# Postprint: Grey Relational Analysis of Human Activities and Watershed Biodiversity Based on Land Use/Cover Change (LUCC)

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## Abstract

Taking the Jinghe River basin in the central Loess Plateau as the study area, this study employs a comprehensive method that integrates InVEST (Integrated Valuation of Ecosystem Services and Tradeoffs) model habitat quality and vegetation coverage to analyze spatiotemporal variations in plant diversity at the grid scale. Combined with grey relational analysis, the relationships between plant diversity and factors such as land use intensity and population density are examined. The results demonstrate that: (1) Plant diversity in the Jinghe River basin is at a medium level (BS>0.53), with distinct spatial pattern changes. During 2000–2015, the average plant diversity in the basin increased from 0.5382 to 0.5951. High plant diversity areas account for 22.1% of the total area, primarily distributed across mountainous regions, national nature reserves, and forested lands. Low plant diversity areas constitute 5.99% of the total area, mainly located in urban areas and northern regions with low vegetation coverage. (2) Land use intensity represents the primary influencing factor on basin-wide plant diversity, followed by solar radiation and population density which also exert substantial impacts; additionally, plant diversity is influenced by the combined effects of other factors.

## Full Text

### Grey Correlation Analysis of Human Activities and Watershed Biodiversity Based on Land Use and Cover Change (LUCC)

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## Abstract

Taking the Jinghe River Basin in the middle of the Loess Plateau as the study area, this study employs a comprehensive method that integrates the Integrated Valuation of Ecosystem Services and Tradeoffs (InVEST) model for habitat quality assessment with vegetation coverage data to analyze spatiotemporal changes in plant diversity at the grid scale. Grey correlation analysis is used to examine the relationships between plant diversity and influencing factors such as land use intensity and population density. The results show that: (1) Plant diversity in the Jinghe River Basin was at a moderate level (BS>0.53), with significant changes in spatial patterns. From 2000 to 2015, the average plant diversity index in the basin increased from 0.5382 to 0.5951. High plant diversity areas accounted for 22.1% of the total area, primarily distributed in mountainous regions, national nature reserves, and forested areas. Low plant diversity areas accounted for 5.99% of the total area, mainly concentrated in urban centers and northern regions with low vegetation coverage. (2) Land use intensity emerged as the primary factor influencing plant diversity in the watershed, followed by solar radiation and population density, which also exerted substantial impacts. Additionally, plant diversity is affected by the combined effects of multiple factors. These findings provide scientific evidence for ecological civilization construction and biodiversity conservation in the basin.

**Keywords:** biodiversity; LUCC; vegetation coverage; grey relational degree; Jinghe River Basin

## Introduction

Biodiversity represents the comprehensive integration of organisms and their environmental contexts, encompassing animals, plants, microorganisms, their genetic resources, and the complex ecosystems they form with their habitats. Regional environmental changes and human interventions have placed biodiversity under tremendous threat. As a critical component of China' s "Two Screens and Three Belts" ecological security framework, the Loess Plateau faces significant challenges in allocating limited financial and human resources for biodiversity conservation to maximize benefits. Consequently, spatial assessment and mapping of regional biodiversity from a geographical perspective have become essential tasks that attract widespread attention.

Traditional biodiversity research and conservation rely on intensive monitoring methods, species tracking, and field surveys, focusing on individual species, populations, and ecosystem levels. However, collecting and compiling biodiversity data across large regions presents substantial challenges for researchers and governments due to budget and human resource constraints. In the Loess Plateau, the lack of comprehensive biodiversity data and spatial information makes it difficult to conduct regional-scale biodiversity assessments, particularly in mountainous areas with complex terrain where even national nature reserves lack sufficient data for spatiotemporal change studies. Therefore, this study attempts to establish a new biodiversity assessment method from the perspective of land use change.

