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Evaluating sampling strategies and logistic regression methods for modelling complex land cover changes

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Summary

1. The role of land cover change as a significant component of global change has become increasingly recognized in recent decades. Large databases measuring land cover change, and the data which can potentially be used to explain the observed changes, are also becoming more commonly available. When developing statistical models to investigate observed changes, it is important to be aware that the chosen sampling strategy and modelling techniques can influence results.
2. We present a comparison of three sampling strategies and two forms of grouped logistic regression models (multinomial and ordinal) in the investigation of patterns of successional change after agricultural land abandonment in Switzerland.
3. Results indicated that both ordinal and nominal transitional change occurs in the landscape and that the use of different sampling regimes and modelling techniques as investigative tools yield different results.
4. *Synthesis and applications*. Our multimodel inference identified successfully a set of consistently selected indicators of land cover change, which can be used to predict further change, including annual average temperature, the number of already overgrown neighbouring areas of land and distance to historically destructive avalanche sites. This allows for more reliable decision making and planning with respect to landscape management. Although both model approaches gave similar results, ordinal regression yielded more parsimonious models that identified the important predictors of land cover change more efficiently. Thus, this approach is favourable where land cover change pattern can be interpreted as an ordinal process. Otherwise, multinomial logistic regression is a viable alternative.

Key-words: land cover change, model accuracy, model selection, multinomial regression, ordinal regression

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Introduction

There is increasing concern within the scientific community about the effects of global changes on ecosystems and ecosystem services (Foley *et al*. 2005). Along with climate change and biological invasions, land cover change is considered one of the most important components of these changes (Vitousek 1994; Fukami & Wardle 2005). Thus, understanding spatial and temporal patterns of land cover change and their resulting effects on ecosystems is one of the important challenges facing ecologists and managers world-wide. One of the most profound land-use and land cover change processes in Europe today is agricultural land abandonment (MacDonald *et al*. 2000). This is particularly evident in Switzerland, where between 1985 and 1997 more than 45 500 hectares of agricultural land (0·015% of the study area) was either converted to settled areas (in the lowlands: *c*. 28 500 ha) or reverted to forest (mainly in steep mountainous areas on marginal land: > 17 000 ha) (SFSO 2001). This represents the continuation of a process which has been under way for over 100 years (Mather & Fairbairn 2000).

Different methods of statistical modelling enable decision makers or land managers to answer different questions (Lambin 1997). One approach to assessing

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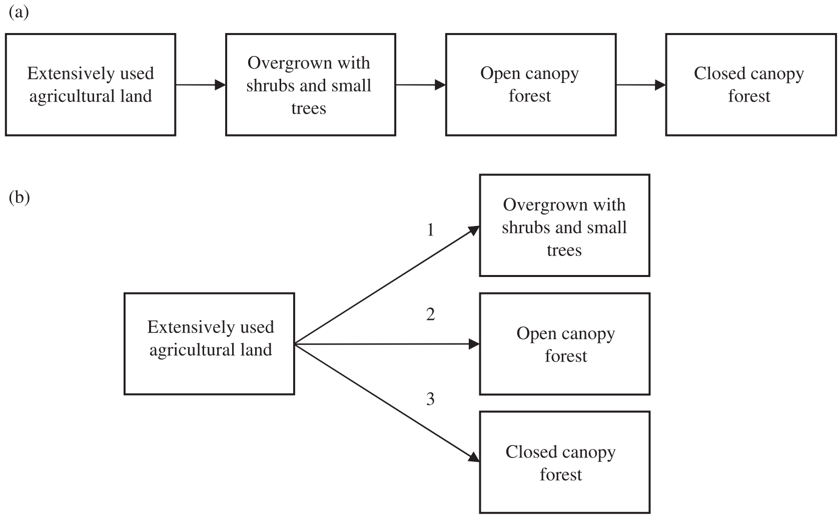

Fig. 1. Conceptual model of land cover change as an ordinal (a) or multinomial (b) process. Labels 1–3 represent the three land cover change types investigated here.

land cover change is to apply the kind of predictive statistical models used widely to predict the distribution of species or habitat types, such as regression techniques (Guisan & Zimmermann 2000). Many statistical modelling methods are currently being used to analyse, describe and understand spatial and temporal patterns of land cover change, of which binary logistic regression is amongst the most common (Aspinall 2004; Verburg *et al.* 2004a). Ordinal and multinomial logistic regressions are both examples of discrete outcome modelling techniques, which allow outcomes with the same initial land cover type to be modelled as a group, and are generalizations of the binomial model (Agresti 1996). Such models are appropriate where transitions starting from one cover type have different possible end states.

Ordinal regression assumes ordinality of the outcomes, e.g. an ordered sequence of change in land cover types between agricultural land-use and forest cover (Fig. 1a) (McCullagh 1980; Guisan & Harrell 2000). It has been used in a few ecological studies that have focused on plant species distributions (Guisan & Harrell 2000; Dirnböck *et al.* 2003), insect development (Manel & Debouzie 1997) and identifying the conservation values of sites (Spooner & Lunt 2004).

