analysis introduced later). As Trexler and Travis (1993) note, and as demonstrated in many of the studies reviewed above, in such cases logistic regression provides an appropriate statistical framework.

GLMs have three components; (1) a dependent variable with a population distribution belonging to the exponential family, (2) the predictor variables, and (3) a 'link function' that links (1) and (2) (Quinn and Keough 2002). For example, the (multivariate) logistic model is:

$$\pi(x) = \frac{e^{\alpha+\beta_1 x_1+\beta_2 x_2+\cdots+\beta_i x_i}}{1+e^{\alpha+\beta_1 x_1+\beta_2 x_2+\cdots+\beta_i x_i}}, \quad (1)$$

Where $\pi(x)$ is the probability that the dependent variable y equals 1, α is the equation constant, and β_i is the coefficient of predictor variable x_i. Consider y as a dependent variable that can potentially take one of J nominal categories, and that these categories are numbered from 1 to J (but not assumed to be ordered). Rather than model Equation 1 directly, the link function (ϕ) allows the dependent variable to be modelled as:

$$\Phi_m = \alpha + x_1\beta_1 + x_2\beta_2 + \cdots + x_i\beta_i, \quad (2)$$

Where m is also a category of y. The probability of observing each category m can now be calculated (where Pr = ($y = m|X$) is the probability of observing m given X, the set of predictor variables) by:

$$\Pr(y = m|X) = \frac{1}{1+\sum_{j=2}^{J} e^{\Phi_j}} \text{ for } m = 1, \quad (3)$$

$$\Pr(y = m|X) = \frac{e^{\Phi_m}}{1+\sum_{j=2}^{J} e^{\Phi_j}} \text{ for } m > 1. \quad (4)$$

To test the statistical significance of the predictor variables in these models, the Wald or likelihood ratio (LR) statistics can be used. However, the Wald statistic is less powerful than the LR statistic (Hosmer and Lemeshow 1989; Venables and Ripley 2002). The LR statistic compares the residual deviance (RD) of the full model (containing all variables) against a reduced model (full model minus the variable of interest):

$$\text{LR statistic} = -2(\log - \text{likelihood}_{\text{reduced}} - \log - \text{likelihood}_{\text{full}}). \quad (5)$$

The LR statistic is compared to the χ^2 distribution, to determine whether the variable has a significant effect on the dependent variable, with:

$$\text{degrees of freedom} = (J-1)(N_{X\text{full}} - N_{X\text{reduced}}), \quad (6)$$

where N_X is the number of predictor variables.

Including spatially-autocorrelated data in regression models violates the assumption of independence between data points (for example, Lennon 2000). Spatial autocorrelation was tested for the land-cover maps here using the row-standardized Moran's I test (Cliff and Ord 1973). Spatial autocorrelation decreased monotonically above a lag of eight map pixels (~ 240 m). Therefore, the raw data were sampled at every tenth pixel in the i and j directions, giving 8,855 independent data points for model calibration (~1% of the data). This method corrects for spatial autocorrelation and has been employed in a number of similar studies (for example, Carmel and others 2001; Cheng and Masser 2003). Coefficient values for the 12 predictor variables were estimated from the training data using the 'multinom' function in R (R-Project 2006). The LR statistic was also calculated in R. A C++ program was used to apply the produced coefficient estimates to predict future land-cover states, based on equations (3) and (4). Multinomial models were run for the ten-class and four-class maps, for all variables, biophysical variables only and socioeconomic variables only. Model performance was evaluated for pixels *not* used for calibration (resulting in 875,646 pixels for evaluation).

A pixel-by-pixel comparison of two maps is often used to assess the proportion of pixels in the projected landscape whose composition was predicted correctly. Alone, however, this simple measure of the models' predictive performance can be misleading. LUCC models frequently fail to provide more accurate predictions than the null model of no change in the landscape, a point that must not be overlooked in their evaluation (Pontius and others 2004). Thus, in evaluating our models, we compare pixel-by-pixel accuracies to the corresponding null model. Pontius (2000) notes that a model with no ability to predict either the quantity or location of categories (for example, land cover) will, by chance alone, correctly predict some proportion of pixels in the landscape (L_C):

$$L_C = \frac{1}{J}, \quad (7)$$

where J = number of categories, in our case land-cover classes. Thus, we can calculate the proportion of those correctly predicted pixels that were predicted correctly *not* by chance (P_{NC}) using:

$$P_{NC} = \frac{L - L_C}{L}, \quad (8)$$

where L is the total landscape pixel-by-pixel prediction accuracy.

