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CHARACTERIZING LANDSCAPE SPATIAL HETEROGENEITY USING SEMIVARIOGRAM PARAMETERS DERIVED FROM NDVI IMAGES

Keywords:
Remote sensing
Geostatistics
Forested areas
Human-modified landscapes

ABSTRACT: Assuming a relationship between landscape heterogeneity and measures of spatial dependence by using remotely sensed data, the aim of this work was to evaluate the potential of semivariogram parameters, derived from satellite images with different spatial resolutions, to characterize landscape spatial heterogeneity of forested and human modified areas. The NDVI (Normalized Difference Vegetation Index) was generated in an area of Brazilian amazon tropical forest (1,000 km²). We selected samples (1 x 1 km) from forested and human modified areas distributed throughout the study area, to generate the semivariogram and extract the sill (σ^2-overall spatial variability of the surface property) and range (φ-the length scale of the spatial structures of objects) parameters. The analysis revealed that image spatial resolution influenced the sill and range parameters. The average sill and range values increase from forested to human modified areas and the greatest between-class variation was found for LANDSAT 8 imagery, indicating that this image spatial resolution is the most appropriate for deriving sill and range parameters with the intention of describing landscape spatial heterogeneity. By combining remote sensing and geostatistical techniques, we have shown that the sill and range parameters of semivariograms derived from NDVI images are a simple indicator of landscape heterogeneity and can be used to provide landscape heterogeneity maps to enable researchers to design appropriate sampling regimes. In the future, more applications combining remote sensing and geostatistical features should be further investigated and developed, such as change detection and image classification using object-based image analysis (OBIA) approaches.

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CARACTERIZACÃO DA HETEROGENEIDADE ESPACIAL DA PAISAGEM UTILIZANDO PARÂMETROS DO SEMIVARIOGRAMA DERIVADOS DE IMAGENS NDVI

Palavras chave:
Sensoriamento remoto
Geoestatística
Florestas
Ação antrópica

RESUMO: Assumindo a existência de uma relação entre a heterogeneidade da paisagem e medidas de dependência espacial obtidas de dados de sensoriamento remoto, o objetivo deste estudo foi avaliar o potencial dos parâmetros do semivariograma derivados de imagens de satélite com diferentes resoluções espaciais, para caracterizar áreas cobertas por floresta e áreas sob ação antrópica. Para isso, o NDVI (Índice de Vegetação da Diferença Normalizada) de cada umas das imagens (SPOT 6, Landsat 8 e MODIS Terra) foi gerado em uma área de floresta tropical Amazônica (1.000 km²), onde foram selecionadas amostras (1 x 1 km) de áreas florestadas e áreas antrópicas. A partir destes dados, foram gerados os semivariogramas e extraídos os parâmetros patamar (σ^2-variabilidade espacial total) e alcance (φ-distância dentro da qual as amostras apresentam-se estruturadas espacialmente). A análise revelou que a resolução espacial das imagens influencia os parâmetros σ^2 e φ, apresentando significativo aumento das áreas de florestas para as áreas sob ação antrópica. A maior variação entre estas classes foi obtida com as imagens Landsat 8, indicando estas imagens, com resolução espacial de 30 metros, a mais apropriada para a obtenção dos parâmetros do semivariograma objetivando a caracterização da heterogeneidade espacial da paisagem. Combinando o sensoriamento remoto e técnicas geostatisticas, demonstrou-se que os parâmetros do semivariograma derivados de imagens NDVI podem ser utilizados como um simples indicador de heterogeneidade da paisagem, gerando mapas que permitem aos pesquisadores delinearem com maior eficácia o regime de amostragem. Outras aplicações combinando estas duas técnicas devem ser investigadas, como por exemplo a detecção de mudanças na cobertura do solo e a classificação de imagens utilizando análises orientada a objetos (OBIA).

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INTRODUCTION

Recent years have seen a dramatic increase in the attention being given to the condition of tropical forests. In recognition of the considerable impact human activities are having on tropical forest systems, a range of initiatives have been launched to mitigate the adverse effects of tropical forest loss (DEVRIES et al., 2016). Remote sensing based approaches play a key role in forest monitoring, as they are of low cost and provide an opportunity for mapping forest change over large areas (DEVRIES et al., 2015).