Multinomial regression makes no statistical assumptions concerning normality, linearity and homogeneity of variance for the independent variables (McCullagh & Nelder 1989). However, it assumes that the different outcome classes (possible land cover types at t_1) are nominal and that they are mutually exclusive (Fig. 1b) (Agresti 1996). It is possible to model multinomial data in an ordinal way and vice versa, but if the wrong method is used this may introduce bias or loss of efficiency and information (Long 1997). Multinomial logistic regression is being used increasingly in studies of land cover change (Müller & Zeller 2002; Munroe *et al.* 2004) and vegetation dynamics (Augustin *et al.* 2001). However, where the possible new cover types following land abandonment can be distinguished along an axis of successional development (Fig. 1a), ordinal regression is conceptually valid as well. Thus, our first goal was to compare different statistical modelling techniques suitable for land cover change assessment and modelling. In using the two forms of grouped discrete outcome modelling techniques we aimed to test the hypothesis that the land cover transition types under investigation were better predicted by either ordinal or nominal regression models, in which cases we would, respectively, expect the ordinal or multinomial logistic regression model to yield better predictions on the independently sampled evaluation data.

The choice of appropriate statistical models is important, as it can affect the outcome and thus the interpretation of results (Olden & Jackson 2000; Guisan 2002). However, sampling design is often of similar importance, as the performance of individual statistical methods is influenced by the nature and the design of sampling strategies (Guisan *et al.* 2006). Various such strategies can be used in ecological studies, e.g. regularly spaced, random and bootstrap resampling of the entire data set (Guisan & Zimmermann 2000). Resampling techniques allow the user to 'obtain nearly unbiased estimates of model performance, without sacrificing sample size' (Harrell 2001). However, when spatial data are being analysed statistically, using all the available data and resampling it will almost certainly introduce spatial autocorrelation into the models, thus violating assumptions of independence (Wagner & Fortin 2005). Dungan *et al.* (2002) recommend determining the minimum distance needed between sampling points and then drawing either a regular or random sample to eliminate spatial autocorrelation. This method has been implemented successfully (Müller & Zeller 2002), but may lead to problems of small sample size, which is a recognized drawback of some singular empirical

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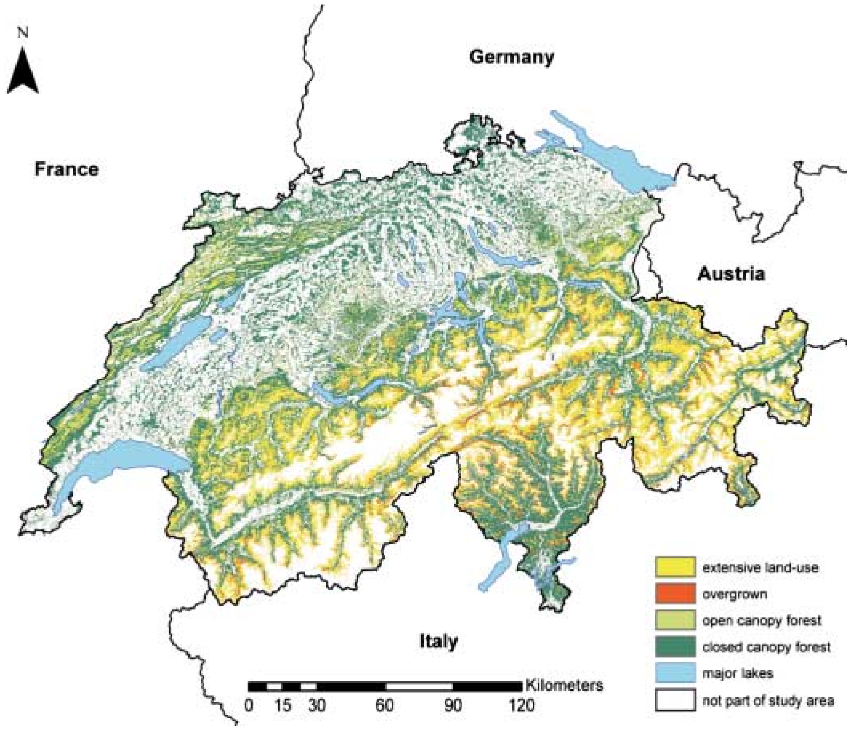

Fig. 2. Map of the study area and the four aggregated land cover classes (state 1997).

models for investigating land cover change (Verburg *et al*. 2004b). A possible solution to the problem of selecting one 'correct' model is multimodel inference and model averaging. Model averaging allows inferences to be made from several models, as opposed to fitting just one model to a particular data set or testing one hypothesis (Burnham & Anderson 1998; Johnson & Omland 2004). The practice of using multiple models to investigate patterns in data is becoming more common in ecological studies (e.g. MacNally 2000; Aspinall 2004) and will probably continue to increase (Clark *et al*. 2001). Thus the second goal of our study was to investigate whether different sampling strategies give rise to different model results and whether a particular sampling strategy appears to favour one modelling technique over the other.

