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Gradient Pattern Analysis Applied to Multitemporal Land Cover Change Detection

Ramon Morais de Freitas, Reinaldo Roberto Rosa, Yosio E. Shimabukuro

Instituto Nacional de Pesquisas Espaciais (INPE)
Av. dos Astronautas, 1758 - São José dos Campos, SP, 12227-010, Brazil

{ramon, yosio}@dsr.inpe.br; reinaldo@lac.inpe.br

Abstract. *In this work, the Gradient Pattern Analysis - GPA was applied for the first time in MODIS spatial-temporal images over the Amazon region. The study area is a Large Scale Biosphere-Atmosphere Experiment in Amazonia LBA study site located in the Pará State, eastern Brazilian Amazonia. Using remote sensing images derived from MODIS - MOD09 8-day composite product from 2000 to 2009 was elaborated the EVI2 spatial-temporal series of the study area. For each pixel we performed smooth time-series applying wavelets transform method for noise reduction. The GPA objective was characterizing small symmetry breaking, amplitude and phase disorder due to spatial-temporal fluctuations driven by the deforestation and flooded changes detected by MODIS images. For the characterization of spatial-temporal series the Gradient Pattern Analysis showed a new approach to understand LULC changes directly in the remote sensing images.*

Keywords**—** Gradient Pattern Analysis, Amazonia, deforestation.

1. Introduction

The land use and land cover (LULC) change monitoring using remote sensing data is an important instrument for Government policy and surveillance of preservation areas. A near real-time computational method for change detection and characterization would allow control of the increase of new anthropic and natural environmental changes. In general, the biodiversity is reduced by LULC change [DeFries et al. 2004].

Remote sensing and geospatial analysis are substantive tools of land change studies because these technologies facilitate observations across large extends of Earth surface. In global scales, the Global Land Cover Facility (GLCF, glcf.umiacs.umd.edu) provides remote sensing data set and products for quantifying the land cover change around the world. The GLCF investigates the land cover dynamics and remote sensing derived products to explain the LULC changes. The multi-temporal MODIS higher-level quality data sets are used to understand this dynamics. In regional scale, Brazilian Government policy has been monitoring Amazonia deforestation process by remote sensing tools as DETER and PRODES INPE's programs (www.inpe.br).

Maps and measurements of LULC changes can be directly derived from remote sensing data using image processing, statistical pattern recognition methods and human interpretation. In general, this processing transforms the remote sensing data to thematic maps or classification images applying supervised or unsupervised procedures. Sophisticated computational methodologies using object image segmentation and neural networking classifiers are not reality on the LULC change operational programs because the computational cost. This is a rule set for multi-temporal monitoring on the global and regional scales operational programs. The feature selection and original dataset dimension reduction is an alternative procedure for this problem. In this context, this work has the objective to propose a low computational cost methodology to detect and to monitor LULC changes using spatial temporal remote sensing data. Traditional methods of LULC changes detection is based on pattern recognition and statistical measurements, while the proposed method encompasses statistical physics and non linear dynamics concepts [Stanley, 1995] to understand the LULC detection.

2. Methodology

The proposed methodology uses Gradient Pattern Analysis [Rosa et al. 1999, Ramos et. al. 2000] a modern technique for analyzing spatially extended dynamics[1]. The measurements obtained from GPA are based on the spatial-temporal correlations between large and small amplitude fluctuations of the structure represented as a dynamical gradient pattern. Based on a scalar elementary field (Fig. 1-a) which can be represented by pixels values of an image or subset image in remote sensing, the first moment is represented by gradient field (Fig. 1-b), the second (Fig. 1-c) and third moments (Fig. 1-d) are a norm and phase representation, respectively, for each element of the first moment. The fourth moment is the Euler's formula for complex representation of the first gradient moment which shows the relationship between the trigonometric and the complex exponential functions. By means of four gradient moments is possible to quantify the relative fluctuations and scaling coherence at a dynamical numerical lattice and this is a set of proper measures of the pattern complexity and equilibrium [Rosa et al. 1999, Ramos et. al. 2000].

[1] Statistical physics concept that is related to 2-D spatial pattern marked by gradual changes through a series of states.

