Postprint: Spatial Heterogeneity of Gravel Particle Size in the Northern Tibetan Plateau

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Abstract

Gravel is the product of comprehensive processes such as various hydrological and erosion processes, and serves as an indicator of grassland and soil degradation and ecosystem deterioration; conversely, these gravels also affect various erosion processes. Investigating the spatial differentiation of surface gravel on the northern Tibetan Plateau holds significant importance for regional ecological environment restoration. This paper takes the particle size and spatial location of surface gravel as research objects, and conducts a systematic analysis of its spatial heterogeneity through methods including Moran' s I index, variogram, Geodetector, and regression analysis. The results indicate: (1) The global Moran' s I index value is 0.481, showing a significant positive correlation. The local Moran' s I index reveals that the gravel aggregation pattern in the eastern part of the study area is high-high clustering, the central part shows low-low clustering, and the remaining areas are mostly randomly distributed. (2) The spatial heterogeneity of gravel is dominated by structural factors, but there are certain differences in both the best-fitting model of the variogram and its characteristic parameter values, indicating certain anisotropic features. (3) Geodetector results show that NDVI and land use type are the main factors influencing the spatial heterogeneity of gravel particle size in the study area, while population density, vegetation type, and annual average precipitation are secondary factors. (4) Regression analysis results show that optimal scale regression is the best regression model, with NDVI having the greatest influence on gravel, followed by land use type, annual average precipitation, and vegetation type.

Full Text

Study on Spatial Heterogeneity of Gravel Size in the Northern Tibetan Plateau

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Abstract

Gravel is the product of various hydrological and erosion processes and serves as an indicator of grassland and soil degradation and ecosystem deterioration. In turn, these gravel deposits influence erosion processes. Investigating the spatial differentiation of surface gravel in the Northern Tibetan Plateau is crucial for regional ecological restoration. This study examines surface gravel size and spatial location, systematically analyzing spatial heterogeneity using Moran’ s I index, spatial variogram, geographic detector, and regression analysis. The results show: (1) The global Moran’ s I index is 0.481, indicating significant positive correlation and strong spatial clustering. Locally, the eastern part of the study area exhibits high-high clustering, the central part shows low-low clustering, and the remaining areas are predominantly randomly distributed. (2) Gravel spatial heterogeneity is dominated by structural factors, though differences exist between the best-fitting variogram models and characteristic parameter values, indicating certain anisotropic features. (3) Geographic detector results reveal that NDVI and land use type are the primary factors influencing gravel size heterogeneity, while population density, vegetation type, and annual precipitation are secondary factors. (4) Regression analysis demonstrates that optimal scale regression provides the best model performance, with NDVI having the greatest influence on gravel size, followed by land use type, annual precipitation, and vegetation type.

Keywords: Northern Tibetan Plateau; gravel size; spatial heterogeneity; geographic detector; regression analysis

Introduction

Gravel represents the integrated product of various hydrological and erosion processes, serving as a marker of grassland and soil degradation and ecosystem deterioration. Conversely, gravel also affects these erosion processes, including infiltration, evaporation, runoff, and water erosion. Studying the spatial differentiation of gravel in the Northern Tibetan Plateau holds significant importance for regional ecological restoration. Most existing research on the

Northern Tibetan Plateau ecosystem has focused on grassland vegetation and soil components, with relatively few studies examining plateau gravel. Previous research has primarily investigated spatial differentiation of sand particles in dunes, coastal areas, and Gobi deserts. For instance, studies have examined spatial differentiation of feather dune sand particles in southeastern California, vertical distribution patterns of sand particles along the Hebei Gold Coast, and changes in bed sand particle size at the Yangtze River estuary, revealing a continuing coarsening trend. Methodologically, most studies have employed classical statistical analysis to examine correlations between altitude, grain size parameters, and particle diameter, or used geostatistical variogram models to analyze spatial heterogeneity of gravel size. Quade studied gravel distribution changes with altitude on the Mojave Gobi surface, constructing a function of gravel coverage versus altitude. Cao et al. analyzed grain size characteristics of surface gravel in the Gashun Gobi alluvial fan using classical statistics, while Wang et al. investigated spatial heterogeneity of sand particle composition in the Otindag Sandy Land using geostatistical theory and methods.

