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Dormant categories and spatial resolution affect the perception of land cover change model performance

1. Introduction

- 1 Demographic, socio-economic and environmental factors provoke unprecedented land cover changes. Globally land cover change is driven by population growth, migration, and in many countries by rural to urban transitions ; other factors include rising competition for land, conservation policies, and a myriad of socio-economic and political dynamics (Müller and Munroe, 2014 ; Munroe and Müller, 2007). The Mediterranean area is subject to significant land cover change due to rapid urban growth, tourism, and diverse socio-economic factors (Cori, 1999 ; Geri et al., 2011 ; Parcerisas et al., 2012 ; Serra et al., 2008 ; Van Eetvelde and Antrop, 2004). Coastal development and abandonment of marginal lands are frequently cited in the literature as dominant trends (Calvo-Iglesias et al., 2009 ; Sluiter and de Jong, 2007), but other land cover transitions, such as intensification of agriculture and suburban sprawl, are common (Falcucci et al., 2007 ; Geri et al., 2011).
- 2 In order to help land use managers and policy makers develop sustainable land use management plans, complex transition processes must be identified (Alo and Pontius, 2008). Several modelling techniques have been developed to explore and predict land cover change (Barredo et al., 2003 ; He et al., 2008), and topographic and socio-economic factors are considered important drivers in understanding and predicting land cover evolution (Munroe and Müller, 2007). However, land cover change prediction accuracy depends not only on the relevance of explanatory variables but also on several other variables : type and number of land cover categories, historical and future time intervals (Roy et al, 2014a), and spatial extent and resolution (Chen and Pontius, 2011), so the nature of geographic information is of prime importance.
- 3 Spatial extent refers to the overall size of a particular area (Turner et al., 1989 ; Qui and Wu, 1996 ; Wu, 2004 ;). A review by the authors of about 27 recent studies (2001-2014) using Ca-Markov and Multi-Layer Perceptron Neural Network (MLPNN) modeling tools reveals that spatial extent ranged from 114.4 km² to 20,000 km² (mean and median values of 3,056.3 km² and 1,200 km², respectively). If land cover change is distributed homogeneously throughout space, then spatial extent probably has little impact on model prediction outcome. However, frequently, perhaps even generally, this is not the case, and an increase in spatial extent often corresponds to an increase in the surface area of one or two large relatively stable categories (forest, for example) around a core (or cores) of actively evolving land covers. Increasing spatial extent can introduce new land cover change dynamics (Kok and Veldkamp, 2001) or land cover categories (Turner et al., 1989), but in this paper, larger spatial extent will be considered synonymous with increasing the proportional area of a relatively dormant category.
- 4 Dietzel and Clarke (2004) proposed guidelines on spatial resolution (10 m-1,000 m) for urban simulation models and found that finer resolutions of less than parcel size (less than 10 m) in land cover simulation may increase error by creating small and false changes. This lower limit is well below the most frequently used 30 m resolution. At the upper limit, Chen and Pontius (2011) showed that predicted built area accuracy increased with increasing spatial resolution from 30 m to 1,920 m. Moreover, the explanatory power of driving variables can also increase with coarser spatial resolutions (minimum resolution was 15 km²) (Kok and Veldkamp, 2001). Geri et al. (2011) found that all kappa indices increased to a perfect level of agreement with increasing cell size. These studies suggest that land cover change prediction can be improved while reducing calculation time with coarser cell sizes. Spatial extent and cell size may affect the analysis of spatial patterns of land cover change individually or together (Wu, 2004).

- 5 The selection of suitable time intervals, spatial extent, and cell size is as important for land cover modeling as modeling strategy and choice of independent variables. Time scale effects for our study area were discussed in Roy et al. (2014b). In this paper, the role of spatial extent (dormant category) and cell size are highlighted using the same explanatory variables and modeling approach. Spatial extent and cell size are interrelated and can have a great impact not only on land cover prediction but also on perceived quality of the prediction since calculated agreement/disagreement statistics depend on the number of cells present in the study area grid. The objective of this study is to test the impact of increased proportional area of a dormant category and cell size on land cover prediction for a Mediterranean catchment in Southeast France. More specifically, it examines the impacts of dormant category and cell size on the strength of relationship (Cramer's V) between predictor variables and land cover change, and validation statistics (quantity and allocation disagreement values) of predicted land cover change.
- 6 Based on aerial photographs from 1950, 1982, 2003, and 2011, change dynamics were first analyzed and then land cover was predicted for 2011 for large (79.1 km²) and small (36.6 km²) windows. Spatial resolution effects were analyzed by upscaling from 25 m to 50 m and 100 m and then downscaling back to 25 m.

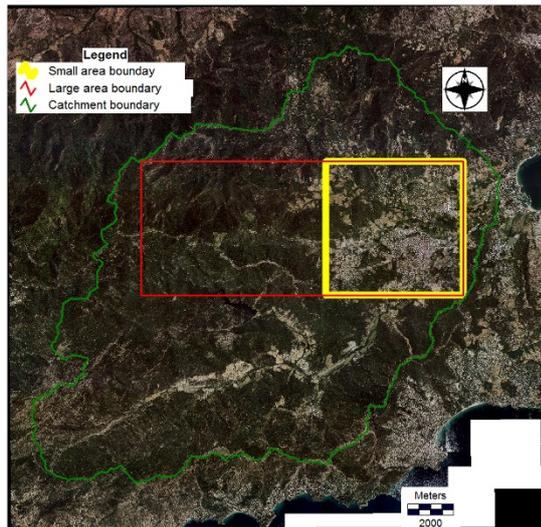
2. Methods

- 7 Study area and land cover modelling steps using different spatial areas and cell sizes are explained below.

