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ANALYSIS OF SPATIOTEMPORAL DIFFERENCE OF NDVI IN AN ARID COAL MINING REGION USING REMOTE SENSING

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Abstract:

Different resolution of remote sensing images will give rise to different perspectives and spatial characteristics. The objective of this study is to compare the spatiotemporal difference of the vegetation index extracted from TM and MODIS images by time series analysis and spatial statistics, and find the relationship among between the vegetation, climate factors, coal mining etc..The study area is located at an arid mine area, where the mining activities and ecology reconstruction is ongoing. It is found that the MODIS-NDVI (monthly or 16 days) products can provide results close to the NDVI derived from atmosphere corrected TM images. Time series analysis found that the monthly NDVI, rainfall and temperature are consistently subject to annual periodical rhythm under the impacts of coal mining. And there is a significant correlation between NDVI and rainfall & temperature in the arid mine area. However, MODIS-NDVI (1 km) is not suitable for spatial statistics for the study area of 3200 km^2, because of the coarse spatial resolution. NDVI-TM (30 m) or NDVI-MODIS (250 m) are feasible for spatial statistics at this study area. Higher value of NDVI is accompanied by higher spatial variation of NDVI with a squared correlation coefficient (R^2 =0.6983). It is probably because the natural arid landform was damaged by human activities, e.g. vegetation construction and industry.

1. INTRODUCTION

Vegetation changes play an important role in the environmental processes, and also is a sensitive indicator for environmental and global changes (Van Wijngaarden, 1991). The vegetation monitoring can provide useful clues concerning our changing environment and help natural resource management. Traditional method to monitor the vegetation is by field investigation. It is low efficiency and high labor demanding, especially for large scale area, and impossible to conduct continuously investigation. Nowadays, advanced Remote Sensing (RS) is a powerful monitoring tool for its convenience and high efficiency. Thereby, it has been widely employed to monitor the vegetation changes (e.g. Justice & Hiernaux, 1986; Townshend & Justice, 1986; Hobbs, 1995; Al-Bakri & Taylor, 2003).

Vegetation coverage, leaf area index and vegetation index are the main indices of vegetation information. However vegetation coverage and leaf area index are often obtained based on vegetation index. Vegetation index is a simple numerical indicator, which can be derived directly from RS image. For example, there are ARVI (atmospherically resistant vegetation index, Kaufman & Tanre, 1992), SAVI (soil adjusted vegetation index, Huete, 1988), NDVI (Normalized Difference Vegetation Index, Rouse et al 1974), EVI (Enhanced Vegetation Index, Liu & Huete 1995), etc. NDVI is one of the most important and commonly used vegetation indexes, defined as equation (1).

$$NDVI = \frac{(NIR - RED)}{(NIR + RED)} \quad (1)$$

where RED is the reflectance in the red channel and NIR is the reflectance in the near-infrared channel. The RED and NIR band contain more than 90% of vegetation information. (Baret et al, 1989)

The NDVI can be derived from many different kinds of RS images, e.g. Landsat, Spot, MODIS, NOAA/AVHRR, etc. with different spatial and temporal resolution. For example, the NDVI derived from TM image is 30 m spatial resolution and 16 days temporal resolution. The MODIS (Moderate Resolution Imaging Spectroradiometer) is at lower spatial resolution, but with a daily temporal resolution. Previous researches showed that multi-temporal NDVI images are useful for analyzing spatial vegetation pattern and for assessing vegetation dynamics (e.g. Justice & Hiernaux, 1986; Townshend & Justice, 1986). Time-series analyses of satellite data enable the observation of seasonal and annual trends of vegetation cover (Vicente et al, 2004). Su et al. (2001) pointed that the results or conclusions for the same area may change with different spatial resolution of research scale. And it is important to understand the effect of different resolution images on the analysis of spatial variation. Suitable resolution of RS image is needed for spatial analysis at a given scale.

Therefore, the objective of this study is to find the spatial and temporal variation of vegetation under the influence of local arid climate, vegetation reconstruction and mining activities, at a mine area with arid and semi-arid climate and located in north of China.