In a continuously evolving landscape, tools that enable managers to monitor, understand and predict land cover changes and the forces behind the changes are invaluable. This is because a better understanding of the processes of land-use and land cover change allows more informed planning and management decisions to be made (Verburg *et al*. 2004b). In this paper our aim was therefore to answer the following questions using the Swiss land-use statistics. (1) How much does the sampling strategy influence model results? (2) Which modelling technique best allows us to predict changes from one initial land cover type to a number of possible end states? (3) From (1) and (2), can we infer transition modes (i.e. ordinal vs. nominal) from spatial and temporal patterns of land cover change and their proximate causal factors?

Materials and methods

STUDY AREA

Switzerland (4·1 million ha) is a mountainous country located in the centre of Western Europe (latitude: 47°00′ N; longitude: 8°00′ E) (Fig. 2; Wachter 2002). The wide diversity of topography associated with altitudes ranging from 193 m to 4634 m a.s.l. contribute to great regional variations in climate. As with the rest of Europe, Switzerland has a long history of human habitation and its landscape is defined by this impact (Tinner *et al*. 2003).

DATA

The response variable represented by land cover was prepared using 18 of the 74 Swiss land-use statistics classes (Sager & Finger 1992) and aggregating them into four classes: extensive agricultural land-use, overgrown, open canopy forest and closed canopy forest. The land-use statistics of Switzerland were recorded for the periods 1979–85 (ASCH85 hereafter) and 1992–97 (ASCH97) by interpreting aerial photographs and allocating each lattice point in a 100-m raster to one of 74 classes. The time span between the two assessments was 12 years for the majority of lattice points, but for 19% it was 13 years. We selected 18 original cover classes for our study and excluded the other classes from our analyses (Table 1). In investigating land cover changes, we considered only the transitions from extensively used agricultural land in 1985 to one of three states in

Table 1. Aggregated classes from the Swiss land-use/land cover statistics (ASCH85 and ASCH97) used in this study. Numbers in parentheses represent the original class codes (Sager & Finger 1992). The criteria used to aggregate the classes are listed

Aggregated class	Classes from Swiss land use statistics	Broad definition
Closed canopy forest	Other forest (10) Normal forest (11) Strips and blocks (14) Bushes (15) Groves and hedges (17)	Vegetation height > 3 m, crown cover density > 60%, composed of tree species
Open canopy forest	On non-agriculturally used land (12) On agriculturally used land (13) Groups of trees on agriculturally used land (18) Other groves (19)	Vegetation height > 3 m, crown cover density 20–60%, composed of tree species
Overgrown areas	Overgrown meadows (84) Overgrown alpine pasture (86) Shrubs and bushes (16)	Vegetation height < 3 m, crown cover density > 50%
Extensive land use	Pasture in the vicinity of settlements (83) 'Maiensässe', hay alps, mountain meadows (85) Sheep alps (87) Favourable to pasturing (88) Stony alpine pasture (89) Grass and herb vegetation (97)	Used for grazing, use not necessarily year-round, not machine-accessible

1997: overgrown with trees and shrubs (11 930 ha), open canopy forest (4836 ha) or closed canopy forest (2064 ha). These new states represent three different stages of successional development.

A pool of potential predictor variables was selected according to factors identified in previous studies and the ecological literature as influencing land cover change and forest succession (Myster & Pickett 1994; Rutherford 2006). These ecologically meaningful factors are mainly biogeophysical and can be summarized broadly into climatic, relief, soil, neighbourhood and distance variables (Table 2). All predictor variables were available as 100-m grids matching the ASCH85 and ASCH97 lattice.

We checked for collinearity of the predictor variables using a hierarchical cluster analysis and selected one representative variable for each group with a Pearson correlation coefficient higher than 0·8 (Menard 2002), which served to reduce data and avoid the presence of multicollinearity in the models (Harrell 2001).

SAMPLING STRATEGIES

We ran three different sampling strategies in order (a) to determine whether different models resulted, and (b) to identify the most effective strategy (i.e. the strategy that produced the best model in terms of predictive accuracy). The three subsampling strategies were:

1. Same: an equal number of 250 random data points for each of four land cover transitions = 1000 points. The 'no change' transition means that extensive grasslands remain the same during the 12 study years. This strategy was chosen based on previous analyses of all possible changes between the five land cover types, where the least common change (overgrown to intensively used agricultural land) occurred on only 250 hectares.

2. Quarter: a random sample of one-quarter of the three observed land cover transitions representing a change in land cover = 4785 points. A smaller sample of a quarter of all points was chosen rather than half, due to computational capacity.

3. Regular: a regular sample of those data points that only show cover transitions, with data points 500 m apart in both *x*- and *y*-directions = 719 points.

The distance of 500 m apart in the *x*- and *y*-directions was selected on the basis of previous investigations into the presence of spatial autocorrelation in binary logistic regression models of land cover transitions (Rutherford 2006). Ideally the points would be 1000 m apart, at which distance spatial autocorrelation would have been absent, but this would have yielded a very small sample size. Both the 'quarter' and 'regular' strategies were designed to represent correctly the correct proportions of each land cover transition type and were hypothesized by us to be the more effective sampling strategies. We eliminated the no change class from these latter two sampling strategies to reduce the influence of the much more prevalent event (Manel *et al*. 2001; Pontius *et al*. 2004a), and because we were interested ultimately in comparing the systematic changes in land cover to each other, and not necessarily to the static state. For each sampling strategy, we sampled an independent data set without replacement from the original data pool by the same methods (data-splitting) for subsequent model evaluation (Wear & Bolstad 1998).