Understanding the negative and positive effects of agricultural land use for the conservation of biodiversity, and its relation to ecosystem services, needs a landscape perspective (TSCHRNTKE et al., 2005). Landscapes exhibit various degrees of spatial heterogeneity due to the interactions of natural and anthropogenic processes (BIE et al., 2012).

Remote sensing using satellite imagery has emerged as a key geospatial tool to meet the growing information needs of landscape and forest managers (COSTANTINI et al., 2012). Different methods to quantify changes in landscape complexity have been developed in the last few decades (WU, 2013). Most of these involve the use of remotely sensed images and geospatial techniques (MONMANY et al., 2015; BERBEROGLU et al., 2000; BERBEROGLU; AKIN, 2009; GARCIA-PEDRERO et al., 2015). Several works have investigated environmental changes, using spatial heterogeneity derived from various types of remote sensing data (WU et al., 2000; CHEN; HENEBRY, 2009

In some studies, the Normalized Difference Vegetation Index (NDVI) has been used to detect and analyse spatial heterogeneity using semivariograms (GARRIGUES et al., 2006; GARRIGUES et al., 2008; BALAGUER-BESER et al., 2013). NDVI, which represents an especially informative vector for landscape structure and temporal change analyses (GRIFFITH et al., 2002), has been used in numerous studies of vegetation dynamics because of its simplicity and close relationship to variables of ecological interest such as land cover change and disturbance propagation at multiple scales (ZURLINI et al., 2006; ZACCARELLI et al., 2008).

Geostatistical semivariograms are used as measures of texture (CURRAN, 1988; WOODCOCK; et al., 1988) and have been widely used for heterogeneity analysis (GARRIGUES et al., 2006, 2008; CADENASSO et al., 2007; HUANG et al., 2013;LAUSCH et al., 2013; BALAGUER-BESER et al., 2013; WU et al., 2000; QIU et al., 2013), improved image classification (BALAGUER et al., 2010;BALAGUER-BESER et al., 2011; WU et al., 2015; YUE et al., 2013; POWERS et al., 2015) and change detection (SERTEL et al., 2007; COSTANTINI et al., 2012; ACERBI JUNIOR et al., 2015; GIL-YEPES et al., 2016). In short, the spatial heterogeneity of surface reflectance values is dependent on the spatial resolution of the image, spectral bands and the size of the image or sample analysed.

Sampling heterogeneity in a statistically robust manner has proven to be a challenge, with researchers often stratifying their sampling regimes along subjectively chosen landscape features (WHITE et al., 2004). Sampling regimes can be improved by an initial estimate of the spatial heterogeneity, provided by an accurate map of landscape heterogeneity. The mosaics of land use and land cover appear with boundaries and edges between them and this variability can be captured and extracted by using the spatial variability of remote sensing images using geostatiscal approaches (GUARRIGUES et al., 2006).

Semivariograms are reportedly an efficient method to characterize the structure of spatial continuity (GUEDES et al. 2015), due to their potential to describe the spatial variability of data. Therefore, assuming a relationship between landscape heterogeneity and measures of spatial dependence of remotely sensed data, the aim of this work was to evaluate the potential of semivariogram parameters, derived from satellite images with different spatial resolutions, to characterize landscape spatial heterogeneity of forested and human modified areas. The questions that motived this study were: (i) How is image spatial resolution linked with the spatial variability of NDVI values? (ii) Which semivariogram parameter and image spatial resolution is the most appropriate to produce a landscape heterogeneity map?

This manuscript makes a significant contribution to the understanding of how the manipulation of satellite imagery parameters can be used to detect variation in the landscape, indicating the most appropriate image spatial resolution to improve the analysis and also the most appropriate semivariogram parameter to generate a map of landscape heterogeneity. This enables researchers to design appropriate sampling regimes to capture landscape heterogeneity.

MATERIAL AND METHODS

We performed three mains steps: (1) Acquisition of SPOT 6 (*Satellite* Pour l'Observation de la Terre), LANDSAT 8 (Land Remote Sensing Satellite) and

MODIS TERRA (Moderate Resolution Imaging Spectroradiometer) imagery and generation of NDVI images; (2) Stratified sampling of forested and human modified areas distributed throughout the study area; (3) Analysis of semivariograms generation using the NDVI pixels inside the samples. The sill (σ^2-overall spatial variability of the surface property) and range (φ-the length scale of the spatial structures of objects or patches) parameters were generated by fitting mathematical models (exponential, spherical and gaussian) to the experimental semivariograms using the weighted least squares method. Figure 1 presents a diagrammatical overview of the methods.

