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Research on vegetation spatial heterogeneity in longitudinal range-gorge region of Yunnan province, China

C.Y. Xu, C.Y. Hao*

College of Surveying & Land Information Engineering, Hennan Polytechnic University, Jiaozuo City, China

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In the southwest of Yunnan Province of China, there are Mt. Laobie, Mt. Bangma, Mt. Wuliang and Mt. Ailao, which influenced its climate and vegetation. It may be one of the main issues of mountain ecology in China. In this paper, Moran Coefficient was adopted to calculate the spatial autocorrelation degree, and semivariance function was used for spatial variability and spatial heterogeneity analysis. The results indicate that the spatial differentiation patterns of main climatic factors have been consistent with the trend of mountains, showed higher autocorrelation in south-north direction and lower in west-east direction. And all these reveal that the barrier function was remarkable in the orientation of the mountains while the topographic corridor effect was rather obvious in the extension direction. The barrier function was stronger with more complicated structure resulted from directivity for Mt. Ailao and Mt. Laobie while it was weaker for Mt. Bangma and Mt. Wuliang. All in all, the corridor-barrier functions of vertical mountains were closely related to the trend and scale of each mountain.

Key words: Enhanced vegetation index, spatial variability, anisotropism, corridor-barrier functions, Mt. Ailao.

INTRODUCTION

Spatial heterogeneity is an important concept in landscape ecology, and is also one of the main properties of ecosystem. In most current researches, the understanding of spatial variability only stays on qualitative or semi-quantitative level, and more importantly, those results cannot explain how the overall pattern forms. So it is not still used in generalization of pattern [1, 2]. It is well known that the quantitative analysis of spatial heterogeneity can be considered from two aspects: spatial characteristics and spatial comparison. And both can be quantified by mathematical statistics methods, allowing the spatial variability analysis to be carried out on different scales [3]. Quantitative description of landscape pattern is the premise for understanding the dynamic states and ecological processes of landscape heterogeneity pattern, as well as their interactions. Only after we figure out the patterns, can it be possible to find out the reasons for pattern formation [4]. Therefore, in this paper, we focus on the study area with complex terrain - the Longitudinal Range-gorge Region in Yunnan, China, and used three statistical indicators, spatial autocorrelation, spatial variability and anisotropy, together with the enhanced vegetation index (*EVI*) and its ecological factors like water, temperature and heat, to show the spatial heterogeneity of vegetation and the reasons for its formation.

* To whom all correspondence should be sent:
E-mail: haocy@hpu.edu.cn

EXPERIMENTAL

Study area

The Longitudinal Range-gorge Region is located in Yunnan Province, China, which includes Hengduan Mountains that is directly associated with the uplift of Qinghai-Tibetan Plateau, and the adjacent mountain valley area in south-north direction. The Longitudinal Range-gorge Region is a set of range/gorge groups that are approximately distributed in north-south direction and aligned in west-east way. From west to east, they are Mt. Laobie / R. Nanding, Mt. Bangma / R. Lancang, Mt. Wuliang / R. Amo, and Mt. Ailao / R. Yuan. These four pairs of range / gorge terrain unit have maximal high relief amplitude, all of which are above 1200m; and they are at the altitude between 2000m and 4000m, belonging to high- and mid-altitude mountains [5]. Among those mountains, Mt. Ailao has the highest elevation, with magnificent overlapping peaks and towering momentum. The unique microhabitats formed by such a kind of combination of complicated topography and warm-humid air current, which cause a great diversity in river hydrology, soil type, and vegetation species. So in this study area, it is very significant of the spatial heterogeneity of vegetation landscape [6].

Data acquisition

The relationship between vegetation and its climate factors is a traditional research subject in ecology, geography and climatology [7]. The plant ecological studies have shown that the main climate factors that determine vegetation coverage changes are radiation, temperature, water, and their combinations [8, 9]. And terrain conditions can indirectly affect vegetation in specific regions by changing the redistribution of main climate factors [10, 11]. Therefore, this study used enhanced vegetation index (*EVI*) and total solar radiation, mean minimum temperature, mean maximum temperature, and mean annual precipitation as the quantitative indicators for vegetation and its climate factors.

