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Effects of Normalized Difference Vegetation Index and Related Wavebands′ Characteristics on Detecting Spatial Heterogeneity Using Variogram-based Analysis

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Abstract: Spatial heterogeneity is widely used in diverse applications, such as recognizing ecological process, guiding ecological restoration, managing land use, *etc*. Many researches have focused on the inherent scale multiplicity of spatial heterogeneity by using various environmental variables. How these variables affect their corresponding spatial heterogeneities, however, have received little attention. In this paper, we examined the effects of characteristics of normalized difference vegetation index (NDVI) and its related bands variable images, namely red and near infrared (NIR), on their corresponding spatial heterogeneity detection based on variogram models. In a coastal wetland region, two groups of study sites with distinct fractal vegetation cover were tested and analyzed. The results show that: 1) in high fractal vegetation cover (H-FVC) area, NDVI and NIR variables display a similar ability in detecting the spatial heterogeneity caused by vegetation growing status structure; 2) in low fractal vegetation cover (L-FVC) area, the NIR and red variables outperform NDVI in the survey of soil spatial heterogeneity; and 3) generally, NIR variable is ubiquitously applicable for vegetation spatial heterogeneity investigation in different fractal vegetation covers. Moreover, as variable selection for remote sensing applications should fully take the characteristics of variables and the study object into account, the proposed variogram analysis method can make the variable selection objectively and scientifically, especially in studies related to spatial heterogeneity using remotely sensed data.
Keywords: spatial variation; spatial structure; NDVI characteristic; semivariogram model; semivariogram analysis

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1 Introduction

Spatial heterogeneity, a widely used ecological term, can be generally recognized as the property of ecological variable (such as soil condition, vegetation type) that vary in space (Wu, 2007; Fu *et al.*, 2011). It often demonstrates unique characteristic at different scales, which can be determined by the pattern generating processes (Riera *et al.*, 1998). At a small scale, spatial heterogeneity can be affected by microenvironment factors; at a medium scale, it could be related to some disturbances such as winds or fires. Not only spatial heterogeneity depends on a specific research scale, but also it can be influenced by different environmental variables selected (Smithwick *et al.*, 2005). For an area with mixed vegetation, vegetation types are highly spatially heterogeneous, and the soil conditions could be rather homogeneous.

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As an important tool for earth observation, remote sensing can provide multi-scale and multi-spectral image data (Li *et al*., 2011). There is a grand opportunity for scientists to investigate geophysical phenomena (ecological processes, enviromental changes, *etc*.) using spatial heterogeneity retrived from various types of remote sensing data (Riera *et al.*, 1998; Wu *et al.*, 2000; Chen *et al*., 2002; Chen and Henebry, 2009; Feng *et al*., 2010). A sizeable literatures have focused on the variation of spaital heterogeneity using multi-scale remote sensing data (Benson and MacKenzie, 1995; Goodin and Henebry, 2002; Zhu *et al.*, 2006; Chen and Henebry, 2009). The characteristics of different variables derived from remote sensing data (e.g., vegetation index, reflectivity of suface, *etc*.) regarding to spatial heterogeneity, however, need to be considered. In some studies, variables such as normalized difference vegetation index (NDVI), red and near infrared (NIR) band images were used to detect and analyze spatial heterogeneity by varigram tool (Oliver *et al*., 2005; Chen and Henebry, 2009), and evident differences in spatial heterogeneity were found when using different variables, but corresponding explainations were not presented. Based on these observations, the issue that how a remote sensing variable affects spatial heterogeneity, therefore, remians to be investigated. Furthermore, the problem, related to how to seclet an appropriate remote sensing variable in a specific application, deserves much more attention. To these ends, by using variogram method, spatial heterogeneities provided by the NDVI, red and NIR bands were quantified, comparied, and analyzed in this paper.

For a specific study objective, it is suggested that spatial heterogeneity should be defined in terms of its underlying components. Here, we mainly focus on quantitative analysis of spatial heterogeneity at a landscape scale using remote sensing data. Spatial heterogeneity is thus described through two components as many authors recommend: 1) the spatial variability of the surface property over the observed scene, and 2) the length scale of the spatial structures of objects or patches that repeat themselves independently within the observed scene at a characteristic spatial scale (Kolasa and Rollo, 1991; Garrigues *et al.*, 2006).

