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Sensitivity of Landscape Indices to Classification Accuracy

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Abstract

The effect of classification accuracy on landscape indices is evaluated using the Monte Carlo simulation method. Class membership information is used to generate a set of equally likely alternative thematic maps. Landscape indices are then computed from each of these maps. The scatter in landscape indices is taken as an estimate of the variability of classification uncertainties. The method is applied on three classified Landsat TM image subscenes.

Introduction

The quantification and analysis of landscape spatial patterns is a major component of landscape ecology (Gustafson 1998). A large number of measures (also referred to as landscape indices or metrics) have been proposed to quantify landscape patterns from thematic maps (McGarigal and Marks 1995). Most of them attempt to capture, in terms of a numerical value, specific spatial characteristics of landscape. Generally, a landscape index value does not provide much information by itself - more information is gained by comparing index values of alternative landscape configurations, such as landscape observed at different times or locations (Gustafson 1998). Remote sensing offers the opportunity to perform such comparisons. Images of a large area can be acquired at one time, with repetitive capability (Gulinck *et al*. 2000). However, land cover maps derived by classification of remote sensing data are not perfect and without errors (Foody 2000 and references therein). These errors will likely introduce biases and uncertainties to landscape measures. The impact of thematic map uncertainties on landscape indices must be determined before they can be considered reliable measures for landscape monitoring (O'Neil *et al*. 1997).

Related Works

Broadly, two approaches have been considered to estimate the effect of thematic map errors on landscape indices. The first approach is empirical. It compares landscape measures derived from overlapping thematic maps based on images acquired over a short period of time (Brown *et al*. 2000; Vencatasawmy *et al*. 2000). The scatter observed in the derived landscape measures serves as an estimate of the amount of error (assuming that there is no landscape change). This approach is interesting because the comparison is performed on the end product and therefore there is no need to identify individual sources of error. The main constraint of this method is that it requires several cloud free and geometrically rectified images that contain no changes over a given period of time.

The other approach uses error information associated with thematic maps. Hess and Bay (1997) make use of the error matrix to correct class proportions and to evaluate the effect of uncertainties associated with the error matrix entries on proportion-based landscape indices. Alternatively, Wickham *et al*. (1997) used Monte Carlo simulations based on misclassification calculated from an error matrix. Errors were introduced into a thematic map according to the statistics provided by an error matrix. The biases and uncertainties were then obtained from statistics derived from landscape measures calculated for each realization. To incorporate spatial autocorrelation into the simulation process (the error matrix provides no information about the spatial distribution of errors), the amount of error was increased for pixels located on patch boundaries (edges).

In this paper, we present the preliminary results of our on-going evaluation of the sensitivity of landscape indices to classification accuracy. We consider a method based on class membership information to evaluate the effect of classification accuracy on landscape indices. Because class membership provides pixel-based information, it takes implicitly into account the spatial aspect of the problem. Class membership supplied by several classifiers has been used to assess the confidence level of classification on a per-pixel basis (Fisher 1994; Maselli *et al*. 1994; Van der Wel *et al*. 1998).

Class Membership

Although thematic maps are generated using hard classification rules, information on class membership can be obtained from several classification techniques (*e. g*. maximum-likelihood, minimum distance, fuzzy classifiers). Class membership gives the degree to which a pixel belongs to each class (cover category). In a gaussian-based maximum-likelihood classification, the probability of a pixel being a member of a class characterized by a mean vector **M** and variance-covariance matrix **V** is given by (assuming equal prior):

$$Pr = (2p)^{-n/2} \, |\, \mathbf{V} \,|^{-1/2} \exp[-\frac{1}{2}(\mathbf{X} - \mathbf{M})' \mathbf{V}^{-1} (\mathbf{X} - \mathbf{M})] \,,$$

where *n* is the number of bands and **X** is the pixel vector (Richard, 1993). The maximum-likelihood *a posteriori* probability is obtained through the Bayes' theorem and leads to a rescaling of *Pr* between 0 and 1 ($\Sigma Pr = 1$). In the maximum-likelihood classification, only the class having the highest *a posteriori* probability is allocated to the corresponding pixel, resulting in the so-called hard classification rule. The scope of this paper is to make use of all class membership information to assess the impact of classifier performance on landscape indices.

