

Spatially-based accuracy assessment of forestation prediction in a complex Mediterranean landscape

Francesco Geri ^a, Valerio Amici ^{a,*}, Duccio Rocchini ^b

^a BIOCONNET, Biodiversity and Conservation Network, Department of Environmental Science "G.Sarfatti", University of Siena, Via P.A. Mattioli 4, 53100 Siena, Italy

^b Fondazione Edmund Mach, Research and Innovation Centre, Department of Biodiversity and Molecular Ecology, GIS and Remote Sensing Unit, Via E. Mach 1, 38010 S. Michele all'Adige (TN), Italy

A B S T R A C T

Keywords:

Cross classification
GEOMOD
Landscape changes
Land-cover mapping
Mediterranean region
Predictive modeling

Changes in land use and land cover can lead to irreversible changes in forests that result in overall reductions in biodiversity and loss of elements of high ecological and cultural value. Land use and cover change models can be an important resource for scientists to develop a sustainable land management program. This paper presents a method to assess the accuracy of a forestation predictive model built through GEOMOD. This model was applied to simulate the pattern of land-use change forward in time from 1933 to 2000, in a Mediterranean area, using topographic parameters as predictive variables. In Mediterranean areas, modeling landscape transformation by stressing the relationship between environmental variables and historical anthropogenic transformation, is crucial for many conservation and management practices. In order to analyze the goodness-of-fit of simulation, a cross-classification map was realized by overlaying the map produced by the simulation model and a reference map (CLC 2000). Then, a statistical validation procedure was carried out based on the kappa index of agreement. Results showed that: *i*) the study area has undergone great changes in the last decades with a marked increase in forest surface, and *ii*) GEOMOD represents a powerful model tool for land-use change prediction, but it is necessary to properly calibrate and validate the model in order to avoid misleading results.

© 2011 Elsevier Ltd. All rights reserved.

Introduction

During recent decades, the study of land-use and land-cover change (LUCC) has become a prominent research topic because it affects ecosystems and biodiversity (Antrop, 2004; Chase, Pielke, Kittel, Nemani, & Running, 1999; Sala et al., 2000; Schulz, Cayuela, Echeverria, Salas, & Rey Benayas, 2010). In many parts of the world, human activities (or their cessation) are the main forces shaping changes in land use (Serra, Pons, & Sauri, 2008). Human activities cause long-lasting changes in the following areas: spatial structure of plant canopies, species' composition and interactions, the soil's organic matter status, and biogeochemical cycles (Cernusca, Tappeiner, & Bayfield, 1999). Biodiversity is often reduced dramatically by LUCC. When land is transformed from a primary forest to a farm, for example, there is an immediate and complete loss of forest species within this deforested area (Foley et al., 2005). Mediterranean ecosystems are also impacted by habitat fragmentation, which exposes forest edges to external influences and decreases core habitat area (De Fries, Asner, & Houghton, 2004). Research also demonstrates that, especially in

proximity to human settlements, species invasions by non-native plants and animals may occur more readily in areas exposed by LUCC (Foley et al., 2005). In many developed areas, a specific pattern of LUCC has taken place during the last decades; plains are being increasingly utilized for human activities, while hills and mountainous areas are being abandoned and subjected to natural reforestation processes (Debussche, Lepart, & Dervieux, 1999; Garcia-Ruiz et al., 1996; McDonald et al., 2000). This process is expected to affect biodiversity patterns, and will produce a dramatic simplification and homogenization of the landscape mosaic and cause a significant loss of diversity (Bengtsson, Nilsson, Franc, & Mengozzi, 2000; Geri, Amici, & Rocchini, 2010).

Areas of the Mediterranean basin have been profoundly transformed by human activity for millennia. For example, in the Central and West Mediterranean regions, the socio-economic changes of the last 60 years, which involved moving a large component of the workforce from agricultural labor to industrial and urban services, have led to profound changes in the landscape (De Aranzabal, Schmitz, Aguilera, & Pineda, 2008; Falcucci, Maiorano, & Boitani, 2007; Geri et al., 2010; Pelorosso, Leone, & Boccia, 2009; Serra et al., 2008). One of the most important aspects of these environmental changes is the abandonment of large areas of land, previously used as pasture or crops that are located in marginal

* Corresponding author. Tel.: +39 (0) 577232864.

E-mail address: valerio.amici@unisi.it (V. Amici).

agricultural areas where agricultural productivity was low due to environmental factors (Pelorosso et al., 2009).

Timely and accurate LUCC detection may provide a better understanding of the interactions between human and natural phenomena and allow for better management and use of natural resources (Bakr, Weindorf, Bahnassy, Mareib, & El-Badawi, 2010). Planners and policy makers are increasingly relying on LUCC models because they allow experts to focus planning decisions on the most threatened areas to prevent and anticipate the adverse effects of land-use change (Klijn & Vos, 2000; Nagendra, Munroe, & Southworth, 2004; Pocewicz et al., 2008; Pontius & Chen, 2006; Turner, Moss, & Skole, 1993). LUCC models have been generally utilized in order to i) predict and simulate future changes in land-use categories (Briassoulis, 2000; Verburg, Schot, Dijst, & Veldkamp, 2004), and, ii) to envision past land-use maps for periods where maps do not exist (Pelorosso et al., 2009; Pontius, Cornell, & Hall, 2001). Models of LUCC vary enormously in terms of internal features (e.g. the number of possible categories, the types of category transitions, their spatial dependencies, their feedbacks, the scale linkages; Lambin & Geist, 2006) and, it is often difficult to validate LUCC models because data are not usually available across long periods of time (Feranec, Jaffrain, Soukrup, & Hazeu, 2010; Pontius et al., 2001).

Many studies based on models of LUCC have focused on the temporal changes in woodlands at a landscape level to understand the spatial patterns and interactions among the elements of the landscape and how they have changed over time (Echeverria, Coomes, Hall, & Newton, 2008). These studies may provide useful information and a more comprehensive understanding of what drives forest dynamics in order to address land-use planning decisions (Echeverria, Coomes, Hall, & Newton, 2008; Verburg, Overmars, Huigenb, De Groot, & Veldkamp, 2006).

The aim of this work was to assess the validity of the spatial component of GEOMOD, a model based on a Geographic Information System (GIS) that uses spatially distributed data to simulate landscape dynamics forwards or backwards in time (Hall, Tian, Qi, Pontius, & Cornell, 1995; Pontius et al., 2001; Pontius & Chen, 2006). The assessment was carried out simulating the pattern of land-use change forward in time from 1933 to 2000 of a forestation process in a Mediterranean area using topographic parameters as predictive variables. These findings will be helpful to ecologists researching the ecological impact of landscape changes, and this data could support the planning for and more effective management of natural resources.

Methods

Study area

The study area was a 3820 km² area located in Tuscany, Italy (centroid coordinates: longitude 11° 26' 54"E, latitude 43° 10' 12"N, datum WGS84), designated as the Siena province. The climate is Mediterranean in the majority of the territory with significant climate diversity at the micro-scale due to differences in altitude and complex relief morphology. The mean annual temperature ranges from 11.8 °C to 14.3 °C, with mean precipitation per year ranging from 554 mm to 1080 mm. The area is mainly characterized by hilly morphology; however, higher mountains (up to 1667 m) are also present.