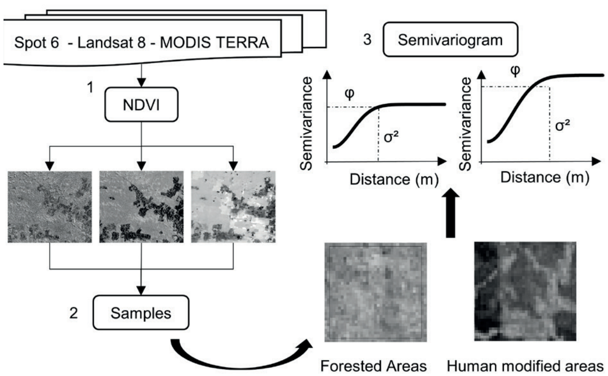

FIGURE 1 Diagrammatical overview of methods divided into three main steps.

Study area

The study area is a total of 1,000 km² set within the Cotriguaçu municipality, located in the northeast of the state of Mato Grosso (MT), Brazil, central coordinates 09° 48' 9.14" south latitude and 58° 47' 40.25" west longitude (Figure 2).

The municipality of Cotriguaçu, which has a total area of 9,149 km², forms part of the Amazon Watershed and is drained by the Juruena River, the largest volume of water in Mato Grosso State. A total of 25% of its landmass has a flat relief, 60% has an irregular relief and 15% has a mountainous relief. The municipality has a mean altitude of 240 meters. This region has a warm and humid equatorial climate with two dry months (June and July). The mean annual rainfall is 2,750 mm, with low rainfall from May to September (period in which the majority of logging occurs) and high precipitation from January to March. Average annual temperatures ranges from 22°C to 35°C (FINGER, 2005).

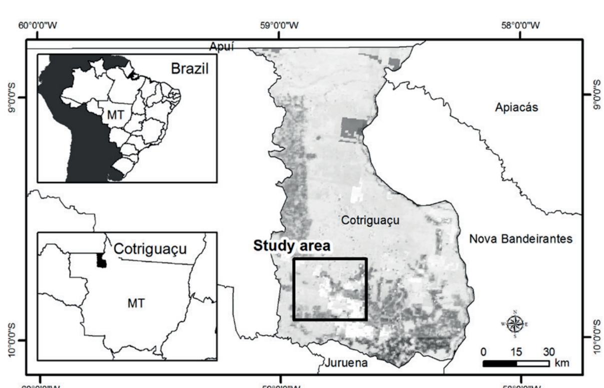

FIGURE 2 Location of the study area in the municipality of Cotriguaçu, Mato Grosso (MT) State, Brazil.

Timber is the main commodity and the forested areas are characterized by a wide diversity of valuable tropical species. By 2004 Cotriguaçu had lost 13% of its forest cover. Extensive livestock farming is the main reason for conversion of forest areas in this region. The wood poles located in the Amazon are established from an economy based exclusively on forestry, on which the local residents depend for socio-economic development. These municipalities are the most susceptible to the effects of predatory exploitation of natural resources. Cotriguaçu is undergoing expansion with excessive pressure on natural resources (FERREIRA et al., 2005).

Image acquisition

We used images with three different spatial resolutions to assess the effect of spatial resolution on the semivariogram parameters generated from NDVI images (Table 1). The SPOT 6 image was provided by ONF (Office National des Forêts) Brazil, a Brazilian Forestry Company, subsidiary of ONF International, a company of the ONF group, leading a reforestation pilot project for carbon sequestration "Peugeot-ONF carbon sink" in the northwest of Mato Grosso.

The LANDSAT 8 and MODIS TERRA images were acquired from the United States Geological Survey for Earth Observation and Science (USGS\EROS). The LANDSAT 8 image was acquired in the CDR processing level (Landsat Surface Reflectance Climate Data Record), that is, with the necessary geometric corrections and reflectance values at ground level. The MODIS product used was MOD13Q1 - Vegetation Index.

NDVI was used to describe the spatial heterogeneity of vegetation cover. This index is based on quotients and uses red spectral and near infrared bands to enhance vegetation and, at the same time,

TABLE 1 Acquisition dates and spatial resolution of SPOT 6, LANDSAT 8 and MODIS TERRA images.