Method

The approach is similar to that of Wickham *et al*. (1997) but instead of using the error matrix information for the Monte Carlo simulations, the likelihood derived by the classifier for a pixel belonging to a specific class is used (Canters and De Genst 2000; Gascoigne and Wadsworth 1999; Fisher 1994). The *a posteriori* probability can be considered to be the chance of each class being the true class. The method consists of randomly assigning a class, to each pixel in turn, with a chance of occurrence for each class being proportional to its associated class membership strength. By repeating this procedure several times, it results a set of equally likely alternative thematic maps. Landscape indices are then computed for each alternative map. The scatter in landscape measure values computed from these maps is taken as an estimate of the potential variability due to classification uncertainties. In particular, the simulation results can be used to estimate the probability, P_I, of obtaining the same landscape index values from two images acquired at different times (or different locations within the same classified image). An estimation of P_I is provided by the overlapping area between the two distributions traced by each simulation set (each distribution must be normalized so that the area under the curve sums to one).

Experimental Results

A 1024 by 1024 pixels image subset was extracted from a Landsat-5 TM image acquired on 4 July 1988 over Goose Bay, Labrador. A gaussian-based maximum-likelihood supervised classifier was used to assign pixels to one out of 10-land cover categories. Forest inventory maps (1:12 500 scale) from Newfoundland and Labrador Forest Resources and Agrifoods were used for training. Two spatially coincident subsets of the same area were also extracted from two other TM images acquired at different times (26 July and 27 August 1999). The same training site locations were used to classify all 3 images. Preliminary estimate of the overall accuracy of the 1988 map is about 80%.

Each 1024 by 1024 pixels classified image subsets was subsequently partitioned into four distinct quadrants (23593 ha per quadrant). Three of these areas, labeled A1, A2 and A3, are believed to be exempt of major disturbances due to human activities. It is reasonable to assume that landscape changes are minor in these areas during the relatively short period between July and August 1999. The fourth area, labeled A4, was affected by changes mainly related to logging activities. Changes in A4 were much more severe between 1988 and July 1999, than between July and August 1999.

Twenty realizations (Monte Carlo simulations) were generated for each area and for each date. Each realization was filtered with a 3 by 3 pixels mode function prior to landscape measure computation. This is a post-classification procedure that is routinely used to reduce the number of very small patches that otherwise make maps look 'noisy' and thus influences (biases) landscape measures. Visual inspection of the spatial distribution of the differences in class labeling between two simulated images revealed that pixels most likely to change are mainly situated on patch boundaries, supporting the procedure adopted in Wickham *et al*. (1997) to take into account spatial autocorrelation.

Landscape indices were computed for each realization using the Fragstats program (McGarigal and Marks 1995). Table 1 provides an example of the results obtained. The mean and standard deviation of edge density (ED) are given. Edge density is defined in terms of the sum of the lengths of all edge segments divided by the total landscape area. It can be seen that the standard deviation for all simulation sets is almost the same, about 0.27 m ha^{-1}. This represents a coefficient of variation of less than 1% and therefore this result seems to be in agreement with the conclusion of Wickham *et al.* (1997) that variability in the spatial distribution of misclassification does not affect the estimates of landscape indices. Differences in mean values of about 3 m ha^{-1} are observed for areas A1 and A3 between the two images acquired one month apart. Such differences are one order of magnitude greater than the standard deviation, thus suggesting a significant difference in landscape patterns (i.e. not attributable to classification uncertainty). We also note that differences of the same order are observed for the areas A1 and A3 between July 1988 and July 1999. The difference of ~0.6 m ha^{-1} for A2, between July and August 1999, indicates that the chance of having the same index values from the two maps is not negligible as the overlapping area between the two distributions gives a probability of P_I ~ 0.2 (normal distribution shapes are assumed). Finally, a change in means of more than 12 m ha^{-1}, far in excess of the standard deviation values, is observed between 1988 and 1999 for A4. This area is known to be affected by logging activities.

Discussion

Results presented in Table 1 reflect those obtained, for example, with contagion and Shannon diversity indices. Because ground reference information is lacking, it is impossible to determine if the approach underestimates the effect of classification uncertainties on landscape measures or if the computed differences are true, or a mix of these two situations. Further works are needed to study the nature of the changes that give rise to the computed differences.

It should be noted that the approach considered in this paper should be internally consistent for the comparison of landscape indices at different locations within a same classified image.

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Table 1. Summary of the results for the edge density (ED) landscape index [meters per hectare]. Results are based on 20 realizations.

Area	ED (mean +/- standard deviation)		
Id.	4 July 1988	26 July 1999	27 August 1999
A1	102.12 +/ 0.28	106.94 +/- 0.30	110.74 +/- 0.35
A2	64.28 +/ 0.22	65.52 +/- 0.24	64.95 +/- 0.23
A3	101.62 +/ 0.24	104.38 +/- 0.26	107.13+/- 0.29
A4	89.06 +/ 0.27	101.74 +/- 0.22	103.64 +/- 0.28