Recent advances in satellite remote sensing, geographic information systems, and ecological models have enabled widespread application of regional biodiversity assessment and quantification across spatial and temporal scales. Numerous scholars have conducted research on spatial biodiversity changes from multiple perspectives. For example, Vihervaara et al. explored Finnish biodiversity monitoring involving essential biodiversity variables and remote sensing issues. Wang et al. studied the habitat status of three waterbird species in Yellow River basin nature reserves using satellite tracking. Li et al. assessed biodiversity and its spatial distribution in China' s Chengdu-Chongqing economic zone at the county level. Xie et al. examined the impact of the Grain for Green Program on regional habitat quality using the InVEST model. Zhu et al. analyzed spatiotemporal evolution characteristics of habitat quality in ecologically sensitive areas of the eastern Qinghai-Tibet Plateau using InVEST model simulations. Consequently, integrating the InVEST model with satellite remote sensing imagery provides a feasible approach for comprehensively evaluating regional biodiversity at medium to large scales.

The Jinghe River Basin, representing the Loess Plateau, possesses rich animal and plant resources, including multiple nationally protected species such as black storks, golden eagles, great bustard subspecies, leopards, forest musk deer, and sika deer. However, these species face significant threats from habitat loss due to population growth, human disturbances (e.g., mining), and environmental disasters (e.g., soil erosion). Changes in vegetation diversity directly affect animal food sources and habitat conditions. Therefore, quantifying and visualizing plant diversity status, clarifying its spatiotemporal distribution characteristics, and identifying influencing factors are urgently needed to provide scientific evidence for ecological civilization construction and biodiversity conservation in the basin.

## 1. Study Area and Methods

**1.1 Study Area Overview** The Jinghe River Basin is located in the middle of the Loess Plateau, spanning 108°14 -108°42 E and 34°46 -37°19 N across Shaanxi, Gansu, and Ningxia provinces (autonomous regions) [Figure 1: see original paper]. Situated in a transitional zone between temperate semi-humid and semi-arid climates, the basin features elevations ranging from 219 to 2908 m. The terrain is highly fragmented with extensive gully networks, severe soil erosion, and a fragile ecological environment. The basin contains relatively intact montane forest ecosystems preserved on the Loess Plateau, serving as an important biodiversity conservation area and ecological barrier. Annual precipitation ranges from 350 to 650 mm, concentrated primarily in summer. The region hosts various rare and nationally protected plants, including *Cypripedium franchetii*, *Ginkgo biloba*, and *Cephalanthera longifolia*, as well as numerous rare animals.

**1.2 Data Sources and Preprocessing** Land use data were obtained from the Chinese Academy of Sciences Resource and Environmental Science and Data Center (https://www.resdc.cn) at 30 m spatial resolution. The dataset includes six primary land use types (cropland, forestland, grassland, water bodies, residential land, and unused land) and 25 secondary types, generated through manual visual interpretation of Landsat TM/ETM+ remote sensing imagery with comprehensive accuracy ratings between 85% and 95% based on field sampling and auxiliary validation.

Meteorological data were downloaded from the National Tibetan Plateau Data Center' s Yang Kun dataset (https://data.tpdc.ac.cn). Preprocessing was conducted using Python, including data resampling and extraction of annual precipitation and solar radiation. NDVI data from MOD13A2 MODIS products were processed using maximum value compositing to generate annual vegetation indices, with study area data extracted using mask operations. Population density data were obtained from the Chinese Academy of Sciences Resource and Environmental Science and Data Center. Digital elevation model (DEM) data were acquired from Geospatial Data Cloud (http://www.gscloud.cn). Population and economic data were sourced from statistical yearbooks of Shaanxi, Gansu, and Ningxia provinces (autonomous regions) for 2000-2015. High-resolution satellite imagery for 2015 was downloaded from Google Earth, integrated from QuickBird and other satellite remote sensing and aerial survey data.

