THE ROLE OF SPATIAL METRICS ON THE PERFORMANCE OF AN ARTIFICIAL NEURAL-NETWORK BASED MODEL FOR LAND USE CHANGE

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ABSTRACT:

The present study examines the role of spatial metrics in the performance of a previously developed ANN model for predicting land use/cover changes. The model outputs are validated against a land-use change map, which has been derived from ortho-rectified aerial photographs, Landsat TM and Quckbird data. The results from the application of the model before and after the use of spatial metrics are presented and evaluated and it is shown that the model can predict reasonably well the patterns of change in the island's olive-groves when parameterised with spatial metrics. Additionally, further analysis has been undertaken for exploring the individual contribution of the input parameters on the model outputs. Finally, the advantages of the model, its applicability and contribution to the understanding of the dynamics of land cover/use changes are discussed.

1. INTRODUCTION

Models of land use/cover change play a significant role in the understanding of mechanisms that drive change and the role of different drivers of land use change. The need to understand land use/cover changes and their driving factors relates to the importance of their impacts in the physical and socio-economic environment. Changes and impacts are a two-way process and only by monitoring and modelling these processes can we increase our knowledge on their relationships.

The modelling of land use/cover change has been recognised as one of the main topics of the Land Use/Cover Change (LUCC) Science and Research Plan, which is a main theme of the International Geosphere-Biosphere Project (IGBP) and the International Human Dimensions Programme (Lambin *et al*, 2005) as well as one of the three basic areas of Global Land Project (GPL) which is the successor of LUCC .

There now exists a very large diversity in modelling approaches, concepts and models striving to describe the mechanisms of land use and land cover change (see Briassoulis, 2000). Artificial Neural Networks is one of the modelling tools that have recently been used in the attempt to explore the complexity of interactions between the parameters that govern the patterns in which land use and land cover change and evolve. They have been employed for modelling land use change due to their ability to model and quantify complex behaviour and patterns (Pijanowski et al., 2000) by taking into account nonlinear relationships between driving variables and the changes in land use (Dai et al., 2005).

In the present study, a spatial model developed by Vafeidis *et al* (2007) has been used, which couples an artificial neural network with a GIS to forecast land use changes. The model has been parameterized for the island of Lesvos (NE Greece) for the time period between 1975 and 1999 and employs an artificial neural network for learning the patterns of change of the island's urban centres and extensive olive groves, based on a series of input parameters. Initially the model is run on basic parameters such as population density, transportation network, location of urban centres, distance from the coastline and urban areas, elevation and slope. In the second phase we make use of spatial metrics derived from land cover maps in order to examine their role in the performance of the model.

Only recently has it been suggested that the use of spatial/landscape metrics can aid the study of land cover/use change and help in understanding and inferring the processes involved in the spatial distribution of land uses and the patterns created (Herzog and Lausch, 2001; Narumalani *et al.*, 2004; Herold *et al.*,2005). These studies have focused on the application of spatial/landscape metrics to each classified image and the use/comparison of the indices derived. Herold *et al.*, *(*2005) moved on to using these metrics in models of urban land use change.

The use of spatial/landscape metrics is an important step towards the correct interpretation of change patterns as it provides additional information about the structure of changes (e.g. changes in patch size, fragmentation of the landscape etc) but it is still difficult to infer on the causal factors of these changes and proceed with the modelling of land cover/use change dynamics. Are changes randomly distributed? Are they aggregated? Do they follow the same pattern everywhere in the study area? These are some questions that we can not answer by simply calculating landscape metrics from land cover maps and comparing them for different time periods (Koukoulas *et al.*, 2007).

With the term spatial metrics here we refer mainly to metrics of changed patches derived from the maps of land cover change in the model calibration phase (1975-1990) and not metrics of the

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original land cover maps. The philosophy behind the use of spatial metrics of change was to enhance the model with parameters related to the change itself rather than individual factors. With this we do not suggest that the spatial metrics of individual land cover maps are not significant, but this has been already investigated by other researchers (Herold *et al.,* 2005). Previous work by the authors (Koukoulas *et al.,* 2007) revealed that spatial metrics of change have increased our ability to interpret maps of changes and to infer on their causes.