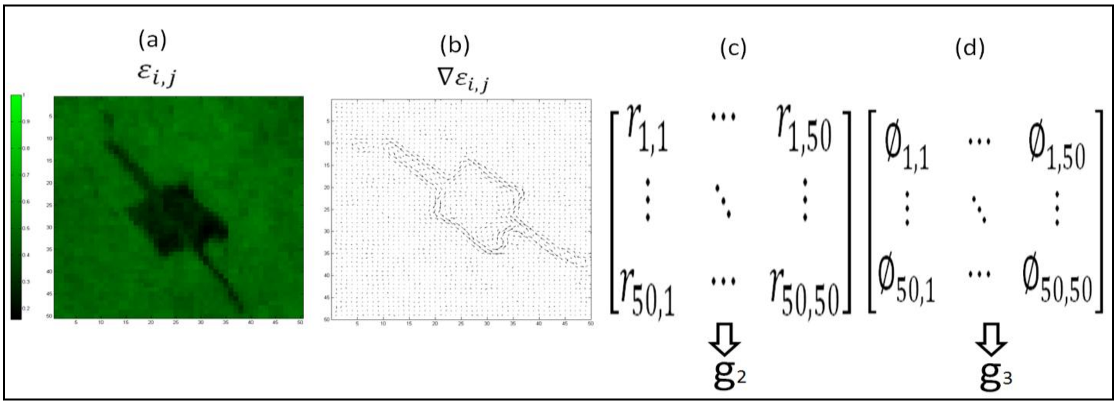

Figure 1. Gradient Pattern Analysis - The gradient moments. a) Image; b)Gradient field; c) Norm representation and d) Phase representation

Using gradient moments we can define computational operators as LULC change metric. The second and third gradient moment represents the norm and phase of gradient field, respectively. Using these moments we could measure the diversity of norm and phase of gradient field applying the Simpson's Index of diversity over the second and third gradient moments. These two computational operators are defining by:

$$D_{g_2} = 1 - \sum_{i=1}^{S} Pr_i^2 \quad (1)$$

$$D_{g_3} = 1 - \sum_{i=1}^{S} P\emptyset_i^2 \quad (2)$$

where, Pr and P∅ are the proportion of norms and phases values on gradient field, respectively. S is total of unique elements in the gradient field base on histogram bins. A perfectly homogeneous gradient field in norm and phase would have a diversity index score of 0. A perfectly heterogeneous gradient element would have a diversity index score of 1. To measure the energy of gradient field, we define a Frobenius metric that relate the total of energy of gradient field:

$$||N_{g_2}||_F = \sum_{i=1}^{m} \sum_{j=1}^{n} |r_{i,j}|^2 \quad (3)$$

being, $||N_{g_2}||_F$ the Frobenius norm of g_2 matrix, m and is row and columns, respectively. The gradient field represented by Cartesian coordinate, x and y directions we can be used the Frobenius inequality [Böttcher and Wenzel, 2005] as a metric.

$$||N_I||_F = \frac{||dxdy - dydx||_F}{||dx||_F \, ||dy||_F} \leq \sqrt{2} \quad (4)$$

where, $||N_I||_F$ is the Frobenius index defined by Frobenius inequality. dx an dy are gradient field represented by Cartesian coordinates. This $||N_I||_F$ value can be used to compare the gradient fields in the same size.

In this work, the computational operators base on GPA was applied for the first time in MODIS spatial-temporal images over the Amazon region. The GPA objective was to characterize small symmetry breaking, amplitude and phase disorder due to spatial-temporal fluctuations driven by the deforestation and flooded changes detected by MODIS images. Combining the diversity index and Frobenius metrics we can establish a dynamics pattern of land cover changes.

3. Experiments

3.1. Remote Sensing Data

The study area is located in the Pará State, eastern Brazilian Amazonia (Figure 2). The region has well-defined dry and wet seasons with yearly rain about 2,100 mm a dry season occurring from June to October. The test site encompasses several landscape types as tropical forest, regrowth, deforested areas, croplands and pasture. It presented high land cover changes rates in the last years. In this region, recent agricultural expansion and flooding episodes occurrences carried out a constant land cover changes. The samples of land cover classes were collected to photo interpretation to demonstrate the method.