2.1. Site description

- 8 The 235 km² Giscle catchment (Figure 1) is located in Southeast France near the Gulf of St Tropez. Physical and topographical characteristics of the catchment are discussed in Roy et al. (2014a). The catchment is typical of many land cover transformation scenarios of the Euro-Mediterranean region where rapid urbanization along the coast and changes in agricultural activities have impacted the ecosystem. The western part of the catchment is forested and has exhibited few changes since about 1950 (Fox et al., 2012 ; Roy et al., 2014a), and much of the land cover change has been concentrated in the alluvial plain located in the east near the coast.
- 9 The "small" zone selected for this study is a 33.6 km² square that encompasses the main populated area in the alluvial plain and the core of much of the land cover change in the catchment (Figure 1). The "large" window is a rectangle that includes the small zone and an extension reaching westward to include a large tract of stable forest cover ; total area of the large zone is 79.1 km². Mean altitudes for the small and large windows are 42 m and 167 m, respectively ; corresponding median values are 32.5 m and 119.5 m, respectively. As expected, mean slope is also gentler for the small window, 10.6 % vs. 24.7 % ; and median values are 7.2 % and 21.5 %, respectively. Much of the plain is developed (urban-suburban) or cultivated (vineyard) with some forest and grasslands.

Figure 1 : Small and large windows within the catchment (the Gulf of St Tropez is just east of catchment).



- 10 The two zones are analogous to a core of dynamic land cover change surrounded by a stable hinterland that allows us to analyze the impacts of spatial extent and the inclusion of a largely dormant category on our perception of land cover change dynamics. The fundamental characteristic of interest is that most of the change is occurring in the small window with very little change in the extended zone.

2.2. Land cover change modelling steps

- 11 IDRISI's (Eastman, 2012) Land Change Modeler (LCM) was used to predict land cover for 2011. LCM is a widely used model initially designed to predict land cover change for the analysis and modelling of impacts on biodiversity using multiple land cover categories (Oñate-Valdivieso and Sendra, 2010 ; Tewolde and Cabral, 2011 ; Mas et al., 2012 ; Silva and Tagliani, 2012 ; Paegelow et al., 2014 ; Camacho Olmedo et al., 2015). The impact of spatial extent and cell size on land cover prediction was carried out by predicting the 2011 land cover from historical changes between 1982 (T_1) and 2003 (T_2) and explanatory driver variables (described below) and comparing the predicted and real images for all spatial extent and cell size combinations. In addition, the 2003 and 2011 maps were compared as recommended by Chen and Pontius (2011), though a full relative operating characteristic (ROC) analysis was not undertaken.

2.2.1. Land cover mapping

- 12 Land cover map digitization and classification procedures were described in Roy et al. (2014a) for the entire catchment and are summarized here for the selected study zones. Firstly, land cover maps were digitized from ortho-rectified 1 m aerial photographs (original resolution of 0.5 m changed to 1 m) of 1950, 1982, 2003 and 2011 using Arc-GIS (ESRI, 2012). Land cover was classified into four categories : forest, vineyard, grassland, and built area. Although aerial photograph resolution was 1 m, small objects (isolated houses, roads, streams, riparian vegetation...) were ignored, so the actual land cover map resolution is more correctly represented at the 25 m scale, and vector land cover maps were converted into 25 m raster layers. In order to investigate the impact of cell size on land cover change modeling, cell sizes were successively converted to 25 m, 50 m, and 100 m. Altitude and distance variables were upscaled using pixel aggregation ; categorical images such as land cover maps and constraints/incentives were upscaled using the majority-takes-all rule. Subsequently, the 50 m and 100 m cell sizes were downscaled to the original 25 m in order to estimate the error introduced during upscaling. To investigate the impact of spatial extent, the small window described above and shown in Figure 1 was isolated from the larger window, so all predictions were run separately (2 spatial extents (Small, Large) * 5 cell size configurations (25 m, 50 m, 100 m, 50-25 m, 100-25 m)).

2.2.2. Independent variables and constraints

13 After an initial analysis of land cover change drivers (Roy et al., 2014a), five independent variables were incorporated in the modelling procedure : altitude, slope, and distances from roads, initial built area, and streams. Distance variables were created from digitized roads, streams, and built area in 1982 using corresponding land cover maps in each cell resolution. Constraints and incentives (forest to built area, vineyard to built area, and grassland to built area) were also included in the prediction process to integrate regional and municipal land use zoning laws. The “Plan Local d’Urbanisme” (PLU) and “Schéma de Cohérence Territoriale” (SCOT) were adapted so that a constraint of 0 was used to characterize areas where urban development was completely restricted (reserve forest and agricultural zones) and 1.1 was used for incentives to emphasize the expansion of built areas in zones selected for development according to urban zoning laws. In addition, disincentive (constraint) areas situated within a distance from streams of 0-25 m, and 25-50 m were defined by values of 0.6 and 0.8, respectively, to maintain the historical trend of less urbanization near stream networks in the study area (Roy et al., 2014a). Explanatory variable cell sizes were matched to the land cover maps in both upscaling and downscaling. The only exception was the slope layer : to avoid introducing excessively artificial errors, the original 25 m slope layer was used for the two 50-25 m and 100-25 m downscaled layers. Other explanatory variables were both upscaled and downscaled, as for the land cover layers.

