Multiscale Analysis of Landscape Spatial Heterogeneity Using Vegetation Indexes

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Abstract—**Remote sensing provides multiscale image data to monitoring the earth surface. The spatial heterogeneity of the surface is a function of image scales. It is also affected by various remote sensing variables. This work uses variogram to assess the abilities of NDVI (normalized difference vegetation index) and DVI (difference vegetation index) to exploit the surface spatial heterogeneity. The decay of spatial heterogeneity as pixel size increases is measured and the spatial variability within coarse spatial resolution pixel is calculated. The results show that: 1) NDVI and DVI display a similar ability in detecting the spatial structure. NDVI variogram modeling outperforms DVI modeling in characterizing the spatial variability of the surface; 2)the spatial variability and the spatial structure both follow logarithmic relationships with stronger fits as the spatial resolution decreases; 3) the loss of spatial variability within pixel increases as spatial resolution decreases. Simple aggregation of fine resolution pixels to a coarse resolution engenders loss of image variability.**

Index Terms—*Spatial heterogeneity, variogram, spatial resolution, NDVI, DVI.*

I. INTRODUCTION

Spatial heterogeneity describes the variability of the observed surface properties in space [1]. It can be defined through two parts: the spatial variability of the surface property and the spatial structures related to objects or patches over the observed scene [2]. The methods of detecting spatial heterogeneity are mainly empirical approaches and probabilistic approaches. The former lacks of theoretical framework such as local variance [3]. The latter relies on stationarity hypothesis such as fractal, multifractal and variogram [4], [5]. The modeling of variogram has been widely used to quantify the spatial variability and the spatial structures [2], [6]. NDVI is a good indicator of vegetation amount and growth [7], which is frequently used to describe the surface spatial heterogeneity [8], [9]. Other variables like red and near red reflectance, LAI (leaf area index) are also employed [10], [11]. The radiometric characteristics of variables response to the landscapes influence the detection of the spatial heterogeneity. So when exploiting the spatial heterogeneity of various landscapes (e.g. forest, crop, wetland and water), the characteristic of the variable used deserves consideration. In this paper, the spatial heterogeneity is quantified by NDVI and DVI and the difference of between these two variables in describing spatial heterogeneity is evaluated using variogram modeling.

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The spatial heterogeneity of the observed surface is scale dependent [12]. Changes of scale may even lead to alternation between heterogeneity and homogeneity. Coarse resolution sensors (e.g. Terra-Aqua MODIS) provide relatively high revisit frequency observations with relatively large pixel size. Since the landcover viewed by sensors are often smaller than coarse resolution pixels, intra-pixel spatial heterogeneity information may be not captured at coarse spatial resolution [13]. A strategy to quantify the spatial heterogeneity of a coarse resolution pixel is to use high spatial resolution pixels (e.g. Landsat TM) [7]. Here, the variogram is applied to multiresolution NDVI and DVI dataset simply aggregated from TM 30 m images to understand the loss of spatial information as spatial resolution decreases. This paper first attempts to use variograms of Landsat TM NDVI and DVI images to describe the spatial heterogeneity of two contrasted vegetation covers. The ability of NDVI and DVI variables to express spatial heterogeneity is compared through sill and range of the variograms. The decay of spatial heterogeneity as a function of spatial resolution is analyzed and the coarse resolution pixel heterogeneity is investigated with fine resolution pixels. Then, we close with a conclusion.

II. MATERIAL AND METHODS

A. Data description

Optical satellite imageries of Landsat-5 TM in SMEX04 project are selected in this study [18]. These images are not contaminated by clouds and are preprogressed. The red and near infrared band are used to calculated NDVI and DVI, which are used to describe the spatial variability of the vegetation cover over the image domain. DVI is linearly related red and near infrared reflectances, while NDVI is not.

TABLE I. CHARACTERISTIC OF TWO STUDY SITES

Site	Date	Size(m^2)	m_{NDVI}	σ_{NDVI}	m_{DVI}	σ_{DVI}
Site1	August 30	8000× 9000	0.33	0.15	0.19	0.07
Site2	August 30	8000× 9000	0.20	0.04	0.10	0.02

B. Variogram modeling of spatial heterogeneity

The regionalized variable $z(x)$ is modeled as one among all possible realizations of $Z(x)$ [14]. The theoretical variogram of $Z(x)$ is calculated by the following expression:

$$\gamma(h) = 0.5Var[Z(x+h) - Z(x)] \qquad (1)$$

A linear model of regionalization [15] accounting for the multiscale spatial structures of the data is defined as a linear combination of two or more functions as follows [2]:

$$\gamma(h) = c\sum_{k=1}^{n} b_k g_k(r_k, h) \quad (2)$$

$\gamma(h)$ is the modeled variogram, c is the overall sill, b_k is the fraction of overall sill related to each range r_k, g_k denotes each elementary function and n is the numbers of functions regionalized (Fig.1).