EVI based on MODIS

Based on the monitoring methods, the ways to measure vegetation coverage can be divided into two categories, field reconnaissance and remote sensing retrieval [12]. Studies have shown that the vegetation index method in remote sensing retrieval is easy to conduct and doesn't depend on experimental data, which was widely used in macro vegetation ecology studies [13]. In vegetation ecology, MODIS data from United States of American (USA) is more widely used, which mainly has two categories of indexes, normalized differential vegetation index (NDVI) and enhanced vegetation index (EVI). Compared to *NDVI*, *EVI* has many improvements, for example, it has increased sensitivity to high biomass areas by revising the surface reflectance, and it has enhanced vegetation monitoring accuracy via coupling the leaf canopy background signal and reducing the atmosphere effect [14, 15]. Therefore, this study used the annual average EVI in 2014 as vegetation index to explore the spatial heterogeneity of vegetation in high biomass areas - Yunnan tropical rainforest in China, with the spatial resolution of 1 km.

Temperature and precipitation based on PRISM

Parameter elevation Regressions on Independent Slopes Model (PRISM) is a climate map based on the geographical spatial characteristic and regression statistical methods, developed by Spatial Climate Analysis Service of Oregon State University of USA. It used Digital Elevation Model (DEM) as the platform, integrated Geographical Information System (GIS) spatial interpolation technology, and considered the effects on temperature and precipitation from elevation, gradient, slope aspect, distance, land and sea locations, vapor sources, etc., to get the spatialization of meteorological elements through windowing technology and linear interpolation [16]. Long term (1961—1990) monthly mean values for minimum and maximum temperature and monthly precipitation at 0.041 decimal degrees spatial resolution in China were got by applying PRISM technology based on observation data of 2450 meteorological stations in China and its surrounding countries. And they have been proved to be very reliable. As to eighteen ecological research stations of Chinese Ecosystem Research Network independent of the national meteorology station network, the average relative errors rates of monthly mean values for minimum temperature, maximum temperature and monthly precipitation are 6.9%, 13.3% and 19.3% respectively, which are better spatial simulation results of both temperature and precipitation in mountainous area under the existing conditions of the distribution pattern of the meteorological stations [17].

Total solar radiation based on model simulation

We combined Angstrom and Bristow-Campbell climatological models for total solar radiation computing, and used DEM, monthly mean temperature and mean percentage of sunshine as the basic data, to achieve the spatialization of monthly total solar radiation, and thereby obtained the annual total solar radiation in this study area. After tested by the measured data, the results generated by this method showed high accuracy: the mean error rate was only 3.69% [18].

Main methods

In geosciences field, the geostatistics methods are used frequently to analyze the spatial patterns and variation rules of different natural variables. Most importantly, these methods have been proved to be effective for studying the spatial patterns and spatial comparisons of vegetation landscape [19, 20].

Spatial autocorrelation

Spatial autocorrelation is used to determine whether a variable correlates with distance and the degree of correlation [21]. Spatial autocorrelation coefficients are used to quantitatively describe the dependency of variables on space. If a variable becomes closer and closer as the measuring distance decreases, then it has a positive correlation with space; if it gets more and more different, then it is negatively; if it doesn't show space dependency, then this variable is spatially uncorrelated. Moran coefficient (MC) is one of the most commonly used indicators for measuring spatial autocorrelation [22].

Semivariogram

By definition, semivariogram can reveal the variation patterns of spatial variables within a certain region. After calculating for the measured data from samples, we can use several theoretical models to fit the data and get four important parameters, range, sill, nugget and fractal dimension, which are very critical for explaining the ecological significance of semivariogram. It mainly has two aspects of meanings.

Anisotropy

For spatial variables, semivariogram is not only related to measuring distance, but also associated with location and directions. When a variation function is constructed along one particular direction, it is called anisotropic variogram. Apparently, anisotropy is an important part of spatial heterogeneity. Higher anisotropy means higher degree of spatial heterogeneity. Studies have shown that the anisotropy and spatial variability, caused by terrain, water and other ecological factors, are more significant [23].