2. METHODOLOGY

2.1 Case study area

The experimental area is Shendong coal mine area located at the border of Shanxi province and Inner Monogolia (figure 1). The total area size is about 3200 km^2; and the elevation is between 1000 m to 1500 m. The average annual rainfall is about 436.7 mm, about 70% of which happens in July, August and September (Cui et al., 2001). And the groundwater is deep below the surface and intermittent. The surface is aeolian landform with sparse vegetation which is typical sandy land vegetation. There is also some grasses and planted vegetation, such as poplar and Salix psammopbylla. In general, this area

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has a fragile and unstable ecological environment and low-level social development, characterized by arid and semi-arid climate.

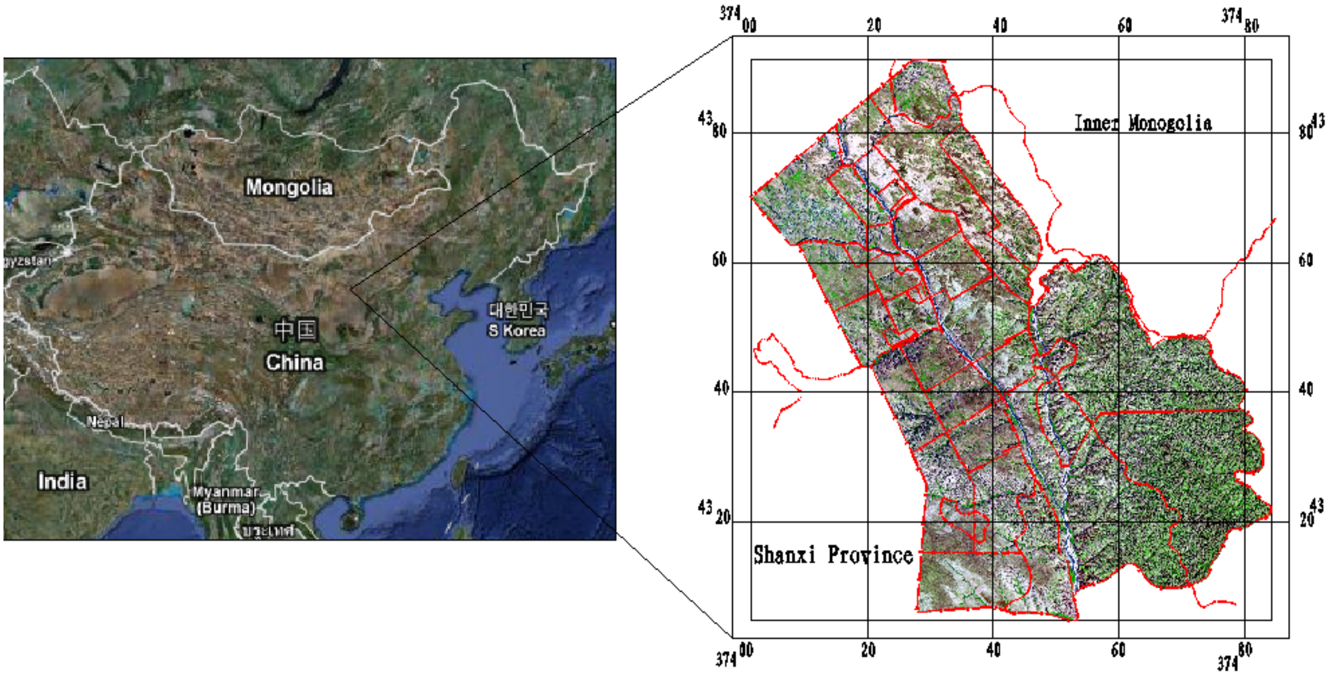

Figure 1. The location of Shendong coal mine area

2.2 Dataset

(1) Landsat TM/ETM+ satellite data

Three Landsat TM images acquired on August 24th 2000, August 6th 2002 and July 5th 2005 were processed. The atmosphere effect was corrected by using FLAASH model (Fast Line-of-sight Atmospheric Analysis of Spectral Hypercubes) (Berk *et al*., 1998) in ENVI 4.3. The NDVI can be calculated based on equation (1), then the mean NDVI of the study area can be obtained by statistics.

(2) MODIS-NDVI products

MODIS launched in December 1999 has high temporal resolution (at least twice per day,) and can be free downloaded (Lu and Zhao, 2005). There are several types of MODIS-NDVI products with different spatial and temporal resolution produced by Earth Observation System (EOS). The spatial resolution of MODIS-NDVI-16days-250m is 250 m. The NDVI images were converted into the projection of WGS84, UTM from Sinusoidal projection, and tailored by the boundary of study area with ENVI4.3. Further study found that the MODIS-NDVI-monthly-1km imagery has the similar average NDVI values as the MODIS-NDVI-16days-250m imagery. In this study, 67 MODIS-NDVI-monthly-1km and several MODIS-NDVI-16days-250m images from January 2000 to August 2005 were processed.