Using MOD09 8-day composite product from 2000 to 2009 was elaborated the spatial-temporal series of the study area. The time-series of MODIS/Terra surface reflectance images are from collection 5 of 8-day L3 Global product at 250 m resolution (MOD09A1), acquired from 2000 to 2009. 414 images were used in this study. This MODIS product is an estimate of the surface spectral reflectance for each band, as it would have been measured at ground level with no atmospheric scattering or absorption effects, generated by applying the atmospheric correction algorithm. The MOD09A1 product includes the RED and NIR bands with originally 250 m spatial resolution data.

The next step we calculate the Enhanced Vegetation Indices 2 - EVI2 [Jiang et al. 2008] using MOD09 RED and NIR infrared spectral bands for each composite. The EVI2 has best similarity with traditional EVI. The EVI2 index was selected due to enhance the vegetation signal with improved sensitivity in high biomass regions as Amazonia forest regions.

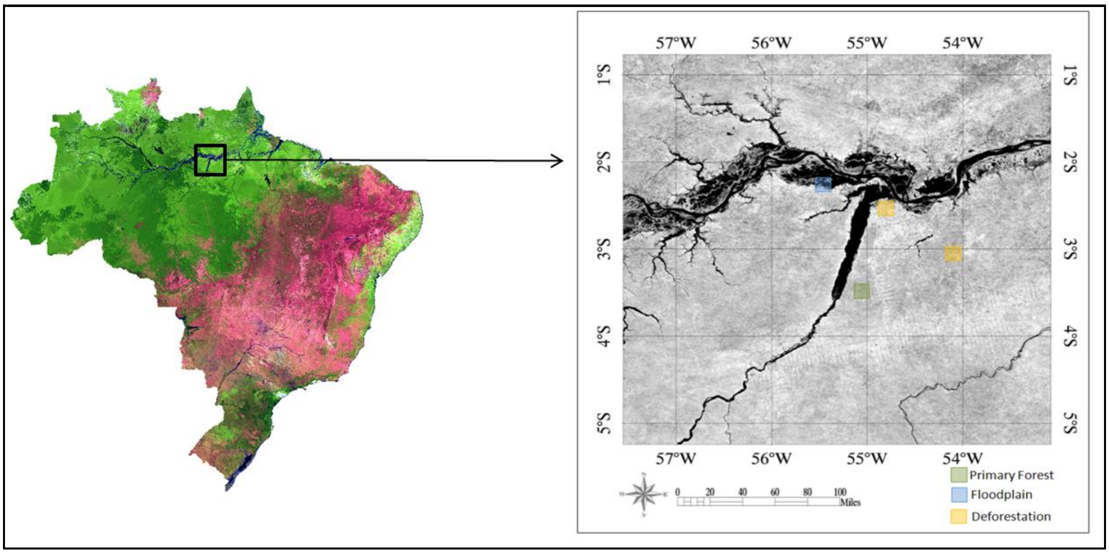

Figure 2. Location of study area with selected plots. The image is an EVI2 filtered 2002 wet season image.

3.2. Noise reduction

For each pixel we performed smooth time-series using wavelets transform method for noise reduction [Freitas and Shimabukuro, 2009] .The procedure was necessary due to high noise data and high diversity of structures in frequency domain. The Meyer wavelet (Eq. 5-8) and scaling function (Eq. 9-11) are defined in the frequency domain (ω).

$$\widehat{\psi}(\omega) = (2\pi)^{-\frac{1}{2}} e^{\frac{i}{2\omega}} sin(\frac{\pi}{2}\nu(\frac{3}{2\pi}|\omega|\text{-}1)), \text{ if } ,\frac{2\pi}{3} \leq |\omega| \leq \frac{4\pi}{3} \tag{5}$$

$$\widehat{\psi}(\omega) = (2\pi)^{-\frac{1}{2}} e^{\frac{i}{2\omega}} cos(\frac{\pi}{2}\nu(\frac{3}{2\pi}|\omega|\text{-}1)), \text{ if } ,\frac{4\pi}{3} \leq |\omega| \leq \frac{8\pi}{3} \tag{6}$$

