THE USE OF REMOTE SENSING IMAGERY TO UPDATE FOREST COVER

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ABSTRACT

This paper intends to present a geostatistical methodology for evaluating and updating forest cover areas using data from sampling plots on aerial photographs combined with information obtained from satellite imagery.

This study is twofold: image filtering and updating of forest cover.

Firstly, in image processing, the behaviour of the structure function (variogram), gives the variance of salt-and-pepper noise within the image. The noise related with nugget effect can be filtered by factorial kriging, estimating the spatial components.

Secondly, a major benefit of multitemporal remotely sensed images is their applicability to change detection over time. The correlation model between satellite information, acquired in different date, and the dot-grid data allowed the estimation of the regional components related with forest cover, by cokriging and updating spatial components.

The results were mapped and the changes were detected.

INTRODUCTION

Forest area estimates are essential in resources inventories, especially for forest management and planning activities. Also, there is a constant demand for update and accurate information for area estimates at a local, regional and global scale.

Remote sensing can be used to provide information at a whole range of spatial, spectral, radiometric and temporal resolutions in a global coverage.

Various analytical approaches differing in mathematical complexity, processing and analysis intensity and classification techniques have been used to detect vegetation changes (Jensen *et al.*, 1995; Jong and Burrough, 1995; Wolter *et al.*,1995; Michener and Houhoulis, 1997). However there is a strong need for a methodological improvement by making the best integrated use of different information,

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focusing techniques such as geostatistics for information purposes, image analysis and processing techniques for pattern recognition (Muge and Pina, 1994), geographical information systems for data integration and expert systems for the design of rule based decision models (Gallaun and Banninger, 1996; Spencer *et al.*, 1997). Geostatistics has proved to be a rather efficient method for estimation of spatial distributed variables needed for natural resources characterisation and modelling. Geostatistics has been applied to forest inventory with air cover (Fouquet and Mandallaz, 1993; Varekamp *et al.*, 1996, Barata *et al.*, 1996, Nunes, 1999), showing an improvement towards the usual methods of estimation in forest inventory.

THEORICAL CONCEPTS

In the last years geostatistical methods have been increasingly applied to image processing (Atkinson and Curran, 1997; Lajaunie and Jeulin, 1989; Ma and Myers, 1993; Wen and Sinding-Larsen, 1997a; Wen and Sinding-Larsen, 1997b; Yfantis and Makri, 1994), mainly for filtering or compression purposes.

Muge *et al*. (1998a) present some of the most important spatial statistics: the direct (univariate) and cross (bivariate) experimental variograms and spatial covariances which are powerful geostatistical tools to identify and to describe image variability. However, the ultimate goal of a geostatistical study never is data description. Usually the goal of the study (estimation of a unknown value, data filtering or compression) requires a model of the population. One essential step in this process is the quantitative modelling of the spatial statistics over the study area (Goovaerts, 1997). All results rely on the model type chosen and the parameters fitted.

Functions must be fitted to those experimental values in order to provide a model of the (direct or cross) spatial variability of the variable(s). The most important theoretical and practical issues of variogram modelling are described elsewhere (Wackernagel, 1995; Goovaerts, 1997).

Most of the times the variogram can be fitted by a sum of N^s+1 basic permissible functions:

$$\gamma(h) = \sum_{u=0}^{N^s} b^u \gamma^u(h)$$

Usually the variogram shows a discontinuity at the origin called nugget effect, which value is b^0. The nugget for the unstructured and/or noisy part of the spatial variability of the variable. One of the most popular basic variogram function is the spherical model, used in the case study presented in this work. This model depends on two parameters: the range a^u and the sill b^u.

In the multivariate case the nested multivariate linear model (linear model of coregionalization) corresponds to (Sousa, 1989):

$$\gamma_{jl}(h) = \sum_{u=0}^{N^s} b_{jl}^u \gamma^u(h)$$

Each direct and cross variogram must be fitted by a sum of basic permissible functions. For each scale u the matrix B=[b_{jl}^{u}] is positive semi-definite and the parameter a is the same.
The nested multivariate linear model corresponds to the following variables' decomposition (Sousa, 1989):

$$Z_j(x) = \sum_{u=0}^{N^s} b_{jl}^u Z_j^u(x) + m_j$$

These spatial components have also zero mean, basic variogram function $\gamma^u(h)$ and are mutually independent. They represent different and orthogonal (micro, local and regional) scales of variability associated with the variables.