2.3 Spatiotemporal statistics

Temporal changes of mean NDVI were derived from monthly MODIS vegetation products to reflect the vegetation change varying with time. Moreover, the correlations between the NDVI and the climates factors, e.g. monthly rainfall and air temperature were analyzed to determine the influences of climate factors on the vegetation in this arid mining region.

A semivariogram analysis was used to describe the spatial variance and spatial structure of the NDVI. The semivariance statistic was calculated as one half of the average squared difference between data values at pairs of points a given distance apart (Journel and Huijbregts, 1978). It is calculated as:

$$\gamma(h) = \frac{1}{2N(h)} \sum_{i=1}^{N(h)} [Z(x_i) - Z(x_i + h)]^2 \qquad (2)$$

where γ(h) is the empirical semivariance for the distance h, N(h) the number of points separated by the distance h, and $Z(X_i)$ is the NDVI at location X_i. In this case, the X_i is the pixel. The γ(h) was then plotted against the lag distance h, yielding the empirical semivariogram, which characterizes the spatial variability of NDVI as a function of distance. For predictions, the empirical semivariogram is converted to a theoretic one by fitting a statistical model. For example, equation (3) is the exponential model.

$$\gamma(h) = C_0 + C\left[1 - \exp\left(-\frac{|h|}{a}\right)\right] = C_0 + C[\exp\ (|h|)] \qquad (3)$$

where C_0 is the nugget, the semivariance at a distance 0. a is the distance at which the semivariogram levels off. C_0+ C = Sill .Sill is the value at which the semivariogram levels off. Higher sill indicates higher spatial variation of NDVI. The semivariance can be calculated in ENVI 4.3, and the empirical semivariogram was regressed in SPSS (Statistical Package for the Social Science).

3. RESULTS AND DISCUSSION

3.1 Temporal change of NDVI

Table 2 shows the NDVI derived from Landsat TM and MODIS images at the same period. It is noticed that the NDVI with FLAASH correction provides a much closer and more reasonable fit with the MODIS-NDVI than the uncorrected NDVI. Therefore, it is necessary to remove the atmosphere effect before calculation of NDVI. Moreover, the difference between the corrected NDVI and MODIS-NDVI is due to the different methods of NDVI acquisition. Specifically, the NDVI of Landsat is for one day; but MODIS-NDVI is the maximum NDVI over a period, e.g. 16 days or one month.

Time	uncorrected	FLAASH corrected	MODIS-NDVI Monthly	MODIS-NDVI 16days
2000-8-24	0.0549	0.3480	0.2542	0.2926
2002-8-6	0.0534	0.3251	0.3346	0.3288
2005-7-5	0.1098	0.2432	0.2894	0.2823

Table 2. Comparison of different NDVI at the same period

Time series of NDVI-MODIS of the study area from January 2000 to August 2005 are presented in figure 3. It is found that the vegetation of the whole Shendong mine area has been improved in recent years, under the influence of climate, mining and ecological restoration. The improvement of vegetation was also found by Hu & Chen (2008). Figure 3 also shows that the NDVI, rainfall and air temperature are well subject to annual periodical rhythm. And there are significant correlations between monthly NDVI and two climate factors. The correlation coefficient of NDVI with rainfall and temperature is 0.760, and 0.84, respectively under the impact of coal mining.