$$\widehat{\psi}(\omega) = 0, if, |\omega| \notin [0, 1] \tag{7}$$

where one possibility to υ is,

$$\nu(a) = a^4(35 - 84a + 72a^2 - 20a^3), a \notin [0, 1] \tag{8}$$

therefore the associate scaling function is,

$$\widehat{\phi}(\omega) = (2\pi)^{-\frac{1}{2}}, if, |\omega| \leq \frac{2\pi}{3} \tag{9}$$

$$\widehat{\phi}(\omega) = (2\pi)^{-\frac{1}{2}} e^{\frac{i}{2\omega}} cos(\frac{\pi}{2}\nu(\frac{3}{2\pi}|\omega|\text{-}1)), \text{ if } ,\frac{2\pi}{3} \leq |\omega| \leq \frac{4\pi}{3} \tag{10}$$

$$\widehat{\phi}(\omega) = 0, if, \ |\omega| \geq \frac{4\pi}{3} \tag{11}$$

The discrete form of this transformation use FIR. The filtered signal was reconstructed excluding high frequencies (level 2 and 3) for each pixel in the EVI2 time series (**Figure 3**). This procedure allows a viewing of original signal without clouds and other noises. The time-series of cloud-free composite images at 8-day intervals provide vegetation phenology information to identify different land cover types from the unique patterns of vegetation. All computational procedures used the MATLAB environment.

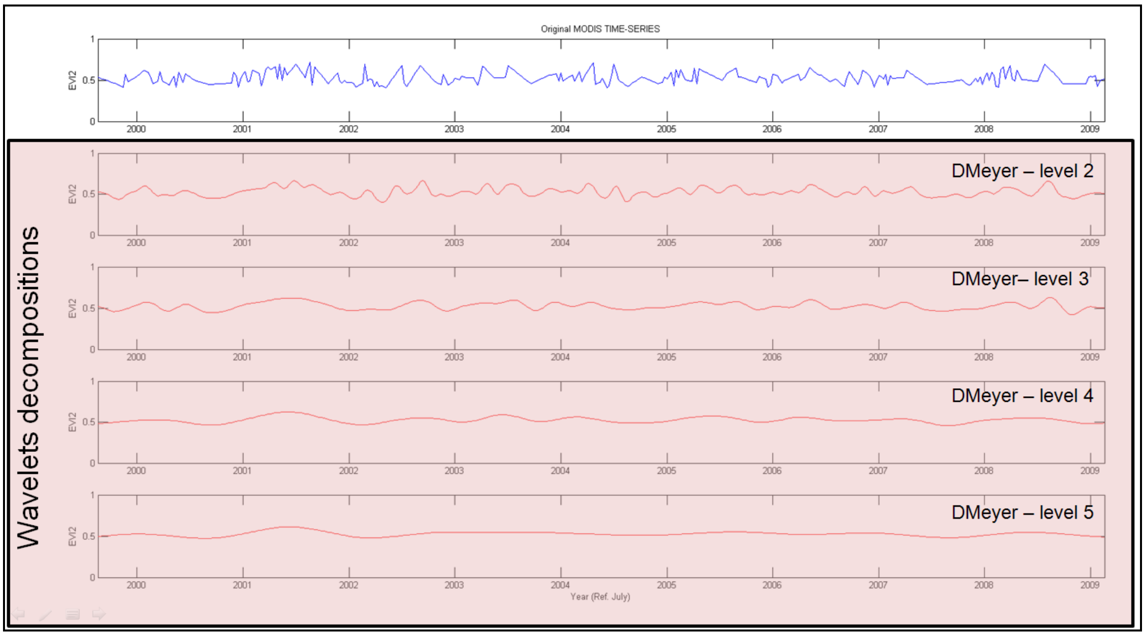

Figure 3. Example of EVI2 MODIS time-series decompositions using wavelets transform.

Utilizing field data and photo interpreter experience, 4-four regions with 50x50 pixels were selected with land use and land cover changes (i.e. deforestation process and seasonally flooded forest region) for demonstrating the method. Using scatter plot of this two metrics we show the dynamics of these areas. The Dg3 versus $||N_{g_2}||_F$ scatter plot represents the space phase of change. In this context, the temporal dynamics changes could be visualized by this scatter plot. The $||N_I||_F$ Frobenius index used for data dimensionality reduction represent the spatial-temporal behavior in the 1-D time-series.