Spatial heterogeneity

Among the four parameters of semivariogram, except for range that only indicates the size of intervals, all the other parameters, including sill, nugget and fractal dimension, can describe the spatial heterogeneity. In practical applications, sill (*C0+C*) and fractal dimension (*D*) are more common. Sill represents system properties or the maximum variation of regionalized variables, in which the greater it is for the same variable in different regions, the higher the spatial heterogeneity will be. However, when comparing different regionalized variables, sill is not valid because it’s largely affected by its own definition and measurement units. Since the fractal dimension represents the curvature of semivariogram curve, the greater it is, the higher the spatial heterogeneity caused by spatial autocorrelation will be. Fractal dimension is dimensionless, so that it is possible to determine the degree of spatial heterogeneity by comparing the fractal dimension of different variables.

RESULTS AND DISCUSSION

After considering the central locations of every longitudinal mountain, we chose 23°39'30"-23°58'0"N as the cross-section in latitudinal direction. By way of moving window control, we confirmed that each sample region has 36×36 valid data points, with a total of 1296.

Spatial autocorrelation

MCs of major climate factors from each sample area are listed in (Figure 1 to Figure 4), calculated by a classical statistical method. From the figures, we can see that the spatial autocorrelation is not only different for different indicators, but also distinct for the same indicator in different directions, on which is an important aspect we want to emphasize in this study.

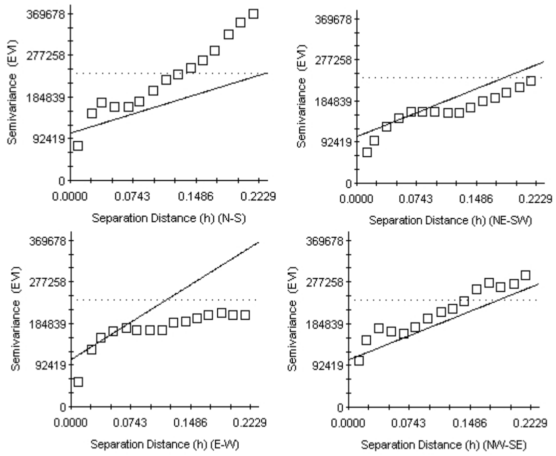

Fig. 1. Semivarigram of EVI in Mt. Laobie.

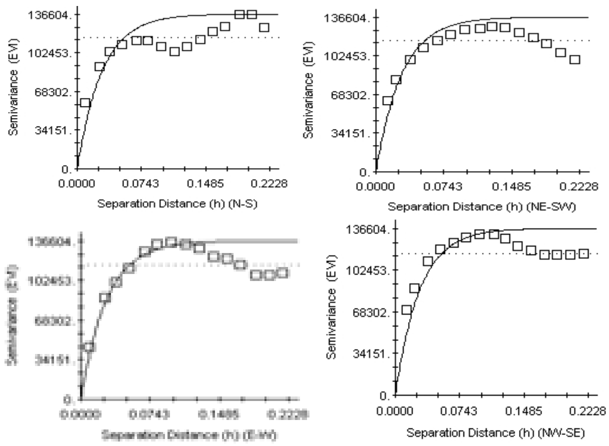

Fig. 2. Semivarigram of EVI in Mt. Bangma.

The major influencing factors of vegetation include annual precipitation, mean minimum temperature, mean minimum temperature, total solar radiation, etc. Most of them showed negative spatial correlation in isotropy; the directions of their maximum anisotropic positive correlation values are consistent with the orientation of mountain ranges, and the directions of their maximum negative correlation values are perpendicular to the mountain trends. Specifically, in Mt. Laobie and Mt. Bangma, which are in northeast-southwest direction, these climate factors have the maximum positive spatial autocorrelation in northeast-southwest direction, except for annual precipitation of Mt. Laobie, whose maximum value of positive spatial autocorrelation is in west-east direction. For negative correlation, most of the factors have maximum values in northwest-southeast direction, such as total solar radiation, mean minimum and maximum temperature. In the north-south trending Mt. Wuliang, the maximum values of positive spatial autocorrelation show south-north direction, especially the mean maximum temperature whose *MC* is up to 0.7481, while the negative correlation stands out in the west-east direction, especially the mean minimum temperature whose *MC* is up to -0.8799.