2 Methodology

2.1 Study area

The core of Yancheng National Natural Reserve (NNR), a coastal wetland located in Jiangsu Province, China, was chosen as the study area. For comparison, a group of study sites (Site 1 and Site 2) with distinct vegetation types and fractional vegetation cover were analyzed (Fig. 1). Site 1 is full of *Spartina alterniflora Lois*, with a mean fractional vegetation cover up to 100% (Zhong *et al.*, 1985; Liu *et al.*, 2010), while Site 2 is covered by *Suaeda glauca* in saline-alkali soil, with very low fractional vegetation cover (Liu *et al.*, 2010). In addition, another group of study sites, namely Site 3 and Site 4 which have similar vegetation conditions corresponding to Site 1 and Site 2 respectively, were also investigated (Table 1).

2.2 Data preprocessing

Optical satellite imagery of SPOT-5 high resolution geometrical (HRG) on October 31, 2005 was selected in this study. The HRG multi-spectral imagery has three wavebands with 10 m nominal spatial resolution: green (0.50–0.59 μm), red (0.61–0.68 μm), near infrared (NIR, 0.78–0.89 μm), and short-wave infrared (SWIR, 1.58–1.75 μm) with 20 m resolution. Then, the reflectance images of NIR (ρ_{NIR}) and red (ρ_{red}) were used to calculate NDVI variable image (Avery and Berlin, 1992).

$$NDVI = \frac{\rho_{\mathrm{NIR}} - \rho_{\mathrm{red}}}{\rho_{\mathrm{NIR}} + \rho_{\mathrm{red}}} \tag{1}$$

2.3 Experimental variogram

An variable image can be denoted as a regionalized variable $Z(x)$, then, the experimental variogram, denoted as $\gamma_{\mathrm{e}}(h)$, determines the average squared difference between the values of pixels, $(z(x_i), z(x_j))$, which is separated by a distance of h as showed in Equation (2) (Burrows *et al*., 2002).

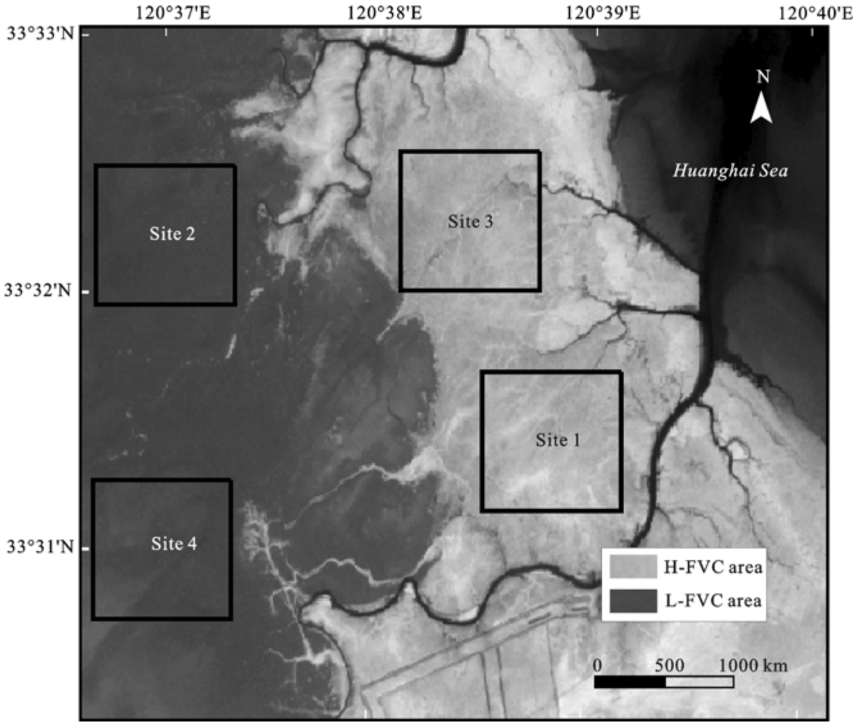
$$\gamma_{\mathrm{e}}(h) = \frac{1}{2N(h)} \sum_{h} [z(x_i) - z(x_j)]^2 \tag{2}$$

where $N(h)$ is the number of pixel pairs separated by h. In order to compare the spatial heterogeneity of different variables, standard variograms, denoted as $SS(h)$, were recalculated by the experimental variograms and image variance σ^2 as follows (Wang, 1999).