4. Results

Fig. 4 shows the multi-temporal images of June for 2000 to 2009 time period. Each image has 50x50 MODIS 250 meters pixels with a total area of 156 km^2. Fig. 5 shows the scatter plot of phase diversity and norm gradient variables from spatial- temporal series. Seasonally flooded forest (Site 1) region has variability in phase data due to permanent edge contrast between the river banks and the forest. High dispersion region is related to the edge presence due to deforestation and natural contrast regions (i.e. deforestation areas and river banks and). The forest without deforestation activity shows the high diversity index and low norm values, that's represent small variation of gradient field. This small variation is related with sensor noise and forest canopy structure. The deforestation region shows permanent areas of non photosynthetic vegetation, this cluster is compact because no land cover change occurs during period. The forest with deforestation activity shows a transition phase from forest cluster region to new cluster of deforestation. The increase of Frobenius norm ($||N_{g_2}||_F$) is related with the biomass losses driven by deforestation activity in June of 2004. For large deforestation regions the cluster dispersion of Frobenius norm axis tends to increase.

Figure 6 shows the multi-temporal $||N_I||_F$ behavior for 4 study sites. The white noise bounds are represented by point lines. This area represents a random gradient field, in this context, forest areas have a similar behavior with white noise. The deforestation process (Figure 5, site 4) is detected by $||N_1||_F$ metric (Figure 6, Cyan line) with rapid increase of metric values. A transition phase in the flooded areas (Red line) is observed in 2005 year probably related to strong drought occurrence.

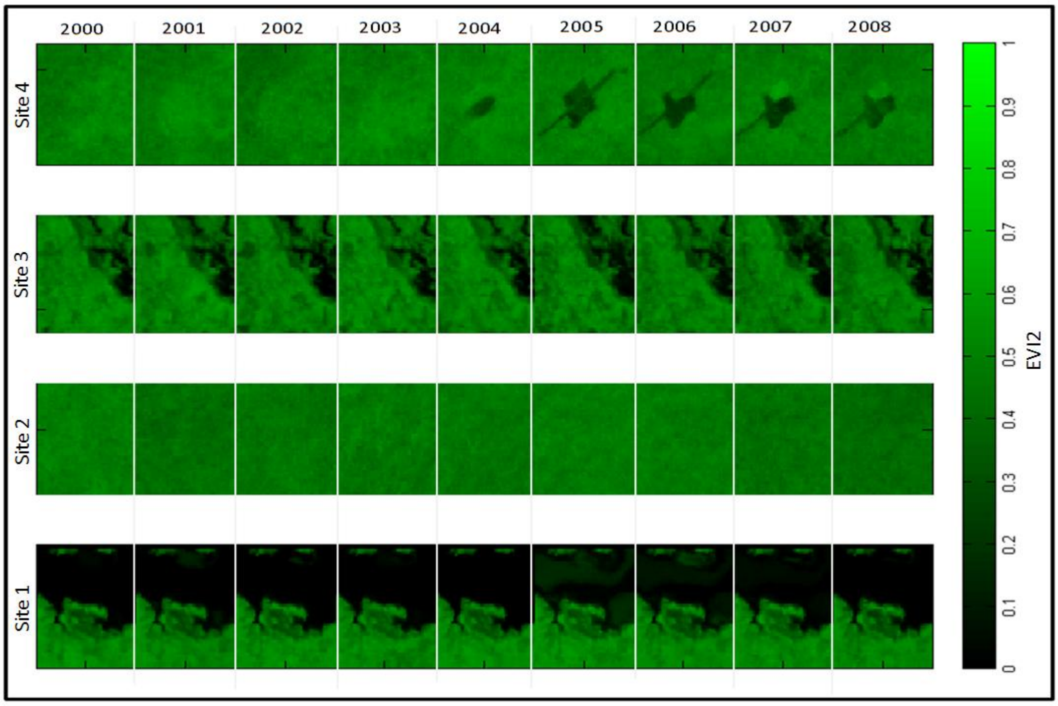

Figure 4. Multi-temporal EVI2 images for 4 study sites. Site 1 – – seasonally flooded forest region. ; Site 2 – forest without deforestation activity; Site 3 – deforestation region and Site 4- forest with deforestation activity .