The overall sill c describes the degree of spatial variability [16]. The ranges r_k and the b_k are summarized in a single parameter: the integral rang A [17], which is computed as $A = \sum_{k=1}^{n} b_k A_k$, where $A_1 = 2\pi r_1^2/9$ for the exponential and $A_2 = \pi r_2^2/5$ for the spherical functions. The mean length scale D_c is the square root of A. It is related to the mean extent of the image spatial structures [2].

The variogram sill c and the mean length scale D_c are applied to characterize the decay of spatial variability for NDVI and DVI images with various spatial resolutions generated through simple spatial aggregation of the 30 m TM scenes.

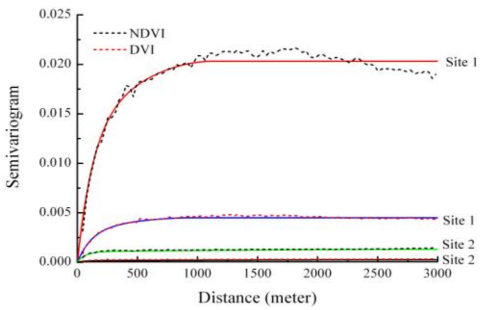

Fig.1. NDVI and DVI variograms of two contrasted sites. The dash lines are the experimental variograms. The solid lines represent the fitted theoretical variogram models.

C. Scales of pixel's spatial heterogeneity

In the previous sections, the variogram is used to quantify the overall spatial variability of the image. A pixel of coarse spatial resolution simply averaged from fine spatial resolution pixels is regarded as a combination of several fine resolution pixels. The heterogeneity occupied by a coarse pixel w can be quantified by n fine resolution pixels x_i. The variability at coarse spatial resolution is described by the dispersion variance [2].

The average dispersion variance of the n fine resolution pixels values within the coarse resolution pixel,

$$s^2(x \mid w) = \frac{1}{m}\sum_{j=1}^{m}\frac{1}{n}\sum_{i=1}^{n}(z(x_i) - \bar{z}_{w_j})^2 \quad (3)$$

where $\bar{z}_{w_j}$ is the spatial average of $z(x)$ over w_j, m is the number of w. As shown in Fig. 4, the variability within the pixel increases as the size of w increases. $s^2(x \mid w)$ is used to quantify the loss of image variability when fine resolution is aggregated to coarse resolution. The $s^2(x \mid w)$ was calculated at pixel size w ranging from 90 to 900 m with an interval of 30 m.

II. Results and Analysis

A. Spatial heterogeneity of two constrasted lanscapes

The empirical variograms (Fig.1) illustrate that the sill c consistently increases as distance increases and then levels off. The spatial variability characterized through the sill increases considerably from site 2 to site1. For site 2 the spatial heterogeneities of NDVI and DVI are much lower than those of site 1. The relative homogeneity of site 2 is denoted by less vegetation types which limit the variability of the vegetation cover. The high variability of site 1 is explained by the mosaic of various vegetation types with high values and water fields with low values in red and near infrared bands (Fig.2). For both sites the variability of NDVI is larger than that of DVI. The NDVI variogram seems to provide a more robust characterization of spatial variability of the vegetation cover than DVI.

The variograms of Fig. 1 have been modeled using a linear combination of exponential and spherical models (Table 2). Both NDVI and DVI variograms increase rapidly and reach almost the whole image variances at short ranges (r_{1NDVI}=200 m; r_{1DVI}=220 m). The short range results from length scale of vegetation and the presence of objects in the site (rivers, roads…). The second ranges of NDVI and DVI are both 3000 m and the fractions explain low parts of the spatial variability (less than 34%). Concerning site 1, the values of r_1 (421 m) and b_1 (73.67 %) calculated from NDVI variable image are close to that of r_1 (371 m) and b_1 (76.49 %) obtained from DVI image. The larger range of NDVI (r_2=1123 m) and DVI (r_2=963 m) are probably related to the spatial structure within the shrub area and subtropical wood area. NDVI and DVI have similar abilities to describe the spatial structure of the landscape. As shown on these two sites, NDVI is better than DVI at describing the spatial variability of the vegetation. They have similar ability to quantify the spatial structure.