We also use Kappa statistics as a simple measure of the extent to which the predicted and observed maps 'match', where Kappa = $K_{\text{Location}} \times K_{\text{Histo}}$, with K_{Location} a measure of similarity of location (comparison of individual pixels' land-cover state between maps) and K_{Histo} a measure of quantitative compositional (comparison of the abundance of land-cover types for entire maps) similarity between maps (Hagen 2002). Using these accuracy measures ensures that model evaluation separates performance in terms of quantities and location (Pontius and Schneider 2001). Finally, we calculate Akaike Information Criteria (AIC) values (Akaike 1978) for each model.

Hierarchical Partitioning

The individual coefficients of a multiple regression model can only be interpreted for direct effects on the dependent variable when the other predictor variables are held constant (James and McCulloch 1990). Chevan and Sutherland (1991) developed hierarchical partitioning (HP) to address this issue. Recently, the method has been extended to provide a statistical method for selecting which variables to retain in a model once they have been ranked for their predictive power (Mac Nally 2002). HP estimates the contribution of each predictor variable to the total variance explained by a model, both independently and in conjunction with all other variables by separating all possible candidate models (that is, combinations of predictor variables) into a set of hierarchies and comparing them. The independent contribution of a predictor variable x_k is calculated by comparing the fit of all models including x_k with their reduced version (that is, omitting x_k from the model) within each hierarchical level. The average improvement in fit for each hierarchical level that considers x_k is then averaged across all hierarchies, giving the independent contribution of x_k (Quinn and Keough 2002). The contribution (to the total explained variance of a model) of a predictor variable in conjunction with all others is found by subtracting the total variance explained by a predictor variable independently from the total variance explained by the predictor variable alone (that is, the total variance explained by that variable in a univariate regression model). Thus, HP does *not* aim to produce any kind of predictive model. Rather, it allows identification of the predictor variables that explain most variance independently of the others, helping to overcome the problems presented by multi-collinearity. HP is a technique that compares multiple models to assess the importance of different variables and so is complementary to multi-model approaches designed to improve understanding of LUCC (for example, Aspinal 2004).

HP was conducted in R (R-Project 2006) using the 'hier.part' package (Walsh and Mac Nally 2004). GLMs were run from the binomial family and the Log-Likelihood goodness of fit measure was used. A logistic model is most appropriate here as the dependent variable is categorical and binary (change vs. no change). A random sample of 8,855 (~ 1% of the data) pixels was taken from each (binary) land-use change map when all changes were considered, but this was reduced to 900 when specific changes between land use categories were considered (as some changes did not occur frequently enough to allow the larger sample size). The statistical significance of each variable (calculated as a pseudo-Z-score) was calculated from 100 randomizations (Mac Nally 2002); this was the most that could be feasibly run with the resources available (100 randomizations for HP of models with 12 variables and 8,855 data points took approximately 24 h using a Pentium 4, 3.2 GHz processor with 512 MB RAM).

Results

Predictive Multinomial Regression Models

All predictor variables used in the multinomial logistic models, for each land-cover classification for each year and time period considered, were found to be statistically significant according to the LR statistic ($p < 0.01$), with the exception of *D_ROAD* (distance to road) for the 1984–1999 and 1991–1999 four class models (for which $p < 0.02$ and $p < 0.33$ respectively, with $df = 3$; Table 3 and Figure 5). On the basis of the pixel-by-pixel accu-

Table 3. Pixel-by-Pixel Accuracy for Full and Null Regression Models

Period	Ten-Class				Four-Class			
	Full model	Null model	Error	P_{NC}	Full model	Null model	Error	P_{NC}
1984–1991	47.8	55.7	7.9	79.1	70.6	73.3	2.7	64.6
1991–1999	54.3	57.0	2.7	81.6	69.9	70.0	0.1	64.2
1984–1999	51.9	49.7	−2.2	80.7	66.0	63.7	−2.2	62.1

Units are percentages of the landscape. Model pixel-by-pixel accuracies are shown for both ten- and four-class land cover resolutions. Accuracies for corresponding null models are presented alongside with errors (null model − full model). The null model assumes no change and is simply the initial landscape upon which the model is based (that is, for a 1984–1991 model the 1984 landscape map is the null model). Ten-class models have greater predictive power when the proportion of correctly predicted pixels in the landscape predicted correctly not by chance is considered (P_{NC}, see Equation. 8).