### 1.3 Methods

**1.3.1 Vegetation Coverage Calculation** Vegetation spatial patterns significantly influence ecosystem biodiversity, habitat quality, and overall function. Vegetation coverage shows strong correlation with biomass and effectively reflects vegetation growth status and biomass magnitude. While NDVI performs poorly in monitoring vegetation coverage at high and low coverage extremes, numerous studies demonstrate that vegetation coverage calculated using the pixel dichotomy model effectively monitors vegetation changes and better characterizes regional vegetation growth and dynamics. This study employed the pixel dichotomy method with the following formula:

$$VFC = \frac{NDVI - NDVI_{min}}{NDVI_{max} - NDVI_{min}}$$

where $NDVI$ represents the normalized difference vegetation index of a pixel, and $NDVI_{min}$ and $NDVI_{max}$ represent the minimum and maximum NDVI values in the study area, respectively.

**1.3.2 Habitat Quality Assessment** Habitat loss and fragmentation are recognized as primary causes of biodiversity decline. At larger scales, habitat quality or biodiversity status cannot be readily obtained through sampling and surveys. Habitat quality is calculated based on the relative impact of each threat, relative sensitivity of each habitat type to threats, distance between habitat and threat sources, and legal protection status of land areas. The InVEST model assesses biodiversity by comprehensively analyzing habitats and threat factors. The calculation method is as follows:

$$Q_{xj} = H_j \left(1 - \frac{D_{xj}^z}{D_{xj}^z + k^z}\right)$$

where $Q_{xj}$ represents the habitat quality of grid cell $x$ in land use type $j$; $D_{xj}$ represents the threat level to grid cell $x$ in land use type $j$; $k$ is the half-saturation constant, generally half of the maximum degradation value; $H_j$ represents the habitat suitability of land use type $j$; and $z$ is a normalization constant set to 2.5 according to InVEST model recommendations. $D_{xj}$ is calculated as:

$$D_{xj} = \sum_{r=1}^{R} \sum_{y=1}^{Y_r} \left( \frac{w_r}{\sum_{r=1}^{R} w_r} \right) r_y i_{rxy} \beta_x S_{jr}$$

where $R$ is the number of threat factors; $r$ represents a threat factor; $y$ is the number of grid cells for threat factor $r$; $Y_r$ is the total number of grid cells occupied by threat factor $r$; $w_r$ is the weight of threat factor $r$ (range 0–1); $i_{rxy}$ is the impact of threat factor $r$ on habitat (exponential or linear); $\beta_x$ is the habitat disturbance resistance level; and $S_{jr}$ is the relative sensitivity of different habitats to each threat factor.

The habitat quality module calculates habitat quality indices based on land use data, threat factors, and habitat sensitivity to threats. Referencing relevant studies and considering the specific conditions of the Jinghe River Basin, six categories were extracted as threat factors through raster calculations, raster-vector conversion, and attribute table assignment: paddy fields, cropland, and construction land. These were selected because they are significantly affected by human activities. Unused land in the basin consists primarily of sand, saline-alkali land, and bare soil, which, despite poor natural conditions, occupy a small proportion of the area and experience minimal human disturbance, and were therefore not included as threat factors. Model parameters were assigned based on relevant studies and actual basin conditions to obtain threat factor and sensitivity indices and .

**1.3.3 Plant Diversity Index** A spatial pattern comprehensive index derived from regional habitat quality and vegetation coverage was used as the plant diversity index:

$$BS = \frac{(1 + VFC) \times Q_{xj}}{2}$$

where $BS$ is the comprehensive plant diversity index; $\alpha$ and $\beta$ are weight coefficients for $Q_{xj}$ and $VFC$, respectively, both set to 0.5 in this study.

**1.3.4 Land Use Intensity and Human Society Comprehensive Index** Land use intensity refers to the degree of human activity interference with land types during a certain period, representing the extent of land development and utilization. Based on previous research, land use intensity levels were classified according to human activity interference across different land use types: Level 1 for unused land, Level 2 for water bodies, Level 3 for forestland, grassland, and cropland, and Level 4 for construction land, with intensity indices ranging from 1 to 4. A human society comprehensive index was constructed using population, economic, and land use intensity data to reflect overall human activity levels. Weights were determined using the mean square deviation method, which is objective and independent of subjective judgment.

$$HAI = \sum_{i=1}^{n} A_i \times \frac{P_i}{TA}$$

where $HAI$ represents regional land use intensity value; $A_i$ is the intensity grading index for land use type $i$; $P_i$ is the area of land use type $i$; $TA$ is the total land area; and $n$ is the number of land use intensity grades.

