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NDVI spatial pattern and its differentiation on the Mongolian Plateau

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Abstract: GIMMS NDVI database and geo-statistics were used to depict the spatial distribution and temporal stability of NDVI on the Mongolian Plateau. The results demonstrated that: (1) Regions of interest with high NDVI indices were distributed primarily in forested mountainous regions of the east and the north, areas with low NDVI indices were primarily distributed in the Gobi desert regions of the west and the southwest, and areas with moderate NDVI values were mainly distributed in a middle steppe strap from northwest to southeast. (2) The maximum NDVI values maintained for the past 22 years showed little variation. The average NDVI variance coefficient for the 22-year period was 15.2%. (3) NDVI distribution and vegetation cover showed spatial autocorrelations on a global scale. NDVI patterns from the vegetation cover also demonstrated anisotropy; a higher positive spatial correlation was indicated in a NW-SE direction, which suggested that vegetation cover in a NW-SE direction maintained increased integrity, and vegetation assemblage was mainly distributed in the same specific direction. (4) The NDVI spatial distribution was mainly controlled by structural factors, 88.7% of the total spatial variation was influenced by structural and 11.3% by random factors. And the global autocorrelation distance was 1178 km, and the average vegetation patch length (NW-SE) to width (NE-SW) ratio was approximately 2.4:1.0.

Keywords: GIMMS NDVI; spatial pattern; spatial differentiation; spatial statistics; Mongolian Plateau

1 Introduction

Land-use and cover change (LUCC) is an important branch of global change research, and spatial pattern and differentiation of terrestrial vegetation is one of the fundamental interests of LUCC. An understanding of the structure, function and relevant processes of regional ecosystems through quantitative, spatial, temporal and multi-scale perspectives is vital in assessing landscape dynamics, and during the past 15 years, many studies have implemented

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these approaches (Zeng and Levy, 1995, Liu and Buheaosier, 2000, Wu and Hobbs, 2002, Liu *et al*., 2003, Weng, 2003, Aragao *et al*., 2005). Furthermore, scientists have recognized the value of evaluating spatial ecosystem patterns and temporal processes using data archives. Rapid developments in earth observation technology and decades of remotely sensed data have enabled scientists to implement these studies more effectively (Zhou *et al*., 2001, Weng, 2002, Liu *et al*., 2003, Fang *et al*., 2004, Gong and Shi, 2004, Hu *et al*., 2008).

As a land-locked highland of the Eurasian continent, the Mongolian Plateau plays an important role in the meteorological and ecological systems of North China, and perhaps even the entire East Asian continent. Many studies have referred to the Mongolian Plateau as the major dust source in North China and East Asia, where dust storms are regarded as one of the most severe environmental problems impacting these regions (Ye *et al*., 2000, Husar *et al*., 2001, Natsagdorj *et al*., 2003, Zhang *et al*., 2003). Therefore, the establishment of regional sustainability research, particularly in relationship to terrestrial vegetation cover and its dynamic evolutionary processes is important for the Mongolian Plateau. Unfortunately, most previous studies have been limited to the Inner Mongolia region of China due to the practical difficulties of cross-national research (Zhuang *et al*., 1999, Hu *et al*., 2003, Liu *et al*., 2004, Hu *et al*., 2005). Few studies have been conducted that include the Mongolian Plateau, with little data on the physical geography, resources and environment of the entire region (Yang *et al*., 2004, Dill *et al*., 2006, Onda *et al*., 2007, Hu *et al*., 2008, Liu *et al*., 2008).

Classical statistical approaches have served as effective tools to address ecological and LUCC research, resulting in several foundational studies (Qi and Wu, 1996, Cain *et al*., 1997, Perry *et al*., 2002, Overmars *et al*., 2003). However, the most important premise in classical statistics applications, i.e. the data independency hypothesis, has conflicted with the nature of geographical data. Therefore, a method to bridge classical statistics and geo-applications has not been feasible, and any results and conclusions drawn from such attempts are suspect. Consequently, a new branch of statistics, i.e. geo-statistics has been developed based on regionalized variables and spatial distribution theory that abandons the classical independency hypothesis and provides a logical approach to study the rules embedded in spatial data.

The purpose of this study was to present a NDVI (Normalized Differential Vegetation Index) spatial pattern and its spatial differentiation rules for the Mongolian Plateau. The main questions posed here include: (1) Is an explicit NDVI distribution pattern indicated for the Mongolian Plateau and if so, what defines the pattern? (2) What factors control spatial patterns and differentiation of NDVI on the Mongolian Plateau and what dictates spatial differentiation? A derived mean annual-maximum NDVI dataset was first composed using the MVC method and validated by other data sources. Subsequently, NDVI temporal stability was assessed using 22 years of archived data to assess the feasibility of the derived dataset as representative for further study. Thirdly, the NDVI spatial pattern was generated, and the relationship between NDVI and vegetation cover was discussed. Finally, three spatial statistical methods were selected to explore NDVI spatial differentiation on the Mongolian Plateau. All together, spatial autocorrelation, factors resulting in spatial differentiation, and direction effects were always concentrated upon, and the geographical natures of statistical indices were demonstrated by combining with other knowledge.