2.2.3. Explanatory variable and transition potential statistics

14 Cramer’s V is based on the chi-square coefficient (Zawadzka et al., 2015) and slightly modified version of Cramer’s V is used in LCM (Eastman, 2012). It was used to evaluate the impact of spatial extent and cell size on the power of explanatory variables. LCM estimates Cramer’s V automatically and displays the association level of explanatory variables with land cover categories. Cramer’s V here is an approximation of the impact of the explanatory variable on category change, and the MLPNN algorithm of LCM provides a more complete and rigorous measure of association (Eastman, 2012). However, values from this measure vary according to specific transitions and to which explanatory variables are held constant (all, one, backward regression), so the results are too extensive for this publication where 2 spatial extents, 5 cell size configurations, and 9 transitions per spatial extent * cell size combination are possible (built area cannot transition to another category) would require at least 90 tables. For the purposes of this study, Cramer’s V provides an indication of the apparent change in explanatory power induced by altering spatial extent and cell size. Generally, the greater the value of Cramer’s V, the greater the impact the explanatory variable has on land cover change. Cramer’s V values ≥ 0.4 and ≥ 0.15 are considered good and useful, respectively (Eastman, 2012).

15 Transition potential (probability of a category changing to another) maps were created for all possible transitions based on historical changes during 1982-2003 and explanatory variables. However, only transition potentials with an accuracy rate $\geq 70\%$ were included in land cover prediction since final results were better than including all potential transitions. As described in Roy et al. (2014a), spatially random swapping between vegetation categories (especially vineyard and grassland) made these land cover changes difficult to model. Accuracy rates $\geq 70\%$ were the following : forest to vineyard, forest to grassland, forest to built area, vineyard to built area and grassland to built area. Although validation values were weaker when all transitions were included, trends with regards to spatial extent and cell size were identical.

2.2.4. Land cover simulation

16 Land cover change was predicted for 2011 for each spatial extent * cell size combination by LCM, which uses a Markov chain model. The Markov matrix defines the quantity of expected land cover transition from T_2 (2003) to the predicted T_3 date (2011) based on the historical trend between T_1 (1982) and T_2 (2003), and LCM allocates the change according to transition potential values calculated by the MLPNN algorithm described above. There are therefore two validation criteria, quantity and location of change (Pontius and Mallones, 2011), when comparing predicted versus real maps.

2.2.5. Validation of predicted land cover maps

17 Disagreement indices described by Pontius and Millones (2011) were used in the study to validate the model's accuracy for the different configurations and test the impacts of dormant category and cell size on model performance. Both quantity and allocation disagreement errors are derived from the error matrix and measured in terms of the percentage of the landscape ; the sum of these errors represents the total prediction error (Chen and Pontius, 2011). Both quantity and allocation disagreement errors are expressed as a % of the study area (Pontius and Millones, 2011).

3. Results

18 Results will be presented in three sub-sections. The first will summarize land cover change dynamics in the two study zones. The second will cover the impacts of spatial extent (dormant category) on Cramer's V and prediction disagreement. The third section will cover the impacts of cell size on the same measures.

3.1. Land cover maps in the small and large zones

19 Figure 2 compares surface areas for the different land cover categories between the small and large zones. In the small zone, forest and vineyard occupy equivalent areas in 1950 (about 43 %), but vineyard area progressively decreases over time as it loses ground to other land cover types. In the small zone, built area undergoes a large relative increase as it changes from only 0.8 % in 1950 to 16.5 % in 2011. Grassland area remains relatively constant over time, but this hides high spatial swapping with forest and vineyard as described in Roy et al. (2014a). As expected, forest dominates land cover in the large zone, where it remains stable at about 74 %. Since most of the other land cover types are concentrated in the small zone, absolute areas of these land covers in the large window closely follow values for the small zone ; however, percentage values shown in Figure 2 change substantially since total area is greater in the large window. For all categories except forest, values expressed in % area are smaller in the large zone than for the small window due to the high forest cover in the large window.

20 Figures 3a-d (showing land cover in 1950, 1982, 2003 and 2011, respectively) and Table 1 confirm that most of the changes occur in the small window, and the western spatial extension added to form the large window remains dominated by forest cover with little change in vineyard and grassland and virtually no change in built area. Apart from forest in 1950-1982 and 1982-2003, the % of total change occurring in the small window is close to 90 % for all categories and time intervals, and values are close to 100 % for built area for all periods. Forest has the lowest % change occurring in the small zone (about 78 % for the first two transition periods), but even it approaches 90 % in 2003-2011.

Figure 2a : Land cover surface areas in small zone for different years (% of window area : 33.6 km²)

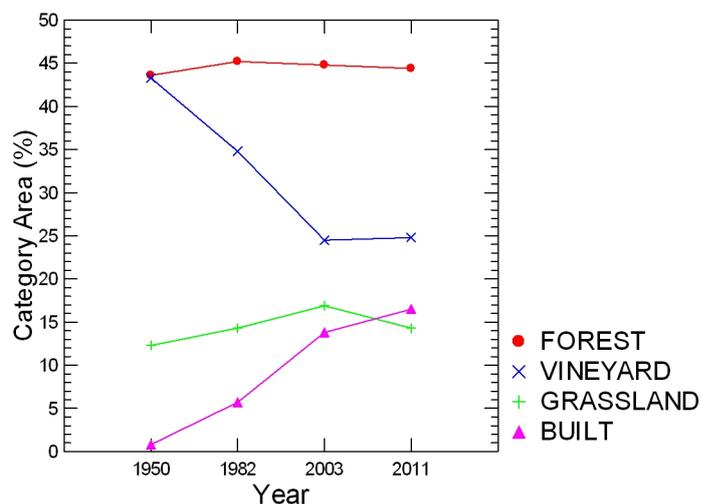


Figure 2b : Land cover surface areas in large zone for different years (% of window area : 33.6 km²)