$$SS(h) = \frac{\gamma_{\mathrm{e}}(h)}{\sigma^2} \tag{3}$$

2.4 Variogram quantifying spatial heterogeneity

Variogram modeling is necessary to provide a parametric



H-FVC: high fractional vegetation cover; L-FVC: low fractional vegetation cover

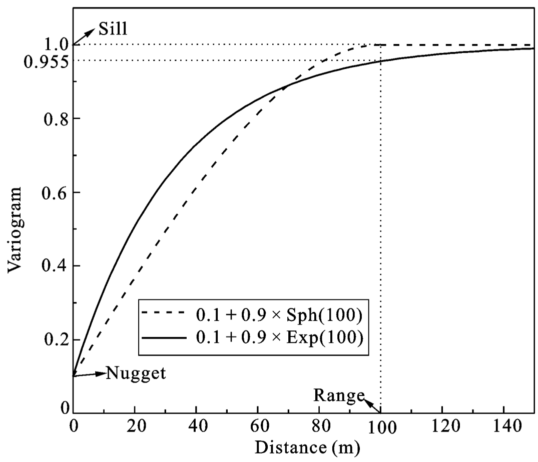
Fig. 1 Four study sites in core of Yancheng National Natural Reserve

Table 1 Characteristic of four study sites

Group	Study site	Location	Size (m^2)	Description
1	Site 1	33°31′28″N 120°38′50″E	1000 × 1000	Covered by *Spartina alterniflora Lois* in very high fractional vegetation cover
	Site 2	33°32′15″N 120°37′01″E	1000 × 1000	Salinized marsh covered by *Suaeda glauca* in low fractional vegetation cover
2	Site 3	33°32′18″N 120°38′26″E	1000 × 1000	Covered by *Spartina alterniflora Lois* in very high fractional vegetation cover
	Site 4	33°31′01″N 120°37′02″E	1000 × 1000	Salinized marsh covered by *Suaeda glauca* in low fractional vegetation cover

quantification of the spatial heterogeneity characteristics, i.e., overall spatial variability and length scale of spatial structure of objects, of the scene. It consists in estimating the theoretical variogram of $Z(x)$, by fitting a valid mathematical model to the experimental variograms computed over the image.

As variogram models (curves) showed in Fig. 2, at a certain distance the model levels out, which is known as the range (denoted as a). The pixels locations separated by distances closer than the range are spatially dependent, while the locations farther apart than the range are not. The value at which the variogram levels off is denoted as c and is called the sill (Wang, 1999), which can be considered as the spatial variability at autocorrelation range of the image. Theoretically, at zero separation



Exp: exponential model; Sph: spherical model

Fig. 2 Examples of two typical theoretical variogram models distance (i.e., distance = 0), the variogram value should be zero. However, at an infinitesimally small separation distance, the difference between measurements often does not tend to zero (Chilès and Delfiner, 1999). This is called the nugget effect and the value is named nugget, denoted as c_0. The nugget effect can be explained by the measurement errors of image and the intra-pixels variability or uncertain.

To account for the multi-scale spatial heterogeneity of the data, we used a linear model of regionalization defined as a linear combination of two or more (count as n) functions as follows (Tarnavsky *et al.*, 2008).

$$\gamma(h) = \sum_{k=0}^{n-1} c_k \gamma(a_k, h) \tag{4}$$

where $\gamma(h)$ is the theoretical variogram model, a_k is the variogram range as associated with the function $\gamma(a_k, h)$, and c_k is the corresponding variogram sill.

GS+ version 7 was adopted to calculate the experiment variograms, and the parameters of the calculated variogram models were then fit interactively under VARIOWIN. The most appropriate curve fit was judged visually, on one hand; and it was characterized by 'indicative goodness of fit' (IGF) stated with VARIOWIN, on the other hand. The calculated IGF values here, ranges from 0.0000621 to 0.0008106 for all models (Table 2), indicating very good fits of the models to the data (Pannatier, 1996). For the lag distance, two-fifths of the image size was selected (i.e., 400 m) in this study, by synthetically taking former researchers' standpoints into account: for instance, Curran and Atkinson (1998) advocated that half of the image size generates variogram in most cases, while one-third was suggested by Chen and Henebry (2009). The distances larger than 400 m indicate that the large spatial structures can not be comprised by the image extent (1000 m × 1000 m) and are not considered in the results of this study.