According to the CORINE Land Cover report, the dominant cover types are represented by cultivated lands, (approximately 55% of the territory) and by forests (34%). The main forest tree species include the following: *Quercus cerris*, *Q. pubescens*, (70% of forest area), *Q. ilex* (13%); *Fagus sylvatica* and *Castanea sativa* woods occur at higher elevations.

This study area is characterized by remarkable geomorphological variability. Previous studies show how it was affected by and is still influenced by a process of spontaneous reforestation as a result of the abandonment of agricultural areas (Agnoletti, 2004; Geri et al., 2010; Vos & Stortelder, 1992). For this reason, the Siena province is an appropriate case for testing a land-cover change forecasting model.

Maps derivation

A historical forest map of the entire territory of the Siena Province (1933), created by Milizia Forestale, was acquired from the archive of Corpo Forestale and georeferenced and digitized within a geographic information system (GIS). This map was produced by field surveys and manual hard copy delineations of forest structures by the Milizia Forestale, using 1:25,000 scale topographic maps as a topographic base. It was, therefore scanned at 1000 dpi and digitized with Quantum GIS software.

In order to smooth the error expected from the process of scanning, rectifying and digitizing the 1933 map, we aligned the old maps with recent topographic maps (scale 1:25,000, year: 1992) by further calculating the residuals in the *x* and *y* axes that were achieved from the co-registration process and by using a pixel size higher than the spatial error for further analysis. In particular, we made use of 100 control points randomly scattered over the study area. We then detected the nearest landscape feature in the two maps, (e.g. crossroads, houses) which had remained unchanged over time. Finally, the deviation between the 1933 and the 2000 maps was calculated by the Root Mean Squared Error (RMSE) as:

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n u^2 + v^2}$$

where *n* = number of control points (in this case *n* = 100), *u* = residual in the *x* axis; *v* = residual in the *y* axis.

The RMSE corresponded to 74.92 m. As a result; we resampled both 1933 and 2000 forest maps using a grid with a spatial resolution of 75 m, i.e., a pixel dimension larger than the spatial inaccuracies calculated by RMSE. These grids were derived from the original vector datasets using a majority filter.

In order to obtain a referenced image, forest area data were extracted from the resampled CORINE Land Cover 2000 report (Bossard, Feranec, & Otahel, 2000). Each map was then reclassified; forests were classified as type 1, and all other land-use types which could be characterized as having undergone some human intervention, such as urban and agricultural areas, were classified as type 2. The final map consists of 3 possible input values as follows:

- 0 : out of the study area
- 1 : non-forested area
- 2 : forested area

Tabular data of the forest cover surface of 1954 were created from a historical land-cover map of the Siena Province. The digitization procedure used can be defined as semi-automatic: it was composed, first, of an operation of automatic segmentation and secondly, of manual photo interpretation (Geri et al., 2010). The automatic segmentation process used is mostly defined as a bottom-up process: clusters of pixels with similar characteristics are aggregated into a series of successive stages up to reach a threshold factor defined by the operator (Burnett & Blaschke, 2003; Carleer, Debeir, & Wolff, 2005). We extracted a grid raster map with a spatial resolution of 75m from the final vector map, in order to guarantee the comparability between the datasets. The

Table 1
Forest topographic variables.

Variable	Forest	Non Forest
Altitude	418.08 ± 179.95	322.98 ± 138.94
Slope	8.25 ± 4.38	5.61 ± 3.86
Solar radiation	0.87 ± 0.05	0.89 ± 0.06

forest cover data were used to calibrate the historical forest map into the model.

Topographical variables calculation

A Digital Elevation Model (DEM) of the Siena Province, with a spatial resolution of 75 m, was created in order to derive slope and aspect variables. The estimation of direct incident radiation was performed by a multiple-regression algorithm based on a trigonometric function of slope, aspect and latitude, as described by McCune and Keon (2002). This parameter provides an approximation of the total amount of radiation received by a point on the ground, given its latitude, slope and aspects (Table 1). The three variables computed within the model were needed to characterize, from a topographical point of view, the different categories of land-use change using fuzzy functions. The three derived maps were resampled in order to obtain the same spatial resolution.

The model

As previously stated, in this paper we assessed one of the most frequently used models for predicting forestation processes named GEOMOD (Pontius et al., 2001). GEOMOD, a GIS-based model, is a straightforward, unidirectional, linear change modeling tool produced to predict the location of change between two time periods by combining a variety of driver images (Pontius & Batchu, 2003). This model can also be used to simulate a forestation process by using spatial data of forest cover at different time intervals (Hall et al., 1995; Pontius et al., 2001). GEOMOD predictions can be improved by testing estimates of both the quantity of future forest areas as well as their spatial location (Pontius, 2000).

The GEOMOD approach has been used to simulate deforestation in Massachusetts (Schneider & Pontius, 2001), Costa Rica (Hall, 2000; Pontius et al., 2001), India (Pontius & Batchu, 2003; Pontius & Pacheco, 2003) and globally, in the tropics (Hall et al., 1995). GEOMOD simulates the change between exactly two categories, state 1 and state 2. For example, it could be used to predict changes from forest (state 1) to non-forest (state 2) in a given time period.

GEOMOD essentially uses non-linear multiple-regression to weight each driver according to its assessed importance in determining the pattern and location of pixels changing over time (Dushku & Brown, 2003). Pontius et al. (2001) gave the most complete peer-reviewed description of GEOMOD. The following minimum input requirements are needed to compute GEOMOD: the beginning time, the ending time, an image of the beginning time for two land-cover types, which must be denoted by 1 and 2, an estimate of the number of pixels of each of the two categories at the ending time, and a suitability map to emphasize pixels with higher suitability to change.

The model selects the locations of land to be converted according to four decision rules. The first decision rule concerns persistence into the landscape. GEOMOD simulates within each stratum a one way change, either from non-forested to forested, or from forested to non-forested. For each stratum, it is necessary to

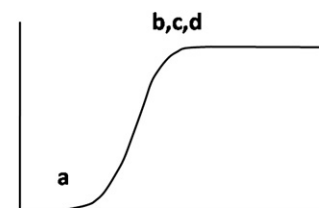
indicate the estimated change in surface between the beginning time and the ending time. In order to define the trend toward forestation or deforestation in each stratum, we used the tabular data for the forest surface in 1954 and, through extrapolation, we obtained the values corresponding to 2000. The second decision rule allows regional stratification. GEOMOD can simulate land change within a series of regions called *strata*. The layer for the stratification used for modeling the forestation process in the Siena Province is related to the Municipal boundaries. For each Municipal boundary, the direction of change and an estimation of the level of future forest covering in term of number of pixels were entered.

The third decision rule concerns the neighborhood constraint. It is based on a nearest neighbor principle that restricts land-use change within each time step to pixels that are on the edge between non-forested and forested land. According to this decision rule, the model selects for intrinsic stability.

The fourth decision rule concerns a map of suitability for a forest category simulating the creation of an additional forest by searching the landscape for the location that has the highest suitability. GEOMOD can create the suitability map empirically, based on driver maps, by using several driver maps and the land-cover map from the initial time. First, it reclassifies each driver map such that the pixels of each category of the driver map are assigned a percent number obtained by comparing the driver map to the land-cover map of the beginning time. Then, it creates the suitability map by computing a weighted sum of all the reclassified attribute maps for each pixel.