In the multivariate case, the kriging estimator is readily extended to incorporate information about all the variables originating the cokriging estimators (Goovaerts, 1997).

The spatial components revealed by the linear nested model of variability can be estimated from actual data (Sousa, 1989).

Galli and Sandjivy (1985) has shown that factorial kriging in the spatial domain is equivalent to spectral analysis in the frequency domain. This geostatistical method, intensively used for analysing various types of geological data, has proven to be especially useful for image filtering (Wen and Sinding-Larsen, 1997a; Nunes *et al*, 1998; Tingting *et al*, 1999). For instance, if we want remove the noise of an image by filtering the nugget (high frequency) component, the factorial kriging system must be slightly transformed:

$$\begin{cases} \sum_{\alpha=1}^{n_0} \lambda_\alpha \gamma(x_\alpha - x_\beta) - \mu = \sum_{u=1}^{N^s} \gamma^u (x_\beta - x_0) \\ \qquad\qquad\qquad\qquad\qquad \beta = 1, \ldots, n_0 \\ \sum_{\alpha=1}^{n_0} \lambda_\alpha = 1 \end{cases}$$

STUDY AREA AND AVAILABLE DATA

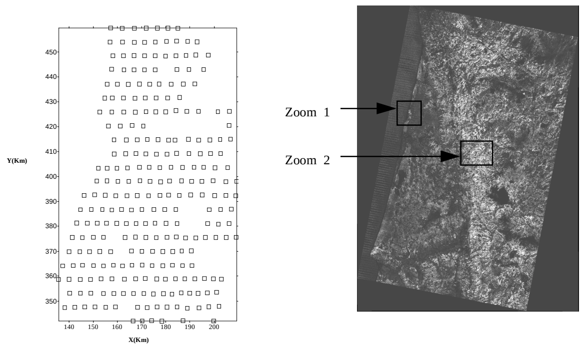
The study area is located in the North-Centre of Portugal, where the forest cover is mainly of p*inus pinaster* and e*ucalyptus globulus* and where the forest cover has been changed very fast by fires, environmental conditions and human activities. Updating by satellite imagery and geostatistics techniques would be an efficient and reliable process for evaluates the forest area.

The available information comes from two different sources: colour infrared aerial photographs and LandSat TM satellite imagery.

The colour infrared aerial photographs (1.35 Km along Ox and 2.4 Km along Oy) come from an aerial survey covering the study area. These aerial photographs have been photointerpreted in a 4 Km x 4.8 Km grid (1 in 3 photos along Ox and 1 in 2 along Oy). The photointerpretation of each photograph of this sampling grid was made by taking a cluster of eight points arranged in a cross. Each point of the cluster was classified in terms of the corresponding dominant forest cover type. The average value taken by a cluster can be considered as an estimation of the proportion of each forest cover type in the respective aerial photograph. Two hundred and thirty three values of the proportion of pure e*ucaliptus globulus* (EC00) were then gathered for the study, corresponding two hundred and thirty three photointerpreted aerial photographs in the study area (figure 1a).

Concerning satellite images, were used a two time data sets of LandSat imageries acquired in November of 1990 and 1992. Figure 1b) shows an extract of the transformed satellite image of 1990 (a vegetation index). All the LandSat-TM multispectral bands (TM1,...,TM7, except TM6), covering the study area, were used in order to find more correlation of TM bands and the photointerpreted data. The dimension of each TM band pixel is $30x30m^2$. So, each aerial photograph is covered by 3600 pixels. The average values of digital numbers related with each photography area were obtained from the vegetation index image.

Traditionally, vegetation indices are used to improve the correlation between the remote sensing data and vegetation cover. Some vegetation indices (Thenkabail *et al.*, 1994), were tested. The vegetation index, which has higher correlation with the variable EC00 is a rationing (STVI2=TM4/(TM3*TM7)), which has a correlation coefficient of 0.61 (Barata *et al.*, 1996).



a) b)

Figure 1 - a) Location of aerial survey data; b) vegetation index image (STVI2).

METODOLOGY AND RESULTS

The importance of this study is show that geostatistics can be either used in image processing and in estimating changes in forest cover.