Images	Acquisition date	Spatial resolution (m)
SPOT 6	09/July/2014	6
LANDSAT 8	09/August/2014	30
MODIS TERRA	10/August/2014	250

minimize the effects of shadows caused by topography (VOROVENCII, 2014). Although NDVI is sensitive to soil and atmospheric effects, it is a good indicator of the total amount of vegetation (HENEBRY, 1993) and is considered important for the analysis of land cover structure and temporal changes (GRIFFITH et al., 2002; SADER, 2003).

Sampling design

According to a previous map provided by ONF Brazil in 2014, the study area comprises six land use/land cover (LULC) classes: croplands, degraded forests, forests, plantation, settlements and water. We merged these LULC into two classes: (1) Forested areas and (2) Human modified areas (Figure 3).

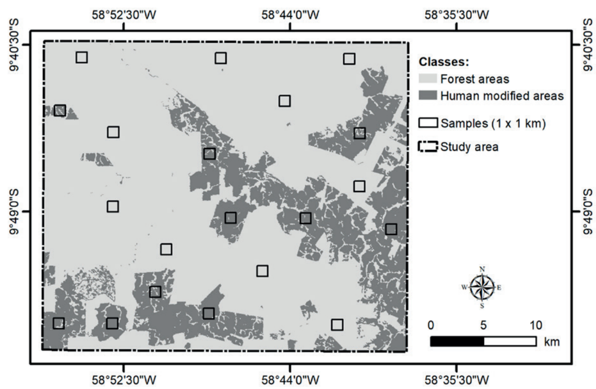

FIGURE 3 Sampling design in forest and human modified areas.

Forested areas are densely tropical rainforest, that have not undergone major changes due to human activities and present only on patch covering the total grid area.

Human modified areas are croplands, settlements, degraded forests and plantations, with more than one patch in the grid. The cropland class is composed of small farm plots around villages and in forest edges (agroforest mosaics), as well as more intensive subsistence agricultural use (large permanent plots). Towns, villages and other human infrastructures were classified as 'settlements'. The water class is composed of rivers and open water surfaces. Degraded forest and saplings were designed to identify areas with significant tree density (typically tree cover in the order of 25 to 35%). The plantation class is composed of tree plantations.

We selected 20 square samples (1 x 1 km) using a stratified sampling approach (Figure 3), comprising 10 samples of human modified areas and 10 samples of forested areas in each image, totalizing 60 samples. We then extracted all the NDVI values from the SPOT 6, LANDSAT 8 and MODIS TERRA pixels inside the sampled areas.

Semivariogram parameters

The semivariogram is a graphical representation of the spatial variability in a given set of data (COHEN et al., 1990). The relationship between a pair of pixels can be calculated with the variogram function (Equation 1), called $2\gamma(h)$, which corresponds to the mathematical expectation of the squared difference between pairs of points separated by a distance h, where $Z(x)$ is the value of the regionalized variable at point x, $Z(x+h)$ is the value at $x+h$. The semivariogram function depends on the location x, and the distance between samples h. For the variogram to be based solely on the distance between the sampling units, it is necessary to adopt the intrinsic hypothesis (stationarity), which implies that the variance of the differences between two sample points depends only on the distance (h).

$$2\gamma(h)=E\left\{\left[Z(x)-Z(x+h)\right]^2\right\} \quad [1]$$

For continuous variables, such as the NDVI, the experimental semivariogram is defined as the half of the average squared difference between values separated by a given lag, where this lag is a vector in both distance and direction (ATKINSON; LEWIS, 2000). It was estimated using equation 2, where $\gamma(h)$ is the estimator of the semivariance for each distance h, $N(h)$ is the number of pairs of points separated by the distance h, $Z(x)$ is the value of the regionalized variable at point x and $Z(x+h)$ is the value of the point $x+h$.

$$\gamma(h)=\frac{1}{2N(h)}\sum_{i=1}^{N(h)}\left[Z(x)-Z(x+h)\right]^2 \quad [2]$$

Spatial variance versus distance h, is the graphical representation of the semivariogram, which allows obtaining an estimate of the variance value for different combinations of pairs of points. The semivariogram (Figure 4) is characterized by three parameters: sill (σ^2), range (φ) and nugget effect (τ^2). The sill parameter is the plateau reached by the semivariance values and shows the quantity of variation explained by the spatial structure of the data. The range parameter is the distance at which the semivariogram reaches the sill, showing the distance at which the data cease to be correlated. The nugget effect is the combination of sampling errors and variations that happen at scales smaller than the distance between the sampled points (CURRAN, 1988).