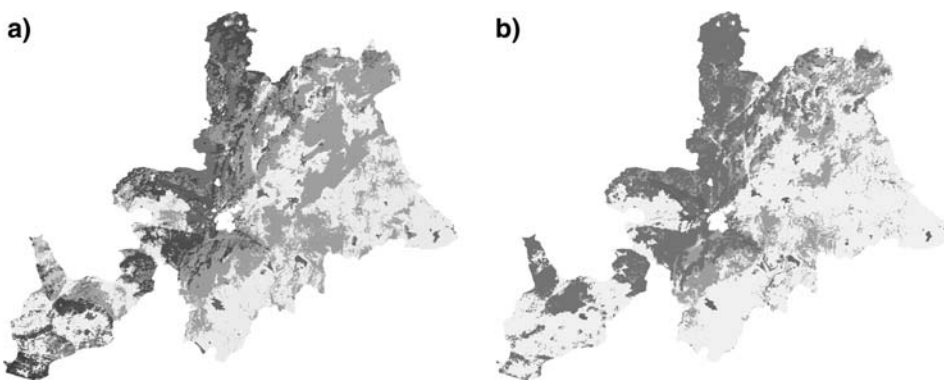

Figure 5. Example landscapes predicted by regression models for 1991 from 1984 for **A** ten-class and **B** four-class land-cover classifications; legends as for Figure 3.

racy measure the four-class models are consistently more accurate than the ten-class models (Table 3); up to 71 and 55% for the four and ten-class models respectively. These values are comparable with those of Carmel and others (2001) who considered a structurally simpler landscape. AIC values were large for all models but four-class models exhibited values approximately half of those for ten-class models (with mean model AIC values of 12,867 and 24,079 respectively). On the basis of the AIC measure, the four-class models are deemed more efficient and parsimonious.

Over shorter periods of change (1984–1991 and 1991–1999) the null model is a more accurate predictor than the regression models on a pixel-by-pixel basis (Table 3); this is common for this type of modelling (Pontius and others 2004). Relative to their corresponding null model, projected maps from four-class models have higher pixel-by-pixel accuracies than those from the ten-class models (Table 3). However, of the percentage of correctly predicted pixels, ten-class model projections achieve a greater proportion than are predicted correctly not by chance (P_{NC} up to 82% and 65% for ten-class and four-class models respectively). Over the longest period observed (15 years; 1984–1999) we observe that; (1) the regression models perform better than the null model and (2) relative to the null model the regression models for the different land-cover classifications are comparable on a pixel-by-pixel basis. The Kappa statistics show broadly similar results (Table 4). Using the standard Kappa statistic the four-class models perform better than the ten-class statistics over all time periods. $K_{location}$ values highlight the diminishing disparity in the performance of the ten-class and four-class models as the length of the period of change increases.

Explanatory Hierarchical Partitioning

All of the variables included in the HP were able to explain a significant proportion of the total variance at the $\alpha = 0.05$ level (Figure 6). *LC* (land cover) and *D_PE* (distance to patch edge) consistently explain the most variance in land-cover change, both independently (*I*) and as joint effects with other predictor variables (*J*). In general, the amount of variance explained by a given variable differs between the periods of change considered, with no consistent trends apparent. However, there are two noticeable differences between the two land-cover classifications in terms of the total explained variance. First, the contribution of independent and joint effects to total explained variance is dramatically different. Joint effects are additive and contribute up to 51% of variance for

Table 4. Kappa, $K_{Location}$, K_{Histo} and AIC Statistics for Regression Models for Each Period Modelled