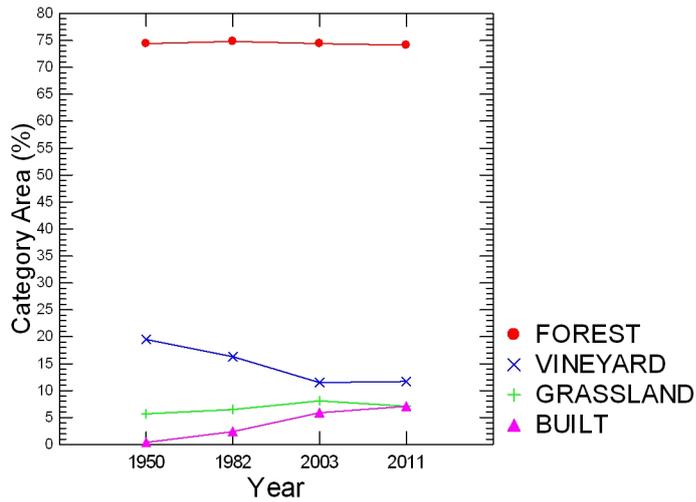


Table 1 : Category land cover and total change during the different time intervals, and % of change occurring in the small window (equal to 100 % everywhere for the top rows).

		Change (ha)			% of change occurring in small window		
		1950-1982	1982-2003	2003-2011	1950-1982	1982-2003	2003-2011
Small	Category						
	Forest	387	398	137			
	Vineyard	703	550	168			
	Grassland	504	577	231			
	Built area	164	271	93			
	TOTAL	1,758	1,796	630			
Large	Forest	491	514	153	78.8	77.4	89.5
	Vineyard	781	631	180	90.0	87.2	93.3
	Grassland	549	653	246	91.8	88.4	93.9
	Built area	164	274	94	100	98.9	98.9
	TOTAL	1,985	2,071	673	88.6	86.7	93.6

3.2. Dormant category impacts on land cover modelling indices

21 In this section, the impacts of dormant category on Cramer’s V and disagreement indices are considered. Figures 4a-c summarize results for both spatial extent and cell size effects. Spatial extent will be examined before analyzing differences between cell sizes.

Figure 3a : Land cover map of 1950

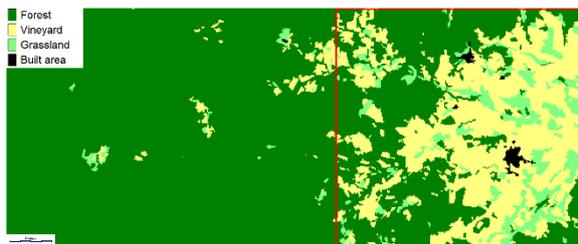


Figure 3b : Land cover map of 1982

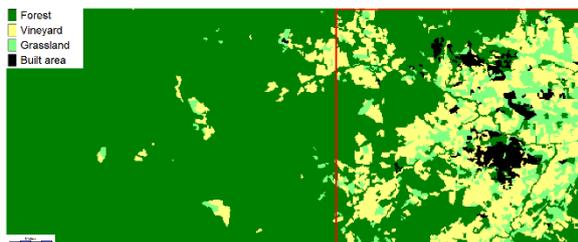


Figure 3c : Land cover map of 2003

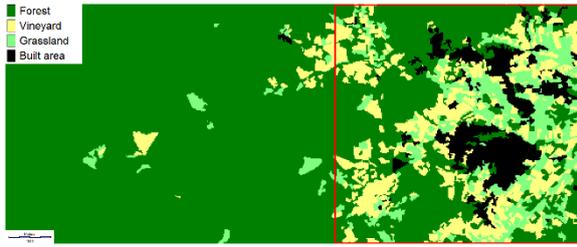
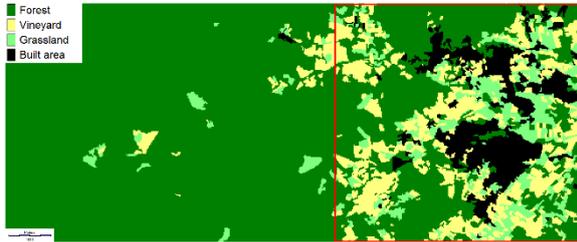


Figure 3d : Land cover map of 2011



3.2.1. Cramer's V

22 Cramer's V values for the initial 25 m resolution are reported in Figure 4a. Spatial extent clearly has a strong impact on Cramer's V values. Mean values in Figure 4a are generally 1.3 to 1.7 times greater for the large zone than for the small window, and this holds for all categories and explanatory variables except for built area and the two strongest predictors of built area change (distances from roads and built area). For these, Cramer's V does not change with spatial extent. For distances from roads and built area, Cramer's V is systematically greater for built area than for forest in the small window but not in the large window. In the large window, Cramer's V values increase substantially for forest (about 0.41 to 0.64) and distance from built area, even though the amount of built area in the larger zone is negligible compared to the small window.