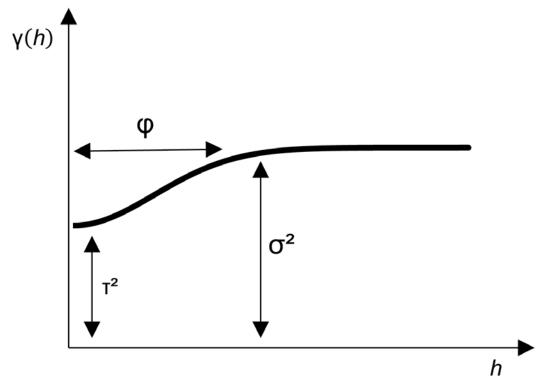

FIGURE 4 S Illustration of a classical semivariogram: σ^2 - sill; (φ) range and (τ^2) nugget effect.

We generate the semivariograms using the NDVI values extracted from the square samples in the SPOT 6, LANDSAT 8 and MODIS images. The size of the samples needs to be larger than the range of influence to characterize the initial part of the semivariogram and large enough to reveal the presence of periodicity (WOODCOCK et al., 1988).

Geostatistical methods are optimal when data are normally distributed and stationary (mean and variance do not vary significantly in space). Significant deviations from normality and stationarity can cause problems, so it is always best to begin by looking at a histogram to check for normality and a plotting of the data values in space to check for significant trends.

Thus, the first step was an exploratory data analysis in order to understand the overall behaviour of NDVI values, i.e. to study the tendency, shape and distribution of the data. The position measures (average, minimum and maximum values), dispersion (standard deviation and coefficient of variation) and normality assessment were determined through the frequency histogram. In addition, to verify the presence of outliers, a boxplot graph was generated. After the exploratory analysis, the semivariograms were generated to analyse the spatial dependence of the data.

Theoretical semivariograms were estimated by fitting mathematical models to the experimental semivariogram using the weighted least squares method. Exponential, spherical and gaussian models were tested (Table 2). The fitted models were cross-validated, analysing the reduced mean error (ER) and the standard deviation of reduced errors (SRE). We used R (R Core Team 2016) and ArcGis version 10.1 (Esri 2010) to perform this analysis.

TABLE 2 Semivariogram models.

Model	Formula
Exponential	$\gamma(h)=\sigma^2\left[1-e^{\left\|-3\left(\frac{h}{\varphi}\right)\right\|}\right]$
Spherical	$\gamma(h)=\left\{\sigma^2\left[\frac{3}{2}\left(\frac{h}{\varphi}\right)-\frac{1}{2}\left(\frac{h}{\varphi}\right)^3\right]\right\}$
Gaussian	$\gamma(h)=\sigma^2\left[1-e^{\left\|-3\left(\frac{h}{\varphi}\right)^2\right\|}\right]$

γ(h) =semivariance; h =distance; σ²=sill and φ=range.

RESULTS AND DISCUSSION

Exploratory analysis

The distribution of NDVI data was found not to deviate from normality. The distribution of latitude and longitude values showed that the data do not have any spatial tendencies, and the spatial dependence can be explained only by the distance among the samples for all images, assuming the intrinsic hypothesis of stationarity.

The descriptive analysis of NDVI values inside samples (Table 3) showed that the average NDVI values for the forested areas were 0.48 for the SPOT 6 image, 0.43 for the LANDSAT 8 image and 0.86 for the MODIS TERRA image. For the human modified samples, the average NDVI values were 0.39, 0.29 and 0.59, respectively. Thus, as the spatial resolution decreases (from 6 to 250 m), the average NDVI values between the classes increases, showing that the NDVI values between the land-use classes are more similar, using high resolution images (i.e. SPOT 6).

For forested and human modified areas, the minimum NDVI values were obtained from samples of the SPOT 6 image; this is probably due to the presence of shadows that are captured by high resolution images, causing a reduction in NDVI values. The maximum values for these classes, were provided by MODIS TERRA, reaching 0.90.