2 Study region, data and methods

2.1 Study region

The Mongolian Plateau is a highland of the Eurasian continent lying between 87°40′-122°15′N and 37°46′-53°08′E. It includes the entire country of Mongolia, a portion of the Russian Siberian region, and part of North China, including the Inner Mongolia and Xinjiang Uygur autonomous regions. In the present study, all of Mongolia and Inner Mongolia Autonomous Region of China were evaluated.

The Mongolian Plateau is a land-locked highland comprised of spacious plains and high mountains that shape the geomorphology of the region (Figure 1). The Greater Hinggan Mountains in the east, the Sayan and Hentiy Mountains in the north, the Altay Mountains in the west, and the Yinshan Mountains in the south define the perimeter of the plateau. In addition to the mountainous regions, spacious high plains with typical steppes and deserts are characteristic components of the area. The Mongolian Plateau typically ranges between 1000–1500 m in elevation. The highest region occurs in the Altay Mountains with altitudes as high as 3000–3500 m, and the lowest region is the 700 m Hulun Buir plateau at the base of the Greater Hinggan Mountains.

The Mongolian Plateau experiences a typical continental climate with low annual precipitation, frequent drought, and windy episodes during the winter and spring seasons. The average temperature is −26℃ in January and 17℃ in July. The annual average precipitation in most regions is less than 200 mm, while it may reach 400 mm or higher in eastern, northeastern, or northern mountainous areas. These climatic conditions is a main cause of steppe vegetation, including meadow steppe, typical steppe and desert steppe. Some forest communities are distributed in the eastern and northern mountains, and deserts are located in large areas of the Gobi and western and southwestern regions. Figure 2 depicts the Mongolian Plateau terrestrial vegetation cover according to the GLCF (Global Land Cover Facility) (Figure 2) (GLCF, 2008).

2.2 GIMMS NDVI

NDVI can be used to coarsely evaluate the ecological status and processes operating in a region, including measurements of vegetation growth, degree of cover, and biomass, among others. Therefore, it is widely used in biogeochemical models to calculate rates of photosynthesis, land-surface evaportranspiration, and the absorption and release of energy by the land surface. GIMMS NDVI is processed by the Global Inventory Monitoring and Modeling Studies (GIMMS) at the National Aeronautics and Space Administration (NASA). The database was launched in 1986, and now provides 22-year monthly records about terrestrial vegetation cover. New database features include reduced NDVI variation resulting from view geometry, volcanic aerosols, and other effects not directly related to actual vegetation (Tucker *et al*., 2005). The GIMMS NDVI dataset is considered the 3rd generation NDVI database and superior to any other existing NDVI database, such as the PAL NDVI (Pathfinder AVHRR Land NDVI).

The original GIMMS NDVI database had an 8-km spatial resolution and a 15-day temporal resolution. The dataset is processed using the Maximum Value Composites (MVC)