Figure 4a : Cramer's V coefficient for 25 m cell size. Values ≥ 0.40 are highlighted in bold and overall accuracy is in italics

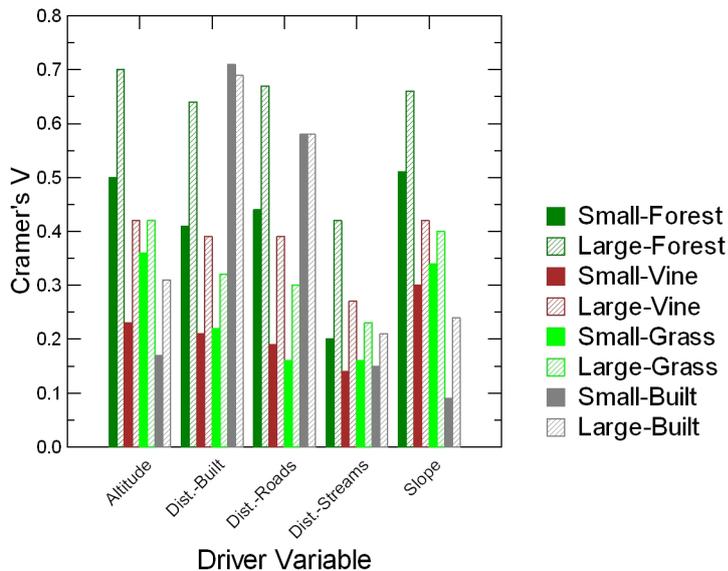


Figure 4b : Cramer's V coefficient for 50 m cell size. Values ≥ 0.40 are highlighted in bold and overall accuracy is in italics

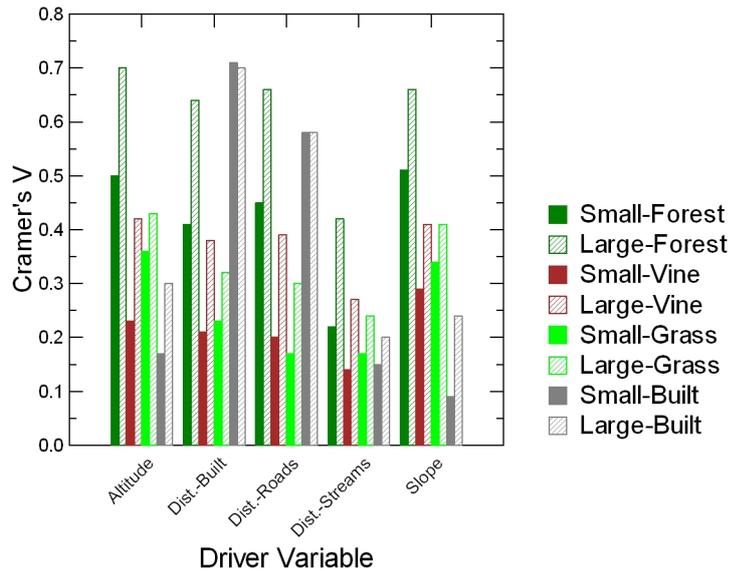
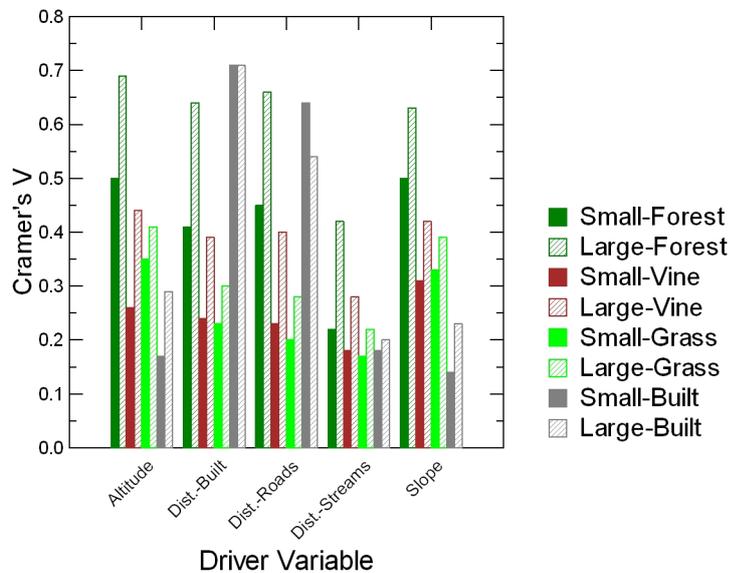


Figure 4c : Cramer's V coefficient for 100 m cell size. Values ≥ 0.40 are highlighted in bold and overall accuracy is in italics



23 Since virtually all the change occurs in the small window, increasing spatial extent should have little impact on land cover change prediction. Despite this, for categories with high surface areas and very little change outside the window, Cramer's V values are greater. Similarly, built area Cramer's V values increase substantially (about 20 % increase) for altitude, slope, and distance from streams though no more than 1 % of built area is located outside the small window (Table 1). The explanatory power of distance to roads and distance to built area for forest increases substantially when spatial extent is extended.

3.2.2. Prediction validation

24 With greater Cramer's V values, one would expect improved prediction statistics for the large window and this is apparently the case as shown by the disagreement values in Figure 5a. Quantity disagreement is smaller than allocation disagreement for both spatial extents (1-2 % versus 5-10 %). Both quantity disagreement and allocation disagreement are roughly half as great in the large window as in the small window : about 1 % versus 2.5 % for quantity, and 5 % versus 10 % for allocation. These values suggest land cover prediction is improved when the large zone is added even though land cover changes occurring in the small zone are the same for both the small and large window predictions.

3.3. Cell size impacts on land cover modelling indices

25 Cell size initially appears to have no impact on Cramer's V since values in Figures 4a-c are nearly identical for the three cell sizes within the two spatial extents. In addition, when the coarser 50 m and 100 m resolutions are downscaled back to 25 m (Figure 6), the relationships between explanatory variables and categories remain the same with no noticeable changes between Figures 4a (original 25 m), 6a (50-25 m downscaled), and 6b (100-25 m downscaled). Based on these values, the initial conclusion would be that cell size does not affect Cramer's V values in this case study.