Semivariogram analysis

The semivariograms reached the sill within the calculated distance (Figure 5), indicating that their spatial extents were sufficiently large to encompass the entire spatial variability. The Gaussian model provided the best fit for the data. The cross-validated models, showed values close to 0 (~ 0.0005) for ER and close to 1 (~ 1.11) for SRE.

We analysed the semivariogram parameters obtained from SPOT 6, LANDSAT 8 and MODIS TERRA in both classes (Table 3). The spatial variability of each image, represented by the sill (σ^2) parameter increases considerably from forested to human modified areas (Table 4). The sill (σ^2) parameter indicates the amount of

TABLE 3 Descriptive statistics.

Image	Samples	Forested areas Min	Forested areas Mean	Forested areas Max	Forested areas Std	Human modified areas Min	Human modified areas Mean	Human modified areas Max	Human modified areas Std
SPOT 6	1	0.12	0.51	0.69	0.06	-0.30	0.35	0.64	0.07
	2	0.09	0.48	0.65	0.07	-0.12	0.44	0.67	0.07
	3	0.00	0.49	0.67	0.06	-0.45	0.41	0.60	0.10
	4	0.11	0.47	0.65	0.06	-0.25	0.37	0.64	0.07
	5	0.12	0.47	0.67	0.06	-0.25	0.38	0.62	0.08
	6	0.11	0.49	0.68	0.06	-0.44	0.41	0.61	0.08
	7	0.10	0.47	0.65	0.06	0.12	0.45	0.63	0.08
	8	0.04	0.47	0.64	0.06	-0.47	0.38	0.63	0.09
	9	0.06	0.48	0.66	0.07	-0.12	0.38	0.64	0.07
	10	0.07	0.48	0.66	0.07	0.14	0.38	0.66	0.08
	Average	0.08	0.48	0.66	0.06	-0.21	0.39	0.63	0.08
LANDSAT 8	1	0.37	0.44	0.53	0.02	0.16	0.25	0.46	0.06
	2	0.33	0.42	0.49	0.02	0.19	0.31	0.48	0.08
	3	0.36	0.43	0.50	0.02	0.01	0.28	0.47	0.07
	4	0.35	0.42	0.48	0.02	0.16	0.27	0.48	0.07
	5	0.36	0.42	0.49	0.02	0.11	0.27	0.46	0.07
	6	0.34	0.43	0.50	0.02	0.04	0.31	0.47	0.08
	7	0.36	0.43	0.50	0.02	0.23	0.37	0.50	0.06
	8	0.33	0.42	0.50	0.02	0.00	0.25	0.47	0.06
	9	0.36	0.43	0.50	0.02	0.18	0.29	0.48	0.07
	10	0.35	0.44	0.50	0.02	0.19	0.31	0.52	0.07
	Average	0.35	0.43	0.50	0.02	0.13	0.29	0.48	0.07
MODIS TERRA	1	0.88	0.89	0.90	0.01	0.41	0.55	0.80	0.08
	2	0.84	0.85	0.89	0.02	0.43	0.56	0.70	0.08
	3	0.86	0.87	0.88	0.00	0.64	0.69	0.71	0.02
	4	0.72	0.85	0.88	0.05	0.49	0.58	0.68	0.05
	5	0.67	0.84	0.88	0.05	0.38	0.48	0.62	0.08
	6	0.82	0.86	0.86	0.01	0.46	0.63	0.79	0.09
	7	0.85	0.86	0.87	0.01	0.59	0.67	0.76	0.06
	8	0.75	0.83	0.89	0.04	0.34	0.55	0.75	0.17
	9	0.86	0.87	0.88	0.01	0.49	0.61	0.73	0.08
	10	0.84	0.87	0.88	0.01	0.55	0.60	0.69	0.04
	Average	0.81	0.86	0.88	0.02	0.48	0.59	0.72	0.08

Min=minimum; Max=maximum; Std=standard deviation.