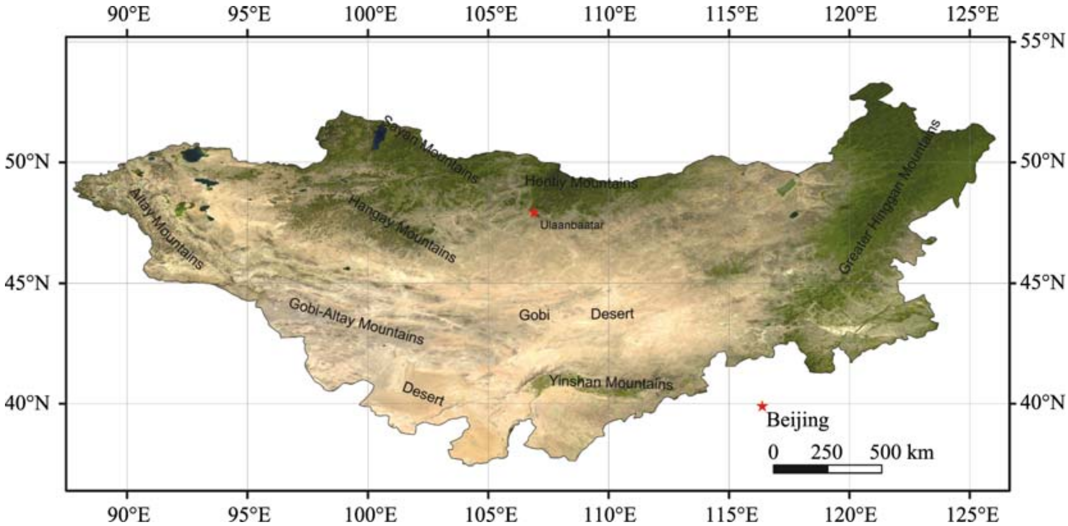

Figure 1 Terrain map of the Mongolian Plateau

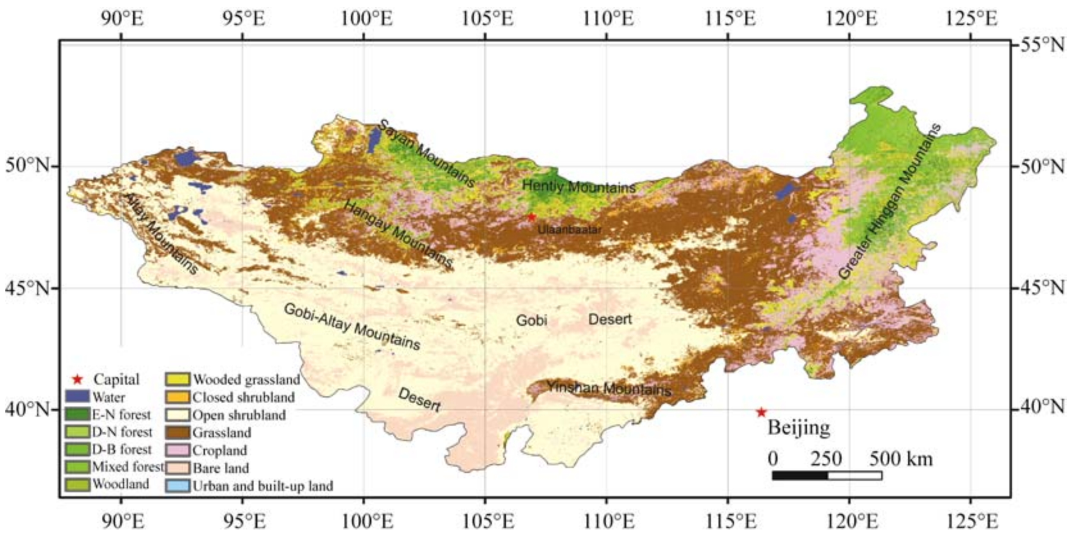

Figure 2 Land cover map of the Mongolian Plateau

Annotation: E-N: Evergreen Needle-leaved; D-N: Deciduous Needle-leaved; D-B: Deciduous Broad-leaved

method, which means the pixel value of each dataset represents the maximum NDVI during the last 15 days. This methodology dramatically reduces the adverse impacts caused by clouds, aerosols, view geometry, solar altitude, as well as other limiting factors. The algorithm of MVC approach can be depicted as the following function:

$$NDVI_i = Max\{ndvi_{i,j}\}$$

where, i=1, 2 …24; j=1, 2…15; $NDVI_i$ is the ith composite value in a year; and $ndvi_{i,j}$ is the jth day value in the ith half-month period.

2.3 Data pre-processing and validation

To improve computing space and time efficiency and decrease seasonal data undulation and long-term data redundancy, long-term NDVI spatial-temporal pattern studies are often conducted on an inter-annual scale. However simply using annual mean NDVI values without other appropriate pre-processing is considered a weak approach, as it may underestimate real values. Therefore, several specific rectification algorithms have been developed, including the BISE method (Best Index Slope Extraction), S-G method (Savitzky-Golay), Fourier transform method, and the wavelet method (Viovy *et al*., 1992, Azzali and Menenti, 2000, Li and Kafatos, 2000, Roerink *et al*., 2000, Lanfredi *et al*., 2003, Chen *et al*., 2004).

In the present study, MVC was combined with BISE and S-G methods and applied to the half-month GIMMS NDVI database to generate reasonable annual NDVI datasets. The MVC method and corresponding annual NDVI products were finally selected as representative due to the following characteristics: (1) the influence of clouds, atmosphere and solar altitude were further lowered and therefore did not underestimate real NDVI value; (2) a practical sense of agriculture, husbandry, and dust storm research identified the periods to best estimate vegetation cover; and (3) the simplest algorithm and better computing efficiency was available among all NDVI pre-processing programs.

GIMMS NDVI databases are derived for global studies, therefore this study necessitated an initial validation to ascertain its utility for a regional study. MODIS (Moderate Resolution Imaging Spectroradiometer) NDVI was selected to validate the derived mean-annual-maximum GIMMS NDVI. Because a higher NDVI variance is typical of mountainous regions, the Greater Hinggan Mountains of the Mongolian Plateau was selected as the case study to conduct a cross validation between 8 km GIMMS NDVI and 1 km MODIS NDVI. Compared with 1 km MODIS NDVI data from 2002, the derived mean-annual-maximum GIMMS NDVI data demonstrated a general mean error less than 11.1%, and the number of pixels with an error of less than 10% accounted for 69.1% of the pixels. Therefore, the derived GIMMS NDVI dataset was reasonable and chosen for further study (Figures 3a–3d).

