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Incorporating Spatial Variability Measures in Land-cover Classification using Random Forest

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Abstract

The spatial variability of remotely sensed image values provides important information about the arrangement of objects and their spatial relationships within the image. The characterisation of spatial variability in such images, for example, to measure of texture, is of great utility for the discrimination of land cover classes. To this end, the variogram, a function commonly applied in geostatistics, has been used widely to extract image texture for remotely sensed data classification.

The aim of this study was to assess the increase in accuracy that can be achieved by incorporating univariate and multivariate textural measures of Landsat TM imagery in classification models applied to large heterogeneous landscapes. Such landscapes which difficult to classify due to the large number of land cover categories and low inter-class separability. Madogram, rodogram and direct variogram for the univariate case, and cross- and pseudo-cross variograms for the multivariate one, together with multi-seasonal spectral information were used in a Random Forest classifier to map land cover types.

The addition of spatial variability into multi-seasonal Random Forest models leads to an increase in the overall accuracy of 8%, and to an increase in the Kappa index of 9%, respectively. The increase in per categories Kappa for the textural Random Forest model reached 30% for certain categories. This study demonstrates that the use of information on spatial variability produces a fundamental increase in per class classification accuracy of complex land-cover categories.

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1. Introduction

The characterisation of spatial variability in remotely sensed images, through textural measures, provides important information about the arrangement of objects and their spatial relationships within the image. Many studies on land cover and land use mapping have demonstrated that including textural variables may provide additional information to the classification process and improve the discrimination of land-use/land-cover categories yielding an increase in the mapping accuracy [1-5].

Texture, in a geostatistical sense, may be analyzed in terms of the two essential characteristics of digital values: local or global variability and spatial autocorrelation. The first characteristic is closely related to the statistical dispersion, which is frequently analyzed by calculating the variance. The second characteristic, spatial correlation, assumes that digital values are not completely randomly distributed within an image and, consequently, that there exists a spatial variability or dependence structure associated with each land-cover class. In this sense, Lark [6] showed that the amount of variability between pairs of pixels depends on their spatial relations and it can be used as a textural descriptor. This result leads directly the use of the goestatistical approach for texture analysis, because it offers the advantage that variability and spatial autocorrelation are jointly analyzed.

The inclusion of multiple textural variables in remote sensing studies implies a large increment in the dimensionality of the data sets being used in image classification. This high volume of data can exceed the ability of classifiers to deal with it. The problem with dimensionality of the data space can be adressed from the selection of a robust classifier. Ensemble learning algorithms have received increasing interest because they are more accurate and robust to noise than single classifiers [7]. Among classifier ensembles we have chosen a relatively new classifier called Random Forest which presents the the following advantages [8]:

- It is unexcelled in accuracy among current algorithms.
- It runs efficiently on large data bases.
- It can handle thousands of input variables without variable deletion.
- It is relatively robust to outliers and noise.
- It is computationally lighter than other tree ensemble methods (e.g., Boosting).

The aim of this study was to investigate the utility of combining various geostatistical texture measures with spectral data for the classification of Mediterranean land cover on a per-pixel basis. The basic methodology used in this paper involved computing several texture images to improve land-cover classification using Random Forest.

2. Study Area and Data

The study area for this project is province of Granada, located in the south of Spain, by the Mediterranean Sea. Spring and summer images have been used for the land-cover classification. To this end, two Landsat Thematic Mapper 5 scenes of the same area in Spanish southeast were acquired. The images were acquired on 18 August and 4 April 2004. Scenes location corresponds with Path 200 Row 34 of Landsat Worldwide Reference System (WRS), with coordinates centre 0030822.7343W 372400.0054N WGS-84.

The imagery was then processed with the Tasseled Cap or Kauth Thomas linear transformation before being used in classification. This transformation produced six features: summer brightness, summer greenness, summer wetness, spring brightness, and both spring greenness and wetness.

Relief complexity and high anthropic influence make it possible to distinguish 14 different thematic categories of the study area (Table 1). In order to train and validate the classification models, a total number of 2050 areas were identified from pre-existing land-cover maps, and each of them was verified by using diverse high-resolution digital true-colour orthophotographs (1:10000) acquired during 2004. The ground reference dataset were randomly divided into 75% and 25% for training and testing, respectively. The number of the training sites per class was kept roughly equal (i.e., approximately 100 training sites and 50 testing sites per category).