In this work we opted to create a customized suitability map through image processing operations and a multi-criteria evaluation process (Eastman, Jin, Kyem, & Toledano, 1995). The images of altitude, slope and solar radiation were standardized with a sigmoid fuzzy-set membership function. Moreover, they were overlaid with the 1933 forest cover map to obtain the respective suitability map for hosting new forest cover. The sigmoid membership function is produced using a cosine function with four control points that manages the shape of the curve (Fig. 1). According to the results of summary statistics extracted by the three images, a monotonically increasing sigmoid function was used for altitude and slope, while for solar radiation a monotonically decreasing sigmoid function was used. Thus the three driver maps were merged together to create the final suitability map, i.e., the potential land-use change map.

Fig. 2 summarizes the entire analysis process.



$$\mu = \cos^2 \alpha$$

where, in the case of a monotonically decreasing function:

$$\alpha = (x - \text{point } c) / (\text{point } d - \text{point } c) * \pi / 2$$

while, in the case of a monotonically increase function:

$$\alpha = (1 - (x - \text{point } a) / (\text{point } b - \text{point } a)) * \pi / 2$$

Fig. 1. Fuzzy-set membership sigmoid function.

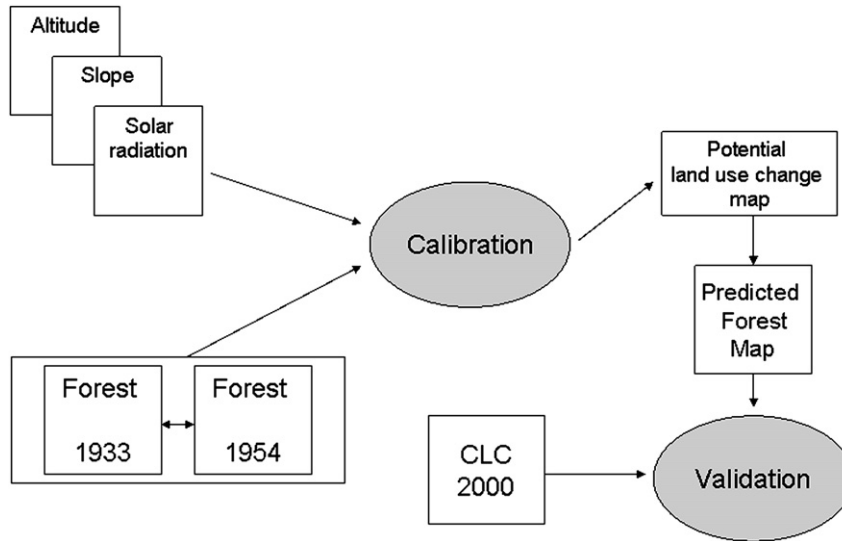


Fig. 2. Flowchart of the logical process followed.

Accuracy assessment

The main objective of accuracy assessment is to provide an index of the degree of ‘correctness’ of a map or classification (Foody, 2002).

Two types of criteria to measure the goodness-of-fit of simulation were used: *i*) a visual approach and *ii*) a statistical

approach. In order to analyze the goodness-of-fit of the simulation, a cross-classification map was created by overlaying the reference and the simulated map. The CLC 2000 map was used as a reference map.

The cross-classification map, produced by the overlay between the reference map (CLC 2000) and the comparison map (produced by simulation model) were composed of four categories:

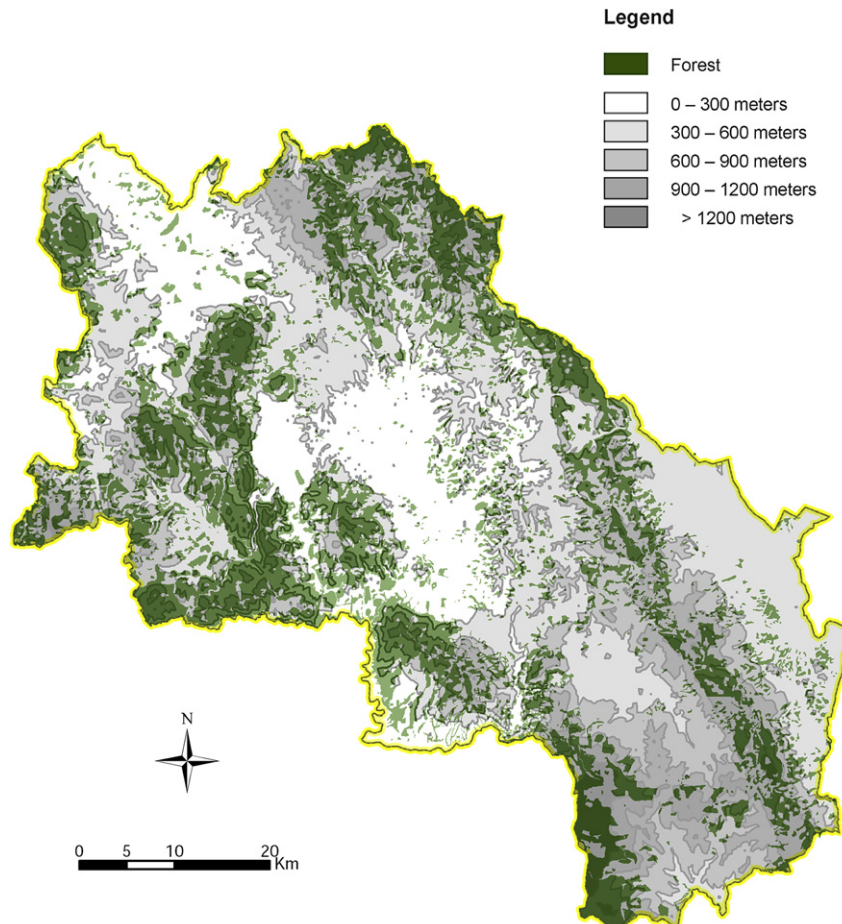


Fig. 3. Forest map of 1933.