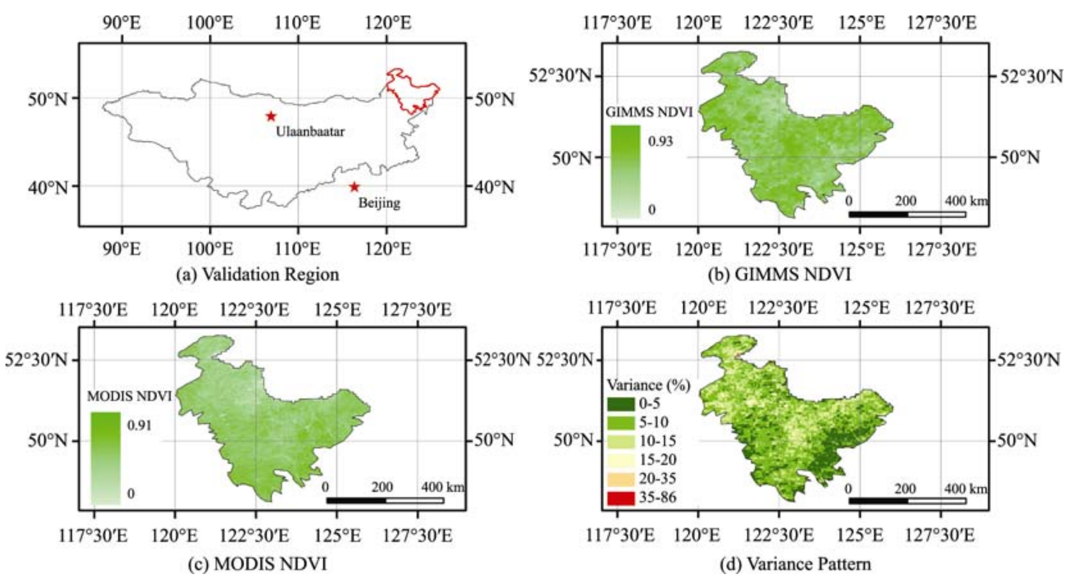

Figure 3 Cross validation between GIMMS NDVI and MODIS NDVI

2.4 Methods

NDVI distribution patterns and spatial differentiation can be investigated by a series of models derived from geo-statistics theory and relevant methodology. The models posed here include a temporal stability analysis based on the coefficient of variance index, spatial autocorrelation analysis based on Moran's I index, semi-variation analysis, and fractal dimension analysis. All models can be implemented on a global extent, and also along different geographic directions.

2.4.1 Temporal stability analysis

The temporal dynamics of NDVI on the Mongolian Plateau during 1982 – 2003 were evaluated using a time series analysis to assess temporal stability. The NDVI coefficient of variation (CV) was calculated according to the following formula:

$$CV = \frac{\sigma}{\overline{x}}$$

where CV is the coefficient of variation, σ is the standard square deviation, and $\overline{x}$ is the NDVI mean value from 1982–2003 (22-year period). Generally, a larger CV indicates a discrete distribution or violent fluctuations, while a smaller CV indicates a close distribution or stability.

2.4.2 Spatial autocorrelation analysis

Several methods are available to measure spatial autocorrelation. Here, Moran's I index was selected. Moran's I coefficient was represented by the following formula:

$$I = \frac{n\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(x_i - \overline{x})(x_j - \overline{x})}{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}\sum_{i=1}^{n}(x_i - \overline{x})^2}$$

where x_i and x_j are values of the variable x in two positions, $\overline{x}$ is the mean value of variable x, w_{ij} is the neighboring weight, and n is the total number of variable x. Moran's I coefficient ranges from –1 to 1. Generally, a higher positive Moran's I coefficient represents a tendency toward aggregation, and similar vegetation cover is inclined to form larger assemblages in space; while lower negative Moran's I coefficient indicates a tendency toward fragmentation, and similar vegetation cover is inclined to scatter as smaller assemblages in space.

2.4.3 Semi-variance analysis

Semi-variance analysis was applied to present integrated information regarding spatial variation and distribution. Semi-variance analysis was derived as follows:

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

where x is a spatial variant, h is the distance between x_i and x_{i+h}, and $Z(x_i)$ and $Z(x_i + h)$ are values in position x_i and x_{i+h}, respectively. In the diagram of semi-variance function, there are three key parameters: semi-variation sill (C_0+C), nugget variance (C_0), and variance range (a_0). The ratio of nugget variance (C_0) to sill (C_0+C) is used to estimate of the variance nature. A higher ratio indicates more random variance components (i.e. the variance is largely influenced by microclimate and local relief), while a lower ratio indicates more structural components (i.e. the variance is mainly induced by regional climatic conditions and regional geological structure). Furthermore, the parameter of variance range (a_0) is used to estimate assemblage's size with convinced spatial autocorrelation.