In this paper we have applied geostatistical methods to carry out the following problems:

- satellite image preprocessing, filtering by factorial kriging the independent and spatially correlated noise in satellite imagery, eliminating the nugget effect component;
- modelling the spatial correlation between photointerpreted data and the selected vegetation index for the entire set of variables at different times (1990 and 1992). Two models of corregionalization were fitted to estimate the spatial components;

- the regional components for 1990 and 1992 were estimated by cokriging;
- cokriged maps were produced and the temporal differences were detected.

Satellite Image Preprocessing

The main function of image preprocessing is the radiometric and geometric corrections of the TM data. The objective of a radiometric atmospheric correction is to convert satellite generated digital counts to ground reflectances (absolute reflectances). Various complex models have been develloped to correct atmospheric effect (Chavez, 1996). However, these models need some data, about atmospheric conditions for the date and time that remote sensing data was acquired, which are not usually available. The minimum histogram (Chuvieco, 1990), an empirical technique to minimize the atmospheric effects was applied to band 3 (red).

Geometric Correction

Image registration is other basic image processing operation used in remote sensing. The tradicional method for rectifying satellite imageries involves the use of polynomials (Welch *et al.*, 1985), using Ground Control Points (GCPs) identified in the image (pixel and line coordinates) and in topographic map of the study area. The accuracy of this step is very important because it affects the success of the correlation between remote sensing and ground data sets.

Second degree polynomials and fifteen GCPs were used to rectify the 12 November 1990 TM image to a Universal Transverse Mercator (UTM) map projection (RMSE=6.7 m / 0.22 pixels), in the same coordinate system as the dot-grid data (EC00). The 1992 image was rectified using thirty GCPs obtained from the 1990 rectified image with an RMSE=2.3m. All images were resampled to a 30 m pixel size using nearest-neighbor resampling technique to retain radiometric integrity (Jensen, 1986; Jensen *et al.*, 1993).

Image Normalization

The spectral and spatial resolution of the sensors can imposed limitations and problems introduced by the effects of atmosphere.

In multitemporal image analysis, the objective is to detect changes, which have occurred over a certain period of time. A simple method to find changes in a pair of images is to overlay the images and detect the differences between them. Because these images are taken at different times and under different conditions they have to be aligned prior to comparative processing.

It is important that multitemporal images be normalized to minimize changes in brightness values due to detector calibration, sun angle, atmospheric attenuation. After scene normalization, changes in brightness values are assumed to reflect changes in surface conditions. Absolute radiometric calibration techniques require ground reflectance data, and information about the sensor and atmosphere for the date of image acquisition, which are often difficult or impossible to obtain for archived imagery (Kim and Elman, 1990; Olsson, 1995). In such cases, empirical normalization techniques based on linear regression models can be used to correct for relative differences in atmospheric and other non-surface conditions among multiple image dates (Eckhardt *et al*., 1990; Jensen *et al.*, 1995). The 12 November 1990 TM scene was selected as the base scene to which the 1992 scene was normalized because aerial photographs were available for that period.

Some radiometric normalization targets were common among all image dates and include: (1) two water bodies (deep ponds and river Douro), (2) two pine forest stands and three eucaliptus forest, (3) two agricultural fields (4) two bare soils and (5) three urban areas. All targets were located in relatively flat areas and were assumed to represent constant reflectors (Michener and Houhoulis, 1997). Digital numbers (about five hundred of pixels in each polygon) were collected inside each polygon over all bands at the same located areas. Regression equations were developed by correlating the target brigthness values obtained for the scene being normalised (1992) with the brightness values of the base band targets (1990) for the three bands of the vegetation index.

Table 1- Regression equations used to normalise radiometric characteristics of the 1992 data with the 1990 TM data.

Date	Band 3	Band 4	Band 7
12 Nov.1990	Y=1.32(x)+4.1 R^2=0.94	Y=0.98(x)+7.2 R^2=0.98	Y=1.07(x)+1.6 R^2=0.95

The derived regression equations were applied to the 1992 image resulting in normalized datasets in which spectral variation was minimized.

IMAGE FILTERING BY FACTORIAL KRIGING

In the last years geostatistical methods have been increasingly applied to image processing (Lajaunie and Jeulin, 1989; Ma and Myers, 1993; Yfantis and Makri, 1994; Atkinson and Curran, 1997; Wen and Sinding-Larsen, 1997a; Wen and Sinding-Larsen, 1997b), mainly for filtering or compression purposes.