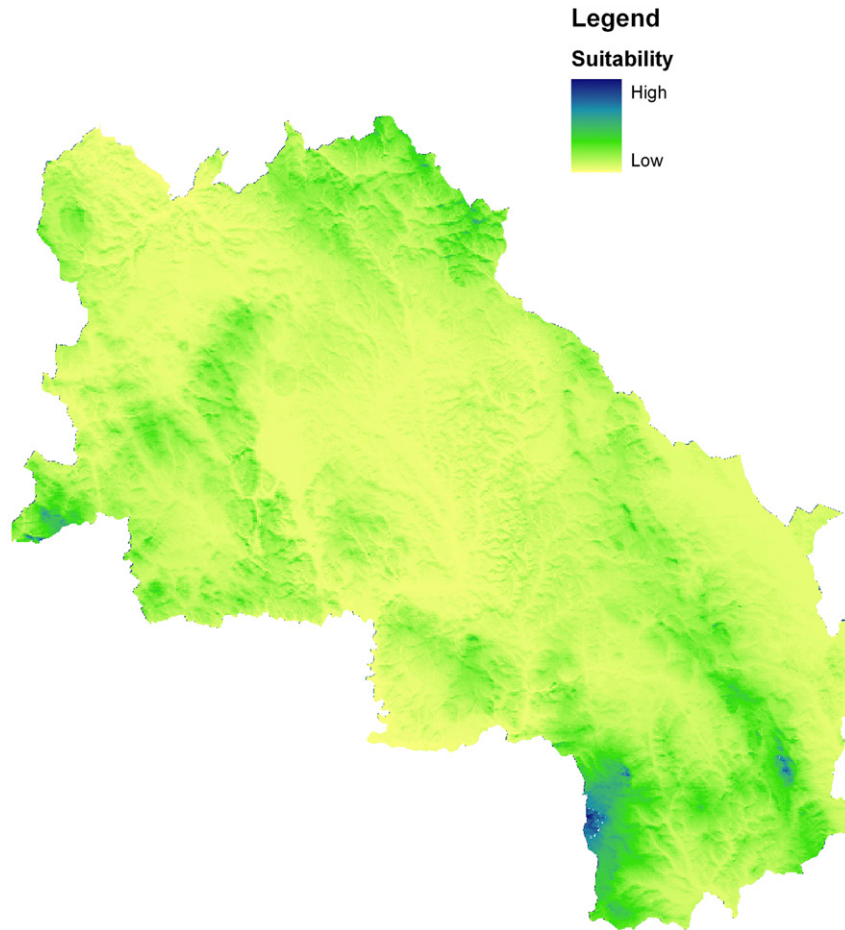


Fig. 4. Potential land-use change map.

1. Agreement between *Non forest types*
2. Agreement between *Forest types*
3. Disagreement, *Forest – Non forest*
4. Disagreement, *Non forest – Forest*

Cases 1 and 2 show a situation with correct model simulations, while cases 3 and 4 show errors of the simulation model (Eastman, 2006), representing omission and commission errors respectively.

The statistical validation procedure was based on the Kappa index of agreement (Cohen, 1960).

In order to assess the reliability of the model, Pontius (2000) developed statistics that allow for the consideration of different components of the Kappa index of agreement: *Kstandard* (equivalent to kappa—the proportion assigned correctly versus the proportion that is correct by chance), *Kno* (measure of the overall proportion correctly classified versus the expected proportion correctly classified), *Klocation* (measure of the spatial accuracy due to correct assignment of values), and *Kstrata* (measure of the accuracy due to correct assignment within predefined strata).

Using the combination of *Kno*, *Klocation* and *Kstrata* for evaluation allows for a determination of an overall success rate while providing an understanding of the factors (*i.e.* location and quantity) that contribute to the strength or weakness of the results. Similar to standard Kappa, the Kappa components equal one for perfect agreement between simulation and reality, and zero for the perfect “disagreement”, when two maps are completely different (Taylor, Brown, & Larsen, 2007). For details to Kappa components formula refer to Pontius (2000).

Landscapes typically contain many types of patterns created by several factors operating at multiple scales (Pontius, Olufunmilayo, & Hao, 2007). Thus it is important to examine the influence resolution plays in map comparison (Veldkamp et al., 2001). For this purpose, we considered Kappa components’ variation by decreasing map resolution starting from a 1×1 “pixel-based” resolution. The change in resolution was accomplished by aggregating neighboring pixels at a finer resolution based on a majority filter (Eastman, 2006; Pontius & Malanson, 2005). The resolution range chosen for validation analysis was 1–1024 pixels, (the total map dimension). The sequence of resolutions used in this paper followed a geometric series, in which the size of a pixel increases to twice the resolution at each resampling step (*i.e.* 1, 2, 4, 8, 16, 32 etc.). Results were displayed with area graphics where the different components of agreement were shown as bars. We considered seven components of agreement: four components of agreement (agreement due to chance, agreement due to quantity, agreement due to pixel location and agreement due to pixel location within each stratum) and three components of disagreement (disagreement due to quantity, disagreement due to pixel location and disagreement due to pixel location within each stratum, see Pontius & Chen, 2006).

In order to better evaluate the performance of the land use-change model, especially for prediction of spatial pattern location, the validation results were compared with a null model that predicts pure persistence of a certain class into the landscape (Hagen, 2002, 2003; Millington, Perry, & Romero-Calcerrada, 2007).

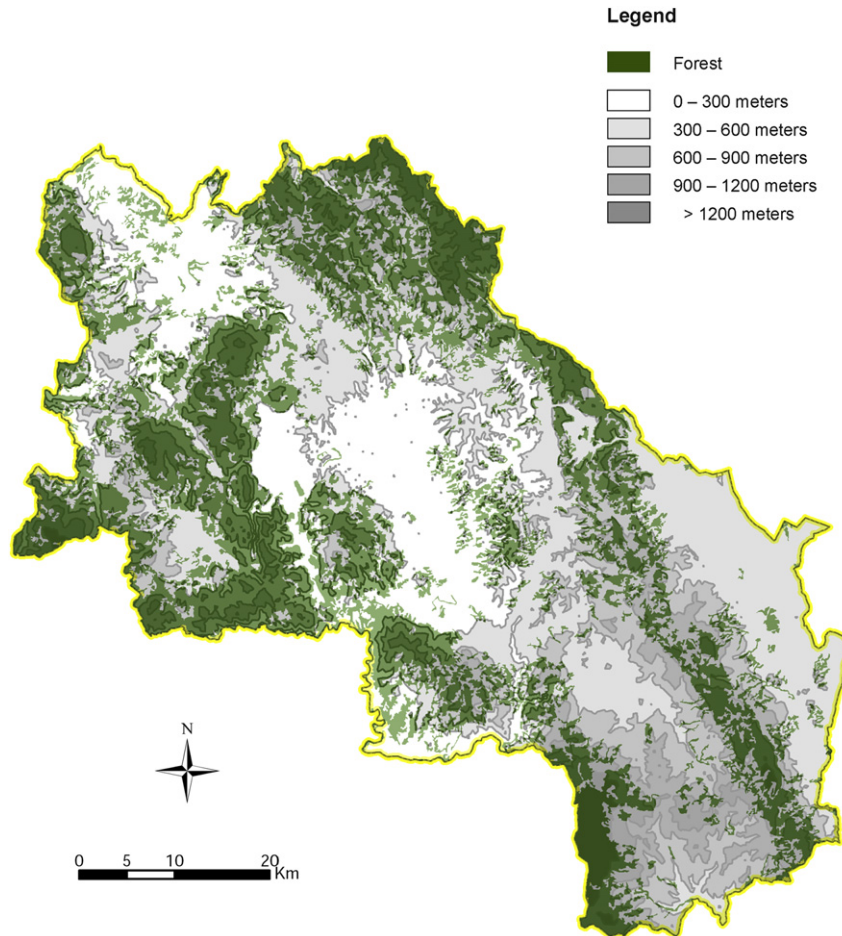


Fig. 5. Predicted forest map of 2000 stratified with township boundary limits.

Results

Fig. 3 shows the dataset of the 1933 forested area digitized from the historical forest map. Forest surface expanded in sites with higher values of altitude and slope, and with slightly low solar radiation values. These differences were used to derive the forest suitability map based on topographic variables. The suitability forestation map, resulting from fuzzy standardization of the topographic variables, is shown in Fig. 4.

The increase of forest surface in 2000, obtained by linear extrapolation of dynamics from 1933 to 1954, was utilized in the GEOMOD simulation as a prediction of quantitative change in forest cover. Comparison of the forest area between the GEOMOD simulation and the reference map showed no differences in forest cover. This allows us to assert that the forestation trend, occurring during the 1933–1954 period, remained unaltered for the following years. Using the potential land-use change map, and land-use change data from Table 1, GEOMOD creates a prediction for the 2000 forest surface shown in Fig. 5.