variance explained by the spatial structure. GARRIGUES et al. (2006) the spatial heterogeneity within the moderate spatial resolution pixel biases non-linear estimation processes of land surface variables from remote sensing data. To limit its influence on the description of land surface processes, corrections based on the quantification of the intra-pixel heterogeneity may be applied to non-linear estimation processes. A complementary strategy is to define the proper pixel size to capture the spatial variability of the data and minimize the intra-pixel variability. This work provides a methodology to characterize and quantify the spatial heterogeneity of landscape vegetation cover from the modeling of the variogram of high spatial resolution NDVI data. NDVI variograms for 18 landscapes extracted from the VALERI database show that the land use is the main factor of spatial variability as quantified by the variogram sill. Crop sites are more heterogeneous than natural vegetation and forest sites at the landscape level. The integral range summarizes all structural parameters of the variogram into a single characteristic area. Its square root quantifies the mean length scale (i.e. spatial scale found that forested areas have a low sill values because the important development of vegetation and the presence of green understory limit the variability of the landscape vegetation cover. The high variability of human modified areas is explained by the mosaic of vegetation with high NDVI values and bare soil and pastures with low NDVI values. The highest sill value was found in the human modified areas using SPOT 6 (0.0064) and the lowest was found in forested areas using MODIS TERRA (0.0001).

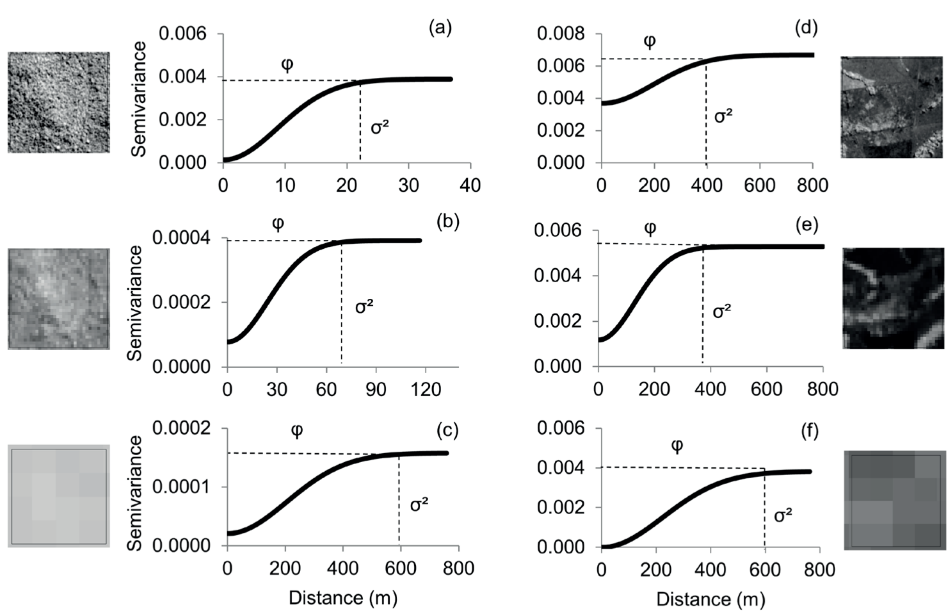

FIGURE 5 Example semivariogram curves for: (a) forested NDVI values of SPOT 6; (b) forested NDVI values of LANDSAT 8; (c) forested NDVI values of MODIS TERRA; (d) human modified NDVI values of SPOT 6; (e) human modified NDVI values of LANDSAT 8; (f) human modified NDVI values of MODIS TERRA. Dashed lines illustrate the σ² (sill) and φ (range) parameters.

TABLE 4 Average semivariogram parameters obtained from 20 samples.

Image	Semivariogram parameters	Forested	Human Modified	Variation
SPOT 6	σ^2	0.0039	0.0064	0.0025
	Φ	22	338	316
LANDSAT 8	σ^2	0.0004	0.0053	0.0049
	Φ	70	400	330
MODIS TERRA	σ^2	0.0001	0.0043	0.0042
	Φ	585	600	15

σ^2=sill; φ=range.

The average range (φ) also increases from forested to human modified areas. The range parameter obtained from satellite images is the ratio of the area covered by the dominant objects (TREITZ, 2000). In forested areas, the range (φ) represents the size of the largest elements, which are the tree crowns of the forest canopy. On the other hand, in human modified areas, the dominant objects will vary according to the land cover classes present in the samples. Using SPOT 6, the sill values of forested areas reach the overall image variance at a short range (22 m), indicating that this class is poorly structured at the observational scale. The nugget effect is high, representing variability at distances smaller than the sample spacing (1 pixel). The greatest range was found in human modified areas using MODIS TERRA (600 m). The semivariogram range can be used to quantify coarse spatial variability since it increases as a result of changes in land-use throughout the landscape (SERTEL et al. 2007).