MODEL FITTING

For multinomial regressions, we fitted a saturated model (terms up to quadratic form; no interactions) in R (R Development Core Team 2006) using the multinom() function in the nnet package (Venables & Ripley

Table 2. Independent variables used to calibrate the predictive models explaining the three land cover transitions between grassland and forest. All grids were available at 100 m spatial resolution

Variable	Abbreviation	Unit	Proxy for	Source
Climate-related variables				
Yearly moisture index	MIND*y*	cm/100	Small-scale water availability	CSD/DEM25
Yearly direct solar radiation	SDIR*y*	kJ/day	Energy input, drought stress	CSD/DEM25
June direct solar radiation	SDIR*6*	kJ/day	Energy input, drought stress	CSD/DEM25
Annual average temperature	TAVE*y*	°/year	Potential evapotranspiration Growing degree days, elevation	CSD/DEM25
Continentality index	CIND		Large-scale weather pattern	CSD/DEM25
Annual average precipitation	PRCP*y*	(1/10 mm)/year	Total water input to system	CSD/DEM25
No. of summer precipitation days	PDAY	number	Frequency of rainfall	CSD/DEM25
May average precipitation	PRCP*5*	(1/10 mm)/month	Precipitation during growing season	CSD/DEM25
Relief-related variables				
Slope	SLOPE	°	Diffuse solar radiation	DEM25
Topographic position	TOPOS	– ∞ to + ∞	Exposure of site, drought	DEM25
Topographic wetness index	TWI		Moisture accumulation	DEM25
Site water balance	SWB	(1/10 mm)/year	Available soil moisture	CSD/DEM25
Soil-related variables				
Soil depth	SDEP	cm	Soil water and nutrient availability	BEK200/DEM25
Soil permeability	SPRM	cm/day	Water infiltration, risk of drought	BEK200/DEM25
Soil stoniness	SSTO	%	Water holding capacity	BEK200/DEM25
Neighbourhood variables				
No. of closed canopy neighbours	#CCAN	number/25	Woody species seed source	ASCH85
No. of open canopy neighbours	#OCAN	number/25	Woody species seed source	ASCH85
No. of overgrown neighbours	#OVGN	number/25	Woody species seed source Density of abandonment	ASCH85
No. of extensively used neighbours	#EXTN	number/25	Density of extensive use	ASCH85
No. of intensively used neighbours	#INTN	number/25	Density of intense use	ASCH85
Distance variables				
Distance to roads	DRDS	m	Accessibility	Vector25
Distance to settlements	DSET	m	Accessibility	SGCH
Distance to avalanches	DAVS	m	Snow-related disturbance Propensity for future avalanches	DADB

CSD: climate station data from the period 1961–90. DEM25: digital elevation model for Switzerland at 25 m resolution from the Swiss Federal Office of Topography (SwissTopo). BEK200: soil suitability map 1 : 200 000 (Bodeneignungskarte der Schweiz, SFSO, 1992). ASCH85: Swiss land-use statistics 1985 (SFSO 2001). Vector25: mapped street data, Vector 25 © 2006, Swiss Federal Office of Topography (DV033594). SGCH: settled areas of Switzerland (Siedlungsgebiete der Schweiz, SFSO, 1992). DADB: destructive avalanches database (SLF, 2006).

2002) and reduced the model by performing a backward stepwise procedure, using the Akaike information criterion (AIC) for variable exclusion. For ordinal regression, we fitted a saturated proportional odds regression model to our data (terms up to quadratic form; no interactions) using the lrm() function of the Hmisc and Design packages (Alzola & Harrell 2002) in R and then reduced the model by performing a backward selection using the model AIC as the criterion for variable exclusion. Both methods predict the most likely transition directly, which is an advantage over fitting models for each transition individually. Although AIC values may possibly be influenced by the presence of spatial autocorrelation in the model residuals it is still used commonly as a model selection criterion. A possible solution to this could be to include a dummy variable representing the spatial relationship of the model residuals, thus ensuring that the statistical assumption of independence would be fulfilled.

MEASURES OF MODEL FIT AND ACCURACY

The many measures of model accuracy in use today include area under the curve (AUC), kappa and correct classification rate (CCR). Harrell (2001) discusses some of the arguments against the use of CCR and the advantages of AUC, which is independent of the prevalence of a positive response, provided that the prevalence is neither very low nor very high (McPherson *et al*. 2004). The kappa statistic corrects for chance agreement and has been used increasingly in land-use and land cover change studies (Monserud & Leemans 1992; Müller & Zeller 2002). MacPherson *et al*. (2004) recommend the use of AUC, stating that the kappa statistic is also sensitive to outcome prevalence, but they did not assess the behaviour of weighted kappa (Cohen 1968). Given the advantages and disadvantages of the various measures of model accuracy, and given that the appropriate measure of accuracy can depend on the question being investigated (Guisan & Zimmermann 2000), there may be good reason to use several measures for any given study (Fielding & Bell 1997).