The nugget effect provides the variance of salt-and-pepper noise in satellite imagery, caused by scattering of the radiometric measurements and striping (Pan, 1989; Chavez, 1992; Wald, 1989). To filter salt-and-pepper from satellite imagery some characteristics of the behaviour of the structure function (variogram) were used with success (Nunes *et al*., 1998). Factorial kriging was used to obtain the three components reveled by the variograms. Figure 2 is the variogram of STVI2 in two directions.

The resulted images in two selected areas are shown in figures 3 and 4. These areas are selected in order to study sensivity of the factorial kriging to local effects. One of them covers sea, shoreline and some forest area with pine and eucaliptus (figure 3a). The second one covers a high density of eucaliptus forest and is crossed by roads (figure 4a). Figures of C0 - 3b) and 4b) show the images related with nugget effect, which is a good readiness of the noise. Figures of C1 - 3c) and 4c) show the first components (local), and the figures of C2 - 3d) and 4d) show the second components (regional). The images of C1+C2 figures 3e) and 4e)) show the resultant images from adding first and second spatial components. They are smoothed images, without noise.

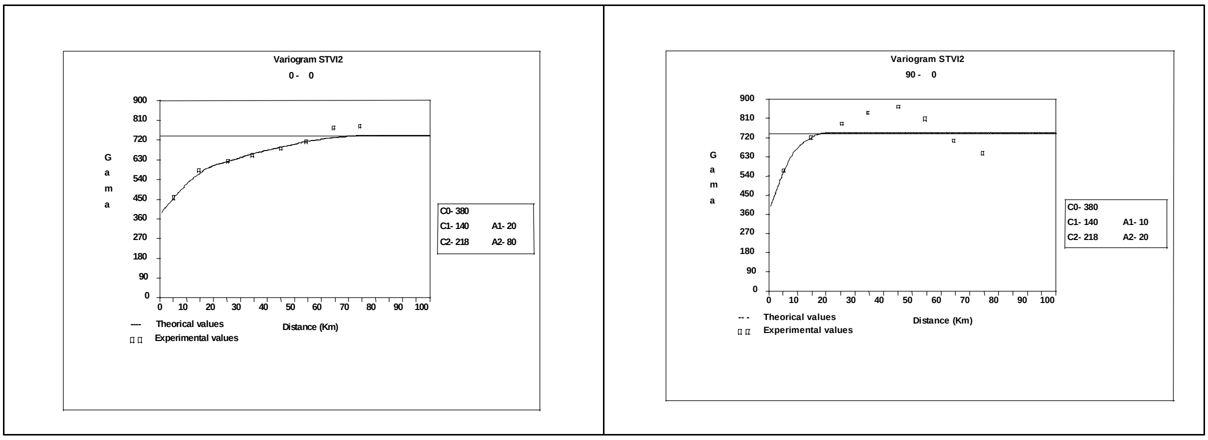


Figure 2 – Variograms of STVI2 (1992).

MULTITEMPORAL ESTIMATION OF REGIONAL COMPONENTS

Correlation Analysis

In 1992 the only available data is the satellite imagery. So, to update the regional component of the variable EC00, some kind of cross estimation must be performed.

The correlation coefficient between the two study variables, EC00 and STVI2 in 1990 and in 1992, were calculated showing that the correlation decreased from 0.61 to 0.49 in 1992.

In order to know what happen at the temporal regional components the spatial components were estimated by factorial kriging, producing the micro (C0), local (C1) and regional (C2) components. The correlation coefficient between the variable EC00 and the regional component were calculated. The correlation between regional components is higher than between the original variables (table 2).

Table 2- Correlation coeficient (R).