2.4.4 Fractal dimension analysis

Fractal theory determines distribution characteristics under different measuring scales. The fractal dimension (D) is decided by the variance function $\gamma(h)$ and the separation distance h:

$$2\gamma(h) = h^{(4-2D)}$$

A higher fractal dimension (D) is also used to characterize the variance. The higher ratio indicates more random components, while a lower ratio suggests more structural factors. The fractal dimension, semi-variation sill (C_0+C), and nugget variance (C_0) possess a certain relationship with each other. When the ratio of semi-variation sill (C_0+C) to nugget variance (C_0) is higher, the fractal dimension is greater. Both of these measures depict the same characteristics from different forms of variance.

In this study, the NDVI pre-handling works were implemented by AML (Arc/Info Macro Language) programming in the Arc/Info Workstation platform; the spatial differentiation modeling works were supported by GS^{+}7.0 package; and the interpretation and analysis of spatial distribution patterns and spatial differentiation were carried out in the ArcMap environment.

3 Results and analysis

3.1 Distribution pattern of NDVI and LUCC on the Mongolian Plateau

The mean value from the annual-maximum-NDVI during 1982–2003 showed clear spatial differentiation for the Mongolian Plateau (Figure 4). The following trends were observed: pixels with high NDVI values were distributed in the mountainous forest regions of the east and north, pixels with low NDVI values were distributed in the Gobi desert regions of the west and southwest, and pixels with moderate NDVI values were distributed in a middle steppe strap from the northwest to the southeast.

The NDVI distribution patterns were closely linked with vegetation cover. According to the GLCF vegetation cover map (Figure 2), the detailed relationship between NDVI and LUCC was consistent with our previous research and was depicted as follows (Hu *et al.*, 2008).

Due to high precipitation and low evaporation, the eastern (Greater Hinggan Mountains and Hulun Buir high plain) and northern (Sayan Mountains, Hentiy Mountains, and Hangay Mountains) Mongolian Plateau was characterized as forest, forest steppe and meadow steppe. Correspondingly, the NDVI in these regions (>0.6) was higher than that in other regions. In the western Mongolian Plateau (Altay Mountains and Gobi Desert), the main terrestrial land cover types were desert steppe, steppe desert, and Gobi desert, supported by low NDVI indices (<0.4). In the transitional regions (from the southeast including Xinlin Gol plateau and Ulan Qab plateau to the northwest including Dornogovi, Dundgovi, Ovorhangay, Arhangay, and Dzavhan), typical steppe zone or agriculture–pasture ecotones were depicted, and the NDVI in these transitional areas was moderate (between 0.4–0.6).

3.2 Temporal stability analysis

Over the past 22 years, the average NDVI variance coefficient for the entire Mongolian Plateau was 15.2%. The number of pixels with a C.V. less than 15% accounted for 53% of the pixels, and the pixels with C.V. less than 30% accounted for 97% of the data. Moreover, the temporal variance was low in the high NDVI regions (i.e. the Greater Hinggan Mountains, Hentiy Mountains, Sayan Mountains, and Hangay Mountains regions with forest, forest steppe, and meadow steppe cover) or high in low NDVI regions (i.e. Gobi–Altay Mountains and Desert regions with desert and Gobi cover), and high in typical steppe regions with moderate NDVI values (i.e. in the transitional zone between the east and west). Figure 5 demonstrated the detail pattern of coefficient of variance for the annual-maximum NDVI

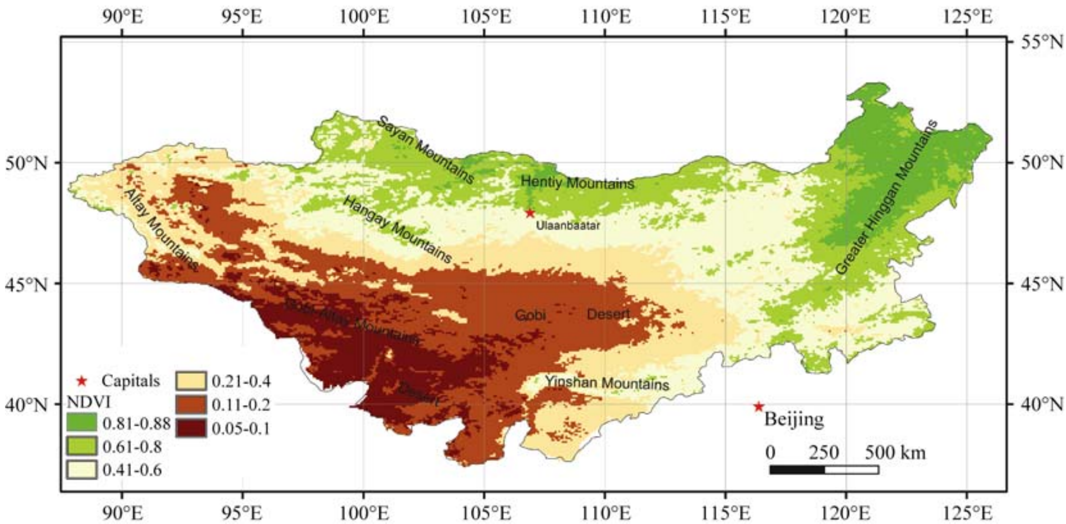

Figure 4 NDVI mean-annual-maximum spatial patterns for the Mongolian Plateau during 1982–2003

