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SciVerse ScienceDirect

Procedia Environmental Sciences 7 (2011) 389–394

Procedia Environmental Sciences

1st Conference on Spatial Statistics 2011– Mapping Global Change

Methodology for the discrimination of areas affected by forest fires using satellite images and spatial statistics

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Abstract

We evaluated the effectiveness of statistical operators Moran's I, Geary's C and Getis and Ord Gi in Landsat ETM satellite images to measure and analyze the spatial dependence of the spectral characteristics of the affected areas, comparing these results with those obtained in the use of spectral indices for discrimination of burned areas. The study was carried out using a multitemporal analysis (before and after the fire) in some areas located in the Tuparro National Park in the department of Vichada, in the northeastern part of the Orinoco region in Colombia, which were affected by the presence of this phenomenon. To perform the analysis used tools provided by the software R version 2.11.1, packages spdep and rgdal for handling raster data and calculation of spatial autocorrelation tests.

The use of statistical operators provide better results with the band of near infrared (NIR) and allow better identification of burned areas, which facilitates the detection of spatial and spectral changes. This methodology provides information that can improve the monitoring of the effects of fire in time and helps to prevent possible disruption and the inventory of locations where this phenomenon has been presented.

Selection and peer-review under responsibility of Spatial Statistics 2011

Keywords: Statistical operator, spectral indices, spatial autocorrelation, forest fire.

1. Introduction.

The fire is one of the most influential natural elements in the modification of the native ecosystems of forest and grassland, often generated by direct or indirect action of man causing ecological damage, economic, human and cultural. Forest fires are an environmental problem that generates negative impacts on forest ecosystems and alter the structure of vegetation and forest, characteristic of the landscape. Effective use of remote sensing to identify areas affected by forest fires, information is obtained from the areas experiencing changes as a result of this phenomenon, which makes the use of this detection system a tool with great ability to study Fire effects on vegetation, which is why various techniques were used to detect and assess changes in forest ecosystems.

The use of statistical operators such as Moran's I, Geary's C and Getis and Ord Gi possible to measure the degree of dependence between the spectral characteristics of burned areas by providing a methodology that can support the design of better environmental policies for constant accompaniment of the state in which the vegetation is making possible the detection of active centers and inventory of affected areas for resource management.

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Selection and peer-review under responsibility of Spatial Statistics 2011

doi:10.1016/j.proenv.2011.07.067

2. Theoretical Framework

2.1. Forest fires

Forest fires are fires that burn natural or forest vegetation, areas suitable for forestry or those without being agroforestry use or comply with an environmental function. Forest fires have become one of the phenomena generating environmental problems in Colombia causing loss of forest resources, increasing deforestation, decreasing floristic diversity.

2.2. Remote sensing and forest fires

Remote sensing or remote sensing can be defined as the process of acquiring information from a distance, without any physical contact between the information source and the receiver of the same (Montoya, 1996). This source serves as the basis for the analysis of dynamic effects of changes in coverage from the study of spatial patterns that can investigate the affected ecosystems in relation to the intensity, severity, size or frequency of fire.

2.2.1. Spectral characteristics of vegetation burned

The visible spectrum reflectivity of a burned area increases as a result of the loss of chlorophyll in leaves and increased bare soil, decreases significantly in case of severe disease in vegetation cover due to the significant prevalence of coal and ash resulting confusion with shaded areas, water bodies and that the coal ash has very low reflectivity in the visible. These similarities reduce the possibility of using the visible range to discriminate burned areas (Pereira et al., 1999).

In the near infrared signal becomes more evident recently burned areas due to the large amount of fuel burned and carbon deposited in the soil thereby reducing the reflectivity. And in the mid-infrared (SWIR), burned areas cause changes in the spectral response leading to an increase of reflectivity by the decrease of moisture in the plant tissues.

2.3. Spectral index to identify areas affected by forest fires

Several spectral index have been used to identify burned areas, the first to use vegetation index were mainly based on the contrast between red and near infrared, which were not very efficient because the spectral response of vegetation is affected confused with other decks. Have therefore been developed other index such as the NBR, developed specifically to identify burned areas.

2.3.1. Calculation of NBR

This technique can highlight areas affected by fire in order to quantify and evaluate the effects of fire severity by relating the band 4 (NIR) and band 7 (SWIR). This index provides a scale of values between -1 and 1 that reflects the effects of fire on vegetation. Is calculated from the following equation:

$$NBR = \frac{(\rho_{i,IRC} - \rho_{i,SWIR})}{(\rho_{i,IRC} + \rho_{i,SWIR})} \qquad (1)$$

Where:
ρi.IRC: Reflectivity for the band 4 (Near Infrared).
ρi.SWIR: Reflectivity for band 7 (middle infrared).