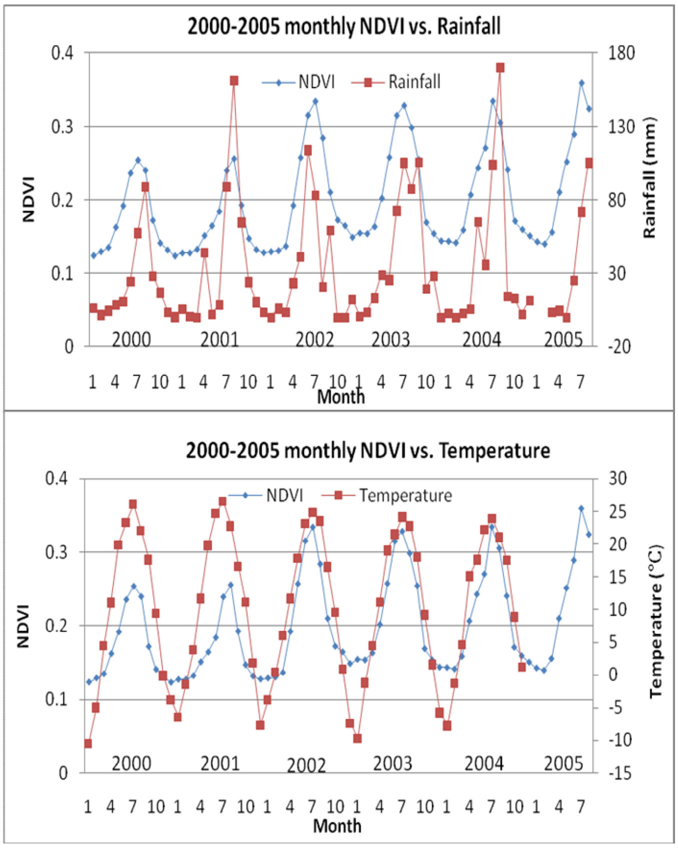

Figure 3. Comparison between monthly NDVI-MODIS and temperature & rainfall

3.2 Spatial characteristics

Different spatial resolution of images will result in different spatial semivariance of NDVI. So it is important to choose the right resolution for spatial characteristics analysis. Figure 4 presents the difference of the semivariance of NDVI-MODIS (250 m and 1 km). For the 250 m NDVI, it is revealed that when the distance is at 1750 m (250 m*7 pixels) the semivariogram levels off. However, for the 1 km NDVI, the semivariogram does not level off, even the distance is up to 50 000 m (1 km*50 pixels). It indicates that NDVI-MODIS with 250 m resolution is feasible for spatial variance analysis in the study area. But the NDVI with 1 km resolution is not suitable for spatial analysis of the study area.

Moreover, the vegetation variance will be reflected by the semivariance. Figure 4 also shows that the semivariance of NDVI in the December (0.1113) is lower than that in summer (0.1932). That is because the study area is in the arid area with sparse vegetation. In winter, most of the vegetation are wilted or died, and the ground is almost bare. Therefore, the homogeneity of ground surface decreases the spatial variation.

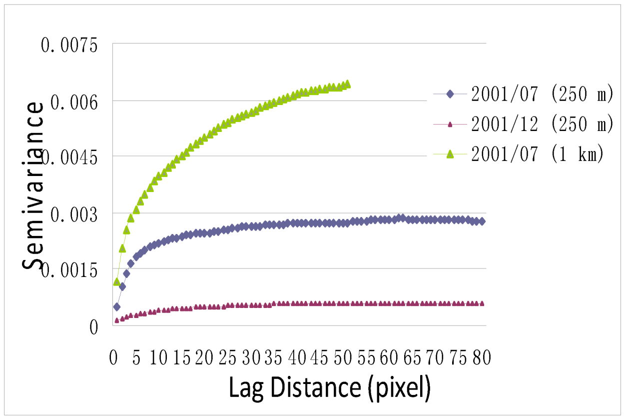

Figure 4. Semivariogram comparison of NDVI-250 m and 1 km. X axis is the lag distance of pixel, the unit of NDVI-1km is 1 km, NDVI-250m is 250 m)

The spatial characteristics obtained from different spatial resolution (30 m, 250 m, 1 km) of NDVI were analyzed and compared by semivariance analysis. The semivariance of NDVI was presented in figure 4 and figure 5. It was found that the NDVI of 2002 and 2003 in July are of higher semivariance, because of the higher value of NDVI. Detailed analysis can be made by using a empirical semivariance model. The exponential model was determined as optimal empirical semivariance model, the key parameters of which were provided in table 6.