The overlay procedure between the GEOMOD model and the reference map produced a cross-classification image (Fig. 6). Errors in the simulated map are equally distributed over the entire results, and are characterized by high fragmentation and dispersion. The surface agreement of the GEOMOD model with the reference map is approximately 80% of the entire study area.

Kappa index of agreement values, however, showed contrasting results. In fact, Cohen standard Kappa and Kappa overall index of

agreement, Kno showed higher values of similarity with the reference map compared with the null model (0.59 and 0.60 vs 0.52 and 0.55 respectively). Conversely, the location index of agreement, Klocation and Kstrata, showed opposite results, with the null model having higher values than the GEOMOD model: GEOMOD Klocation and Kstrata values were 0.59 and 0.49 while the null model equaled 0.62 and 0.56.

Fig. 7 shows the trend of the proportion of pixels correctly classified (which gives the overall accuracy of a simulation run) at multiple resolutions in the GEOMOD simulation in comparison with the null model. The trend lines of the two models was very similar with that of the GEOMOD; these lines increased to perfect level, while the null model curve increased up to an asymptotic value equaling 0.9211.

The trend in variation of the kappa index of agreement, at multiple resolutions, showed a similar status (Fig. 8A and B). In the GEOMOD model, all the Kappa components increased by decreasing the resolution up to the perfect level of agreement. Concerning null model components of agreement, indices characterized by a location factor, Klocation and Kstrata, showed a growth up to 1, while Kstandard and Kno, which are indices of agreement also having a quantitative factor, decreased to a lower value equaling 0.3971.

Finally, Fig. 9 shows the variation in components of agreement or disagreement as a percent of the entire landscape. At the finest resolution, the GEOMOD model presents four components of agreements: agreement due to chance, agreement due to quantity,

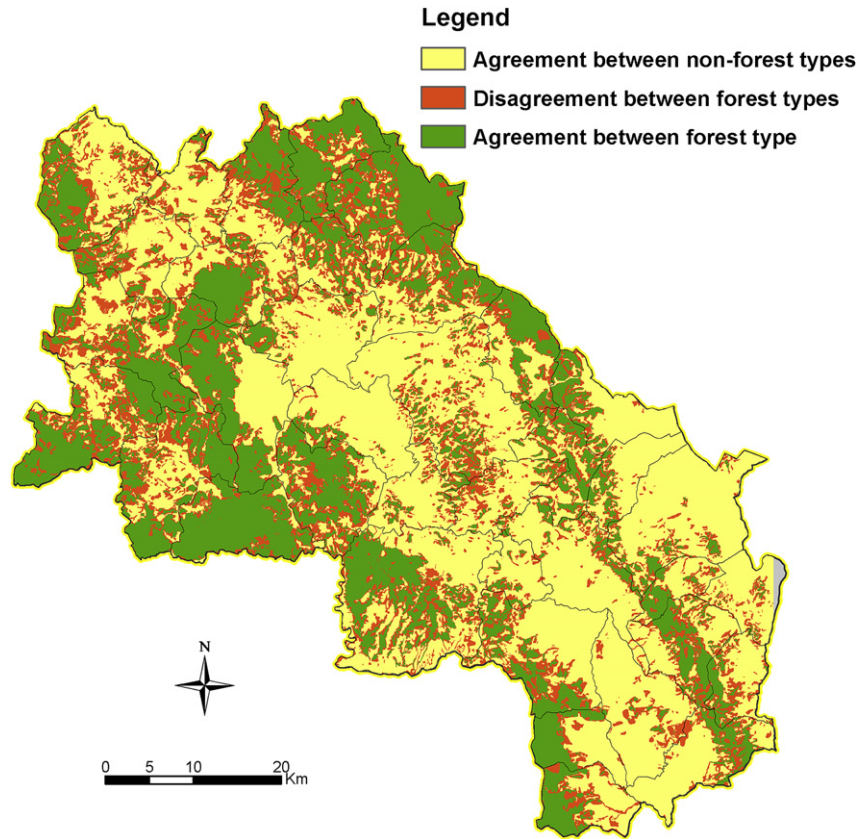


Fig. 6. Cross-classification map results of overlay process of 2000 forest reference map and predict model map.

agreement due to pixel location and agreement due to pixel location within each considered strata, and only one component of disagreement (disagreement due to pixel location). The border that separates the four components of agreement from disagreement due to location represents the percentage which was correctly attributed (percentage of pixels correctly classified, which is approximately 80% of all the study area). No disagreement due to quantity was found. Therefore, the only error found was due to pixel location. As the size of the pixels increases, both agreement and disagreement due to location decreases because the pixel-level location becomes less important as pixels become coarser. Considering the null model, there is a constant error due to quantity, equaling 0.08% of the entire landscape. At the coarsest

resolution, there were no errors due to location, the only error being due to quantity.

Discussion

The high percentage of pixels, correctly estimated by the GEO-MOD model (80%) promotes it as a powerful approach for estimating landscape trends. Nevertheless, when considering different K components, a very different outcome prevails. In fact, only Kstandard and Kno resulted in a positive outcome, in line with previous results based only Cohen’s K coefficient (see e.g. Landis & Koch, 1977; Carletta, 1996). The K components that, account the spatial component of cross-validation (Klocation and Kstrata), led

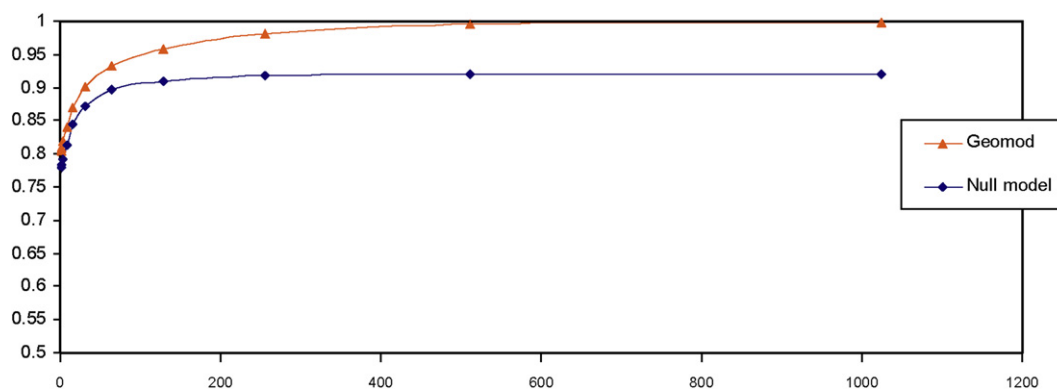


Fig. 7. Multiresolution approach to define percent of correct pixels.