2.4. Spatial statistics

Spatial statistics is the branch of statistics that deals with scientific methods for the collection, description; visualization and data analysis have geographic coordinates. Thanks to the use of spatial information in the analysis of satellite imagery have developed various studies that must be taken into account the measurement and quantification of spatial patterns to perform the mapping of a particular region according to the characteristics of landscape.

Spatial autocorrelation generally implies the absence of independence between the observations discussed or what is the same, "the existence of a functional relationship between what happens at a particular point in space and what happens elsewhere." Another concept to consider is the "weight matrix which reflects the intensity of the interdependence between each pair of regions, is constructed considering the most appropriate neighborhood criterion for the study.

2.4.1. Techniques for exploratory spatial data analysis

The techniques of exploratory spatial data analysis distinguish between global and local indicators of spatial association, providing an overview of the different methods of quantification of spatial autocorrelation in satellite images.

2.4.1.1. Global measures of spatial Autocorrelation

The most common tests used to compare the presence of the global spatial correlation are:

•*Statistical Moran'I:* Moran (1948), values can vary from 1 to -1, where 1 indicates strong positive spatial autocorrelation, the neighboring pixels are similar and -1 if strong negative autocorrelation, meaning that neighboring pixels are not appear. The expected value of 0 indicates no spatial autocorrelation. This statistic is calculated using the following expression:

$$I = \frac{N}{\sum_i \sum_j w_{ij}} \frac{\sum_{ij}^{N} w_{ij}(x_i - \bar{x})(x_j - \bar{x})}{\sum_{i=1}^{N}(x_i - \bar{x})^2} \quad i \neq j \qquad (2)$$

Where:

x_i, x_j: DN value at location xi, $\bar{x}$: Sample mean and w_{ij}: Spatial lag between pixels i and j

• *Geary C statistic:* Geary (1954), values ranging from 0 to 2, where 0 indicates the maximum positive spatial autocorrelation, 2 maximum negative spatial autocorrelation. The expected value of 1 means a lack of spatial autocorrelation. Is calculated by the following expression:

$$C = \frac{N-1}{2\sum_i \sum_j w_{ij}} \frac{\sum_{ij}^{N} w_{ij}(x_i - x_j)^2}{\sum_{ij}^{N}(x_i - \bar{x})^2} \quad i \neq j \qquad (3)$$

Where:

x_i, x_j: DN value for pixels i and j, $\bar{x}$: Media sample, w_{ij}: Delay space between pixels i and j and N: Number of observations

2.4.1.2. Local measures of spatial Autocorrelation.

In response to the inability to detect homogeneous groups and the lack of significant local variations in the data, Getis and Ord (1992) presented a local measure of correlation, the statistic Gi. Later Anselin (1995) proposed local indicators of spatial association (LISA) so you can evaluate the individual contribution of each observation, and "hot spots" local.

• Statistical Getis and Ord: High levels of digital level are represented by a high value of Gi, while low values of digital level indicates negative values of Gi. The expected value of 0 indicates that the grouping does not occur at the specific distance (d). The Getis and Ord statistic in the context of remote sensing is calculated from the following equation:

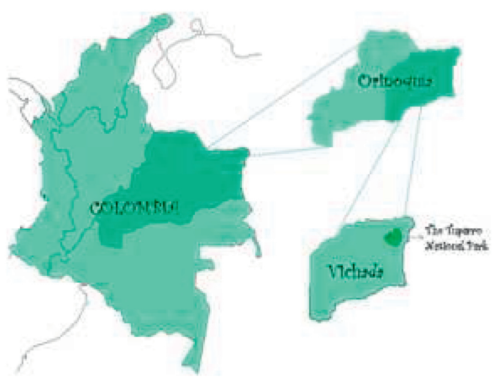
$$G_i(d) = \frac{\sum_j w_{ij}(d)x_j - W_i x}{s^2 \sqrt{\frac{W_i(n - W_i)}{(n-1)}}} \quad i \neq j \qquad (4)$$

Where: $W_i = \sum_j w_{ij}(d)$, $w_{ij}(d)$= weighted distance (d) between pixels i and j, and x_i, x_j: DN value for pixels i and j

3. Materials and Methods

3.1. Location

The study area is the Tuparro National Park, in the department of Vichada the northeastern tip of the Colombian eastern plains, and assess the damage to the vegetation cover by the presence of forest fires in that area. When viewing the reports of the various entities responsible for monitoring forest fires, it was observed that the present study area affected by the phenomenon.



3.2. Images used

We used Landsat ETM +, path 004, row 056 in which is located the National Park the Tuparro for 2009 and 2010 (1 December and 02 January respectively) with atmospheric and radiometric acceptable to the area study.