These studies have advanced understanding from statistical and spatial analysis perspectives, but few have reported on spatial differentiation of plateau gravel size or the 叠加 contribution rates of different factors. The geographic detector model, a spatial heterogeneity-based method, can quantitatively detect the main driving factors of spatiotemporal phenomena and interactions between different driving factors. Compared with other spatial heterogeneity detection tools, geographic detector offers higher explanatory efficiency. Therefore, building on previous research methods, this study incorporates the geographic detector model to conduct multi-factor quantitative attribution of gravel size spatial differentiation in the Northern Tibetan Plateau, combined with regression analysis to establish a spatial prediction model for gravel size, providing a scientific basis for ecological restoration and environmental protection.

1. Materials and Methods

1.1 Study Area

The Northern Tibetan Plateau covers a vast area, and gravel distribution in some regions lacks representativeness. To systematically analyze spatial heterogeneity of gravel, this study selected the southern Naqu region where gravel distribution characteristics are prominent, including southern Anduo County (excluding Sewu Township), Bange County, Shenzha County, southern Shuanghu County (including Duoma Township, Cuozhe Luoma Town, Baling Township, and Xiede Township), and Seni District. The study area covers 18.31 km^2 with an average altitude above 4,100 m. The terrain is high on all sides and low in the middle, with a cold and dry climate. The annual mean temperature is below 0°C, and annual precipitation decreases from 548.8 mm in the east to 216.3 mm in the west, concentrated primarily from June to September. Soils are dominated by frigid calcic soils and felty soils, with relatively simple vegetation types, primarily alpine meadows. Economic development is poor, relying mainly on animal husbandry and tourism, with low population density and only sparse population distribution in the eastern part.

1.2 Data Sources

Gravel size spatial distribution data were obtained through field sampling and indoor inversion. Field sampling points were located in the southern Naqu region of the Northern Tibetan Plateau. Due to the large area and non-representative gravel distribution in some parts, sampling was conducted along transects. Each transect contained multiple sample plots, with each plot measuring 0.5 m × 0.5 m. At each plot, five individual gravels representing the dominant size fraction were selected, and their Feret diameters were measured with vernier calipers, while recording basic information including altitude, slope, aspect, and gravel quantity. Due to complex regional conditions, some areas could not be sampled as planned, resulting in 76 sample plots total.

Indoor inversion primarily involved using Landsat 8 imagery. After preprocessing original images, spectral index factors, and other data, factors with multicollinearity were removed. Correlation analysis between measured gravel sizes and these factors identified significant variables. Multiple linear stepwise regression and GWR-based multiple regression analysis were used to construct a gravel characteristic parameter inversion model, which was validated with 16 verification plots, achieving an RMSE of 22.75% and an average error of 19.32%. Following Wentworth' s gravel classification theory, gravel sizes were divided into three grades: very fine gravel (2-4 mm), fine gravel (4-8 mm), and medium gravel (8-16 mm). The inverted gravel size distribution shows that fine gravel (4-8 mm) dominates the central-western part (76.99% of total area), medium gravel (8-16 mm) is mainly distributed in the eastern part (19.32%), and very fine gravel accounts for only 3.69%.

Environmental variables included natural and human factors with seven proxy variables (Table 1). Since geographic detector requires categorical data, land use type, soil type, and vegetation type retained their original classifications, while other factors were discretized using the natural breaks method. After iterative testing with factor and differentiation detectors, final classifications were determined: NDVI (6 classes), annual precipitation (6 classes), elevation (6 classes), population density (6 classes), and nighttime light intensity (5 classes). The study area was divided into 10 km × 10 km grid cells using ArcGIS, and bilinear interpolation extracted gravel size values (Y) and classified environmental variables for each cell.

1.3 Methods

1.3.1 Data Preprocessing The data processing flow is illustrated in [Figure 2: see original paper]. Geographic detector requires categorical data, so continuous variables were appropriately discretized as described above.

1.3.2 Spatial Heterogeneity Analysis (1) Local Spatial Heterogeneity (Moran' s I)

Moran' s I index analyzes local spatial heterogeneity, measuring spatial autocorrelation between gravel sizes in a region and its surroundings:

$$I = \frac{n}{S^2} \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} W_{ij}(Y_i - \bar{Y})(Y_j - \bar{Y})}{\sum_{i=1}^{n} \sum_{j=1}^{n} W_{ij}}$$

where I is Moran' s I index; n is the number of gravel units; Y_i and Y_j are gravel sizes at units i and j; $\bar{Y}$ is the mean gravel size; W_{ij} is the spatial weight matrix; and S^2 is the variance of observations. Moran' s I ranges from -1 to 1, where values closer to 1 indicate stronger positive correlation, values closer to -1 indicate stronger negative correlation, and values near 0 indicate random distribution.