The human society comprehensive index was calculated as:

$$dx = \sum_{j=1}^{m} b_{xj} \times \frac{W_j}{\sum_{j=1}^{m} W_j}$$

where $W_j$ is the weight of index $j$; $\delta_j$ is the standard deviation of index $j$; $b_{xj}$ is the standardized data of index $j$ in unit $x$; $M_{xj}$ is the actual value; and $M_{xj}^{min}$ and $M_{xj}^{max}$ are the minimum and maximum values, respectively.

**1.3.5 Grey Correlation Analysis** Grey Relational Analysis (GRA) is a multi-factor statistical method that measures the degree of association between factors based on the similarity or dissimilarity of their development trends, described as "grey correlation degree." Grey theory posits that ecosystems and ecological benefits constitute a grey control system with complex factor relationships, uncertain conditions, and unclear internal mechanisms. Due to interference from unknown and uncertain factors, the grey level of ecosystem services continues to increase. GRA imposes no mandatory requirements on sample size or explicit geographical differentiation patterns for factors, involves relatively small computational demands, and yields results consistent with qualitative analysis. Therefore, applying grey system theory to analyze correlations between human activities and biodiversity is feasible.

The calculation formula is:

$$\xi_i(k) = \frac{\min_i \min_k |y(k) - x_i(k)| + \rho \max_i \max_k |y(k) - x_i(k)|}{|y(k) - x_i(k)| + \rho \max_i \max_k |y(k) - x_i(k)|}$$

$$r_i = \frac{1}{n} \sum_{k=1}^{n} \xi_i(k)$$

where $\rho$ is the resolution coefficient (typically 0.5); $\min_i \min_k |y(k) - x_i(k)|$ is the two-level minimum difference; $\max_i \max_k |y(k) - x_i(k)|$ is the two-level maximum difference; $|y(k) - x_i(k)|$ is the absolute difference between each point on the comparison sequence $x_i$ curve and each point on the reference sequence $y$ curve; and $r_i$ is the grey correlation degree of comparison sequence $x_i$ to reference sequence $y$, where values closer to 1 indicate stronger correlation.

## 2. Results

**2.1 Land Use Change** The percentage of various land use types in the basin from 2000 to 2015 is shown in . Overall, the dominant land use types did not change significantly during this period, with grassland consistently occupying the largest area, followed by cropland, which together accounted for over 85% of the total basin area. After implementing the Grain for Green Program, cropland, forestland, grassland, and construction land exhibited the most substantial changes. Land use transfer characteristics show that grassland had nearly equivalent transfer-in and transfer-out areas (329 $km^2$ and 292 $km^2$, respectively), with the primary source being cropland and the main destination being forestland. Cropland experienced the most transfers, primarily converting to grassland (266 $km^2$) and forestland (149 $km^2$), with 191 $km^2$ converting to construction land. Forestland transfers mainly originated from grassland and cropland, with grassland accounting for 64.8% of total forestland transfers. Construction land expansion primarily came from cropland conversion (83.8% of total construction land increase), consistent with rapid urbanization, with additional transfers from forestland and grassland.

**2.2 Vegetation Coverage** From 2000 to 2015, vegetation coverage in the Jinghe River Basin showed an initial decrease followed by an increase, rising from 0.48 to 0.58. Areas with sparse and moderate vegetation coverage dominated the landscape initially. After 2010, areas with lush vegetation coverage increased significantly, with the area of lush vegetation coverage nearly doubling compared to 2000, reaching 53.85% of the total basin area. As the Grain for Green Program continued, the proportion of lush and very lush vegetation coverage areas increased continuously, reaching 21.82% of the basin area by 2015. However, sparse vegetation areas also increased in the northern region, indicating vegetation degradation trends. The spatial distribution [Figure 2: see original paper] reveals that areas with increased vegetation coverage accounted for 28.28% of the total area, while sparse vegetation regions showed slight degradation. Compared with 2000, the proportion of relatively sparse areas decreased substantially from 33.81% to 12.27%.