Period	Ten-Class				Four-Class			
	Kappa	$K_{Location}$	K_{Histo}	AIC	Kappa	$K_{Location}$	K_{Histo}	AIC
1984–1991	0.35	0.43	0.83	24,615	0.54	0.62	0.87	12,281
1991–1999	0.39	0.55	0.70	24,149	0.56	0.59	0.95	13,600
1984–1999	0.35	0.52	0.67	23,474	0.50	0.54	0.93	12,721

Kappa is the product of $K_{Location}$ and K_{Histo}. $K_{Location}$ is a measure of similarity between maps for individual pixels' land cover and K_{Histo} is a measure of similarity between maps for proportional representation of each land cover class. Larger values indicate greater similarity between maps. Lower AIC values indicate greater efficiency, in informational terms, of models.

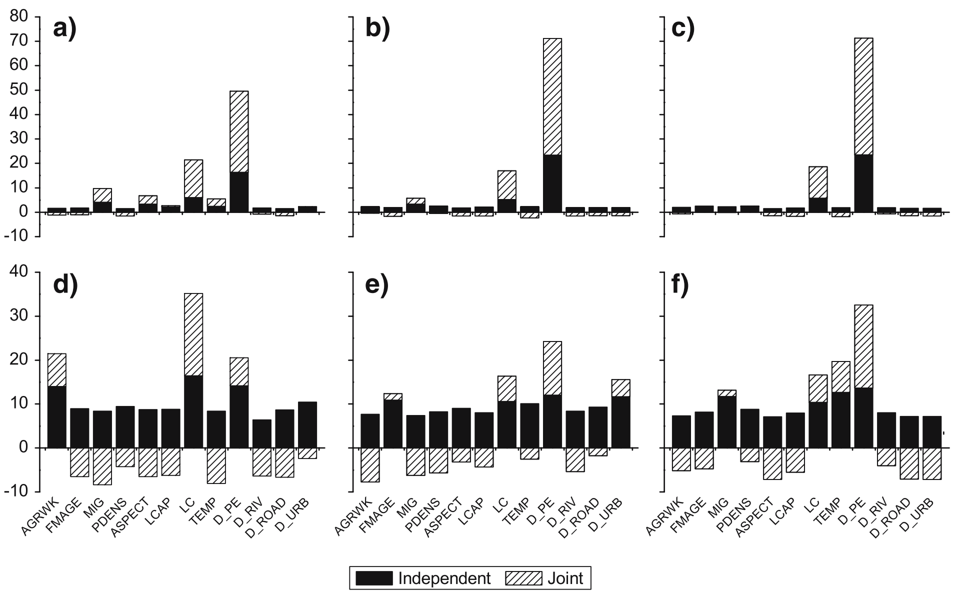

Figure 6. Independent and joint contributions by predictor variables to total variance explained for all LUCC across the periods 1984–1991, 1991–1999 and 1984–1999 for ten-class landscapes (**A**, **B** and **C** respectively), and four-class (**D**, **E** and **F** respectively) landscapes. Contributions are presented as percentages of the total explained variance and may be positive (additive) or negative (suppressive). Variables' abbreviations are as listed in Table 1.

the ten-class models. However, joint effects for the four-class models are suppressive and reduce total variance explained by up to 22%. Second, total explained variance is markedly lower for four-class than for ten-class models across all periods of change considered, explaining 50% less than the corresponding ten-class model. We attribute both differences to the relatively low explanatory power of *D_PE* in the four-class models as compared to the ten-class models; if the contribution of *D_PE* to total explained variance is discounted, the models' total explained variances are comparable.

We also used HP to examine pixels changing from agricultural land to scrubland (as representative of the key process of land abandonment) over the period 1984–1999 (see Figure 4). We used HP to explore the 'agriculture' to 'scrub' transition in the four-class classification and the 'cropland', 'Holm Oak with pasture' (HOP) and 'pasture' to 'scrub' transitions in the ten-class classification (Figure 7). *LCAP* (land capability; 45% of total explained variance), *D_PE* (21%), *FMAGE* (mean farmer age; 11%) and *AGRWK* (percentage of population employed in agricultural sector; 7%) explain the most total variance for the transition from agricultural land to scrubland in the four-class model. Analysis of the three ten-class agricultural-to-scrubland transitions suggests different drivers of abandonment for more 'traditional' agricultural practices compared with relatively more intensive land uses. *LCAP*, *D_PE* and *PDENS* (population density) are the variables that explain most total variance for both cropland and pasture abandonment, but not HOP. *AGRWK*, *TEMP* (mean annual temperature), *D_RIV* (distance to river) and *MIG* (migration) explain most total variance for HOP abandonment, and are the only variables for which joint effects are additive to total explained variance.