Table . Land-cover classification scheme

Class ID	Class name	Class ID	Class name
1	Urban	8	Quercus sp.
2	Poplar Grove	9	Herbaceous Irrigated
3	Conifers	10	Ligneous Irrigated
4	Greenhouses	11	Herbaceous Dry
5	Shrublands	12	Bare soils
6	Olive Trees	13	Tropical Crops
7	Grasslands	14	Water

3. Methods

3.1. Geostatistical texture

To introduce texture information into the image classification process we have calculated a set of texture measures: variogram, rodogram, madogram, cross variogram and pseudo-cross variogram [4, 5]. These entire textural features haven been calculated from the multispectral bands (band 1 to 5 and 7) of the Landsat TM5 spring and summer images. To account for the different spatial variability patterns of the land-cover categories of the study area, the textural measures have been computed over three different window sizes: 5x5, 15x15 and 31x31. The computation of geostatistical texture has been carried out from omnidirectional variogram derived measures, considering the first lag, the second lag and the slope between the first and the second lag.

3.2. Random Forest

Random Forest (RF) is an ensemble of classification trees, where each tree contributes with a single vote for the assignation of the most frequent class to the input data [8]. RF uses the best split of a random subset of input features or predictive variables in the division of every node, instead of using the best split variables, which reduces the generalization error. Additionally, in order to increase the diversity of the trees, RF uses bagging or bootstrap aggregating to make them grow from different training data subsets.

Bagging is a technique used for training data creation by randomly resampling the original dataset with replacement, i.e., with no deletion of the data selected from the input sample for generating the next subset. Thus, each subset selected using bagging to make each individual th-tree grow contains a certain proportion of the calibration dataset. The samples which are not present in the calibration subset are included as part of another subset called out-of-bag (OOB). Note that a different OOB subset is formed for every th-tree of the ensemble, from the non-selected elements by the bootstraping process. These OOB elements, which are not considered for the trainining of the th-tree, can be classified by the th-tree to evaluate his performance.

4. Results and Discusion

The geostatistical measurements were used in RF classification directly together with the spectral data (multi-seasonal Kauth-Thomas bands; MKT). The first column of Table 2 shows the results of the RF classification using MKT features only. Table 2 shows that the highest classification accuracies were achieved when geostatistical measurements at a 1-pixel lag were used in combination with the MKT bands, probably because the variability computation at one lag is more stable and less affected by class variation [3]. The second lag led to slightly lower accuracies and the results obtained from the slope between the first and the second lag did not result in a significant increase in accuracy. The slope parameter did not make any significant contribution to the differentiation of categories as, for lags close to the origin, there is a proportional effect between the variograms of each category and, hence, the slope is very similar. Therefore, GT measurements at first lag were selected for the present analysis.

Table 2. Random Forest parameters and best classification accuracy (% and Kappa) for the GT models at different lags. MKT refers to the multi-seasonal Kauth Thomas model. GT, GT5, GT15 and GT31 refer to the multi-scale textural model and to the models at 5x5, 15x15 and 31x31 window sizes, respectively.

		Lag 1				Lag 2				Slp. lag 1 and 2			
	MKT	GT	GT5	GT15	GT31	GT	GT5	GT15	GT31	GT	GT5	GT15	GT31
O. acc.	0.85	0.92	0.89	0.91	0.91	0.90	0.88	0.89	0.91	0.87	0.84	0.87	0.88
Kappa	0.84	0.92	0.88	0.90	0.91	0.90	0.87	0.88	0.91	0.86	0.83	0.86	0.87

Table 3 shows an increasing trend of accuracy by adding geostatistical textural features to multi-seasonal RF models. The overall accuracies for the multi-scale geostatistical model (GT), and for the models of window sizes 5x5 (GT5), 15x15 (GT15) and 31X31 (GT31) were, 0.92, 0.89, 0.91 and 0.91, respectively, with Kappa statistics of 0.92, 0.88, 0.90 and 0.91. The inclusion of the geostatistical textural bands in RF models meant an increase of 8.04%, 4.36%, 6.87% and 7.04% in the overall accuracy and of 8.78%, 4.75%, 7.50% and 7.68% in the Kappa index for GT, GT5, GT15 and GT31, respectively (Table 3).