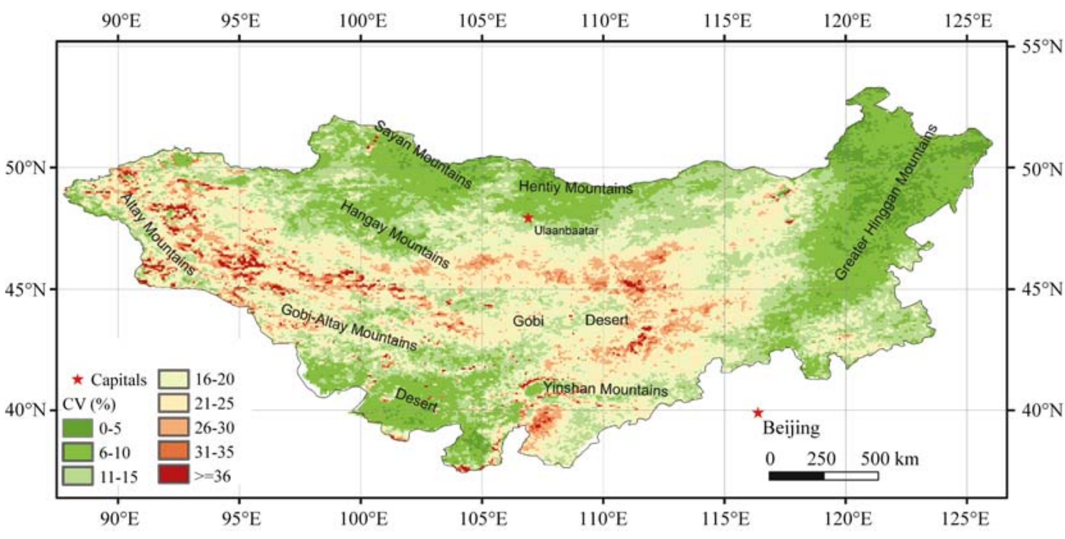

Figure 5 Coefficient of variance for the annual-maximum NDVI spatial pattern during 1982–2003

during 1982–2003. Temporal analysis indicated a low variance for the annual-maximum NDVI during the past 22 years, suggesting vegetative cover stability. Therefore, the mean-annual-maximum NDVI dataset is likely representative of the Mongolian Plateau vegetation cover, and is suitable for further spatial differentiation analysis.

3.3 Spatial differentiation analysis

3.3.1 Spatial autocorrelation analysis

Results of the Moran's I coefficient at the global scale showed a positive value (0.21) (Figure 6a and Table 1), indicating a strong spatial autocorrelation for NDVI and the terrestrial vegetation cover distribution in the Mongolian Plateau. The pixels with similar NDVI values tended to coalesce, and the terrestrial vegetative cover of the Mongolian Plateau was intact with negligible fragmentation at this scale. These results were consistent with the distribution patterns observed for terrestrial vegetation cover. According to the land cover map (Figure 2), the vegetation cover of the Mongolian Plateau can be divided into large vegetation assemblages with clear boundaries, including forest assemblages in the mountainous regions, waste land assemblages in the Gobi desert regions, and large areas of typical steppe assemblages on the plateau.

Further analysis along different geographic directions also showed that the NDVI pattern and vegetation cover has clear anisotropy (Figures 6b–6e and Table 1). A higher positive spatial correlation was revealed in the NW–SE direction (Moran's I coefficient = 0.41), followed by the W–E direction, while a negative spatial correlation was indicated in the N–S and NE–SW directions. The higher positive spatial correlation for the NW–SW direction indicated that vegetation cover in this orientation maintained better integrity and vegetation assemblages. Such results are reasonable when compared with the land cover map. Most terrestrial vegetation cover for the Mongolian Plateau was distributed as strips or assemblages along a NW–SW orientation. From E–W the vegetation followed a water/moisture availability gradient progressing from forest, meadow steppe, typical steppe, to Gobi and desert.