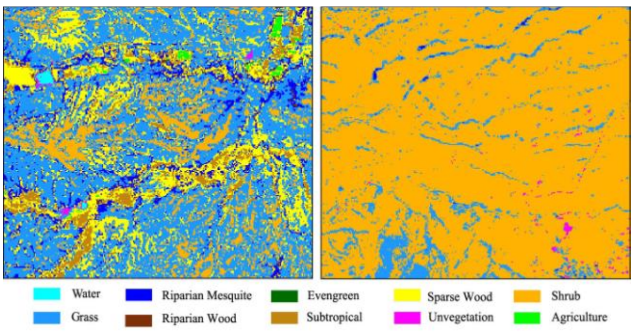

Fig.2. Landcover classification of site 1 (left) and site 2 (right) [18].

TABLE II. VARIOGRAM MODEL PARAMETERS FOR THE TWO SITES

NDVI data	c	$g_1(r_1)$	b_1	$g_2(r_2)$	b_2
Site1	0.0203	Exp(421)	73.67	Sph(1123)	26.32
Site2	0.0013	Exp(200)	82.41	Sph(3000)	17.59
DVI data					
Site1	0.0045	Exp(371)	76.49	Sph(963)	23.51
Site2	0.0003	Exp(220)	66.21	Sph(3000)	33.79

c—variogram sills; r1，r2—variogram ranges, in meter; b1，b2—fractions of total variance. Exp: exponential model; Sph: spherical model.

B. The decay of spatial variability as a function of spatial resolution

This part is applied to characterize the decay of spatial variability of site 1 NDVI and DVI products with various spatial resolutions aggregated from the 30 m TM original scenes (Table 3). The overall sill and the mean length scale were used to evaluate spatial variability in relation to spatial resolution. Fig. 3a illustrates the loss of spatial information for various spatial resolution images. Assuming the 30 m image approximates the overall spatial variability, the rate of sill decrease relative to the sill of the 30 m image characterizes the loss of spatial heterogeneity as spatial resolution decreases. For the NDVI image, the decay rate of spatial variability at 600 m spatial resolution is 73.89% and the spatial variability is almost lost at 900 m (Table 3, column 4). The decay rate of the DVI spatial variability is faster than that of NDVI. As the weighted average of the different ranges, D_c identifies the typical length scales within the image. It increases as the pixel size increases (Fig.3b). For the NDVI and DVI shows different spatial properties, the choice of the optimal spatial resolution is related to the remote sensing variable to be inversed.

The sill and the mean length scale followed logarithmic relationships with stronger fits as a function of pixel size. For NDVI, the R^2 of the sill is 0.9761, the R^2 of the mean length scale is 0.9411.

TABLE III. PARTIAL PARAMETERS OF VARIOGRAM MODELS FOR THE SPATIALLY AGGREGATED 30-M TM VEGETATION INDICES DATA.

Vegetation indices	Spatial resolution (m)	Spatial variability	Decay rate of spatial variability (%)*	Mean length scale Dc (m)
NDVI	30※	0.0203	--	545.96
	150	0.0138	32.02	633.1
	300	0.0099	51.23	748.65
	600	0.0053	73.89	839.93
	900	0.0037	81.77	1451.31
DVI	30※	0.0045	--	457.31
	150	0.0026	42.22	537.93
	300	0.0018	60	663.28
	600	0.0009	80	1012.88
	900	0.0007	84.44	1451.34

*Source for aggregated datasets; *relative to the sill of TM 30m.