In this paper, due to space limitations only few of these metrics are presented and discussed. We concentrated on metrics derived from spatial statistics such as kernel density and from ordinary GIS operations such as cost distances. Also, for the same reasons, only the results of agricultural land use change are presented.

Further to the application of the model, its overall performance is assessed and the contribution of the individual parameters to the results is evaluated.

2. METHODS

2.1 Study Area

The study area is the island of Lesvos (North Aegean - Eastern Greece) (Figure 1). It was selected due to the fact that the island's ecosystems are faced with disturbance as a result of limited available natural resources, insularity, and the development of monocultures in the agricultural sector (Giourga *et al*., 1994). At the same time, Lesvos has limited prospects for development other than that of tourism.

Extensive fields of olive groves and variable natural and agricultural landscapes characterize the island, while the main income of the local population comes from the agricultural and stock-farmer activities. The size of farm holdings in the island is very small with the average area of a farm being approximately 2.3 ha, of which 2 ha are olive groves. Olive cultivation in Lesvos had been in the past a monoculture that virtually sustained the island's economy. However, the agricultural sector currently suffers from significant underemployment as employment in olive groves is required for only 70 days per year and per holding (Loumou *et al*., 2000). Moreover, the spread of competitive substitute products of olive oil, such as seed oils, has resulted in its economic decline followed by integral migration to the capital or to the bigger urban centers of the mainland (Giourga *et al*., 1994). Thus, socioeconomic processes that have taken place, combined with the physiographic characteristics of the island, have played a significant role in the formation of the natural, agricultural and urban land cover, and are responsible for the alterations of the agricultural landscape. In particular, the last three decades the island has experienced significant land cover/use changes despite being far from the mainland and without intense tourist growth.

Figure 1: Study area

2.2 Spatial Analysis of land change patterns

Initially, multispectral supervised classification techniques were employed in order to map land use and land cover changes that have taken place in the last 25 years. This task was achieved by devising a simple and operational rule-based approach to map land cover changes, based on the maximum likelihood (ML) classification of Landsat imagery and the expert analysis of the information regarding change detection. The use of ancillary GIS data such as a Digital Elevation Model, existing thematic maps and the knowledge of the island's vegetation dynamics, formed the basis for setting the rules for the post-processing of the classified images that led to a more accurate assessment and mapping of land cover changes (this work is described by Gatsis *et al* 2006).

Change detection was followed by the analysis of the spatial patterns of changes which involved a) the use of common GIS overlay techniques (e.g. buffers, cost distance, spatial queries) to find where the changes occur in relation to physiographical characteristics and the structured environment of the study area; b) the use of Landscape metrics on the change map to characterize the geometrical properties of the "changed" patches (such as fragmentation, connectivity, diversity, density metrics, isolation / proximity and contrast metrics); and c) the use of spatial statistics (such as spatial autocorrelation, kernel density) to study the spatial distribution of patches and reveal the "hot spots" of changes (Koukoulas *et al* 2007; Koukoulas and Blackburn 2004).

In this paper we restrict our presentation to cost (elevation) distance and the kernel density of changes. Kernel estimation is an extension of the 'moving window' technique. It was originally developed to obtain a smooth histogram from an observed sample and it has since been adopted to estimate intensity of an observed pattern using a function known as *kernel* (Bailey and Gatrell, 1995). The kernel function can be conceptualised as a moving function usually in the shape of a circle or square that is applied over a fine grid of locations in the area of interest and 'visits' each point in this fine grid. Distances to each observed event that lies within the region of influence (e.g. within a radius r for a circle) are measured and contribute to the intensity estimate of the origin according to how close are to the origin. Again here the problem of choosing the right radius (if it is a circle) exists, as a very large r will obscure local features and make the area look 'flat' and a very small *r* will result in a 'spiky' surface. As a solution, methods have been proposed to adjust (and to optimise) the 'radius' of the kernel function for regions with different density in order to improve the intensity estimate (see Bailey and Gatrell, 1995 for details of the kernel function).