3.3. Software

Mainly, the working tool used was the free software R Project, together with the use of packages spdep and rgdal for raster data manipulation and analysis of spatial dependence. In addition, ERDAS Image and Ilwis implemented to perform pre-processing of satellite images.

3.4. Methodology

Discrimination in areas affected by fire from multitemporal comparison of images acquired before and after the fire to detect changes in burned areas is developed with spectral indices that facilitate the detection of changes in coverage and from them and use of spatial statistics is detected through the dependency tests are commonly used for testing for the presence of spatial autocorrelation, which leads to detect the spectral variability once vegetation is removed.

Images used must have a pre-processing to correct all possible difficulties in developing a profitable study. A cut is made to cover the affected area and let the software run smoothly. Apply different methodologies to work and compare results.

4. Analysis of results

4.1. Índice Normalizado para áreas quemadas (NBR)

By applying the index over the images, allowed to see the difference between the coverages affected and unaffected by the phenomenon. This process generates a class for December and January SpatialGridDataFrame where each of the regions took values between -1 and 1, which are then used to detect the change generated in the study area.

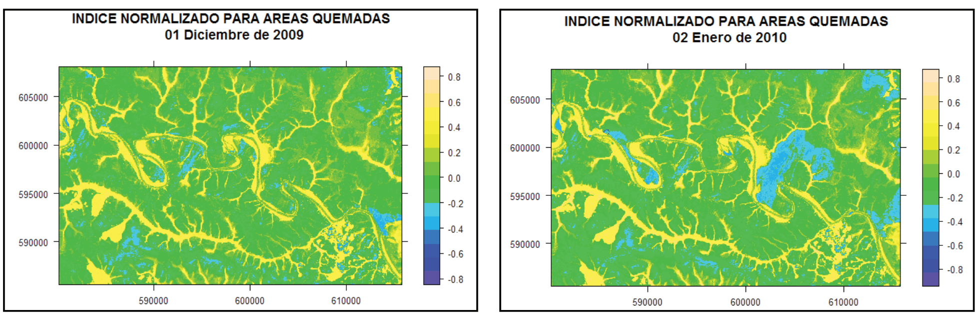


Fig. 2 **(a)** NBR image of December 1, 2009. **(b)** NBR image of January 2, 2010.

The result graph, allow to differentiate the severity of the fire. To this was taken as the basis that vigorous vegetation has high reflectance in the near infrared band and reflectance relatively low in the mid-infrared band. Thus it is said that green and yellow represent those areas where vegetation was not harmed by the presence of fire taking high values of NBR, however the bluish hues match mostly with the affected areas or who are in recovery after submission of the phenomena associated with low values of NBR.

4.1.1. Multitemporal comparison

Multitemporal difference of the indices can help identify the affected area compared to the image obtained post-fire, offering a definition of the affected area.

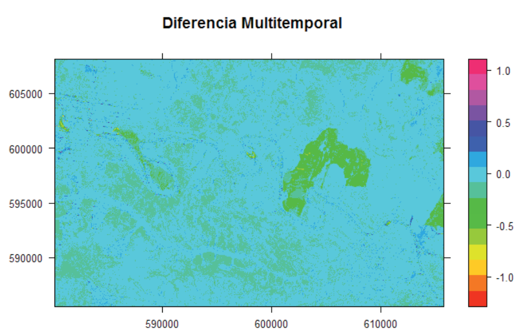


Fig.3. Multitemporal difference for the index NBR

4.2. Statistical calculation of spatial correlation

4.2.1. Calculation of global measures of spatial autocorrelation

Initially producing the array of neighborhoods that identifies the number of neighbors for each pixel, with the neighborhood criterion of "queen", because this approach believes contiguity with respect to a pixel of the eight neighboring pixels with which it shares border. Subsequently generates the spatial weight matrix which assigns zero value to the pixels that are neighbors and the value of one otherwise.

According to the global test of Moran and Geary for the variable of interest (digital level values for the near infrared band) is determined:

H0: There is no spatial correlation.
H1: There is a spatial correlation.

The results given by the global spatial correlation index Moran's I show enough statistical evidence to reject the null hypothesis of no spatial autocorrelation, since the p-value in both cases is less than the level of significance of 5%. This index can take values between 0 and 2 where the results for the period under study are close to zero indicating positive correlation is the similarity of the value of a pixel with its neighbors taking.

4.2.2. Calclatinglocal tests of spatialautocorrelation

The local index of Getis & Ord Gi is calculated for each pixel based on the spatial relationships of a region with its neighbors within a certain distance "d" in this case it is analyzed at 60 meters. The software displays the number of links that exist between a pixel and pixels that are at a maximum distance determined, to later to be able to generate the spatial weights matrix.