3 Results and Analyses

The experiment variograms of the three variables (NDVI, NIR, and red) of the four study sites are showed in Fig. 3, and the parameters of their corresponding fitted variogram models are showed in Table 2, respectively.

3.1 Spatial heterogeneity at landscape scale

As mentioned above, the spatial heterogeneity in this study is represented as the length scale of spatial structure and the spatial variance, and they are quantified by variogram range (a_k) and corresponding sill (c_k), respectively. We mainly analyzed the first range (a_1) and sill

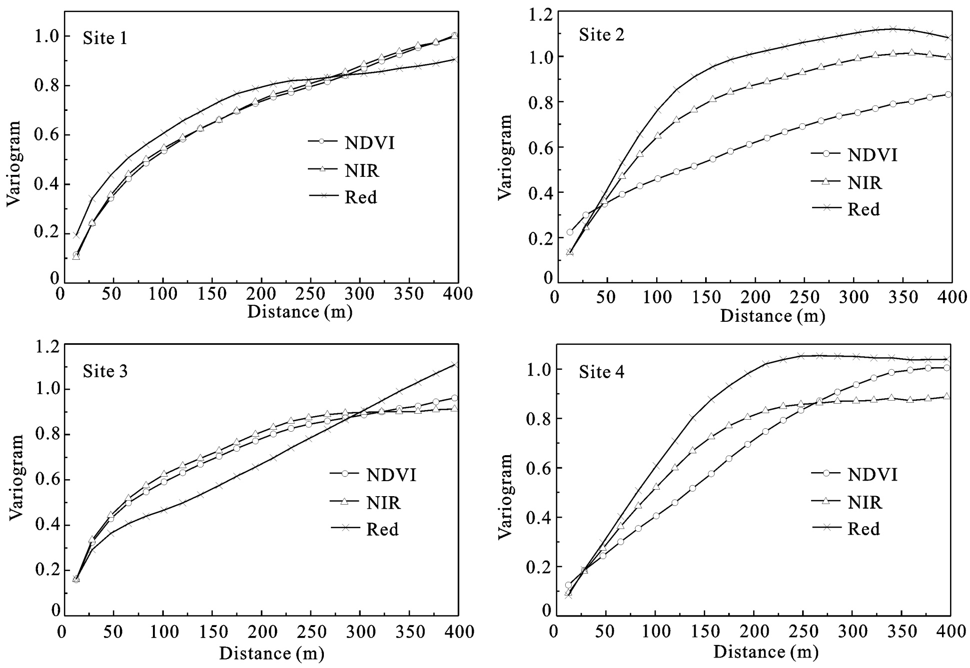


Fig. 3 Experimental variogram of four study sites

Table 2 Variogram parameters of different variable images of four study sites

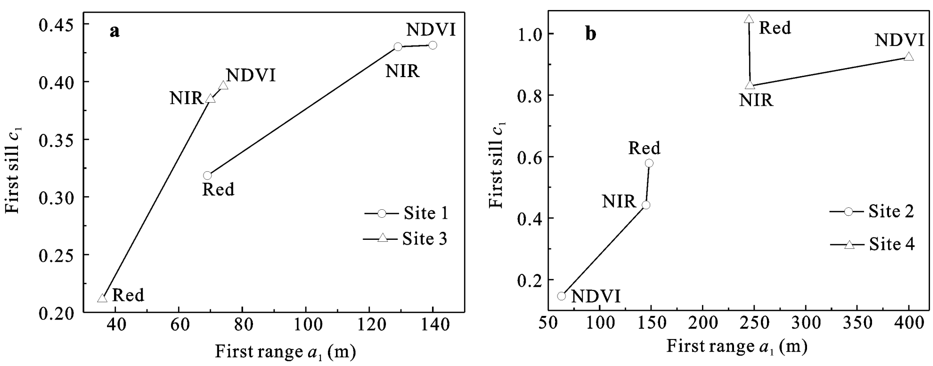
Study site	Variable	a_1 (m)	a_2 (m)	c_1	c_2	c_0	CV (%)	IGF (10^{-4})
	NDVI	140	700	0.431	0.751	0	9.30	1.270
Site 1	NIR	129	750	0.430	0.804	0	5.56	0.621
	Red	69	256	0.319	0.475	0.040	2.22	8.106
	NDVI	63	500	0.147	0.577	0.144	49.30	0.527
Site 2	NIR	145	365	0.443	0.510	0.059	2.26	0.637
	Red	148	332	0.579	0.509	0.040	1.93	2.598
	NDVI	74	388	0.396	0.552	0	9.92	3.040
Site 3	NIR	70	314	0.385	0.524	0	4.69	1.719
	Red	36	1000	0.211	1.500	0.040	2.64	4.980
	NDVI	400	–	0.922	–	0.090	38.00	5.130
Site 4	NIR	246	–	0.830	–	0.037	2.95	1.197
	Red	245	–	1.044	–	0.010	2.75	0.935

