



Chinese Rural Landscapes at Multiple Scales: Typologies and Diversity

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Abstract

Due to the increased demand for agricultural products, the agricultural industry has become intensified, resulting in a homogenization of the rural landscape. Our study defines rural landscape types at three scales (national, regional, and local) using a multi-scale method. We generated three landscape element datasets using literature and gray statistical analysis. Subsequently, we used the overlay approach and two-step cluster analysis to identify landscape regions, types, and subtypes. The findings indicate the presence of 47 landscape regions at the national scale, 448 landscape types at the regional scale, and 44 landscape subtypes at the local scale with Dahongshan Mountain Region serving as the empirical study site. Furthermore, we have developed a novel method to evaluate landscape diversity index (LDI) which utilizes the proportion of land area occupied by landscape elements in various landscape types. This method incorporates diverse elements, such as topography, landform, land cover/use, vegetation, and agroforestry industries. To examine the role of LDI in landscape planning, we analyzed the relationship between LDI and recreation services using the geographically weighted regression model. The result facilitates landscape planning and management at different administrative levels.

Article Highlights

- **Definition of landscape regions, types, and subtypes at multiple scales through overlay method and two-step cluster analysis method.**
- **An assessment approach of landscape diversity was carried out using data from the agricultural and forestry industries, topography and landform, land cover and use, and other elements.**
- **The GWR regression model of LDI and RS provides a potential use of LDI.**
- **This broadly applicable strategy and its results enable landscape monitoring and policy implementation at all scales, from the national to the regional to the local.**

Keywords Rural landscape · Landscape element · Landscape type · Landscape classification · Landscape diversity · Cluster analysis

Introduction

Because of the rising demand for agricultural products, industry intensification has expanded. As a result, the landscape is gradually becoming more homogeneous. Traditional

landscapes are changing at an increasing rate, and are gradually replaced by industrial and urban landscape (Van Eetvelde and Antrop 2004). Many countries have issued landscape classification maps for the development of sustainable land-use strategies and policies by identifying landscape characters, pressures, and driving factors (Simensen et al. 2018). There is an urgent need in China for a universal tool to define rural landscape types at different scales, so as to facilitate site-specific landscape planning and design for each landscape type to preserve the uniqueness and heterogeneity of the rural landscape.

Rural landscape is a highly dynamic and non-linear human-environmental system (HES), where socio-economic,

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cultural, and biophysical forces are constantly interacting with and affecting each other in both time and space (Palacios et al. 2013; Matthews and Selman 2006). Landscape characters are unique, identifiable, and consistent patterns characterized and composed by a series of landscape elements, making a landscape different from another (Swanwick 2002). Rural landscape elements generally include topography, vegetation, land cover, land use, farming types, and rural settlements. The combination of these individual elements can create a unique rural landscape.

Previous research on landscape/land classification of the entire China has mostly classified natural landscape attributes or biophysical land attributes, such as land cover, topography, and soil texture (Jiang et al. 2013; Liu et al. 2008; Yansui Liu 2001). Some studies were focused on a specific aspect of the land, such as land-use intensity (Yan et al. 2017). A few studies have examined the multidimensional properties of HES, resulting in the development of an integrated land classification system involving land-use intensity, environmental conditions, socio-economics, biodiversity conservation, and cultural characteristics (Václavík et al. 2013; Xiaolong Jin et al. 2022). The selection of rural landscape elements in the previous studies was not exacting and thorough.

Furthermore, because data like land cover are typically aggregated into larger units on a macroscale, the vast majority of landscape/land classification results are rather coarse. To some extent, these results may lead to the neglect of heterogeneity of mosaic landscapes and functionally important land-use/cover types (Verburg et al. 2011), and therefore fail to reflect the differences in landscape change at different scales. For example, it can be roughly estimated that the overall reduction of agricultural landscape area is 5% in a province on a large scale; however, not all counties in the province have the same trend of change, which apparently cannot be reflected by the above data. Therefore, such single large-scale classification results cannot support policy making on a smaller scale.

To fill this research gap, classification and assessment of landscape at different scales are highly necessary, which can help more accurate identification of critical regions and places that are most vulnerable to these changes (Li et al. 2022). Here, based on the scaling characteristics of landscape elements, we attempted to classify rural landscapes at different scales in China, taking into account all relevant natural and human elements.