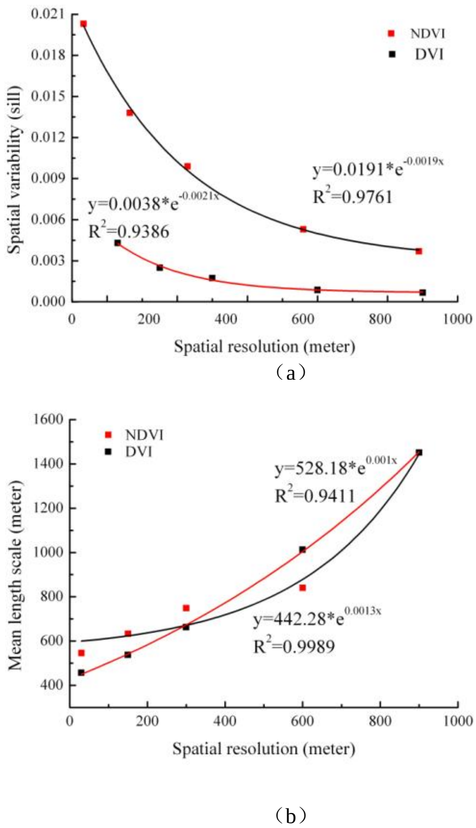

Fig. 3 The spatial variance (a) and the mean length scale (b) as functions of spatial resolution.

C. The loss of spatial variability within a coarse resolution pixel

$s^2(x\,|\,w)$ quantifies the degree of spatial heterogeneity within *w* of the image. It generally exhibits an increasing trend as a function of spatial resolution (Fig.4).The size of w ranges from 90m to 900m. The aggregated pixel variability of NDVI is larger than that of DVI. This also indicates that the spatial heterogeneity of NDVI is larger than that of DVI. The breakpoints of NDVI are 360 m 540 m, 630 m, 720 m, 750 m, 810 m and 840 m. The DVI has the same decreased points. These points indicate that the spatial variability within these pixels is relatively lower. The aggregation of the pixels to a coarse resolution engenders loss of image variability.

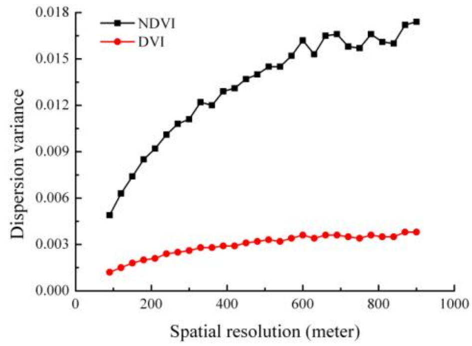

Fig. 4 Pixel heterogeneity as a function of spatial resolution.

III. DISCUSSIONS

Both NDVI and DVI combine red and near infrared variables in one synthetic variable. DVI, defined as the subtraction of near infrared and red reflectance variables, increases linearly with near infrared band. NDVI saturates when the sensed surface is covered by dense vegetation. As the red reflectance is sensitive to soil, NDVI and DVI both carry the spatial information of soil. But the ratio operation of NDVI reduces more soil interference than DVI. As mentioned in Section 3.1, NDVI variogram modeling appears to be more efficient than DVI modeling to characterize the spatial variability of the vegetation cover under this study. The surface spatial heterogeneity is strongly dependent on the radiometric variable used to characterize it [19]. The choice of an appropriate variable or several variables to detect the properties of different types of landscapes deserves more attention.

The mean length scale assesses the length scale differences and the effect of pixel size on spatial variability. This information may be used to define a sufficient spatial resolution at which the landscape spatial variability is fully described [2]. The dispersion variance quantifies the loss of image variability when aggregating the high resolution pixels to a coarse resolution. Simple aggregation to rescale the image is essentially an average of the existing measurements, without considering the effect of PSF that occurs in a real imaging system. Simple average gives equivalent weight to every pixel. Distinct transitions or contrasting edges apparent at finer spatial resolution are submerged or lost at coarse spatial resolutions [11], which leads to a change in spatial variability and spatial structure.

IV. CONCLUSIONS

This work used variogram to model TM 30 m NDVI and DVI data and showed that NDVI and DVI can characterize and quantify the spatial heterogeneity of vegetation covers. Results showed that NDVI and DVI which had similar ranges exhibited similar ability to investigate the spatial structures of the sites. NDVI was more robust to evaluate the spatial variability of the two sites. Moreover, we discussed the relationship of the decay of spatial heterogeneity as spatial resolution decreased. The overall sill and the mean length scale followed logarithmic relationships with stronger fits as a function of pixel size.

Simple aggregation failed to consider the effect of spatial heterogeneity of the surface in the process of rescaling that may bring in discrepancy of images to be rescaled and compared. A method which considers the spatial heterogeneity in rescaling is well worth research.

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