Discussion

Statistical LUCC Modelling in the Mediterranean Basin

We have distinguished between the use of regression analyses for the projection of land-use change

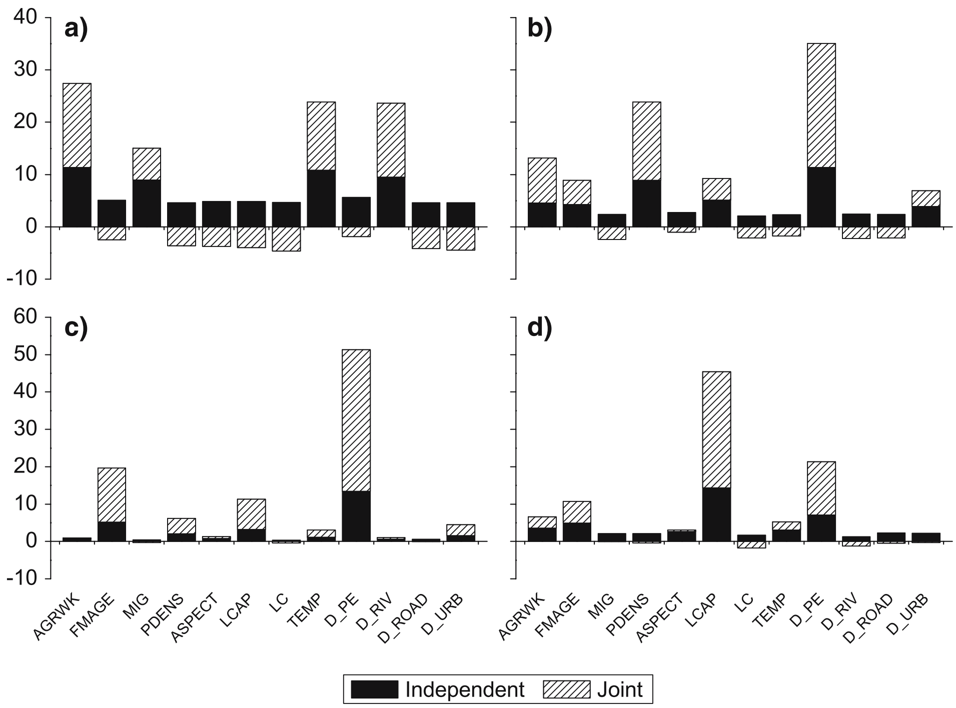

Figure 7. Independent and joint contributions by predictor variables to total variance explained for agricultural to scrub land-cover change; **A** Holm Oak and Pasture to scrub [ten-class], **B** pasture to scrub [ten-class], **C** crops to scrub [ten-class], and **D** agriculture to scrub [four-class]. Variables' abbreviations are as listed in Table 1.

(that is, maps of projected change from multinomial logistic regression models) and for assessing the importance of the drivers of such change (that is, hierarchical partitioning). The success of the regression model projections implemented here differed according to land-cover classification, as expected according to Equation (7). In absolute terms, models based on the less specific four-class classification provided more accurate projections of landscape composition than those derived from the ten-class classification. However, although the ten-class models are less accurate in proportional terms, over longer time periods their performance is similar to that of the four-class models, relative to the null model. Further, when the proportion of the landscape predicted correctly not due to chance is calculated, we find that the ten-class models are 10–15% more accurate on average (Table 3).