Figure 5a : Disagreement values according to spatial extent and cell size for 25 m, 50, and 100 m cell sizes.

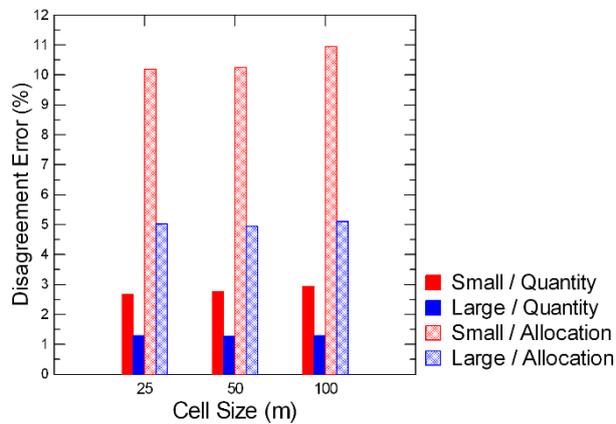


Figure 5b : Disagreement values for upscaling/downscaling effects for 25 m, 50-25 m, and 100-25 m.

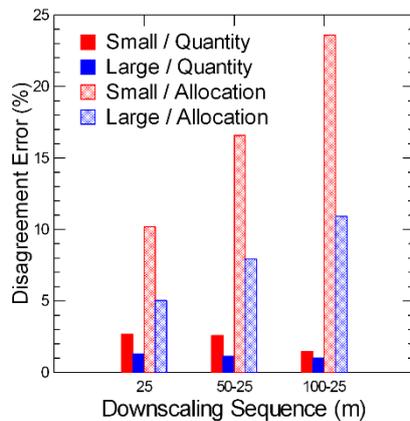
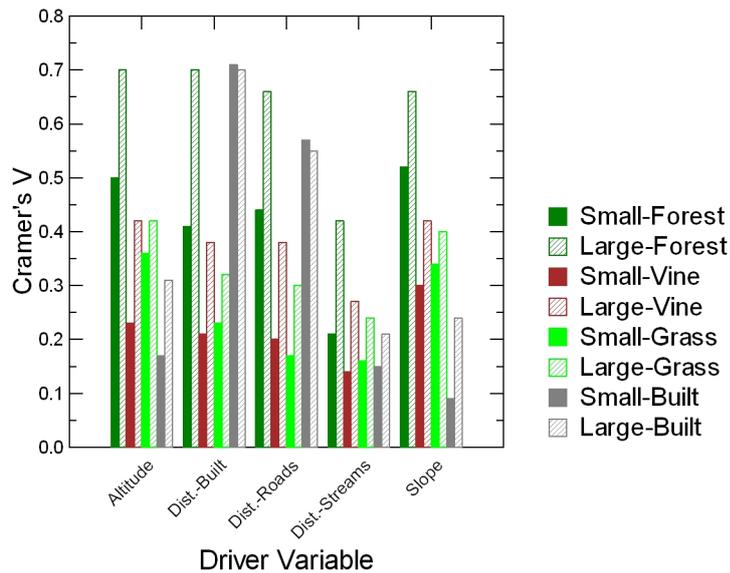
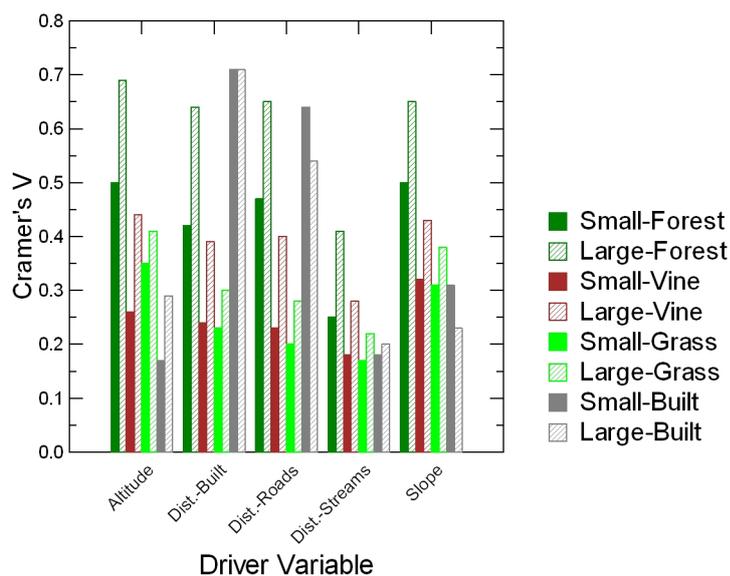


Figure 6a : Cramer's V coefficient for 50-25 m upscaling/downscaling cell size (values are to be compared to Figures 4a and 6b).



26 The lack of an impact of cell size on model prediction values is also apparently confirmed by similar disagreement values between the 25 m, 50 m, and 100 m spatial resolutions (Figure 5a). However, when the upscaled/downscaled predicted images are compared to the initial 25 m 2011 reference image, disagreement values respond differently (Figure 5b). Cell size has little impact on quantity disagreement which remains stable in Figure 5b, but allocation disagreement rises sharply for the 50-25 m and 100-25 m land cover predictions for both the small and large study zones : allocation disagreement for the original 25 m image is about 10 %, and this value increases to about 17 % and 24 % for the 50-25 m and 100-25 m predictions, respectively. The implications of this are discussed below.