**2.3 Habitat Quality** Habitat quality in the Jinghe River Basin generally exhibited a "high-medium-low" distribution pattern from southeast to northwest, with no significant overall spatial changes from 2000 to 2015 [Figure 3: see original paper]. Low-value areas accounted for a relatively large proportion, primarily distributed in flat terrain with concentrated urban centers and frequent human activities, such as the Jingchuan-Zhengning urban belt and surrounding areas. High-value areas were concentrated in forested or mid-to-high mountain regions with minimal human disturbance. Temporally, habitat quality showed an overall improvement trend from 2000 to 2015, with high-value areas increasing from 6.05% to 6.48% and low-value areas decreasing from 44.42% to 43.28%.

**2.4 Plant Diversity** Plant diversity in the Jinghe River Basin showed significant spatial pattern changes. High plant diversity areas (BS>0.715) increased notably, with their areal proportion rising from 11.84% to 22.10%. Moderately high diversity areas (BS>0.569) increased from 24.8% to 32.21%. Conversely, medium, relatively low, and low diversity areas decreased. Spatially, high plant diversity areas were concentrated in nature reserves, southwestern mountainous regions, and eastern forested areas, characterized by relatively high vegetation coverage, good habitat quality, and minimal human disturbance. Medium diversity areas were mainly distributed in grassland and cropland, accounting for 24.14% of the basin area. Relatively low diversity areas accounted for 15.55%, while low diversity areas reached 5.99%, concentrated primarily in southern urban construction zones and northern semi-arid regions with low vegetation coverage and poor habitat quality, featuring either fragile ecological environments or intensive human activities [Figure 4: see original paper] and .

**2.5 Grey Correlation Analysis** Since implementing the Grain for Green Program, plant diversity and land use conditions in the Jinghe River Basin have undergone continuous changes. To evaluate the relationships between human activities and plant diversity, grey correlation analysis was performed using annual-scale data for human society comprehensive index, land use intensity, precipitation, solar radiation, and population density. shows that the three factors most closely correlated with plant diversity changes were land use intensity, solar radiation, and population density.

Land use intensity represents human utilization and investment in land—higher intensity indicates greater ecosystem disturbance and direct impacts on habitat quality and biodiversity. Changes in land use intensity resulted from two processes: (1) urban expansion converting low-intensity to high-intensity land, causing habitat loss and increasing threat levels to surrounding habitats, thereby reducing habitat quality and plant diversity; and (2) implementation of ecological restoration programs outside urban areas that reduced land use intensity, optimized habitat conditions, improved habitat quality, and increased biodiversity.

Solar radiation primarily affects plant growth and development, indirectly influencing biodiversity through slow processes. Population density impacts biodiversity mainly through habitat effects, but since populations are concentrated in urban areas, its direct impact on habitats is relatively reduced, resulting in lower correlation.

## 3. Discussion

This study combined vegetation coverage and habitat quality to develop a comprehensive plant diversity index reflecting spatiotemporal changes in plant diversity in the Jinghe River Basin. Grey correlation analysis was used to assess the relationships between plant diversity and both anthropogenic (land use intensity, population density) and natural (solar radiation) factors. Although this approach has certain limitations and uncertainties, it provides a beneficial attempt for conducting plant diversity spatial pattern and change studies in medium- and large-scale basins lacking biological observation data.