One of the early uses of the kappa statistic in ecological studies was in remote sensing for assessing the accuracy of land cover maps derived from satellite images, i.e. for nominal data (Monserud & Leemans 1992). Kappa can be weighted (e.g. Fleiss–Cohen weights), giving more importance to more similar classes while remaining

Table 3. Predictor variables resulting from the backward stepwise regression for three sampling strategies and the multinomial and ordinal logistic regressions. 'Same', 'Reg', and 'Quarter' stand for the three sampling schemes, 'Multi' and 'Ord' represent the multinomial and the ordinal regression models, respectively. Abbreviations of variables are according to Table 2

	Same		Regular		Quarter		
Predictor variables	Multi	Ord	Multi	Ord	Multi	Ord	Presence numbers
TAVE*y*		x	x		x	x	6
^2	x	x	x	x	x	x	
PRCP*y*	x		x	x	x	x	5
^2	x			x	x	x	
PRCP*5*	x				x	x	4
^2	x		x		x	x	
MIND*y*	x	x			x		3
^2	x				x		
PDAY	x		x	x	x		4
^2			x	x	x		
SDIR*y*		x	x		x		4
^2	x	x			x		
SDIR		x			x	x	5
^2	x		x		x	x	
CIND			x	x	x	x	4
^2			x	x	x	x	
SLOPE				x	x		2
^2					x		
TOPOS	x				x		2
^2					x		
SWB	x				x	x	3
^2					x	x	
SDEP	x				x		2
^2	x				x		
SSTO					x		1
^2					x		
#CCAN	x	x	x		x		4
#OCAN	x	x	x		x	x	5
#OVGN	x	x	x	x	x	x	6
#EXTN			x	x	x	x	4
#INTN					x		1
DSET	x		x	x	x		4
^2	x				x		
DRDS					x		1
^2					x		
DAVS	x	x	x	x	x	x	6
^2	x	x			x		
Total number of variables	15	8	13	9	21	10	

fully chance-corrected (Cohen 1968), i.e. where a class is incorrectly predicted, more weight is given to its kappa if it is predicted as a similar class as opposed to a dissimilar class. We calculated the kappa statistic for each model as a whole (i.e. all classes evaluated at once) using the Kappa() function of the vcd library in R (Meyer *et al*. 2005) with Fleiss–Cohen weights (Fleiss & Cohen 1973). Despite the fact that the CCR is influenced by the prevalence of positive outcomes (Harrell 2001), we chose to use it as an additional measure of model performance, particularly as we were investigating different sampling strategies. By using it we were able to ascertain at which state the points were being falsely predicted. Müller & Zeller (2002) also followed this method in checking the predictive ability of their multinomial model for land cover change. As a further measure, we calculated the AUC (Swets 1988) for each outcome individually using the performance() function from the ROCR library (Sing *et al*. 2004), which is a measure independent of a cut-off level. All measures were determined for both the calibration and independently sampled evaluation data sets. This allowed us to check for (a) overfitting of the model (Pontius *et al*. 2004b); and (b) agreement between both data sets (Wear & Bolstad 1998).

MODEL SIMILARITY

We checked for model similarity based on the presence/absence of predictor variables, by calculating the Jaccard dissimilarity index in R. This was performed using the vegdist() function in the vegan package (Oksanen 2006). We then performed an average linkage agglomerative cluster analysis using the daisy() and agnes() functions from the cluster package (Maechler 2005) and plotted the dendrogram to visualize model similarity.

Results

CALIBRATION OF THE SIX REGRESSION MODELS

A summary of the statistically significant variables showed some striking similarities among the models, irrespective of sampling strategy and modelling technique (Table 3). In general, climate and neighbourhood variables were most commonly retained. These included three variables – annual average temperature, number of already overgrown neighbours in 1985 and distance to destructive avalanche sites – that were present in all six models. Annual average precipitation, June direct solar radiation and the number of open canopy forest neighbours in 1985 remained in five of the six models. In four of six models the following variables were retained: May average precipitation, number of precipitation days per year, annual direct solar radiation, continentality, the number of closed canopy forest neighbours in 1985, the number of extensively used neighbours in 1985 and distance to settlements. Soil stoniness, the number of intensively used neighbours in 1985 and distance to roads remained only in the multinomial model calibrated using the random sample of a quarter of all points. This model retained all variables after the stepwise selection. The multinomial regression models were in all cases more complex than their ordinal counterparts, in that they retained a greater number of predictor variables following a stepwise reduction of the saturated model.