Figure 6b : Cramer's V coefficient for 100-25 m upscaling/downscaling cell size values are to be compared to Figure 4a and 6a)



27 Although the disagreement values shown in Figure 5a are reasonably satisfactory, none of the spatial extent / cell size combinations performed better than simply comparing the 2003 image to 2011, though the spatial extent trends remain the same. Quantity and allocation disagreement values for this comparison are in the order of 3.0 % and 6.0 % for the small window and 1.3 % and 3.0 % for the large zone. Although this has no implications for the findings of the study, it reinforces the necessity to compare the predicted image to both the synchronous and historical images as described by Chen and Pontius (2011).

4. Discussion

28 Before discussing the results, it should be noted that although the location and category types used here represent a real case study, the findings with regards to spatial extent and cell size are independent of location and land cover type : replacing the dormant Mediterranean forest category by rice paddies, savannah or tropical forest would produce the same statistics so long as the number and relative areas of land covers are maintained. Similarly, a range of spatial areas can be concerned by the findings so long as neither new processes nor new land categories are introduced as spatial extent is increased. The approach therefore has global applications even though the demonstration is a Mediterranean case study. Impacts of dormant category on change prediction will be discussed before addressing spatial resolution effects.

4.1 Spatial extent and land cover change prediction

29 Predictive power of explanatory variables is strongly affected by spatial extent, and the presence of the persistent forest cover gives the impression that explanatory variables were better predictors in the large window than in the small zone for the same land cover change. Similarly, disagreement values appear to indicate a better prediction for the large zone than the small zone even though the actual prediction is virtually identical for both windows in the small active zone, so lower disagreement values for the large window are misleading. Adding a large area of persistent land cover reduces quantity and allocation errors due to changes in three different values used to calculate these indices : total area, total absolute change, and correctly predicted area. Both disagreement values (quantity and allocation) are calculated as the % of the study area, so values decrease with increasing study area if other components remain constant. Quantity disagreement depends mainly on absolute total change and allocation disagreement relies on the number of wrongly predicted cells. Therefore, both disagreement values are smaller in the large window because denominators (study area) increase more than numerators in calculating both fractions. Lower disagreement (apparent increase in model performance) is therefore related to the number of correctly predicted stable cells. In the small window, about 86 % of pixels are correctly predicted persistent cells, and in the large window this value increases to about 91 % for all cell sizes. Hence, lower disagreement values for the large window can be attributed to the correct prediction of persistent cells and not to better prediction of actual land cover changes. Persistence is easy to predict in a large expanse of continuous forest. This agrees with observations by Chen and Pontius (2010) and Pontius and Spencer (2005) that persistence is easier to predict than change. Virtually all the change occurs in the small window, and the extended part of the large window is essentially persistent. Actual land cover change prediction is the same for the large and small windows, but the model appears to perform better in the large window for most variables.

30 Why Cramer's V improves so strongly with spatial extent for most categories is not clear since about 90 % of change for all categories (built is almost 100 %) occurs in the small zone. One possible explanation is that explanatory variable range increases with increasing window area. For example, the ranges in altitude are 237 m and 663 m for the small and large windows, respectively. Similarly, range values for slope are 70.5 % and 123 %, respectively. Even though little area changes outside the small window, these small differences may have a large impact on the Chi-Square value used to calculate Cramer's V, just as a few high values can strongly influence a correlation coefficient in linear regression.

31 The selection of spatial extent for modelling land cover change can be driven by process, data constraints, or arbitrary decision. Land cover change modelling using data based on administrative units is restricted by the administrative boundaries, which may or may not add large areas of dormant land covers. Most raster-based land cover studies probably extract arbitrary rectangular windows from satellite images or air photos. In such a case, researchers should seek to minimize the presence of large dormant categories to avoid artificially inflating prediction results.

4.2 Spatial resolution and change prediction

- 32 Grid cell size is driven by many factors and can be subject to different interpretations. It can depend on initial cell size of input data (eg. 30 m Landsat vs. 10 m SPOT images) or can refer to final cell size after expansion and contraction procedures when harmonizing images. Only this second aspect was considered here. We assume that finer spatial and spectral resolutions of source data lead to better category identification and therefore to more reliable land cover maps. In this study, 1 m air photos were digitized to represent land cover but without integrating details at the 1 m scale. Distances from roads and streams were calculated from the initial road and stream networks, but roads, isolated buildings, and stream channels were excluded to avoid creating low-interest categories that would complicate land cover change analysis. The advantage of using high resolution images here therefore resides in a more accurate classification of land cover types and not in a more detailed land cover map.
- 33 Land cover map resolutions smaller than 25 m would lead to a greater number of categories and to smaller patches of isolated covers (riparian vegetation, for example, would have been included in forest) which were considered of little interest in this context. Modelling land cover change becomes increasingly difficult as the number of categories and small isolated patches increases.
- 34 The initial results indicated that cell size had no impact on land cover change modelling since Cramer's V and disagreement values were unchanged by upscaling. However, the upscaling / downscaling procedure revealed that during upscaling considerable information was lost. The impacts of spatial extent and cell resolution on landscape data are discussed in Turner et al. (1989), in which the probability of small or rare information loss increases with increasing cell size : land cover types with scattered distributions lose area rapidly with coarser cell resolutions whereas clustered land covers disappear more slowly. As cell size increases, details are lost, isolated pixels disappear, and the landscape becomes increasingly simpler. It also becomes progressively less representative of real land cover distributions. Improved statistics with coarser resolutions (Chen and Pontius, 2011 ; Geri et al., 2011 ; Pontius et al., 2008) may simply be the result of an oversimplified landscape composed of larger category patches. The simpler the landscape - the better the prediction ; in short, the model gets better at predicting a landscape that grows progressively further from reality. Downscaling does not restore the initial information, but it allows the modeler to measure the amount of information lost by changes in the disagreement values. Studies considering cell size effects should systematically downscale back to the original spatial resolution to avoid the potentially false impression that the upscaled model leads to a better prediction of reality.