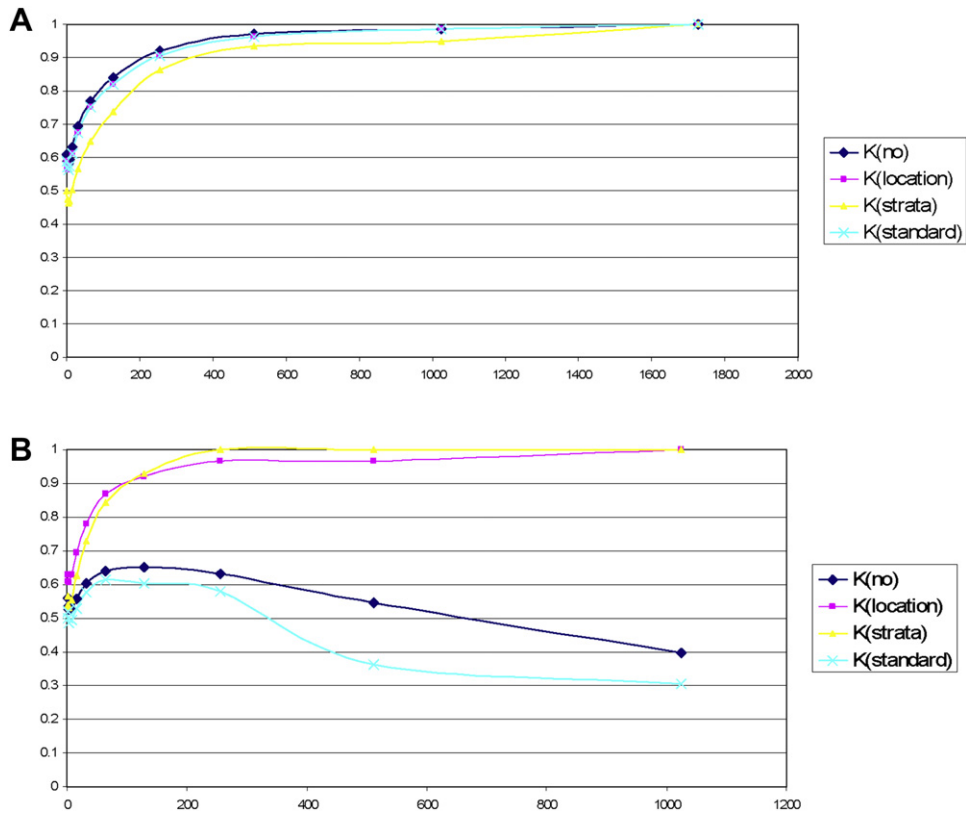


Fig. 8. A. Kappa index components versus resolutions in the GEOMOD model; B. Kappa index components versus resolutions in the null model.

to the worst results. In fact when considering the spatial arrangement of pixels, the null model led to better results than the GEOMOD model.

In other words, the spatial arrangement of forested areas, rather than simply occupation, led to bias in the GEOMOD simulation. Therefore, the GEOMOD model was poorly tested with the

Mediterranean environment. As stressed by Rocchini (2010), aside from thematic attribution, mapping error may derive from spatial boundaries among classes. As previously stated, the quality of land use and land-cover maps is generally assessed by relying on the area covered by each class without considering the spatial location of the classifier. A possible drawback of this procedure is that it does

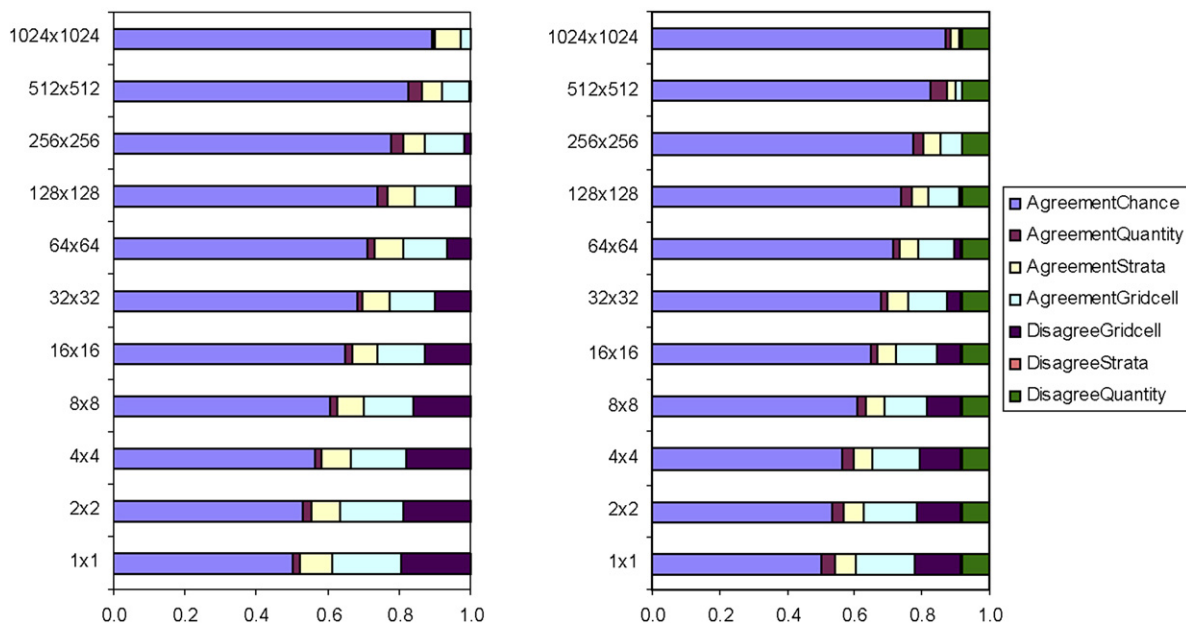


Fig. 9. The agreement space shows the proportion of correct classification versus resolution for the agreement between the reference map and the simulated map (on the left) and between the reference map and the null model (on the right).

not take into account the spatial localization of the classifier, thus overwhelming a-priori the “spatial problem” without solving it (Gomez, Biging, & Montero, 2008).

While man-made boundaries are frequently sharp, landscape ecotones are not easy to detect or model. In these cases, frequently used techniques to detect these boundaries are expected to fail because no peaks in the variability of pixel reflectivity are expected alongside gradual change (Fortin & Dale, 2005). Therefore, boundaries of discrete objects may be uncertain as a result of uncertainties about locating gradual transitions (Unwin, 1996). Obtaining a spatial disagreement becomes more likely, even in the presence of a general thematic agreement only related to quantity, e.g., to percent of pixels correctly classified.

Multiresolution analysis is a fundamental step in evaluating landscape patterns (Wu, Jelinski, Luck, & Tueller, 2000). The study of the landscape must take into account the scale of observation and analysis (O'Neill et al., 1991; Turner, Dale, & Garner, 1989; Wu et al., 2000). Results of analyses for the same area can vary because of the spatial resolution (Wu, 2004), and some patterns or processes can be recognized only at specific resolutions (Jelinski & Wu, 1996). As expected, decreasing the resolution in this study led to a higher proportion of correctly attributed pixels, reaching an asymptote of 1 and 0.9211, considering the GEOMOD and the null model respectively. At a coarser resolution, the spatial component is expected to bring a lower weight on the whole accuracy, thus allowing the GEOMOD model to reach the maximum accordance. The null model, while it showed a similar trend, did not reach the maximum accordance because an implicit bias, related to quantity of pixels correctly attributed, persists (see e.g. Fig. 9).

Conclusions

The Tuscany landscape, as with a large number of Mediterranean areas, has experienced great changes in the last few decades, with a marked increase in forest surface, due to the socio-economic changes such as the abandonment of countryside and mountains, and the subsequent natural colonization of woody vegetation (Feranec et al., 2010; Geri et al., 2010; Serra et al., 2008; Vos & Stortelder, 1992).

Similar patterns were observed in mountain and hill habitats, leading to an increase in their naturalness, while the diffusion of intensive monocultures and the enlargement of urban settlements determined a parallel reduction of the naturalness in the plain areas (Luoto, 2000; Zechmeister & Moser, 2001; Baessler & Klotz, 2006).