In order to apply kernels in our maps of changes, the pixels of the land cover change image (olive losses presented here) were extracted and converted to points (each point occupied the centre of the pixel). Subsequently, a normal kernel function was applied with a fixed 2km bandwidth, producing absolute densities.

2.3 Spatial metrics and land cover change modelling

The above analysis and its outputs were the inputs for the model which was developed by Vafeidis *et al* (2007) for predicting land-use change. The model is based on a feed-forward multi-layer neural network with one hidden layer and employs a log-sigmoid transfer function. It is loosely coupled to a GIS and is run in two steps: In the first step, the neural network is trained, using and independent data set, for the actual changes in land use that occur between 1975 and 1990. The training of the network is supervised and is performed in batch mode using a back-propagation algorithm. In the second step the model is run to project patterns of olive grove cultivations, for the year 1999.

The model, is parameterised for the island of Lesvos (NE Greece), based on a series of initial parameters such as population density, road networks, locations of urban centres, distance from urban areas and the coastline, elevation and slope. Subsequently the model is parameterised with parameters based on spatial metrics developed above and its outputs were evaluated each time.

2.4 Validation

Validation was based on the ROC (Relative Operating Characteristic) method. The applications of ROC and its utility as a measure of the accuracy of diagnostic systems were discussed by Swets (1988). This measure was introduced in geographical studies by Pontius (2001). On the ROC curve the proportion of true-positives (agreement between the model and the reference map that the feature exists) is plotted against the proportion of false-positives (where the model suggests that the feature exists but it is not according to the reference map) for various threshold values of the predicted map. The predicted map has values on the range of 0 to 1 and the reference map is binary (0,1). The area below the curve is the ROC statistic and takes values up to 1. A value of 0.50 suggests that there is an agreement that could be caused by chance alone.

3. RESULTS

3.1 Spatial metrics of land cover change

In figure 2 the results from the cost (elevation) distance from the tourist areas are shown together with the real changes, as estimated from the processing of satellite images. The accuracies of the individual land cover maps were 90% and that of the produced land cover change map was estimated to 85% (more details in Gatsis *et al* 2006; Koukoulas *et al* 2007).

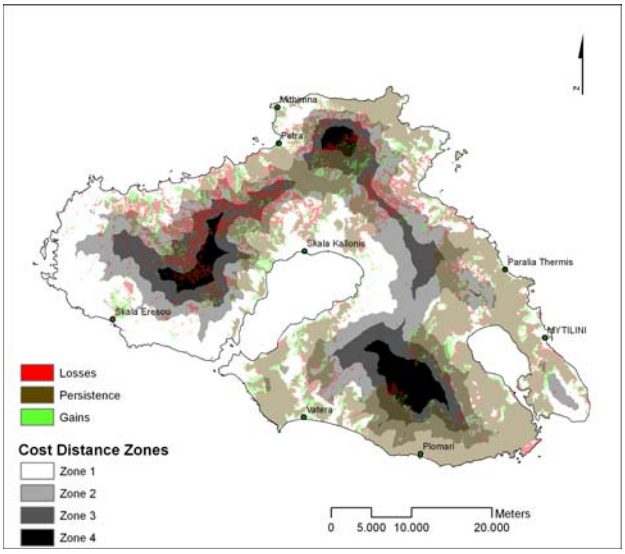

Figure 2: Distribution of olive cultivation changes and persistence in relation to cost distance zones (derived from the main touristic areas, shown as dots with labels)

It is shown that the main changes occur in the north and north-west part of the island and near the main city (Mytilene).

Subsequently in figure 3, we see the results of the Kernel density of losses of olive grove land use (shown in figure 2). This image makes clearer the pattern of the distribution of losses in areas of olive cultivations.