The Jaccard indices showed differences between models based on the presence/absence of predictor variables (Table 4). The models showing the greatest similarity were multinomial models using the same number of sample points per transition type (SM) and using a quarter of randomly selected points (QM), which yielded a dissimilarity coefficient of 0·43. The two models calibrated using the regular sampling method (RM and RO) were also more similar to each other than to the other

Table 4. Dissimilarity matrix showing the Jaccard dissimilarity coefficients for the six models, where similarity is determined by the presence/absence of particular predictor variables, subsequent to the backward stepwise regression. Coefficient values approaching 0 indicate similarity and those approaching 1 indicate dissimilarity

	Same multi	Same ordinal	Regular multi	Regular ordinal	Quarter multi
Same, ordinal	0·67				
Regular, multi	0·63	0·65			
Regular, ordinal	0·73	0·85	0·44		
Quarter, multi	0·43	0·70	0·57	0·68	
Quarter, ordinal	0·63	0·71	0·48	0·60	0·57

Table 5. Area under the curve (AUC) values for the calibration data sets for each land cover change, under each modelling and sampling strategy. The differences between the values for the calibration and evaluation data sets are shown

Land cover change	Model and sampling strategy					
	SM	SO	RM	RO	QM	QO
0	0·78 – 0·01	0·50 – 0·00	–	–	–	–
1	0·65 – 0·03	0·45 + 0·01	0·64 + 0·01	0·69 + 0·03	0·65 – 0·01	0·71 – 0·02
2	0·69 – 0·03	0·46 + 0·02	0·66 + 0·02	0·69 + 0·02	0·67 – 0·03	0·70 – 0·03
3	0·68 – 0·03	0·63 – 0·00	0·52 – 0·01	0·50 – 0·00	0·51 + 0·01	0·50 – 0·00

0 = no change; 1 = change to overgrown; 2 = change to open canopy forest; 3 = change to closed canopy forest; SM = same number, multinomial model; SO = same number, ordinal model; RM = regular, multinomial model; RO = regular, ordinal model; QM = quarter, multinomial; QO = quarter, ordinal.

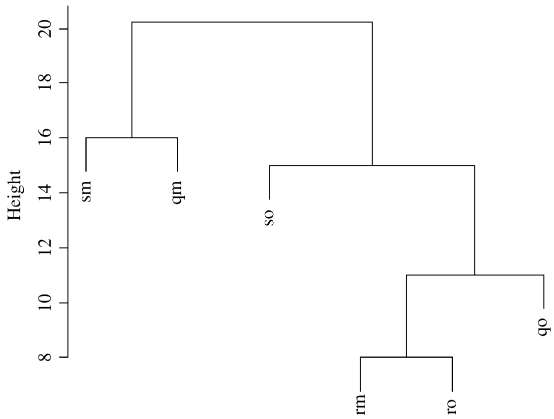

Fig. 3. Dendrogram showing the model groupings according to their similarity based on the presence/absence of predictor variables. Height refers to the average 'distance' between the clusters; sm = same number of sample points, multinomial regression; so = same number of sample points, ordinal regression; rm = regular sample, multinomial model; ro = regular sample, ordinal model; qm = quarter random sample, multinomial model; qo = quarter random sample, ordinal model.

models (dissimilarity coefficient = 0·44). The least similar models were the ordinal regression models with a regularly spaced sample (RO) and with a sample of the same number of points per transition type (SO) (dissimilarity coefficient = 0·85). The dendrogram of the cluster analysis confirmed these statements (Fig. 3). Note that the nature of the two most similar groupings differed in terms of sampling and modelling strategy. The multinomial models appeared to be inherently more similar to one another (SM, QM) than ordinal models. Similarly, models calibrated using a regularly spaced sample (RM, RO) were more similar than other strategies.

SAME NUMBER OF SAMPLE POINTS PER TRANSITION, MULTINOMIAL REGRESSION (SM)

The AUC values for this model were highest for the no change transition (calibration data: 0·78; evaluation data: 0·77) and the change to overgrown (calibration data: 0·65; evaluation data: 0·62) (Table 5). On average, only about half of all points were predicted correctly (Table 6). The best predicted were those that remained the same (no change) in the 12-year study period (68·4%). The outcome that was predicted least correctly was the change to overgrown (38·40%). Misclassifications to other classes were distributed evenly for the no change transition and change to overgrown transition. In contrast, the highest incidence of misclassification of open canopy forest were closed canopy forest and vice versa. The weighted and unweighted kappa values differed somewhat (weighted: 0·46; unweighted: 0·35), indicating that there was some likelihood of similar classes being classified as one another.

SAME NUMBER OF SAMPLE POINTS PER TRANSITION, ORDINAL REGRESSION (SO)

The overall percentage of correctly classified points was low, which can be largely attributed to the very high misclassification rates of the classes 'closed canopy forest' (CCR = 3·6%), mainly as 'open canopy forest' (Table 7),

Table 6. Observed vs. predicted land cover transitions according to the multinomial logistic regression model calibrated using the same number of sample points per land cover change. The predicted values were calculated using the evaluation data set

	Predicted by model				
Observed	Same	Overgrown	Open canopy forest	Closed canopy forest	% correct
Same	171	26	29	24	68·40
Overgrown	46	96	56	52	38·40
Open canopy forest	30	31	126	61	50·40
Closed canopy forest	31	46	53	120	48·00
Total predicted	278	201	264	257	

Table 7. Observed vs. predicted land cover transitions according to the ordinal model calibrated using the same number of sample points per land cover change. The predicted values were calculated using the evaluation data set

	Predicted by model				
Observed	Same	Overgrown	Open canopy forest	Closed canopy forest	% correct
Same	86	115	49	0	34·40
Overgrown	10	101	136	3	40·40
Open canopy forest	0	84	163	3	65·20
Closed canopy forest	0	59	182	9	3·60
Total predicted	96	359	530	15	