(2) Spatial Structural Heterogeneity (Variogram)

To further analyze the range of spatial autocorrelation and structural heterogeneity, spatial variograms were used to explore spatial structural heterogeneity and calculate best-fitting models and characteristic parameters under isotropic and anisotropic conditions:

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

where $\gamma(h)$ is the variogram value at lag distance h; $z(x_i)$ and $z(x_i + h)$ are regionalized variable values at locations x_i and $x_i + h$; and $N(h)$ is the number of point pairs at lag h.

(3) Spatial Stratified Heterogeneity (Geographic Detector)

Gravel spatial heterogeneity is highly susceptible to environmental conditions. The geographic detector model, based on spatial heterogeneity, quantitatively detects driving factors and their interactions. The model stratifies variables to explore spatial stratified heterogeneity and reveal associations between variables. It has been widely applied in land use, regional economics, and poverty alleviation studies. In this research, it detects spatial differentiation of gravel size and the explanatory power of environmental variables, measured by q value:

$$q = 1 - \frac{\sum_{h=1}^{L} N_h \sigma_h^2}{N\sigma^2}$$

where N is the total number of units; σ^2 is the variance of the indicator; h represents strata of variable X ($h = 1, 2, ..., L$); and L is the number of strata.

Larger q values indicate stronger spatial stratified heterogeneity, while smaller values suggest more random distribution.

2. Results

2.1 Local Spatial Heterogeneity Based on Moran' s I

The global Moran' s I index for the study area is 0.481, with a Z-value exceeding the 2.58 confidence test, indicating significant positive correlation and strong spatial clustering with evident heterogeneity. Local Moran' s I results ([Figure 3: see original paper]) reveal that gravel size clustering patterns are primarily high-high in the east, low-low in the center, and predominantly random elsewhere. In the southern part, random distribution prevails, while in the western and northern parts, random and low-low clustering appear alternately.

2.2 Spatial Structural Heterogeneity Based on Variogram

Spatial variograms calculated a series of variation parameters, with best-fitting models selected to obtain spatial variation curves ([Figure 4: see original paper]). Considering directional differences in gravel size variation, anisotropic analysis was conducted in four directions: 22.5°, 67.5°, 112.5°, and 157.5°. From an isotropic perspective, the overall variogram is linear, while anisotropic analysis shows exponential models in the 22.5° and 157.5° directions, a Gaussian model in the 67.5° direction, and a linear model in the 112.5° direction.

Characteristic parameters () show that from an isotropic viewpoint, the nugget value (C_0) is 0.13, indicating non-negligible nugget effect from random factors. The partial sill (C) is 0.41, greater than the nugget, showing that spatial heterogeneity is mainly caused by structural factors. The sill (C_0+C) of 0.54 represents total variation from both random and structural factors. The nugget-to-sill ratio of 0.24 indicates that random factors account for 24% and structural factors for 76% of spatial heterogeneity, with structural factors dominating. The range of 26.178 km indicates the spatial autocorrelation extent of gravel size.

Anisotropic analysis reveals differences in characteristic parameters across directions, but in all directions, the partial sill exceeds the nugget, confirming structural factor dominance. The range reflects the rate of change along a direction: larger values indicate slower change and weaker heterogeneity. The 157.5° direction shows the largest range (minimum heterogeneity), while the 67.5° direction shows the smallest range (maximum heterogeneity), demonstrating pronounced anisotropy with a principal anisotropy axis of 157.5°.

2.3 Spatial Stratified Heterogeneity Based on Geographic Detector

Factor Detector results () show the explanatory power (q values) of each factor after significance testing, ranked as: X_1 (NDVI) > X_2 (land use type) > X_5 (population density) > X_3 (vegetation type) > X_4 (annual precipitation), with q values of 0.56, 0.41, 0.17, 0.27, and 0.13, respectively. NDVI shows the strongest explanatory power, indicating that vegetation coverage most strongly controls gravel size spatial distribution. Land use type is also a significant factor with $q = 0.41$.

Interaction Detector results () reveal that except for the interaction between X_5 (population density) and X_7 (nighttime light intensity) showing nonlinear enhancement, all other interactions exhibit bi-factor enhancement. The strongest interaction is $X_1 \cap X_2$ (NDVI land use type) with $q = 0.72$, while the weakest is $X_5 \cap X_6$ (population density nighttime light intensity) with $q = 0.28$. All factor interactions significantly enhance explanatory power compared to individual factors, indicating that gravel size spatial distribution results from combined effects of multi-dimensional environmental factors.