Landscape diversity is one of the primary indicators of the integrated nature of the rural area. It is critical to the sustainability of socio-ecological systems, and also for aesthetic preference and cultural retention. Landscape diversity contributes to the stability of socio-ecological systems and is a major determinant (Peter Schippers et al. 2015) of ecosystem and socio-economic resilience (Abson

et al. 2013). Diverse landscapes possess more types of ecosystems per unit area, and therefore a wider variety of species (O'Farrell et al. 2010; Poggio et al. 2010). However, due to some factors such as poor management practices, the diversity of rural landscapes is rapidly declining (Fu and Chen 2000; J. Bartolomé et al. 2000; Nagaike and Kamitani 1999; Zaizhi Zhou 2000). Homogenization of rural landscapes can have negative effects such as reducing resilience and causing fluctuations in the overall health of rural socio-ecological systems. Hence, landscape managers should set goals for maintaining high landscape diversity (Fu and Chen 2000; Nagendra 2002). Previous research had mainly calculated landscape diversity based on a single landscape element of land cover. We propose a method for calculating landscape diversity index (LDI) based on landscape elements, which can include topography, landform, land cover/use, agro-industry, forestry industry, and so on.

Recreational services (RS) represent one of the vital non-material ecosystem services provided by rural landscapes, falling under the category of cultural ecosystem services (CES). Due to their intangible nature and the challenges associated with quantification and evaluation, RS are often underestimated in the current research and landscape management decisions. Yet, like any other ecosystem service, they hold significant importance for local communities (Casado-Arzuaga et al. 2014). The supply of RS is anchored in the "resources and environment" of natural systems (Daniel et al. 2012; Valánszki et al. 2022), while landscape characters and their elements are regarded as the tangible carriers of the ecosystem, more readily resonating with humans and enhancing aesthetic and recreational experiences. This facilitates the effective identification and quantification of non-material services (Crouzat et al. 2022), benefiting management practices. RS depend on the aesthetic value and recreational conditions of the ecosystem, where the aesthetic value is largely influenced by landscape elements (Crouzat et al. 2022). The landscape diversity as a specific pattern formed by the interaction among landscape elements (Wang et al. 2021). And the LDI is a composite index derived from the diversity of landscape elements, significantly impacting aesthetic values. This study further validates the importance of LDI for RS using the Geographically Weighted Regression (GWR) model.

The aim of the research is to generalize rural landscapes across multiple scales and to assess landscape diversity when many landscape elements are taken into account. We address the following research questions:

1. Q1: How can landscape elements and corresponding datasets for rural landscapes at multiple scales be identified rigorously and systematically?

2. Q2: How can landscape regions, landscape types, and landscape subtypes be defined at different scales?
3. Q3: How is a landscape diversity indicator assessed when different landscape elements (topography, landform, land cover/use, forestry industry, agricultural industry, and so on) are taken into account? What role does it play in landscape management?

Material and Methods

Study Area

The land area of mainland China is vast, spanning 62 degrees of longitude from east to west and 33 degrees of latitude from north to south. It has a variety of natural conditions in climate, topography, soil, flora, and fauna (Wang 2016).

R8 (Fig. 1a) is a landscape region of 106,526.62 km². It is located within the meeting place of the Huaihe and Yangtze River basins. The climate is mostly humid north subtropical, with four distinct seasons: hot and humid in summer and mild and humid in winter. Forests dominate the natural vegetation, and crops are often planted two-to-three times per year, mainly rice, winter wheat, cotton, and rapeseed. The Huaiyang Mountains and river valley plains dominate the terrain.

Dahongshan Mountain Region (DM) (Fig. 1b), a physiographic area in R8, is 9,893.59 km². The topography is predominantly hilly, with low mountains, gullies, valleys,

and intricate landforms. Agricultural crops primarily include double-season rice, wheat, and cotton. Timber forests, economic forests, and fruit trees are the most common types of cash forests. The vegetation types are evergreen and deciduous broadleaf mixed forests.

At the national scale, the study area is the Chinese mainland. For empirical analysis, we use the examples of R8 and DM at the regional and local scales.

Data

To answer Q1, we used a three-step process to select landscape elements and generate three datasets. In the initial stages, alternative landscape elements were found through systematic review and statistical analysis. The scale characteristics of the landscape were then investigated through literature review, based on which different landscape elements were screened. Finally, the datasets were chosen based on operability and accessibility.

Alternative Landscape Elements

We initially conducted a systematic review on rural landscape characteristics, aiming to identify the 20 most prevalent elements. Subsequently, we assessed the importance of these landscape elements through a specially designed questionnaire (Supplementary A Table A1), which was completed by 18 rural stakeholders. The questionnaire utilized a grading system based on a 7-point Likert scale, where a