R	C_2-STVI2(90)	C_2-STVI2(92)
EC00	0.52	0.52
C_2 (EC00)	0.75	0.67

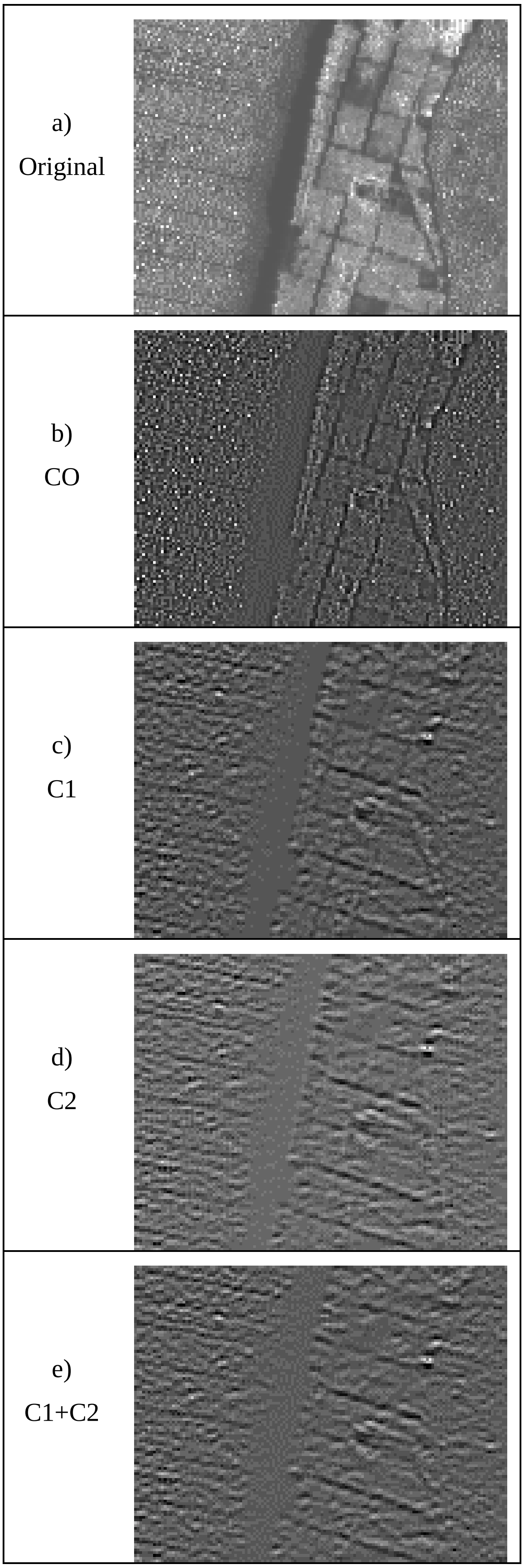


Figure 3. - Images related to zoom 1.