Risk Detector results ([Figure 5: see original paper]) identify significant differences among strata for each factor. For NDVI, the 0.79-0.92 stratum shows the largest mean gravel size, significantly different from other strata except 0.24-0.32. Land use types show the largest mean size in sparse forest land and smallest in saline-alkali land, with most strata significantly different. In vegetation types, alpine cushion vegetation shows the largest mean size, significantly different from others. Annual precipitation shows the largest mean size in the 470.4-548.8 mm range and smallest in 261.3-281.4 mm, with a positive overall correlation. Population density also shows positive correlation with gravel size.

2.4 Regression Analysis: Multiple Linear, Random Forest, and Optimal Scale Regression

Based on geographic detector results, regression models were developed. Multiple linear regression of NDVI, land use, vegetation type, and annual precipitation showed no multicollinearity ($VIF < 5$) but low adjusted R^2 of 0.29. Random forest regression with the same five factors (including population density) achieved $R^2 = 0.68$, significantly outperforming multiple linear regression. However, both models inadequately handle categorical variables like land use and vegetation type.

Optimal scale regression was therefore introduced, treating NDVI, annual precipitation, and population density as numeric variables and land use and vegetation type as nominal variables. Initial optimal scale regression achieved adjusted $R^2 = 0.58$. However, population density failed the significance test ($P > 0.05$), likely due to spurious correlation with gravel size arising from similar spatial distribution patterns rather than direct causation. After removing population density, the improved optimal scale regression model achieved adjusted $R^2 = 0.65$, with all factors passing significance tests. The standardized coefficients () show NDVI has the largest effect, followed by land use type and annual precipitation, consistent with geographic detector results.

3. Discussion

Geographic detector results indicate that NDVI and land use type are the primary factors controlling gravel size spatial differentiation, determined by local ecological conditions. NDVI reflects vegetation coverage and growth status, which directly influence erosion processes by water and wind. Higher vegetation coverage reduces erosion intensity, leading to larger gravel sizes, while lower coverage increases erosion and produces smaller gravels. Conversely, larger gravel sizes enhance soil water infiltration, potentially increasing vegetation coverage. This reciprocal relationship suggests that population density may exhibit spurious correlation with gravel size, as both show similar "high in east, low in west" patterns influenced by underlying vegetation and environmental factors.

Human activities have caused severe degradation of natural grasslands in the Northern Tibetan Plateau, transforming medium-high coverage grasslands to low coverage, increasing residential and industrial land, and altering land use types. These changes reduce watershed soil and water conservation capacity, exacerbating soil destruction. The interaction between vegetation degradation and land desertification creates a vicious cycle that wastes water resources, increases livestock pressure on irrigated grasslands, and intensifies grassland degradation, desertification, and soil erosion. Consequently, soil and water conservation capacity declines, external erosion intensifies, gravel quantity increases, and particle size decreases. However, due to data limitations, long-term time series of gravel size distribution are unavailable, preventing determination of temporal change patterns. Future research should examine spatial differentiation across time scales to provide scientific references for ecological restoration.

4. Conclusions

1) Gravel size in the study area shows significant positive spatial correlation (Moran' s I = 0.481) with strong clustering and heterogeneity. High-high clustering dominates the east, random distribution prevails in the south, and random and low-low clustering appear alternately in the west and north.

2) Gravel size exhibits pronounced anisotropic characteristics dominated by structural factors. The isotropic variogram is linear, while anisotropic directions show exponential, Gaussian, and linear models. The 157.5° direction shows minimum heterogeneity (largest range), while the 67.5° direction shows maximum heterogeneity (smallest range).

3) Factor detector identifies NDVI and land use type as primary influencing factors, with vegetation type, annual precipitation, and population density as secondary factors. Interaction detector reveals significant bi-factor enhancement effects, with NDVI land use type showing the strongest interaction ($q = 0.72$). Risk detector demonstrates significant differences among factor strata, with land use type showing the strongest interval effects.

4) Optimal scale regression provides the best model performance (adjusted $R^2 = 0.65$). Population density fails significance testing, likely due to spurious correlation. Standardized coefficients show NDVI has the greatest influence, followed by land use type, annual precipitation, and vegetation type, all positively correlated with gravel size. These results align with geographic detector findings.

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Note: Figure translations are in progress. See original paper for figures.