The validation phase of land-cover change models represents a crucial step when considering forest dynamics in many areas of the world (He, 2008). If the validation and calibration processes of the model used are not subject to a robust accuracy assessment, prediction errors may go unaccounted for. In this study, considering only the Cohen's Kappa index, or the component of agreement related to the quantity of pixels correctly classified with respect to a reference map, the real bias of the model would be underestimated, a fact which has been demonstrated to be due mainly to spatial disagreement. In this paper, only the GEOMOD approach has been selected to simulate the forestation process, primarily because it is one of the most frequently used GIS-based models for land-use change prediction. Moreover, a long-lasting literature has been built about spatial statistics of agreement developed based on GEOMOD (Pontius, 2000). This allowed us to apply such statistics to one of the most complex landscapes (Mediterranean habitat) in the world, and to test for spatial discrepancies in accuracy assessment in a robust manner. In this paper, we demonstrated the need to properly calibrate and validate the simulation mod to avoid misleading results. This is mandatory, at least in highly complex ecosystems such as those belonging to the Mediterranean region.

Acknowledgments

We are grateful to the Editor and to two anonymous reviewers for their precious suggestions on a previous draft of this manuscript.

References

- Agnoletti, M. (2004). Cultural landscape and biodiversity: a case study suggesting a different approach in conservation strategy in Italy. In M. Marchetti (Ed.), *Monitoring and indicators of forest biodiversity in Europe – From ideas to operationality*. EFI Proceedings No. 51.
- Antrop, M. (2004). Landscape change and the urbanization process in Europe. *Landscape and Urban Planning*, 67, 9–26.
- Baessler, C., & Klotz, S. (2006). Effects of changes in agricultural land-use on landscape structure and arable weed vegetation over the last 50 years. *Agriculture, Ecosystems and Environment*, 115, 43–50.
- Bakr, N., Weindorf, D. C., Bahnassy, M. H., Mareib, S. M., & El-Badawi, M. M. (2010). Monitoring land cover changes in a newly reclaimed area of Egypt using multi-temporal Landsat data. *Applied Geography*, 30, 592–605.
- Bengtsson, J., Nilsson, S. G., Franc, A., & Mengozzi, P. (2000). Biodiversity, disturbances, ecosystem function and management of European forests. *Forest Ecology and Management*, 132, 39–50.
- Bossard, M., Feranec, J., & Otahel, J. (2000). *Technical report no.40. Corine land cover technical guide - Addendum 2000*. European Environment Agency.
- Briassoulis, H. (2000). Analysis of land use change: Theoretical and modeling approaches. In S. Loveridge (Ed.), *The web book of regional science*. Morgantown: West Virginia University. <http://www.rri.wvu.edu/regscweb.htm>.
- Burnett, C., & Blaschke, T. (2003). A multi-scale segmentation/object relationship modelling methodology for landscape analysis. *Ecological Modelling*, 168, 233–249.
- Carleer, A. P., Debeir, O., & Wolff, E. (2005). Assessment of very high spatial resolution satellite image segmentations. *Photogrammetric Engineering and Remote Sensing*, 71, 1285–1294.
- Carletta, J. (1996). Assessing agreement on classification tasks: the kappa statistic. *Computational Linguistics*, 22, 249–254.
- Cernusca, A., Tappeiner, U., & Bayfield, N. (1999). *Land-use changes in European mountain ecosystems*. Berlin-Wien: Blackwell Wissenschafts-Verlag.
- Chase, T. N., Pielke, R. A., Kittel, T. G. F., Nemani, R. R., & Running, S. W. (1999). Simulated impacts of historical land cover changes on global climate in northern winter. *Climate Dynamics*, 16, 93–105.
- Cohen, J. (1960). A coefficient of agreement for nominal scale. *Educational and Psychological Measurement*, 20, 37–46.
- De Aranzabal, I., Schmitz, M. F., Aguilera, P., & Pineda, F. D. (2008). Modelling of landscape changes derived from the dynamics of socio-ecological systems: a case of study in a semiarid Mediterranean landscape. *Ecological Indicators*, 8, 672–685.
- De Fries, R. S., Asner, G. P., & Houghton, R. A. (2004). *Ecosystems and land use change*. Washington DC: American Geophysical Union.
- Debussche, M., Lepart, J., & Dervieux, A. (1999). Mediterranean landscape change: evidence from old postcards. *Global Ecology and Biogeography*, 8, 3–15.
- Dushku, A., & Brown, S. (2003). *Spatial modeling of Baselines for LULUCF Carbon Projects: The GEOMOD modeling approach*. Paper presented at the International Conference on Tropical Forests and Climate Change: “Carbon Sequestration and the Clean Development Mechanism”, Manila, Philippines.
- Eastman, J. R. (2006). *IDRISI Andes: Guide to GIS and image processing*. Worcester: Clark University.
- Eastman, J. R., Jin, W., Kyem, P. A. K., & Toledano, J. (1995). Raster procedures for multi-criteria/multi-objective decisions. *Photogrammetric Engineering and Remote Sensing*, 61, 539–547.
- Echeverria, C., Coomes, D. A., Hall, M., & Newton, A. C. (2008). Spatially explicit models to analyze forest loss and fragmentation between 1976 and 2020 in southern Chile. *Ecological Modelling*, 212, 439–449.
- Falcucci, A., Maiorano, L., & Boitani, L. (2007). Changes in land-use/land-cover patterns in Italy and their implications for biodiversity conservation. *Landscape Ecology*, 22, 617–631.
- Feranec, J., Jaffrain, J., Soukrup, T., & Hazeu, G. (2010). Determining changes and flows in European landscapes 1990–2000 using CORINE land cover data. *Applied Geography*, 30, 19–35.
- Foley, J. A., DeFries, R., Asner, G. P., Barford, C., Bonan, G., Carpenter, S. R., et al. (2005). Global consequences of land use. *Science*, 309, 570–574.
- Foody, G. M. (2002). Status of land cover classification accuracy assessment. *Remote Sensing of Environment*, 80, 185–201.
- Fortin, M. J., & Dale, M. R. T. (2005). *Spatial analysis: A guide for Ecologists*. Cambridge: Cambridge University Press.
- Garcia-Ruiz, J. M., Lasanta, T., Ruiz-Flano, P., Ortigosa, L., White, S., Gonzales, C., et al. (1996). Land-use changes and sustainable development in mountain areas: a case study in the Spanish Pyrenees. *Landscape Ecology*, 11, 267–277.
- Geri, F., Amici, V., & Rocchini, D. (2010). Human activity impact on the heterogeneity of a Mediterranean landscape. *Applied Geography*, 30, 370–379.
- Gomez, D., Biging, G., & Montero, J. (2008). Accuracy statistics for judging soft classification. *International Journal of Remote Sensing*, 29, 693–709.