3.3.2 Semi-variance analysis

The semi-variance analysis generated a variance range (a_0) of approximately 1178 km on a global scale (Figure 6f and Table 1), which supported a vegetation autocorrelation with a correlation radius equal to 1178 km. Furthermore, the ratio of nugget (C_0) to sill (C_0+C) was small (0.113), which indicated that random factors have less impact on NDVI spatial distribution patterns, while structural factors have the greatest influence. The proportion of the spatial variance induced by random factors accounted for 11.3% of the total with structural factors comprising 88.7% of the variance. Structural factors included broad climatic regimes, regional topography, and geological structure, while random factors are likely influenced by micro-climate, local relief, and human activities.

Furthermore, detailed calculations along different geographic directions were developed (Figures 6g–6i and Table 1). The ratios of nugget (C_0) to sill (C_0+C) were less than 2%, suggesting that the spatial variance induced by random factors was weaker and structural factors prevailed in all different geographic directions. In addition, variance range (a_0) analysis was the largest (3183 km) along a NW–SE direction. These results demonstrated

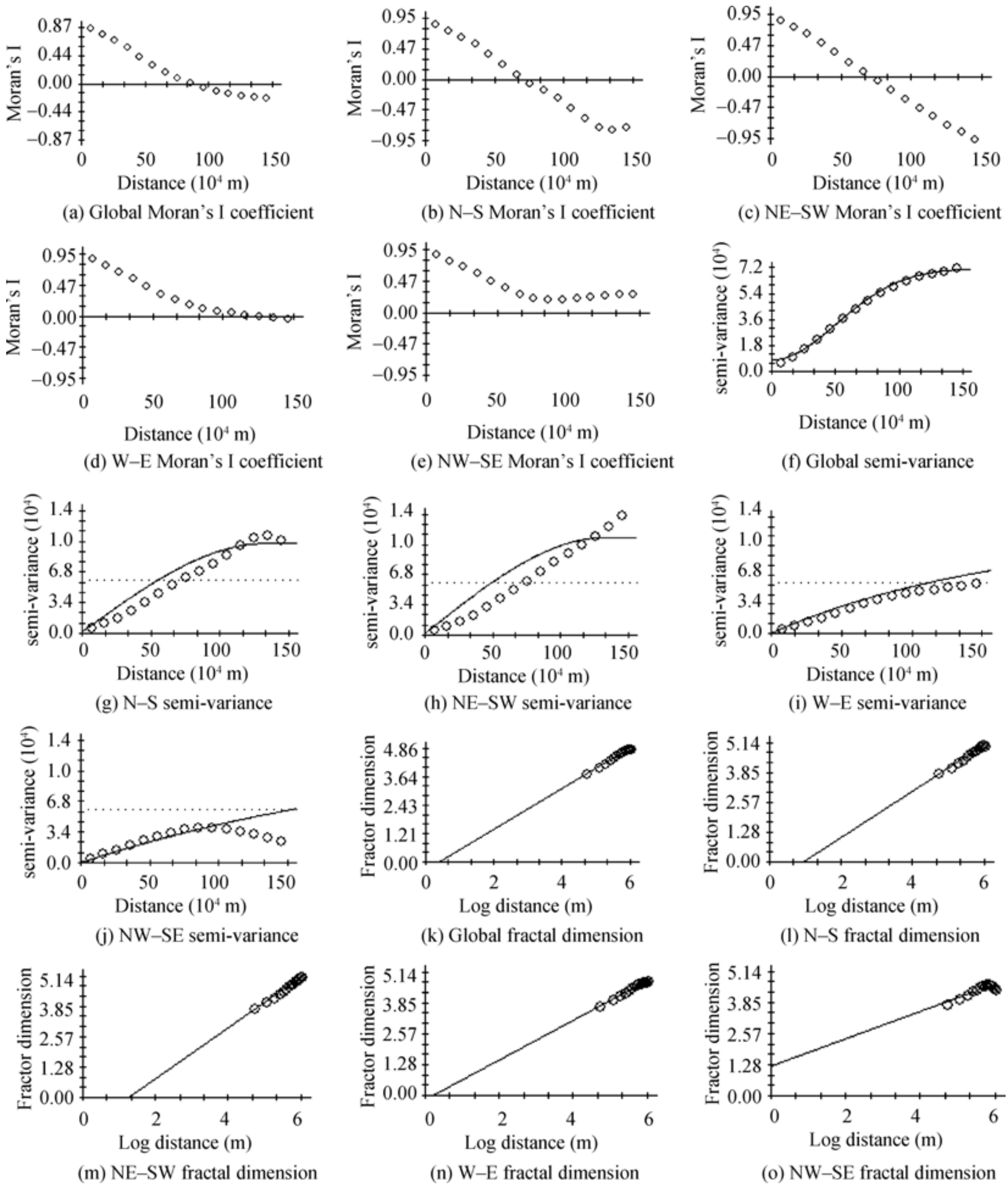

Figure 6 Moran's I coefficient, semi-variance and fractal dimension model

Table 1 Semi-variance function index and Moran's I coefficient

Extent or direction	C_0 ($\times10^3$)	Sill ($\times10^3$)	a_0 (km)	C_0/sill	r^2	Fitting model	Moran's I coefficient
Global	8	72	1178	0.113	0.998	Gaussian model	0.21
N–S	2	100	1259	0.018	0.860	Spherical model	–0.0042
NE–SW	2	111	1314	0.016	0.882	Spherical model	–0.038
W–E	0	119	2916	0.001	0.865	Exponential model	0.30
NW–SE	0	135	3181	0.001	0.864	Exponential model	0.41