Notes: IGF represents indicative goodness of fit, and '–' indicates that there is no value for the cell

(c_1) since most of the second range (a_2) and sill (c_2) are unreliable for $a_2 > 400$ m (Table 2). Figure 4a demonstrates the properties of spatial heterogeneity from NDVI, NIR and red variables in high fractal vegetation cover (H-FVC) area and low fractal vegetation cover (L-FVC) area. In Site 1, the values of a_1 (129 m) and c_1 (0.430) calculated from NIR variable image are close to that of a_1 (140 m) and c_1 (0.431) obtained from NDVI variable image. Such pattern can also be noted in Site 3 as well, as Fig. 3 and Fig. 5 shown. These indicate that the spatial heterogeneity in NDVI variable image (Fig. 5a) is more similar to that in NIR variable image (Fig. 5b). In addition, for both Site 1 and Site 3, a_1 and c_1 of NDVI, NIR and red respectively decrease (Fig. 4a), with a large difference between NDVI and RED accordingly. It indicates that the larger length scale of spatial structure in H-FVC with large spatial variability could be detected by the NDVI and NIR variable images, while the small spatial structure with low variability could be examined by the red variable image.

In L-FVC area (i.e., Site 2 and Site 4), the values of a_1 from NIR and those from red variable images are almost equal, with a distinct difference to those from the NDVI variable image (Fig. 4b). The values of a_1 obtained from NIR and red in Site 2 are 145 m and 148 m respectively, while that from NDVI variable image is 63 m (Table 2). In the H-FVC area, the monotonic trends of a_1 and c_1 could not be noticed.

It could be found that the NIR and red variable images have similar spatial structures in L-FVC area, and that can also be visually spotted in Fig. 3, Fig. 5e (the NIR variable image) and Fig. 5f (the red variable image). Since NDVI is sensitive to vegetation cover and background signals (such as soil and moisture), the spatial



H-FVC: high fractal vegetation cover; L-FVC: low fractal vegetation cover

Fig. 4 Comparison of spatial structure (a_1) and spatial variability (c_1) in H-FVC area (a) and L-FVC area (b)