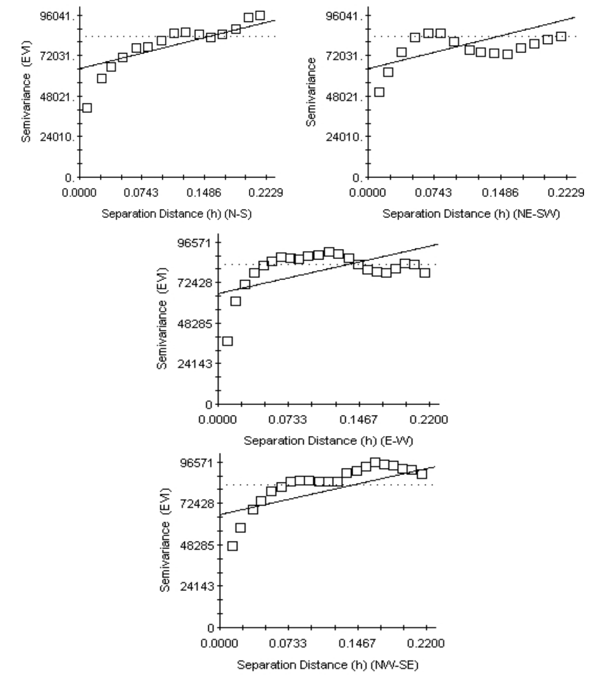

Fig. 3. Semivarigram of EVI in Mt. Wuliang

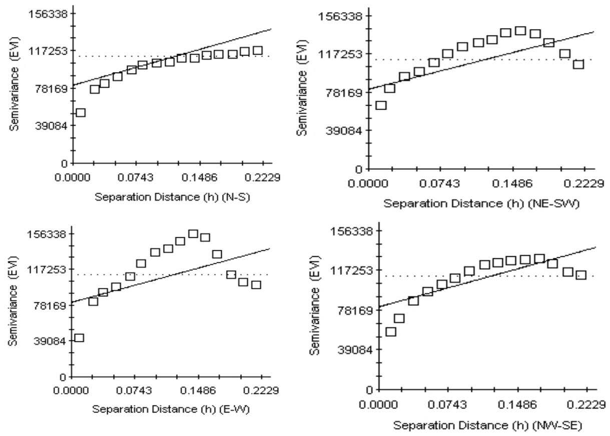

Fig. 4. Semivarigram of EVI in Mt. Ailao

In Mt. Ailao which is in northwest-southeast direction, the maximum positive correlation values of *MC* are also in northwest-southeast direction, and the maximum negative correlation values are more significant in both northeast-southwest direction and west-east direction: the *MC* of annual precipitation and mean maximum temperature have the biggest absolute value in west-east direction, while mean minimum temperature and total solar radiation have the maximum *MC* value in northwest-southeast direction. These results demonstrate that the trend of mountain barrier effect is closely related to the mountain trend: the maximum barrier effect of each mountain is perpendicular to the mountain trend, and the maximum corridor effect of every valley is in the same direction as valley trend.

Spatial variability

We used GS+ 7.0 to analyze the spatial variability of *EVI* and its climate factors, and the results are shown in these figures. This study mainly compared *C0+C* and *D* values of the four sample areas in order to analyze their spatial heterogeneity, because these two values can illustrate the spatial variability and distribution features of vegetation from different aspects.

From the figures, we can see that the five variables, *EVI*, annual precipitation, mean minimum temperature, mean maximum temperature and total solar radiation, have the comparing orders of 2, 1, 1, 2, 1 in Mt. Ailao, with an average of 1.4; for Mt. Laobie, Mt. Bangma and Mt. Wuliang, the average comparing orders of the five variables are 1.8, 2.8 and 4 respectively. Therefore, the overall ranking of these four mountains from big to small is Mt. Ailao, Mt. Laobie, Mt. Bangma and Mt. Wuliang, which reflects the order of barrier effect of these mountains. This result is related to the mountain height, mountain trend, and the angle of main airflows. Among these mountains, Mt. Ailao is the most magnificent one, whose northwest-southeast direction is almost perpendicular to the most influencing airflow in the study area - southwest summer monsoon, so that *EVI* and its major climate factors have the most significant spatial heterogeneity. In contrast, Mt. Wuliang has more gentle topography with the direction of north-south, so its interception to southwest summer monsoon is not significant, and the spatial heterogeneity is ranked last.