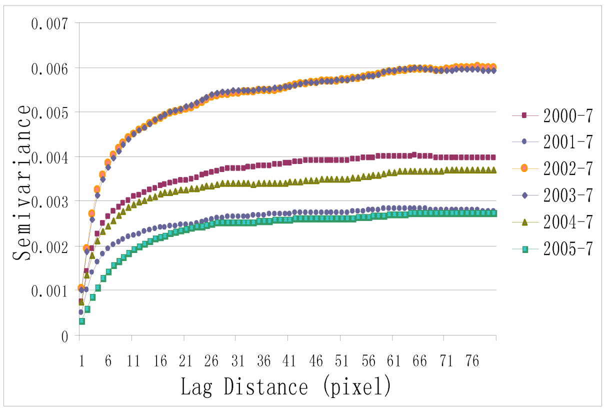

Figure 5. Semivariogram of NDVI-MODIS (250 m), in July, from 2000 to 2005; X axis is the lag distance, 250 m per pixel

TM	2000-8-24	2005-7-5	MODIS	2000/7	2001/7
C_o	0.00208	0.00149	C_o	0.00101	0.00063
C	0.00629	0.00407	C	0.00290	0.00212
a	11.94064	8.84545	a	9.29724	7.97316
$C+C_o$	0.00836	0.00556	$C+C_o$	0.00391	0.00275
NDVI	0.3480	0.2432	NDVI	0.2423	0.1932
MODIS	2002/7	2003/7	2004/7	2005/7	2001/12
C_o	0.00151	0.00130	0.00080	0.00020	0.00011
C	0.00429	0.00449	0.00274	0.00249	0.00048
a	10.14961	9.51552	7.71630	9.55438	12.70900
$C+C_o$	0.00580	0.00579	0.00354	0.00269	0.00059
NDVI	0.3288	0.3403	0.2766	0.2823	0.1113

Table 6. Key parameters of exponential semivariance model for NDVI-TM (30 m) and NDVI-MODIS (250 m), a is pixel distance. For the exponential semivariance model, when the distance is 3*a, the semivariogram levels off.

A high correlation (R^2=0.6983) between NDVI and Sill ($C+C_o$) was found, shown in figure 7. It indicates that the higher value of NDVI is accompanied by higher spatial variation of NDVI. For example, the mean NDVI in July 2003 is 0.3403, and the $C+C_o$ is 0.00579. But the $C+C_o$ is only 0.00275 for July 2001, when the NDVI is 0.1932. It is probably because the sparse vegetation coverage of the study area is lower than 50%. And the wide natural bare landform is damaged by different kinds of human activities, which will increase the spatial variation, e.g. vegetation construction or mining industry, etc.

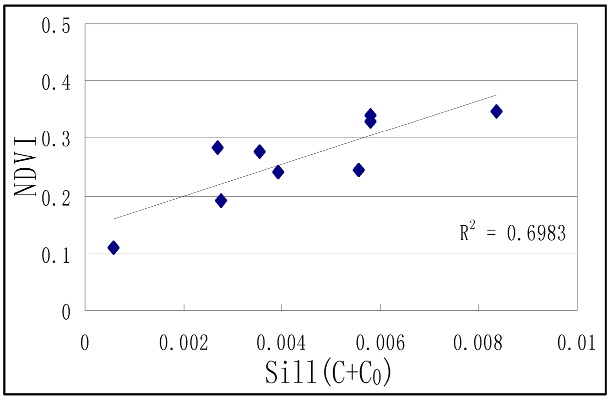

Figure 7. Correlation between NDVI and Sill ($C+C_o$)

4. CONCLUSIONS

MODIS-NDVI and Landsat-TM images were processed to study the spatiotemporal variance of vegetation in an arid mining area. It is found that MODIS-NDVI (monthly or 16 days) products can provide results close to the NDVI derived from atmosphere corrected TM images. Time series analysis found that the monthly NDVI, rainfall and temperature are consistently subject to annual periodical rhythm. The arid climate variables are still the dominating factors, instead of underground coal mining. Furthermore, there is a high correlation between NDVI and rainfall & temperature in arid mine area, where the mining activities and ecology reconstruction is ongoing. Therefore, the NDVI-MODIS (1 km) is good for time series analysis at large scale, e.g. region scale or global scale.

Different resolution of images, e.g. TM (30 m), MODIS (250 m or 1 km) will give rise to different spatial characteristics. However, 1 km MODIS-NDVI is not suitable for spatial statistics for the study area, which is about 3200 km^2, because of the coarse spatial resolution. NDVI-TM (30 m) or NDVI-MODIS (250 m) are feasible for spatial statistics at local scale. Higher NDVI is accompanied by higher spatial variation. A high positive correlation (R^2 =0.6983) between the value of NDVI and the spatial variation of vegetation (sill) was found. It is probably because the homogeneous natural arid landform was damaged by human activities, e.g. vegetation construction and industry.

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