• December 1, 2009
Min. = -13.140000
1st Qu. = -1.867000
Median = -0.159400
Mean = 0.000057
3rd Qu. = 1.475000
Max. = 12.110000

• January 2, 2010
Min. = -11.040000
1st Qu. = -1.410000
Median = -0.374600
Mean = -0.000064
3rd Qu. = 1.111000
Max. = 12.480000

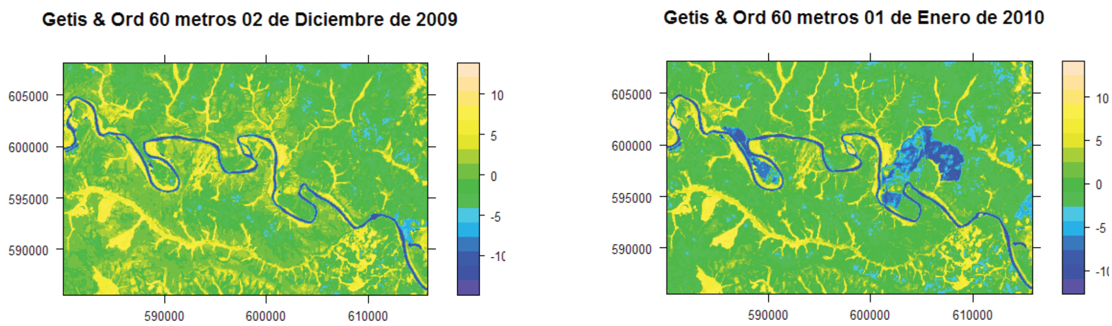


Fig. 4 (a) Muestra gráfica del índice local de Getis y Ord a 60 metros para la imagen del 01 de Diciembre de 2009. **(b)** Muestra gráfica del índice local de Getis y Ord a 60 metros para la imagen del 02 de Enero de 2010.

Above results show clusters of positive values that indicate the presence of groups of pixels with high spectral response in the near infrared band for healthy vegetation represented in green and yellow tones, unlike the blues that represent clusters of values digital low level for the affected vegetation and water bodies.

4.2.3. Multitemporal comparison

To identify areas affected by forest fires examine the spatial and spectral variability after to presented the phenomenon, looking for a change in the post-fire spatial structure. So, analyze the spatial dependence that may indicate variability in the area of interest from the use of statistical operators.

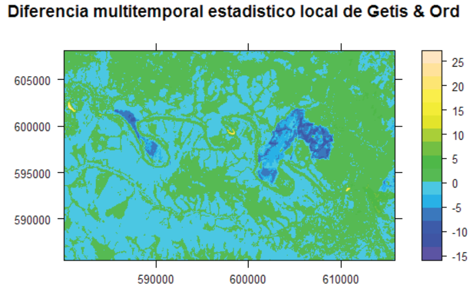


Fig.5. Multitemporal difference Getis and Ord statistic.

To identify areas affected by forest fires examine the spatial and spectral variability after presented the phenomenon, looking for a change in the post-fire spatial structure. Thus, an analysis of the spatial dependence that may indicate variability in the area of interest from the use of statistical operators.

Conclusions

• The use of global operators such as spatial correlation Moran's I and Geary's C generate a single summary measure, small that it cannot discriminate if the spatial dependence varies significantly in the area of interest.

• The local statistics of Getis & Ord discriminates the areas affected by the presence of a forest fire in this way to improve the monitoring of the effects of fire in time to provide information on vegetation affected. This statistic shows the image of January 2010, the grouping of low values of reflectivity for the area in which the phenomenon is present difference of the values obtained for the same area in December 2009.

• The use of a statistical software as R Project 2.11.1 for the prosecution of images satellite make possible to carry out similar procedures to the facts for a GIS detecting space groupings, advancing processes for temporary comparisons, among other, although it presents limitations for the inability of supporting big sizes of the images.

• When making a comparison among the two developed (ghastly indexes and exploratory analysis of the data) methodologies, a bigger effectiveness is observed in the application of statistical operators, because the delimitation of the area becomes more remarkable in this case. Also if one observes the process from the indexes to comparison with that of the statistical ones, the indexes are of the operation of two bands whose behavior makes him to be less remarkable the difference of coverings, on the other hand the statistical operators are of intervention of some factors in the digital levels of the band that makes simpler the discrimination of the affected area.

Acknowledgements

For the development of the project were indispensable several people, to all a heartfelt hug and a thank, in particular:

• To God for giving us the opportunity to initiate and complete development of this project.

• To each of our families who supported us and gave us their trust.

• To our project director, Luis Fernando Santa Guzmán who was pending constantly of the advances and gave us ongoing advice in the development of the project.

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