Table 8. Observed vs. predicted land cover transitions according to the multinomial model calibrated using a regularly spaced selection of sample points per land cover change. The predicted values were calculated using the evaluation data set

	Predicted by model			
Observed	Overgrown	forest	Open canopy forest	Closed canopy % correct
Overgrown	419	58	0	87·84
Open canopy forest	94	95	1	50·00
Closed canopy forest	58	18	1	1·30
Total predicted	571	171	2	

Table 9. Observed vs. predicted land cover transitions according to the ordinal model calibrated using a regularly spaced selection of sample points per land cover change. The predicted values were calculated using the evaluation data set

	Predicted by model			
Observed	Overgrown	forest	Open canopy forest	Closed canopy % correct
Overgrown	349	134	0	73·17
Open canopy forest	50	139	1	73·16
Closed canopy forest	29	48	0	0
Total predicted	428	321	1	

and 'no change' as either 'overgrown' or 'open canopy forest'. Both transitions to overgrown and open canopy forest areas were classified more effectively from this model (40·4 and 65·2%). More than half the overgrown points were classified as open canopy forest. The latter was the only class which was predicted well. Transitions to closed canopy forest were rarely predicted (15 times of 1000) in contrast to those to open canopy forest (530 times). All AUC values were low for this model ranging from 0·45 to 0·63 (Table 5). The weighted and unweighted kappa values differed greatly (weighted: 0·43; unweighted: 0·15), indicating that similar classes were likely to be classified as one another.

REGULAR SELECTION OF CHANGE ONLY POINTS, 500 M APART IN *X*- AND *Y*-DIRECTIONS, MULTINOMIAL REGRESSION (RM)

The influence of outcome prevalence on CCR was also evident in this model, where the most common outcome was best predicted (87·84%), and falsely classified points were predicted as the most common transition (overgrown) (Table 8). Only two points were predicted as closed canopy forest. The AUC values, ranging from 0·51 to 0·68 (Table 5) indicate poor accuracy (Swets 1988). The weighted and unweighted kappa values (0·22; 0·31) were both fairly low.

REGULAR SELECTION OF CHANGE ONLY POINTS, 500 M APART IN *X*- AND *Y*-DIRECTIONS, ORDINAL REGRESSION (RO)

The regular sample ordinal regression model showed the highest correct classification rates of all the models and sampling strategies, with 73% of the observed changes to both overgrown and open canopy forest areas being predicted correctly (Table 9). Closed canopy forest was predicted only once. The weighted and unweighted kappa values were similar (0·35; 0·34). The AUC values (Table 5) for the changes to overgrown (calibration: 0·69; evaluation: 0·72) and open canopy forest (calibration: 0·69; evaluation: 0·71) indicate that they are useful for applications (Swets 1988).

RANDOM SELECTION OF A QUARTER OF ALL POINTS REPRESENTING A CHANGE, MULTINOMIAL REGRESSION (QM)

The influence of outcome prevalence on the CCR was highly evident using this sampling strategy and modelling technique, where the most common outcome (overgrown) had a high CCR (87·96%) and the least common (closed canopy forest) a very low CCR (3·82%) (Table 10). This is supported by the fact that a high number of open and closed canopy forest points were classified falsely as the most common transition, i.e. overgrown. The AUC values ranged from 0·51 to 0·68 (Table 5), indicating low accuracy (Swets 1988). Both kappa values were low and similar (weighted: 0·23; unweighted: 0·27).

RANDOM SELECTION OF A QUARTER OF ALL POINTS REPRESENTING A CHANGE, ORDINAL REGRESSION (QO)

Overgrown areas and open canopy forest were predicted successfully for 70·0% and 69·3% of points, respectively

Table 10. Observed vs. predicted land cover transitions according to the multinomial model calibrated using a random selection of a quarter of sample points per land cover change. The predicted values were calculated using the evaluation data set

	Predicted by model			
Observed	Overgrown	Open canopy forest	Closed canopy forest	% correct
Overgrown	2681	348	19	87·96
Open canopy forest	694	501	15	41·40
Closed canopy forest	336	143	19	3·82
Total predicted	3711	992	53	

Table 11. Observed vs. predicted land cover transitions according to the ordinal model calibrated using a random selection of a quarter of sample points per land cover change. The predicted values were calculated using the evaluation data set

	Predicted by model			
Observed	Overgrown	Open canopy forest	Closed canopy forest	% correct
Overgrown	2126	922	0	70·0
Open canopy forest	371	839	0	69·3
Closed canopy forest	176	322	0	0·0
Total predicted	2673	2083	0	

(Table 11). However, in all cases the model failed to predict transitions to closed canopy forest. The effect of outcome prevalence was less evident in the ordinal regression method compared to the multinomial model above, where the CCR for overgrown and open canopy forest were approximately equal. Falsely classified closed canopy forest tended to be classified as open canopy forest rather than the most common transition (overgrown). This, and the fact that closed canopy forest was not predicted, shows that the model did not distinguish between open and closed canopy forest. The weighted and unweighted kappa values were similar (0·31; 0·29). The AUC values (Table 5) were 'useful' for both the change to overgrown (calibration: 0·71; evaluation: 0·69) and open canopy forest (calibration: 0·70; evaluation: 0·67) (Swets 1988).