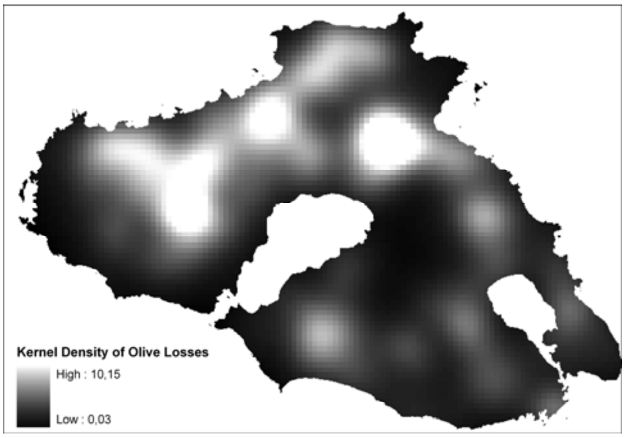

Figure 3: Kernel density of Olive losses 1975-90 (normal, bandwidth 2km).

3.2 Modelling results

The results show that the addition of spatial metrics has increased the overall accuracy of the predictions. Specifically the model run with the initial parameters had a relatively poor performance in the prediction of changes with ROC statistic equal to 0.53 for the area of changes (areas of persistence were excluded). The addition of cost (elevation) distance from the touristic areas increased only marginally the performance with ROC statistic for the same area equal to 0.54. The addition of kernel density of olive land use changes increased significantly the performance of the model (see figures 4, 5, 7) bringing the ROC statistic to 0.61 and the use of both spatial metrics raised the ROC value to 0.64.

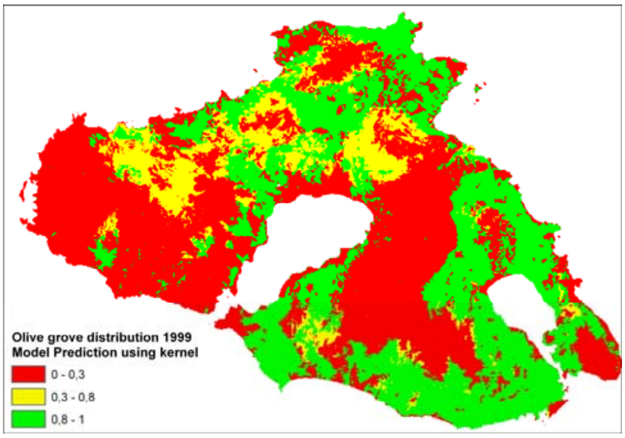

Figure 4: Model output in the scale 0-1 as a measure of probability of olive grove land use in 1999 (with the addition of kernel density of changes).

The ROC curves for each run of the model are shown in figure 5. These curves were computed only for the area that changed, excluding the area of persistence of olive grove land use. This was decided in order to get a clearer picture of the performance of the model on predicting changes in land cover/use. This is the reason why the initial points of the curve are below the performance of a chance model.

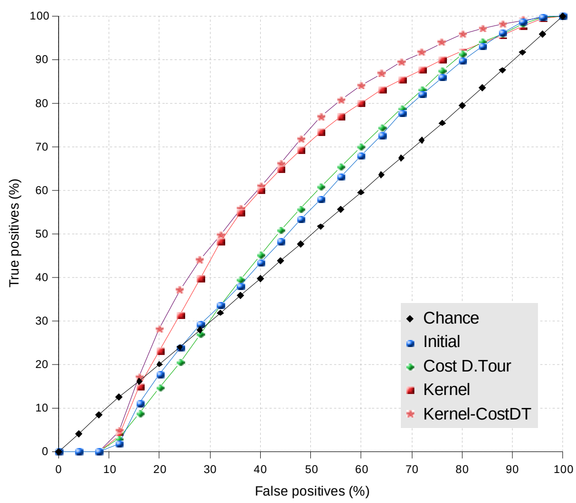

Figure 5: ROC curves to validate modelled olive cultivation land use change using initial parameters and spatial meters. The areas that remained unchanged were masked out.