Over periods of 7–8 years (1984–1991 and 1991–1999) no model performed better than the null model of no change. However, over a period of 15 years (1984–1999) the regression models had higher predictive accuracy than the null model. The period of time over which regression models become useful (that is, become a better predictor than the null model) will vary by region, depending on the rates at which LUCC is occurring. More than 36 and 50% of pixels in the landscape changed for the four- and ten-class data respectively over the period 1984–1999. Thus, LUCC is occurring rapidly in SPA 56, and the 15-year period at which the null model is bettered is relatively short. Over the longer (15-year) time period considered here, we find that relative to the null model the predictive accuracy of models of different LU classifications is equal. From this perspective, the performance of the ten-class model could actually be considered better than the four-class model when compared to the proportion of the landscape that changed in each classification (and reflected by the proportion predicted correctly not by chance).

Models that included biophysical or socioeconomic variables alone performed poorly relative to models that incorporated both data types in locational terms (K_{Location}). However, models that included only socioeconomic variables continued to perform poorly in compositional terms (K_{Histo}), whereas biophysical variables performed considerably better. Visual examination of the predicted landscapes highlights the failings of either socioeconomic or biophysical variables to predict LUCC adequately without using land cover (*LC*; Figure 8). For example, socioeconomic variables are able to represent LUCC at a 30-m resolution (as they are aggregated at the municipality level), but municipality boundary artefacts are evident.

The poor predictive performance of the socioeconomic variables highlights the problems of using aggregated socioeconomic variables (in this case at the municipality level) in regression techniques that examine LUCC over local to regional extents. Although the literature (for example, Caballero

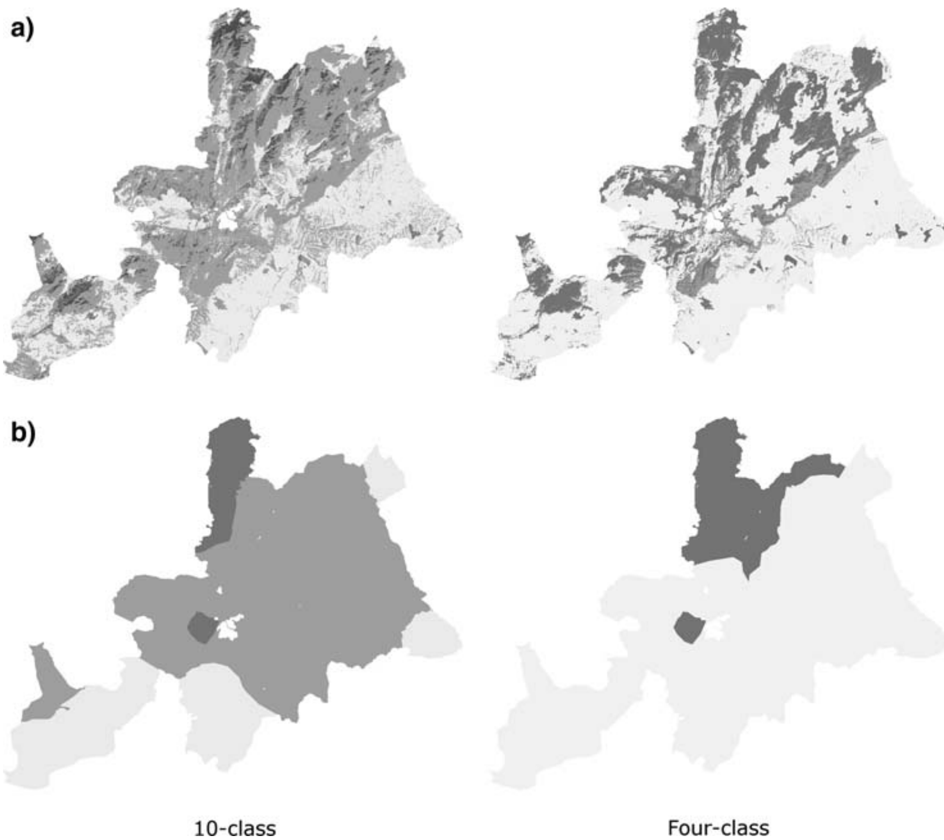

Figure 8. Example ten - class and four-class landscapes predicted by regression models for 1991 from 1984 using **A** biophysical variables only and **B** socioeconomic variables only; legends as for Figure 3.