Discussion

We have provided an example of using several models to identify the most important relationships between variables. How a modeller or manager may approach this depends also upon the purpose of the study, where 'prediction' requires a single best model fit and 'explanation' of pattern may be answered more effectively by the use of multiple models (MacNally 2000). Irrespective of sampling strategy or type of modelling, several variables were retained consistently in our models after the stepwise regression, indicating their proximal importance. The composition of the neighbourhood, a proxy for propagule availability, annual average temperature, direct solar radiation, precipitation and continentality (a measure of large-scale weather pattern, particularly related to temperature and precipitation) are the variables most commonly present. This result seems ecologically meaningful, as we would expect these variables to influence the rate of secondary succession (Myster & Pickett 1994; Donnegan & Rebertus 1999; Duncan & Duncan 2000).

Our results indicate that the models that fitted the data best were not necessarily those that were the most similar in terms of the predictor variables remaining after stepwise elimination. Two relatively dissimilar models were shown to fit the data better than all others in terms of the diagnostic tests we used here (CCR, kappa, AUC) – the ordinal model using the regularly spaced selection of sample pixels per outcome and the ordinal model with the random selection of a quarter of all pixels representing a change transition. This is further evidence that there is generally more than one plausible model that can be fitted to data (Aspinall 2004). It also indicates the importance of a chosen sampling regime and the effect that it can have on results yielded (Olden & Jackson 2000).

There were more predictor variables retained in the multinomial models than that of the ordinal models. Preference may be given here to a simpler model, i.e. with fewer variables, due to the principal of parsimony (Harrell 2001), despite the fact that relationships between predictor and outcome variables can be as complex as a model with many variables might reflect. However, if the nature of the process under investigation is truly ordinal, then including that ordinality yields a model which can be more easily interpreted (Agresti 1996). It seems from our results that both direct (nominal) transitions and successive (ordinal) transitions occurred in the landscape, and a particular sampling strategy may emphasize one type rather than the other. Results showed a pronounced lack of distinction between open and closed canopy forest, especially those of the ordinal regression models. We attributed this to three factors: (a) we may not have the data for the variables which truly distinguish the two classes, such as disturbance and historical land-use data; (b) the Swiss land-use statistics classes based on aerial photograph interpretations are not necessarily the same as a given ecological interpretation (Sager & Finger 1992), and thus our aggregations are not necessarily ecologically accurate (only percentage density in canopy cover separates the two classes according to our definitions, which does not take into account that some of the 'open canopy forest' is still agriculturally used); (c) there may be either positional or photo-interpretation error in the data, for which we do not have a measure of magnitude. The other explanation is that the proposed sequence of open to closed canopy forest is not, in fact, ordinal. The process can be construed as ordinal in terms of the broad sequence of land-use to overgrown to forest, as reflected by the good fit of two of the ordinal regression models and their successful classification of overgrown and open canopy forest categories. We suggest that the latter part of the process (succession to closed canopy forest) is represented more effectively by a nominal scale, as evidenced by the multinomial model's successful classification of some, albeit few, closed canopy forest pixels. This reflects more effectively the possibility that our open canopy forest class is not necessarily the forerunner of our closed canopy forest class, and takes into account the fact that some of the classes within our open canopy forest category are still used for grazing purposes. As an alternative approach, we could have combined the open and closed forest canopy classes in to a simple forest category. We chose not to do so, as we suspected that the process was ordinal but that the assumptions of ordinality may not have been entirely fulfilled (e.g. not all of the predictor variables were accordingly ordinal in nature).

The differences between the AUC values of the calibration and evaluation data sets were not large for any transition or any model. This further suggests statistical robustness, in the sense that the models are not over-fitted and that our samples are representative of the whole data set, even when the predictive power is not high. In general, the different measures of accuracy, fit and predictive power reflect different aspects of 'model quality'. The AUC rendered values for each transition within each model, as did the CCR, whereas we used the kappa statistic here as an overall value for each model. Despite the fact that the CCR and kappa statistics are prevalence-dependent, they still yield useful information to the user, as prevalence is often part of the judgement. The comparably low model quality can be explained by the high local variability and stochasticity of land use change processes (Braimoh 2005). Aggregating local points to larger analysis units may be a solution for this, although the ecological detail of identifying local causes may be lost if such a regional-scale aggregation were to be implemented.

The results presented here are relevant for landscape managers and ecological modellers alike, highlighting the need for consideration of different analytical approaches. As Johnson & Omland (2004) and Aspinall (2004) state, fitting multiple models to data is a valid and useful method of data analysis. This study has shown how inferences (in this case about aspects of land cover change) may be drawn from a set of discrete outcome models. We have identified successfully some of the proximate and underlying factors influencing the successional patterns under investigation. We have also shown that ordinal logistic regression, until now not employed commonly in ecological or land cover change research, is a useful tool in such investigations and can be used to predict future land cover changes based on the processes driving them. However, with too few classes that follow an ordinal sequence, multinomial models are still a valid approach for land cover change analyses and predictions.

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