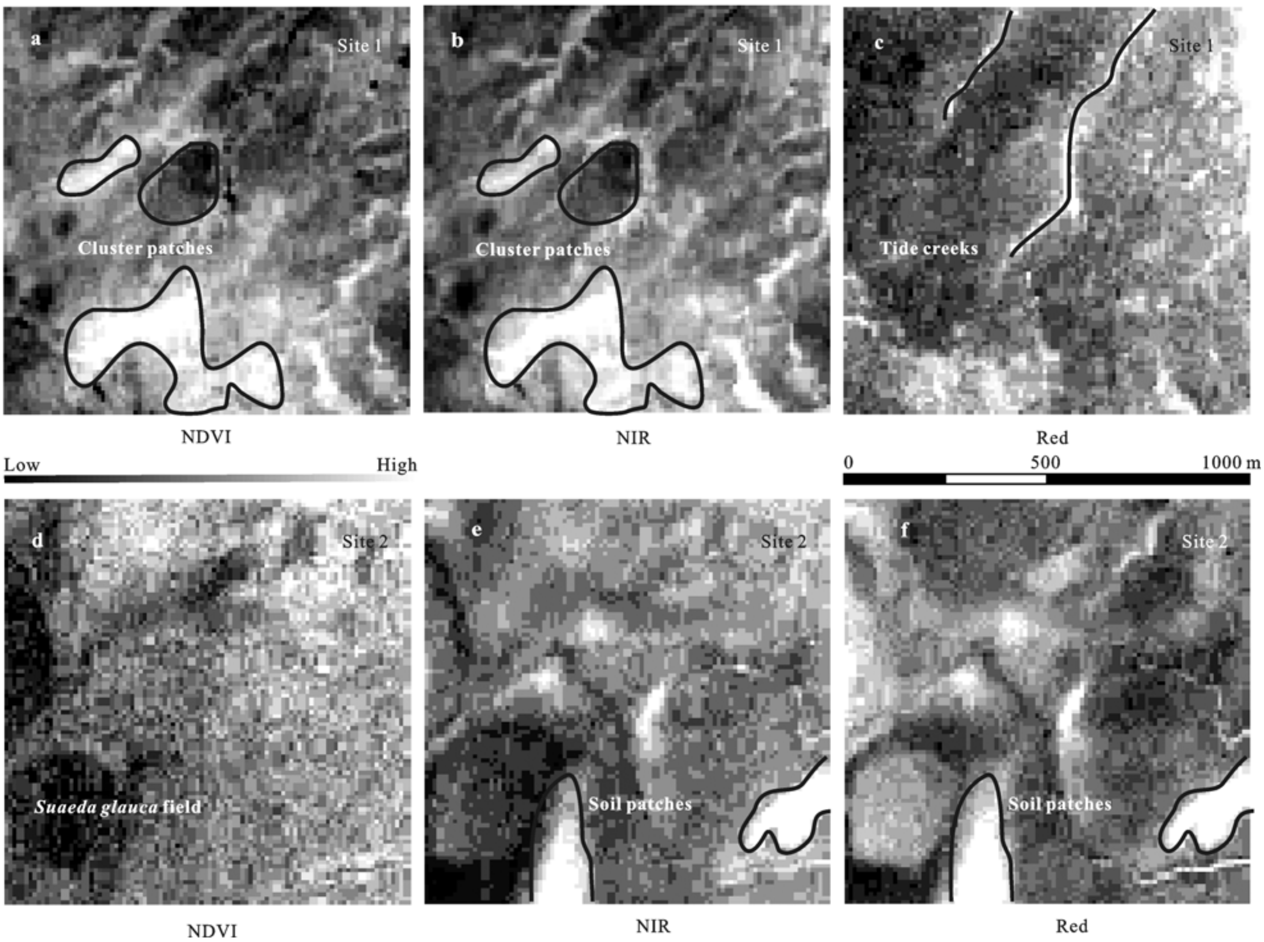


Fig. 5 NDVI, NIR and red variable images of Site 1 and Site 2 corresponding to high and low factional vegetation cover

heterogeneity contained by this variable image in L-FVC area is a mixture of vegetation cover and backgrounds that hard to be explained.

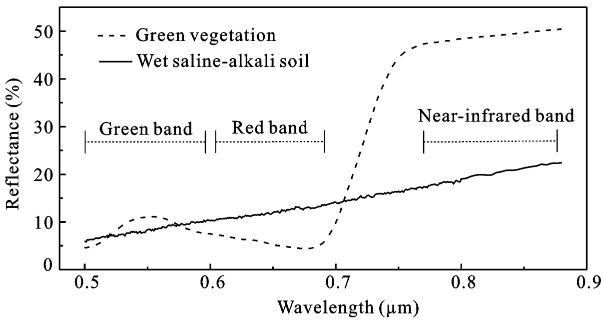
3.2 Micro scale spatial heterogeneity

The nugget effect, characterized by c_0, in variogram model is generally caused by sample errors (sensor condition) and spatial variability (surface nature condition, i.e. the micro scale spatial heterogeneity) or uncertain at the sample scale (10 m spatial resolution in this study). Since the value of c_0 of NIR band variable image in H-FVC is zero, sample errors can be neglected. Hence, c_0 reflects the magnitude of the micro scale spatial heterogeneity in a certain degree.