2001; Hoggart and Paniagua 2001; MAPA 2003; Mazzoleni and others 2004b; Romero-Calcerrada and Perry 2004) and our own 'expert' understanding of the type of agricultural LUCC occurring in the landscape suggest that the level of agricultural employment, the aging and diminishing of the agricultural population of the study area is driving the observed change (from a human-activity perspective), selecting variables solely on the basis of this understanding failed to provide adequate predictive statistical models of change. It is variables at finer scales, such as the age of individual farmers, the structure of individual family farm households, and the income of individual farms, which drive changes in individual land parcels. Data at the 'farm' level (of a quality that will hopefully become increasingly available in SPA 56) could be more suitable for a predictive regression model as the decision-making influences would be represented more explicitly and there has been some progress on incorporating this type of data into regression models (for example, Pan and others 2004; Overmars and Verburg 2005; Pan and Bilsborrow 2005). Further, these findings have highlighted the need to represent farm households as decision-making agents driving land use change in the simulation model we are currently developing.

It should be noted that although our models do not contain any explicitly 'economic' variables (for example, European Size Units, total annual agricultural subsidy received, and so on) they do implicitly assume economic decision-making via the inclusion of 'distance to road', 'distance to urban' (that is, the transportations costs to product and labor markets of the von Thünen model) and 'land capability' (that is, farmers will farm the land that provides greatest yields). There is a clear sense of tradition and culture associated with the way in which land is used in the study area (and other traditional Mediterranean landscapes—Gómez-Límon and de Lucío Fernández 1999; Plieninger and others 2004). Many farms in SPA 56 are small (77% ≤ 5 ha in 1999, INE 2005), are run by farmers past retirement age (49% older than 65 in 1999, INE 2005) and operate at an economic loss. Often these farms are not the primary income for a family but instead provide supplementary income through seasonal crops. In these traditional Mediterranean agricultural landscapes conventional accounting measures have been found to only partially account for total environmental goods and services (Campos and Caparros 2006). However, omitting explicitly economic variables, and the lack of farm-level data, is a drawback of the

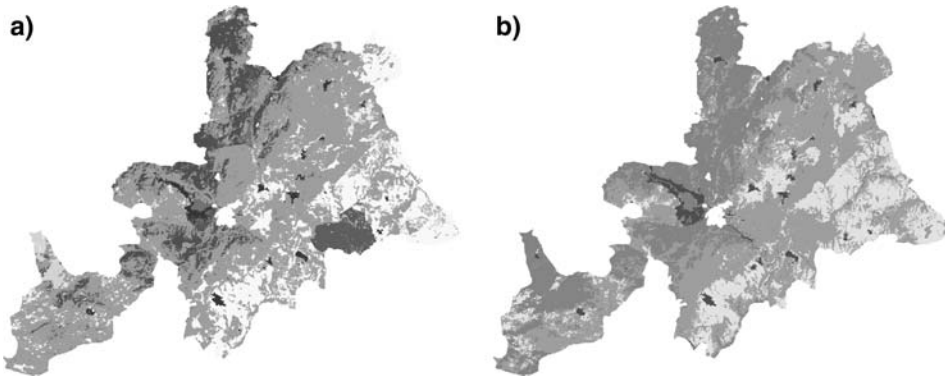

Figure 9. Projected land cover for 2014 using empirical regression models for **A** ten-class and **B** four-class data. Shifts from agricultural land uses to a domination of scrubland are projected in both cases.

implementation of the methods presented here. Specifically, omitted variable bias—the omission of variables that have an influence on the dependent variable and are correlated with other independent variables, producing error in parameter estimates—is certainly a possibility in the models used here. Unfortunately, as one author has recently highlighted, this problem is logically unavoidable (and cannot be solved simply by adding increasing numbers of predictor variables) but can be ameliorated by ensuring appropriate research design (Clarke 2005). To reiterate, the availability and analysis of data at scales that match causal processes is vital to the performance of the regression modelling techniques employed here.