that mainly impacted by structural factors, the terrestrial vegetation cover on the Mongolian Plateau is distributed in a NW–SE direction, and the average length (NW–SE) to width (NE–SW) ratio for the vegetation assemblages was approximately 2.4:1.0.

3.3.3 Fractal dimension analysis

Fractal dimension analysis generated a NDVI global fractal dimension value of 1.573 for the Mongolian Plateau and the fractal dimension along different directions ranged from 1.474 to 1.723 (Figures 6k–6o). The fractal dimension along a NE–SW direction was small, which determined that the vegetation cover along this direction was fragmented and the spatial variance was mainly caused by random factors. The fractal dimension in a NW–SE direction was large, indicating that the vegetation cover along this direction was intact and the spatial variance resulted from structural factors. The analyses based on semi-variance and fractal dimension were congruent in terms of NDVI spatial distributions, and explained by the same physical and geographical influences.

4 Conclusions and discussion

4.1 Conclusions

The results of this study provided a depiction of NDVI spatial distribution and temporal stability on the Mongolian Plateau based on GIMMS NDVI data analysis. Furthermore, a detailed analysis of spatial variability derived from Moran's I coefficient, semi-variance function and fractal dimension was developed to explore NDVI spatial differentiation. The results were as follows:

(1) The derived mean-annual-maximum GIMMS NDVI dataset exhibited less error, which was indicated by validation analysis from 1 km MODIS NDVI data in Greater Hinggan Mountains of the Mongolian Plateau in 2002. Temporal analysis also verified that the maximum NDVI values during the past 22 years showed little variation i.e. values remained stable. Both analyses supported the derived mean-annual-maximum GIMMS NDVI dataset as robust for further study.

(2) Based on these derived datasets, the basic NDVI distribution patterns were investigated in detail, and a close relationship between NDVI and terrestrial vegetative cover was demonstrated. Regions of interest with high NDVI values were distributed primarily in forested mountainous regions of the east and north, areas with low NDVI indices were primarily distributed in the Gobi desert regions of the west and southwest, and areas with moderate NDVI indices were mainly distributed in a middle steppe strap from northwest to southeast. The maximum NDVI values maintained for the past 22 years showed little variation. The average NDVI variance coefficient for the 22-year period was 15.2%. Furthermore, the temporal variance was low in both the high (forests) and low (deserts) index regions, while it was high in steppe regions that demonstrated moderate NDVI values.

(3) NDVI distribution and vegetation cover showed spatial autocorrelations on a global scale. Pixels with similar NDVI values showed a tendency to coalesce, and vegetation cover was generally intact for the Mongolian Plateau. NDVI patterns from the relevant vegetation cover also demonstrated anisotropy; a higher positive spatial correlation was indicated in a NW–SE direction, which suggested that vegetation cover distributed in a NW–SE direction maintained increased integrity, i.e. vegetation assemblages were mainly distributed in this

specific direction.

(4) Based on semi-variance and fractal dimension analysis, the factors controlling spatial variance on the Mongolian Plateau were investigated. Although simultaneously affected by both structural and random factors, the NDVI spatial distribution was mainly controlled by structural factors; 88.7% of the total spatial variation was influenced by structural and 11.3% by random factors.

(5) Spatial autocorrelation analysis from both semi-variance and fractal dimension analyses showed anisotropy in NDVI distribution on the Mongolian Plateau. Further analysis indicated a global autocorrelation distance of 1178 km, and an average length (NW–SE) to width (NE–SW) ratio for the vegetation assemblages was approximately 2.4:1.0.

4.2 Limitations and future research

The results of this research provided evidence that the derived mean-annual-maximum NDVI can serve as a reliable representative dataset for future studies, and spatial statistics can characterize the physical attributes of spatial variants. However, the following limitations were noted:

(1) Although the dataset derived from this study was determined acceptable, it is important to stress that the purpose of this study was to elucidate long-term spatial distribution and differentiation patterns, and not transient patterns on an annual basis.

(2) Spatial statistics and spatial analysis were both characterized, including spatial scale and temporal scale effects. However, an increase in detailed distribution and change pattern detection could be obtained if datasets with higher spatial and/or temporal resolution are applied in the future, although the basic patterns and principles would remain largely unaltered.

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