As informative as the ROC curves and overall statistics may be, they are just a global measure. We were more interested in specific areas where we have seen different dynamics of change. The true changes are shown in figure 2 as derived from the processing of satellite images (Gatsis *et al* 2006; Koukoulas *et al* 2007)

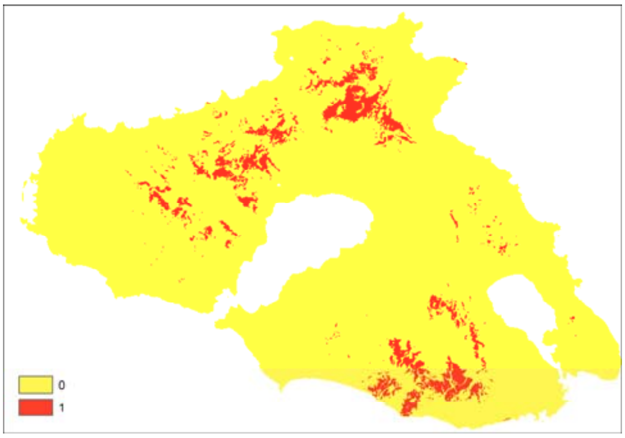

Figure 6: Model prediction of olive losses (1) run with initial parameters

In order to test the model's performance of the changes in specific areas we produced maps of predicted changes (losses and gains) for each land cover/use class. Here the predicted losses of olive groves during the period of 1990-99 are shown in figures 6 and 7.

Figure 6 shows the predicted losses in olive groves using the initial basic parameters, while figure 7 next shows the same changes as produced by adding the kernel density of changes for the period 1975-90. It is clear that the two outputs differ substantially both in the density of changes as in the area where the changes occur. Figure 6 shows that the changes occur mainly in mountainous areas away of main urban centres. Figure 7 is closer to the reality predicting changes close to the capital of the island (Mytilene, shown in figure 2) as well as in areas where the phenomenon has mainly occurred. However the prediction of losses in figure 7, has greater density than there is in reality.

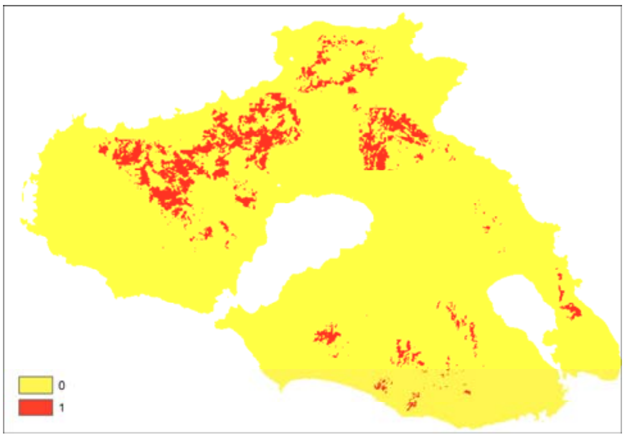

Figure 7: Model prediction of olive losses (1) run with the addition of kernel density of changes parameter

4. DISCUSSION

We discuss mainly the ability of the model to predict changes because the prediction of areas of persistence was a more straight-forward task and the model has performed remarkably well for these areas (with ROC statistic values over 0.95 for the whole area), as expected.

Results presented above have shown that the addition of more parameters based on spatial metrics of changed patterns did enhance the ability of the model to predict changes in olive cultivations. With the initial parameters, the model performs poorly generally predicting losses in all mountainous areas and areas of high slopes. It is evident here that we can not predict changes in agricultural land use based only in basic theory. There are complex global as well as local factors that affecting these changes. For example, we included the cost distance from the main touristic areas because we know that in these areas olive groves are likely to be sustained due to the fact that farmers complement their income from offering tourist services during the summer (Loumou *et al*., 2000; Koukoulas *et al* 2007). The results from this addition were more realistic near the main tourist centres but the overall pattern did not change and so the ROC statistic value. This is probably partly to the correlation of this parameter to the initial ones. The information added was minimal.

The addition of kernel density of changes did however made a difference since it carried new information based on the existing previously recorded losses in olive groves. This parameter proved to be valuable to our application; however the information brought into the modelling process referred to intensity of past changes. With the hypothesis that the same patterns of changes will continue into the future this parameter will produce reliable results. The degree of absolute intensity seemed not to be as important as the local relative differentiation depicted in the image.

5. CONCLUSIONS

The addition of spatial metrics is important in the modelling process of predicting land cover/use changes; however caution is needed in the inter-correlation of the parameters and the transferability of the information that is carried by them through time.

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