5. Conclusions

- 35 Spatial extent and cell size are two fundamental aspects of land cover change modeling that are subjectively decided upon by modelers. In this study, increasing spatial extent was synonymous with integrating a large dormant category (i.e. effects related to adding new categories or processes were not considered), and simply adding a substantial area of a stable land cover improved model performance without improving change prediction. Quantity and allocation disagreement were greater in the small (33.6 km²) window than in the large (79.1 km²) zone because most of the land cover change occurred in the small zone, and the large persistent area in the extended window generated greater prediction accuracy statistics associated with the stable forest cover. More generally, as the surface area of stable land increases, the number of correctly predicted persistent cells also increases. Large contiguous unchanging zones are easy to model due to their low conversion (high persistence) transition potentials, so increasing the proportion of correctly predicted stable cells improves model statistics. The model therefore appears to predict change well but this is artificially generated by the dominant unchanging land cover. Limiting the spatial extent of the study zone to a core area where most of the land cover change is occurring provides a more realistic measure of how a model performs.
- 36 Spatial resolution changes from 25 m to 50 m and 100 m initially appeared to have no impact on model performance. However, when the 50 m and 100 m land cover images were

subsequently downscaled back to the initial 25 m, allocation errors increased substantially, so coarser resolutions performed less well despite initial output statistics. Published results showing that coarser resolutions improve land cover change modelling may be misleading. As cell size increases, small isolated land cover patches disappear and the landscape becomes progressively simpler. As the landscape is simplified, real land covers are replaced by dominant neighboring categories, and both the landscape and land cover change dynamics are simplified. As complexity decreases, land cover change model performance increases. In none of the studies where upscaling to coarser resolutions improved modelling statistics was spatial resolution subsequently downscaled back to the initial cell size to estimate the amount of distortion introduced by upscaling. Finer resolution land cover images are inevitably better representations of reality than upscaled images where detail is lost, so better validation statistics at coarser resolutions do not indicate a more faithful representation of real land cover changes. As spatial resolution gets coarser, actual land covers are simplified, and the model provides better prediction results for landscapes that are increasingly different from actual land covers.

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Résumés

Most models of land cover change predict change using physical and socio-economic factors in raster grids where temporal and spatial scales must be selected to optimize prediction and calculation time. This study tests the impacts of spatial extent and spatial resolution (cell size) on land cover change modelling. Spatial extent here is equivalent to increasing the area of a dormant category. Two extents (33.6 km² and 79.1 km²) and three resolutions (25 m, 50 m and 100 m) were tested on study zones located in SE France in the Var department. The 50 m and 100 m resolutions were downscaled back to 25 m and compared to the initial 25 m maps. Land cover maps dated from 1950, 1982, 2003 and 2011, and IDRISI's Land Change Modeler (LCM) was used to predict 2011. Dormant category improved Cramer's V values (1.3 to 1.5 time greater) and quantity and allocation disagreement values. Actual change predictions were similar for the two zones, but the high persistent forest in the large window artificially improved prediction statistics, so increasing dormant category area (spatial extent) artificially inflates prediction statistics. Spatial resolution appeared to have little impact at first, but upscaling/downscaling revealed that coarser cell sizes lose predictive power (1.5-2 times greater allocation errors). Dormant category area should be minimized and upscaling/downscaling should be done if data are modelled at coarser resolutions than original cell size.

La présence d'une catégorie d'occupation du sol stable ainsi que la résolution spatiale influencent les statistiques de performance de modélisation de l'évolution de l'occupation du sol

La modélisation de l'évolution de l'occupation du sol utilise souvent des modèles SIG en mode raster où des choix doivent être effectués sur l'étendue et la résolution spatiale des données du modèle. Dans notre étude, l'étendue spatiale correspond à l'intégration dans la

zone d'étude d'une catégorie à faible activité – dite « dormante ». L'impact de l'intégration d'une catégorie dormante sur la modélisation de l'évolution de l'occupation du sol a été étudié à l'aide de deux zones (33.6 km² et 79.1 km²) situées dans le département du Var. Les effets liés à la résolution spatiale ont été déterminés en comparant trois tailles de cellules (25 m, 50 m, et 100 m), dont deux (50 m et 100 m) qui ont été par la suite restaurées à la taille initiale de 25 m. Des cartes d'occupation du sol de 1950, 1982, 2003 et 2011 ont été utilisées dans l'analyse. Le modèle affiche de meilleures statistiques de performance (V de Cramer et autres indices) pour la zone de 79.1 km² parce que cette zone possède un taux de cellules persistantes élevé et les cellules stables sont plus facilement prédites que les changements réels. Pour les mêmes changements d'occupation du sol, le lecteur a donc l'impression que le modèle donne des prévisions meilleures pour la grande superficie (79.1 km²). La performance du modèle pour les différentes résolutions spatiales paraît stable, mais en réalité la descente d'échelle (« downscaling ») de 50 m et de 100 m à 25 m montre clairement que ces statistiques cachent une perte d'information. En conclusion, l'intégration de catégories peu actives dans les modèles d'évolution de l'occupation du sol doit être minimisée et les pertes d'informations liées à la résolution spatiale ne peuvent être évaluées que par une succession de généralisation / descente d'échelle (« upscaling/downscaling »).

Entrées d'index

Mots-clés : occupation du sol, modélisation paysagère, modélisation spatio-temporelle, land change modeler, analyse spatiale, résolution spatiale

Keywords : land use and land cover, landscape modelling, land change modeller, area, spatial resolution