ACERBI JUNIOR et al. (2015) analysed semivariogram parameters to detect changes in a Brazilian savanna biome using NDVI LANDSAT TM images. They showed that sill and range semivariogram parameters were different when deforestation occurred and were similar when the area had not been changed.

The sill and range semivariogram parameters extracted from NDVI images are affected by image spatial resolution. Images with high spatial resolution have lower internal intra-pixel variability and high inter-pixel variability. This inter-pixel variability is linked with the sill and range parameters and is affected by the LULC classes. As image spatial resolution decreases, inter-pixel variability also decreases (Figure 6). Low inter-pixel variability provides low sill values and high range values, meaning that NDVI SPOT 6 should provide higher sill and lower range values than LANDSAT 8 and MODIS TERRA. For forested areas, this pattern is more pronounced than in human modified areas.

To select the most appropriate semivariogram parameter and image spatial resolution we analysed which one provided the greatest variation between the LULC classes. The variation of sill and range values between the classes increases between SPOT 6 (0.0025-316) and LANDSAT 8 (0.0049-330) and decreases from LANDSAT 8 to MODIS TERRA (0.0042-15).

In the SPOT 6 image, the variation in sill values between the LULC classes is low and the variation in range values is high. SPOT 6 images have high spatial resolution (6 meters), and the largest elements in forested areas are the tree crown shadows. The high NDVI values of trees and low values of shadows increase the overall variability captured by the sill semivariogram parameter, making the sill values of forested areas as high as the sill values of human modified areas. The range parameter is low in forested areas due to the size of the elements also being low. In human modified areas, the overall variability is influenced by the type of landscape (bare soil, plantation, pasture and cropland), presenting high range values, thus increasing the variation in range values between the classes.

In the LANDSAT 8 images, the sill and range present a high variation between the LULC classes. MODIS TERRA presents a high variation in sill values and low variation in range values.

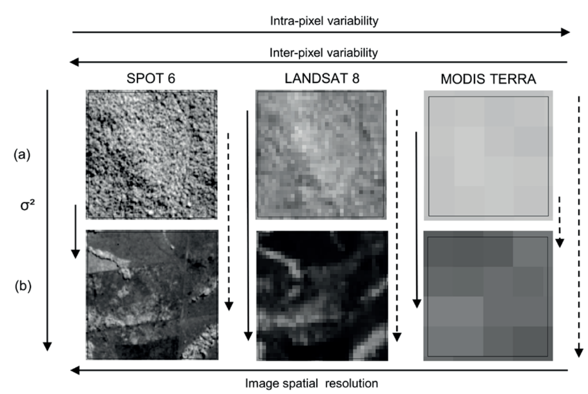

FIGURE 6 Effect of image resolution on sill (σ^2) and range (φ) parameters for the characterization of landscape spatial heterogeneity: (a) Forest areas and (b) Human modified areas.

The spatial heterogeneity between the LULC classes follows the same pattern using the semivariogram parameters obtained from three different image spatial resolutions. The sill (σ^2) and range (φ) parameters increase from forested to human modified areas. This increase is more pronounced using medium spatial resolution images (Landsat – 30 m).

The semivariogram parameters were efficient at describing landscape spatial heterogeneity, being able to distinguish the analysed classes. LANDSAT 8 showed the greatest differentiation of land cover classes with the sill and range parameters. We advise using both sill and range parameters derived from NDVI LANDSAT images to identify forested and human modified areas, to capture the landscape heterogeneity.

CONCLUSIONS

We have evaluated the potential of semivariogram parameters derived from NDVI images to describe landscape spatial heterogeneity of forested and human modified areas.

Our analyses have revealed that image resolution does in fact influence the sill and range parameters. Average sill and range values increased from forested to human modified areas at the three image spatial resolutions analysed, however the greatest between-class variation was provided by LANDSAT 8 imagery, indicating that medium spatial resolution is the most appropriate for deriving the sill and range parameters with the intention of capture and map the landscape spatial heterogeneity.

By combining remote sensing and geostatistical techniques, we have shown that the sill and range parameters of semivariograms derived from NDVI images are a simple indicator of landscape heterogeneity and can be used to provide landscape heterogeneity maps to enable researchers to design appropriate sampling regimes. In the future, more applications combining remote sensing and geostatistical features should be further investigated and developed, such as change detection and image classification using object-based image analysis (OBIA) approaches.

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