In H-FVC areas (Site 1 and Site 3), except for $c_0 = 0.04$ for red variable images, values of c_0 for NDVI and NIR variable images are all zero (Table 2). It indicates that the nugget effect appears only in red variable images. Therefore, spatial heterogeneity at micro scale can only be detected by red variable images, rather than by NDVI or NIR variable images. This illuminates that the values of a_1 (the first spatial structure) of red variable images are normally lower than those of NDVI or NIR variable images as shown in Table 2. In L-FVC areas (Site 2 and 4), NDVI variable images have the largest nugget than the others (Table 2). It indicates that compared with red and NIR variable images, NDVI variable images contain larger spatial heterogeneity at micro scale.

4 Discussion

The reflectivity characteristics of various surface features (e.g., vegetation, soil, water, *etc*.) differ distinctly in visible and near-infrared bands in an optical remote sensing image (Penuelas and Filella, 1998). Significant differences of spectral reflectance occur in the two major surface features in the study area, namely, the wet saline-alkali soil (WSA-soil) and green vegetation in red and NIR bands (Fig. 6). At the same time, the following properties can be found: 1) red band is more sensitive to the WSA-soil than to green vegetation; 2) variances in green vegetation are easily to be detected by NIR band, as the reflectivity of green vegetation is much higher than that of WSA-soil in this band; and 3) little spectral reflectance difference occurs in WSA-soil between the two bands while a large discrepancy exists in green vegetation. Based on red and NIR bands, NDVI, a commonly used vegetation index, is calculated. NDVI is more sensitive to vegetation variability than other background information (soil, water, *etc*.) in H-FVC area. However, in L-FVC area, NDVI can be easily disturbed by the background information (Myneni *et al.*, 1995). These characteristics of variables (NDVI, NIR, and red) can be used to explain the differences of spatial heterogeneity obtained in this study.



According to USGS Digital Spectral Library, available at: http://speclab.cr.usgs.gov/spectral-lib.html

Fig. 6 Reflectance of two typical surface features and labeled bands referenced to SPOT5 HGR multi-spectral bands

In H-FVC area, the results of this study show that NDVI and NIR variable images have the same ability to detect the spatial heterogeneity at landscape scale, while red variable image detects the spatial heterogeneity at micro scale. Actually, landscape spatial heterogeneities are mainly caused by the variability of status clusters in the vegetation growing process with similar NDVI or NIR reflectance values. For example, large cluster patches clearly present in NDVI variable image (Fig. 5a) and NIR variable image (Fig. 5b). Micro scale spatial heterogeneities, however, result from the structure mixture between vegetation and its environment conditions. The spatial structures appeared in red variable image are mainly at micro scale, except for some caused by tide creeks at landscape scale (Fig. 5c).

In L-FVC area, NIR and red variable images have similar spatial structure and spatial variability, which mainly reflects the gathering patches with similar soil conditions (Fig. 5e, Fig. 5f), at either landscape scale or micro scale. It is because that larger portion of WSA-oil exists in L-FVC area, and there is little spectral reflectance difference occurring in WSA-soil between the two bands. In addition, these two bands exhibit smaller spatial variability than that of NDVI variable image at micro scale. It indicates that NDVI variable presents a relatively large uncertainty in spatial variability due to the information combination of vegetation and its background in L-FVC area.

5 Conclusions

To investigate how the characteristics of NDVI, NIR, and red bands affect the properties of spatial hetereneity, two groups of H-FVC and L-FVC study sites in coastal wetland area were investigated. For a specific landscape ecology reasearch, the following conclusions were drawn: 1) in H-FVC area, NDVI and NIR variables are suitable for monitoring the spatial structure of vegetation growing status, while red variable is suitable for monitoring the spatial variation of background environment with respect to vegetation; 2) in L-FVC area, NIR and red variables are more reliable than NDVI variable for the spatial heterogeneity of soil condition; and 3) compared with NDVI and red variables, NIR variable is more robust, which can be used to different fractal vegetation covers for spatial heterogeneity moniloring.

In practice, the selection of variable images of remote sensing mainly depends on the study object and the characteristics of the variables themselves. It is because that only if the variables can objectively represent the nature of our world to be monitored, the retrieved spatial hetergeneity can thus be reliable. There might be numerous variables for a specific research that can be subjectively selected through the existing expert knowledge or experience. However, through variogram analysis of spatial heterogeneity contained by the variable image, an objective variable selection strategy (i.e., variogram analysis based method) is proposed here. In the future, more applications by using this method should be further investigated.

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