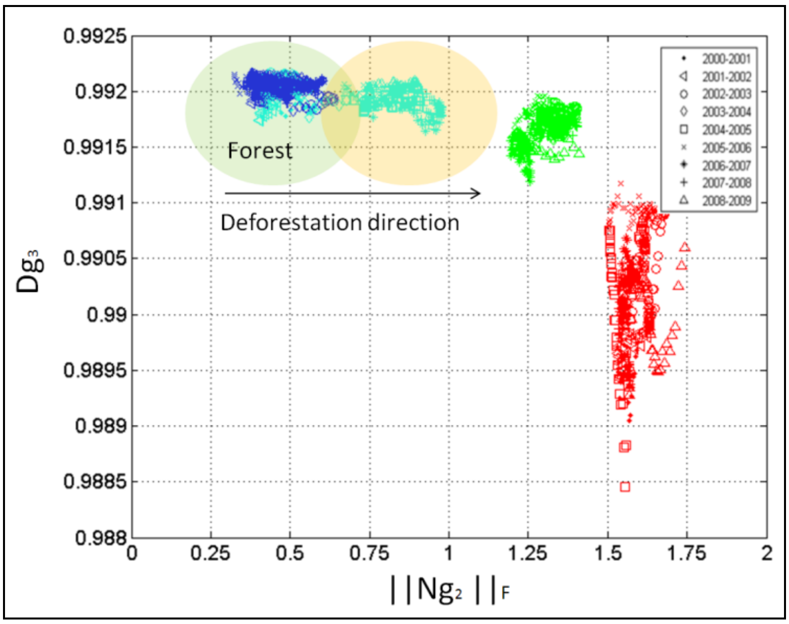

Figure 5. Scatter plot of Phase Diversity Index and Frobenius norm of g_2. Red - Site 1; Blue - Site 2; Green - Site 2; and Cyan - Site 4 ;

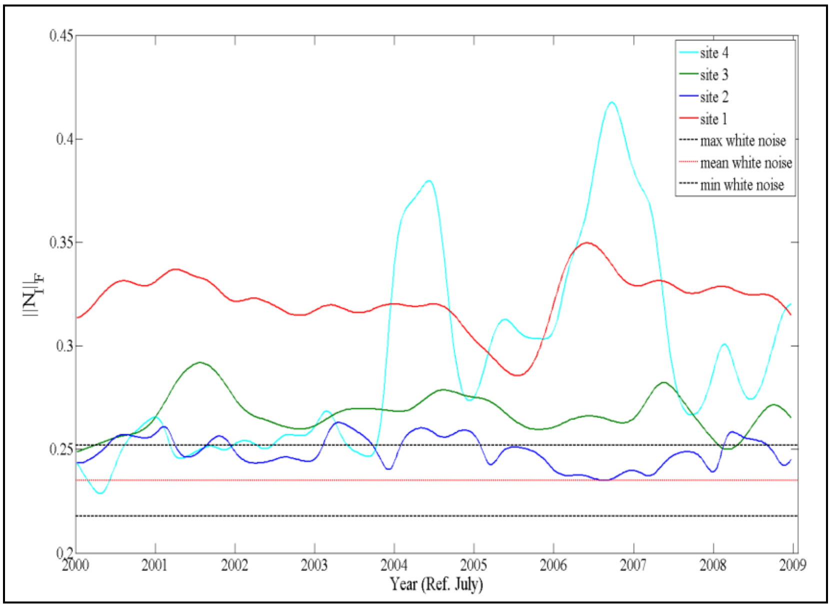

Figure 6. Multi-temporal $||N_I||_F$ behavior for 4 study sites.

5. Conclusion

This work showed the preliminary results of characterization of spatial-temporal remote sensing series. The Gradient Pattern Analysis showed a new approach to visualize land cover change directly in the remote sensing images. The temporal behavior of these three metrics series indicated a new potential metric to understand the land cover and land use dynamics applied directly to remote sensing images. Future work will concentrate on the development of procedures for selecting appropriate thresholds for phase diversity versus norm scatter plot.

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