Plant diversity spatial patterns changed significantly in the Jinghe River Basin. Specifically, high plant diversity areas were mainly distributed in the mountainous region west of Jingyuan to Huating County, the Guyuan-Pingliang-Chongxin-Lingtai mountainous area, and the forested region of Heshui-Ningxian-Huangling-Xunyi County. This result aligns with China' s plant diversity priority conservation area reports. Comparison with high-definition imagery [Figure 5: see original paper] reveals clear similarity between plant diversity spatial patterns and visible changes in satellite imagery. Validation through scientific expedition reports from nature reserves (e.g., "Meridional Ridge Woody Plants" ) and national wild higher plant and animal inventories, combined with field investigations, confirms that watershed-scale plant diversity evaluation provides clearer and more objective representation of spatial distribution patterns than traditional methods.

The Grain for Green Program has restored surface vegetation to varying degrees, leading to overall ecological improvement in the basin. Ecosystem services such as soil conservation and water retention have continuously improved, land use intensity has decreased, and relatively stable climate conditions have facilitated vegetation recovery, creating a positive cycle of sustainable ecological development. Particularly, forestland with high plant diversity has maintained steady growth, and grassland has shown continuous expansion, contributing to favorable plant diversity trends in the Jinghe River Basin from 2000 to 2015.

Traditional methods such as infrared monitoring have advanced animal species surveys, and combining these with local environmental characteristics and human activity intensity enables biodiversity assessment and quantification at multiple levels. However, these methods remain limited to small-area observation studies. Additionally, mapping biological habitat ranges at larger spatial scales still shows significant deficiencies in reflecting overall species distribution and richness. Therefore, integrating ecological models (e.g., InVEST) with remote sensing imagery provides effective solutions for overcoming these limitations in medium- and large-scale biodiversity research, particularly for plant diversity spatial pattern visualization, mapping, and conservation planning.

The InVEST model' s habitat quality module combines habitat threats with minimal input requirements to assess habitat quality, making it widely applicable for analyzing biodiversity status and spatiotemporal changes at medium and large scales. Land use serves as the carrier of ecological processes, and land use change inevitably affects biodiversity. Vegetation coverage shows strong correlation with biophysical parameters such as biomass and can effectively reflect vegetation growth status, biomass magnitude, and coverage extent. Remote sensing data (e.g., thermal imaging, NDVI) provides possibilities for monitoring and studying biodiversity by combining regional spatial scales with ecological models and land use change research.

## 4. Conclusions

This study used the ecologically fragile Jinghe River Basin in the middle Loess Plateau as a case study. Based on land use change and remote sensing data, we first constructed a regional plant diversity index and analyzed spatiotemporal pattern changes in plant diversity from 2000 to 2015. We then applied grey correlation analysis to evaluate the relationships between plant diversity changes and human activities (land use intensity) and natural factors (solar radiation), exploring their associations. The main conclusions are:

1) The Grain for Green Program has achieved certain successes. The combined proportion of forestland and grassland in the Jinghe River Basin increased from 51.86% to 52.62%, with forestland increasing from 9.62% to 10.47%. The program reduced cropland area by 603 $km^2$, with 266 $km^2$ converting to grassland and 149 $km^2$ to forestland. Additionally, 191 $km^2$ of cropland converted to construction land due to urbanization and socio-economic development.

2) Plant diversity in the Jinghe River Basin exhibits distinct spatial pattern changes. Low and relatively low plant diversity areas are mainly distributed in cropland, urban-rural interfaces, and regions with low vegetation coverage. High and relatively high plant diversity areas are concentrated in nature reserves and high-elevation forested regions. High plant diversity areas account for 22.1% of the total area, primarily in southwestern mountainous and eastern forested regions, while low plant diversity areas (5.99%) are distributed in northern semi-arid regions and central areas with intensive human activities (e.g., cities and surrounding areas).

3) Plant diversity in the Jinghe River Basin is improving, with the average index increasing from 0.5382 to 0.5951. However, some areas experienced degradation. Grey correlation analysis demonstrates unique advantages in

studying factors affecting ecosystem services. The analysis indicates that plant diversity is most closely related to land use intensity and solar radiation, followed by population density. During ecological protection and restoration, reducing land use intensity and increasing vegetation coverage in densely populated areas can ensure favorable ecological conditions for plant survival and development.

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