Table . Random Forest parameters, classification accuracy and increments in accuracy (% and Kappa) produced from MKT and textural models. MKT refers to the multi-seasonal Kauth Thomas model. GT, GT5, GT15 and GT31 refer to the multi-scale textural model and to the models at 5x5, 15x15 and 31x31 window sizes, respectively.

	MKT	GT	GT5	GT15	GT31
O. Acc.	0.85	0.92	0.89	0.91	0.91
Kappa	0.84	0.92	0.88	0.90	0.91
Inc. in O. Acc. (%)	--	8.04	4.36	6.87	7.04
Inc. in Kappa (%)	--	8.78	4.75	7.50	7.68

Table 4 shows the per-category Kappa index and the Kappa increase pattern for the geostatistical models, respectively. Textural models increased inter-class separability between the most miss-classified categories with respect to the MKT models. Multi-scale models presented the highest increase in overall inter-class separability, while the textural features at single-scale window sizes produced a more moderate increase of the mapping accuracy. The ranking of increases in Kappa for each of the categories varied depending on the window sizes used. The ligneous irrigated crops, urban and bare soils, were the categories which experienced the highest increases in Kappa for the multi-scale models, with increments of 30.53%, 20.21% and 21.19% for GT, respectively. In the case of models for 5x5 window sizes, the most heterogeneous categories, with a greater spatial variability, bare soils and urban, experienced the highest increments (21.19% and 20.21% for GT5, respectively). Other heterogeneous categories such as ligneous irrigated and urban were also well distinguished at 31x31 window size, with increments equal to 33.60% and 23.06% for GT31, respectively. It may be reported from Table 4 that considering the textural features did not affect the classification of the shrubland and water classes for which the summer Kauth-Thomas bands were sufficient.

Table 4. Per class Kappa values of MKT and geostatistical textural RF classifiers and increments in kappa of textural models over MKT model. MKT refers to the multi-seasonal Kauth Thomas model. GT, GT5, GT15 and GT31 refer to the multi-scale textural model and to the models at 5x5, 15x15 and 31x31 window sizes, respectively.

Class nº	MKT	GTO	GT5	GT15	GT31	Inc. in Kappa GTO	Inc. in Kappa GT5	Inc. in Kappa GT15	Inc. in Kappa GT31
1	0.74	0.94	0.89	0.94	0.91	25.94	20.21	25.94	23.06
2	0.94	1.00	0.91	0.96	0.98	6.87	-2.29	2.28	4.57
3	0.76	0.83	0.85	0.83	0.83	8.49	11.18	8.42	8.38
4	0.98	1.00	1.00	1.00	0.98	2.20	2.20	2.20	0.00
5	0.85	0.83	0.83	0.83	0.83	-2.59	-2.63	-2.69	-2.66
6	0.91	1.00	0.96	0.98	0.94	9.44	4.69	7.07	2.36
7	0.81	0.81	0.81	0.83	0.85	0.11	0.07	2.67	5.28
8	0.76	0.85	0.74	0.78	0.83	11.83	-2.09	3.42	9.02
9	0.89	0.91	0.91	0.91	0.94	2.41	2.39	2.41	4.76
10	0.70	0.91	0.81	0.87	0.94	30.53	15.28	24.40	33.60
11	0.94	1.00	0.98	1.00	1.00	6.94	4.62	6.94	6.94
12	0.72	0.85	0.87	0.79	0.79	18.31	21.19	9.53	9.58
13	0.78	0.91	0.80	0.98	0.89	16.49	2.56	24.74	13.73
14	1.00	0.98	0.98	0.98	1.00	-2.15	-2.15	-2.15	0.00

5. Conclusions

This study aimed to evaluate the potential of geostatistical textural measures together with the RF algorithm to classify the land-cover of a complex Mediterranean environment. RF performed well in the context of classifications of fourteen categories using a high dimensional feature space composed by spectral and textural variables.

Geostatistical textural models achieved a more reliable classification of the most heterogeneous categories, which are the most difficult to classify, e.g., ligneous irrigated crops, urban and bare soils, which were better mapped by GT than by MKT. Moreover, considering textural features did not affect the classification of the shrubland and water class. The bare soil category experienced the highest increments at window sizes of 5x5, while other categories like ligneous irrigated and urban were better distinguished at 31x31 window size.

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