- Hagen, A. (2002). *Multi-method assessment of map similarity*. Paper presented at the Fifth AGILE Conference on Geographic Information Science, Palma, Spain.
- Hagen, A. (2003). Fuzzy set approach to assessing similarity of categorical maps. *International Journal of Geographic Information Science*, 17, 235–249.
- Hall, C. A. S. (2000). *Quantifying sustainable development: The future of tropical economies*. San Diego: Academic Press.
- Hall, C. A. S., Tian, H., Qi, Y., Pontius, G., & Cornell, J. (1995). Modelling spatial and temporal patterns of tropical land use change. *Journal of Biogeography*, 22, 753–757.
- He, H. S. (2008). Forest landscape models: definitions, characterization, and classification. *Forest Ecology and Management*, 254, 484–498.
- Jelinski, D. E., & Wu, J. (1996). The modifiable areal unit problem and implications for landscape ecology. *Landscape Ecology*, 11, 129–140.
- Klijn, J., & Vos, W. (2000). A new identity for landscape ecology in Europe: a research strategy for next decade. In J. Klijn, & W. Vos (Eds.), *From landscape ecology to landscape science*. Wageningen: Kluwer Academic Publishers.
- Lambin, E. F., & Geist, H. (2006). *Land-use and land-cover change: Local processes and global impacts*. Berlin: Springer-Verlag.
- Landis, J. R., & Koch, G. G. (1977). An application of hierarchical kappa-type statistics in the assessment of majority agreement among multiple observers. *Biometrics*, 33, 363–374.
- Luoto, M. (2000). Modelling of rare plant species richness by landscape variables in an agriculture area in Finland. *Plant Ecology*, 149, 157–168.
- McCune, B., & Keon, D. (2002). Equations for potential annual direct incident radiation and heat load. *Journal of Vegetation Science*, 13, 603–606.
- McDonald, D., Crabtree, J. R., Wiesinger, G., Dax, T., Stamou, N., Fleury, P., et al. (2000). Agriculture abandonment in mountain areas of Europe: environmental consequences and policy response. *Journal of Environmental Management*, 59, 47–69.
- Millington, J. D. A., Perry, G. L. W., & Romero-Calcerrada, R. (2007). Regression techniques for examining land use/cover change: a case study of a mediterranean landscape. *Ecosystems*, 10, 562–578.
- Nagendra, H., Munroe, D. K., & Southworth, J. (2004). From pattern to process: landscape fragmentation and the analysis of land use/land cover change. *Agriculture, Ecosystems and Environment*, 101, 111–115.
- O'Neill, R. V., Turner, S. J., Cullinan, V. I., Coffin, D. P., Cook, T., Conley, W., et al. (1991). Multiple landscape scales: an intersite comparison. *Landscape Ecology*, 5, 137–144.
- Pelorusso, R., Leone, A., Leone, A., & Boccia, L. (2009). Land cover and land use change in the Italian central Apennines: a comparison of assessment methods. *Applied Geography*, 29, 35–48.
- Pocewicz, A., Nielsen-Pincus, M., Goldberg, C. S., Johnson, M. H., Morgan, P., Force, J. E., et al. (2008). Predicting land use change: comparison of models based on landowner surveys and historical land cover trends. *Landscape Ecology*, 23, 195–210.
- Pontius, R. G. (2000). Quantification error versus location error in comparison of categorical maps. *Photogrammetric Engineering & Remote Sensing*, 66, 1011–1016.
- Pontius, R. G., & Batchu, K. (2003). Using the relative operating characteristic to quantify certainty in prediction of location of land cover change in India. *Transactions in GIS*, 7, 467–484.
- Pontius, R. G., Cornell, J. D., & Hall, C. A. S. (2001). Modeling the spatial pattern of land-use change with GEOMOD2: application and validation for Costa Rica. *Agriculture, Ecosystems & Environment*, 85, 191–203.
- Pontius, R. G., & Chen, H. (2006). *Land change modeling with GEOMOD*. Worcester: Clark University.
- Pontius, R. G., & Malanson, J. (2005). Comparison of the structure and accuracy of two land change models. *International Journal of Geographical Information Science*, 19(2), 243–265.
- Pontius, R. G., Olufunmilayo, T., & Hao, C. (2007). Components of information for multiple resolution comparison between maps that share a real variable. *Environmental and Ecological Statistics*, 15, 111–142.
- Pontius, R. G., & Pacheco, P. (2003). Calibration and validation of a model of forest disturbance in the Western Ghats, India 1920–1990. *Geojournal*, 61, 325–334.
- Rocchini, D. (2010). While Boolean sets non-gently rip: a theoretical framework on fuzzy sets for mapping landscape patterns. *Ecological Complexity*, 7, 125–129.
- Sala, O. E., Chapin, F. S., Armesto, J. J., Berlow, E., Bloomfield, J., Dirzo, R., et al. (2000). Biodiversity: global biodiversity scenarios for the year 2100. *Science*, 287, 1770–1774.
- Schneider, L., & Pontius, R. (2001). Modeling land-use change in the Ipswich watershed, Massachusetts, USA. *Agriculture, Ecosystems & Environment*, 85, 83–94.
- Schulz, J. J., Cayuela, L., Echeverria, C., Salas, J., & Rey Benayas, J. M. (2010). Monitoring land cover change of the dryland forest landscape of Central Chile (1975–2008). *Applied Geography*, 30(3), 436–447.
- Serra, P., Pons, X., & Sauri, D. (2008). Land-cover and land-use change in a Mediterranean landscape: a spatial analysis of driving forces integrating biophysical and human factors. *Applied Geography*, 28, 189–209.
- Taylor, J. J., Brown, D. G., & Larsen, L. (2007). Preserving natural features: a GIS-based evaluation of a local open-space ordinance. *Landscape and Urban Planning*, 87, 1–16.
- Turner, M. G., Dale, V. H., & Garner, R. H. (1989). Predicting across scales: theory development and testing. *Landscape Ecology*, 3, 245–252.
- Turner, B. L., Moss, R. H., & Skole, D. L. (1993). *Relating land use and global land-cover change: A proposal for an IGBP-HDP core project*. A Report from the IGBP/HDP Working Group on Land-use/Land-cover Change. A Study of Global Change and the Human Dimensions of Global Environmental Change Programme. Stockholm: IGBP.
- Unwin, D. (1996). Integration through overlay analysis. In M. Fischer, H. J. Scholten, & D. Unwin (Eds.), *Spatial analytical perspectives on GIS*. London: Taylor & Francis.
- Veldkamp, A., Verburg, P. H., Kok, K., Koning, G. H. J., de Priess, J., & Bergsma, A. R. (2001). The need for scale sensitive approaches in spatially explicit land use change modeling. *Environmental Modeling & Assessment*, 6, 111–121.
- Verburg, P. H., Overmars, K. P., Huigenb, M. G. A., De Groot, W. T., & Veldkamp, A. (2006). Analysis of the effects of land use change on protected areas in the Philippines. *Applied Geography*, 26, 153–173.
- Verburg, P. H., Schot, P., Dijst, M., & Veldkamp, A. (2004). Land use change modelling: current practice and research priorities. *Geojournal*, 61, 309–324.
- Vos, W., & Stortelder, A. (1992). *Vanishing Tuscan landscapes*. Wageningen: Pudoc Scientific Publishers.
- Wu, J. (2004). Effects of changing scale on landscape pattern analysis: scaling relations. *Landscape Ecology*, 19, 125–138.
- Wu, J., Jelinski, D. E., Luck, M., & Tueller, P. T. (2000). Multiscale analysis of landscape heterogeneity: scale variance and pattern metrics. *Geographic Information Sciences*, 6, 6–19.
- Zechmeister, H. G., & Moser, D. (2001). The influence of agricultural land-use intensity on bryophyte species richness. *Biodiversity and Conservation*, 10, 1609–1625.