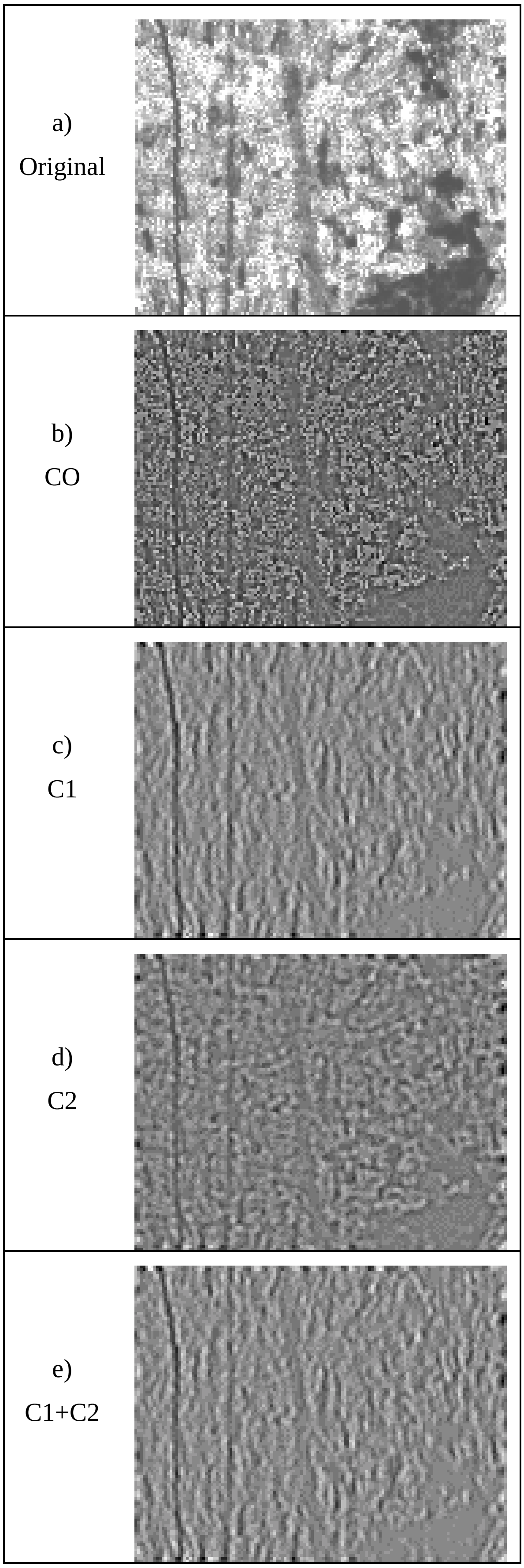


Figure 4 - Images related to zoom 2.

The regional component was interpreted as being related with the forest regional variation. So, the regional component of EC00 for 1992 was obtained by cokriging using this regional component, as the auxiliary variable and the EC00 data points (only one for each estimate) for 1990. This methodology implies that in dot grid data points the EC00 do not vary significantly from 1990 to 1992.

Cokriging Regional Component of Eucaliptus

Estimation the variable EC00 was carried out based on regional component of the variable STVI2 .

Cross-correlation between regional components of dot-grid (EC00) and STVI2 were calculated for different spare lags thus enabling to model the structure of coregionalization for the entire sets of variables. Cross and single variograms were calculated and fitted, modelling the spatial structure for 1990 and 1992. Based on this model, regional component of EC00 was estimated in the study area.

Cokriged thematic maps were produced for proportion of EC00 in 1990 (figure 5) and 1992 (figure 6). The differences between these two maps are mainly in areas of higher density.

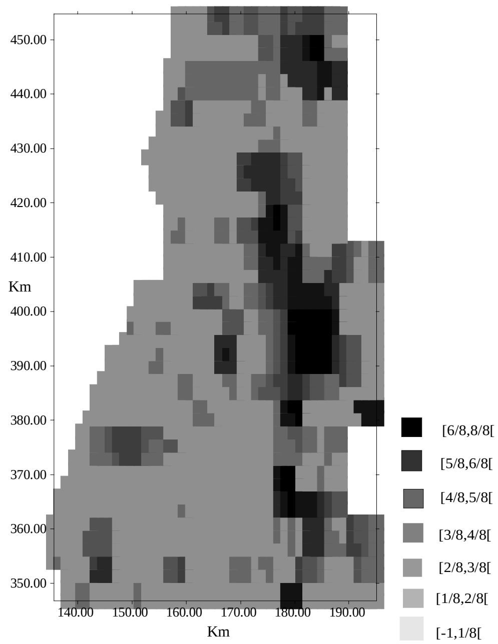


Figura 5 - Cokriged map of EC00 (1990).

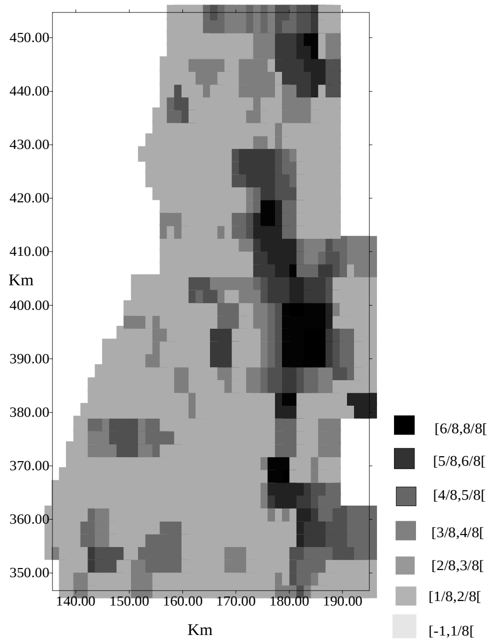


Figure 6 - Cokriged map of EC00 (1992).

DISCUSSION

Image processing procedures can be improved by applying factorial kriging to remove random and periodic noise in multispectral satellite data.

The methodology used in multitemporal analyse, which is based on the estimation of spatial components and cokriging estimator, can be used to detect changes in forest cover. The degree of success depends upon the correlation between the sample data and the remote sensing data.

Satellite imagery is an important source of information for forest monitoring, planning and research, and can be optimized using geostatistics methods to update forest cover. However, these results must be validated with actual ground data. The results obtained, with the methodology, would be more obvious if the period of time was longer than only two years.

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