From the figures, we can also see that the *D* values of *EVI* and its major climate factors within the study area are all between 1.116 and 1.906. By comparison, the *D* values of *EVI* and total solar radiation are both higher than 1.817, indicating that their spatial variability caused by random factors is high, and the spatial distribution is more complex; the *D* values of annual precipitation, mean minimum temperature and mean maximum temperature are all lower than 1.577, suggesting that they have low levels of spatial variability caused by random factors, and their spatial autocorrelation is more significant.

In a word, from the spatial heterogeneity comparison of each longitudinal mountain, we find that Mt. Ailao and Mt. Laobie have bigger barrier effect and more complex spatial heterogeneity, while Mt. Bangma and Mt. Wuliang have smaller barrier effect and more regular spatial distribution. From the spatial heterogeneity comparison of *EVI* and its climate factors, we come to a decision that *EVI* and total solar radiation have high fractal dimension and more complex spatial distribution, while annual precipitation, mean minimum temperature and mean maximum temperature have small fractal dimension and stronger spatial autocorrelation.

Anisotropy

To further explore the spatial variability of vegetation on different directions, we used GS+7.0 to plot the *EVI* variability of each longitudinal mountain along four directions, south-north, northeast-southwest, east-west and northwest-southeast (Figure 1 to Figure 4). From the plot we can see that the *EVI* of each mountain has different anisotropy. The *EVI* anisotropy features of Mt. Laobie and Mt. Bangma are very similar: they have more variations on south-north direction, followed by east-west direction, and have smaller variations on northeast-southwest and northwest-southeast directions. This is mainly because the directions of these two mountains are both northeast-southwest. The *EVI* spatial pattern of Mt. Wuliang in south-north direction shows higher variation on east-west and northeast-southwest directions, but lower variation on northwest-southeast direction; the *EVI* anisotropy of Mt. Ailao is higher in east-west and southeast-northwest directions, but lower in south-north and northwest-southeast directions, which is closely related to its north- west to south-east direction.

In summary, affected by the main airflow – southwest summer monsoon, the *EVI* variation of each longitudinal mountain has larger or largest values on the east-west direction, indicating that the east-west direction of study area should be the dominant direction of barrier effect; the maximum *EVI* variation direction is perpendicular to the mountain direction, also suggesting that the *EVI* anisotropy is formed by mountain barrier effect. Oppositely, the terrain effect of each longitudinal mountain on south-north direction should be the main direction of corridor effect. Therefore, we arrive at a conclusion that the different *EVI* anisotropy of each mountain is controlled by mountain trending and the major airflow movement from west to east.

CONCLUSION

Firstly, the *EVI* of major influencing climate factors mostly have negative spatial autocorrelation, indicating that the terrain influence is mainly based on barrier effect; the maximum positive autocorrelation value of *MC* is in the same direction as mountain trend, the maximum negative autocorrelation value is perpendicular to the mountain direction, suggesting that the barrier effects of different mountains are strictly related to mountain trends.

Secondly, water, temperature and heat of Mt. Ailao have complex spatial heterogeneity and large barrier effect, while these factors have more regular spatial distribution and smaller barrier effect for Mt. Bangma and Mt. Wuliang.

Thirdly, the *EVI* values of longitudinal mountains have different anisotropy, and are strictly related to mountain directions. Its formation is controlled by both the north-south direction of mountains and the main airflow movement from west to east.

Fourthly, for vegetation parameter *EVI* and water, temperature, heat, both the statistical anisotropy characteristics and spatial variability are consistent with the terrain scale and direction of these mountains, indicating that the topographic features have constraint effects on vegetation and its ecological factors.

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