Nevertheless, all the predictive models used here performed comparably to those of Carmel and others (2001), who considered a less complex (that is, fewer land-cover classes and interacting processes driving LUCC) Mediterranean landscape with little anthropogenic pressure. Compared to simpler binary regression models of LUCC (that is, models of change/no change) multinomial models are able to project transitions between particular land covers, and so can be used to extrapolate for LUCC in the future to produce maps of potential land cover by using values of the model coefficients estimated from an observed period with values of the predictor data from the end of that period. Projections for land cover in 2014 (from a model for the observed period 1984–1999) suggest that the current shifts from agricultural land uses to scrubland will continue (Figure 9). However, the quality of these projections is highly dependent upon both the performance of the model over the observed period, and the important assumption that the observed causal processes used to develop the model are stationary. Acknowledgement of this stationarity assumption is perhaps more important (and more likely to be invalid) from a socioeconomic perspective than biophysical. Although biophysical processes may be assumed to be relatively constant over decadal timescales (consideration of climatic change aside) this will not be the case for many socioeconomic processes. With regard to SPA 56 for example, the recent expansion of the European Union to 25 countries, and the consequent likely restructuring of the common agricultural policy (CAP), will lead to shifts in the political and economic forces driving LUCC in the region. Where socioeconomic factors are important components of landscape change, and where these are likely to change during the projected period due to social, economic, political or technological innovation, regression models are unlikely to be useful for future projections and subsequent ecological interpretation.

Hierarchical Partitioning for LUCC Studies

The use of HP to explore the importance of drivers for all agricultural abandonment-type land-use transitions in SPA 56 proved inconclusive. This is possibly due to the suite of independent variables used and the presence of omitted variable bias (as outlined above); the following discussion should be read with these issues in mind. We find that joint effects of ten-class variables are additive but four-class variables suppressive. That is, the combined effect of variables increases the total explained variance (in LUCC) in ten-class regressions, but reduces total explained variance in the dependent variable for four-class models. The aggregated nature of the four-class models means that the broad changes observed (for example, from agricultural land to forested land) masks specific changes within the classes (for example, from pasture to pine or from Holm Oak with Pasture to Holm Oak). These specific transitions may have explanatory variables (that is, causes) that oppose one another for the different specific transitions, thus decreasing the explanatory power of models that use both variables to explain a single broader shift. Examination of smaller 'sub-regions' of the study area that are dominated by particular land-use types may reveal stronger relationships, and may also reduce the suppressive effects of some variables when used jointly in the hierarchical partitioning. By considering more specific transitions, the utility of HP for elucidating important causal factors will increase. This systematic examination of specific LUCC transitions is important for elucidating specific drivers of change, and is one that has been underused in the literature.

The multinomial regression models used here project LUCC spatially, based upon historical landscape dynamics. Such models provide only limited opportunity to draw any conclusions about the importance of individual predictors or the interactions between them. The use of HP, however, highlighted the clear importance of 'distance to patch edge' (*D_PE*) as the predominant contributor to the total explained variance in LUCC (Figure 8). An examination of the proportion of edge pixels that change in ten-class versus four-class landscapes highlights the importance of the contribution of *D_PE* to explained variance; for the periods 1984–1991 and 1991–1999, 15% of four-class 'edge pixels' change, compared with 67% of ten-class 'edge pixels'. Although difficult to explain causally, change may be concentrated at the patch margins either because of the underlying processes driving change in the landscape (abandonment of marginal agricultural land at patch edges or ecological processes such as invasion and colonization of woody shrubs) or due to data classification errors (classification of Mediterranean land cover is notoriously troublesome because of high spatial heterogeneity, for example, Shoshany 2000). The important point however, is the insight potentially provided by HP into the causal importance of predictor variables that multinomial regression modelling is unable to provide.

Summary

Here we have emphasized the two distinct purposes of regression-based models of LUCC: to aid explanation of the processes driving the change or projection of the change itself spatially. Our results highlight that the pixel-by-pixel accuracy of projected maps produced using multinomial logistic models varies for different land-cover classifications and re-emphasize that LUCC regression models frequently fail to reach predictive accuracies as good as the null models of no change. Projected maps were found to have a pixel-by-pixel accuracy of up to 71%, comparable with another study in a less complex Mediterranean-type environment influenced by human activity. Using hierarchical partitioning, we find that more coarse land-cover classifications (that is, fewer classes) cause the joint effects of variables to suppress total variance explained in LUCC. We suggest the use of hierarchical partitioning for the assessment of the importance of causal mechanisms should be useful for LUCC studies in many regions.

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