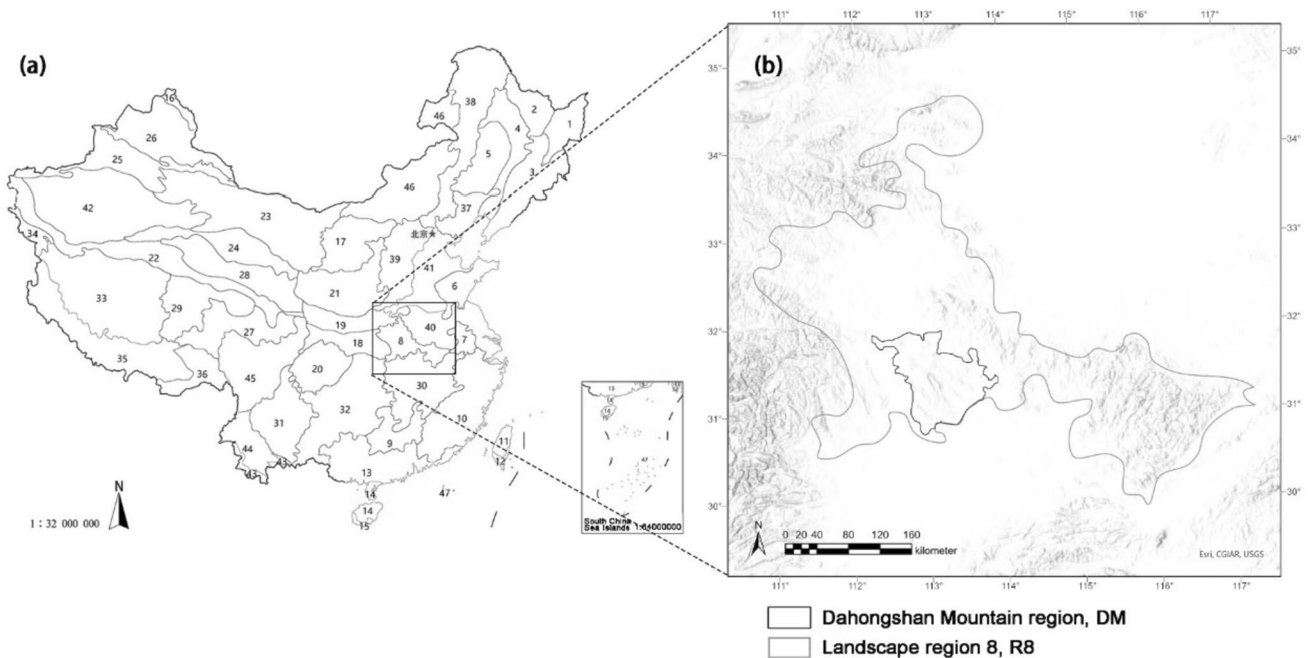


Fig. 1 Study area. **a** National scale: 47 landscapes regions; **b** landscape region 8 (R8) and Dahongshan Mountain Region (DM)

score of 1 to 7 indicated varying degrees of importance, with scores 2 through 6 representing intermediate levels of importance. Finally, the collected scoring data were analyzed using the GRA (Grey Relational Analysis) method.

First, for each landscape element, three types of grey class whitening function values (high, $k = 1$; moderate, $k = 2$; low, $k = 3$) were calculated with the following segmentation functions:

Type 1: High, $k = 1$

$$f_1(ab) = \begin{cases} 1 & h_{ab} \geq 7 \\ \frac{h_{ab}-4}{7-4} & 4 < h_{ab} < 7 \\ 0 & h_{ab} \leq 4 \end{cases} \quad (1)$$

Type 2: Moderate, $k = 2$

$$f_2(ab) = \begin{cases} 0 & h_{ab} \geq 7 \\ \frac{7-h_{ab}}{7-4} & 4 < h_{ab} < 7 \\ 1 & h_{ab} = 4 \\ \frac{h_{ab}-1}{4-1} & 1 < h_{ab} < 4 \\ 0 & h_{ab} \leq 1 \end{cases} \quad (2)$$

Type 3: Low, $k = 3$

$$f_3(ab) = \begin{cases} 0 & h_{ab} \geq 4 \\ \frac{4-h_{ab}}{4-1} & 1 < h_{ab} < 4 \\ 1 & h_{ab} \leq 1 \end{cases} \quad (3)$$

In the equations, a is the rating score, $a = 1, 2, 3, \dots, 7$; b is the landscape element, $b = 1, 2, 3, \dots, 20$; $f_k(ab)$ is the value of the whitening function that gives b a rating of a in type k , $k = 1, 2, 3$; h_{ab} is the scoring value for landscape element b with an importance rating of a .

Then, the grey decision factor is calculated as follows:

$$\eta_k(b) = \sum L(ab) \times f_k(ab), \quad (4)$$

where $\eta_k(b)$ is the decision factor indicating b in type k ; $L(ab)$ indicates the number of scorers with an importance level rating of a for landscape element b .

The grey decision vector for each pre-screened landscape element is composed of three categories of grey decision factors, namely “High”, “Medium”, and “Low”, i.e., $\{\eta_1(b), \eta_2(b), \eta_3(b)\}$. Finally, the grey decision vectors for each landscape element are compared to filter the elements. The largest grey decision factor indicates the importance level of this pre-screened landscape element. The pre-screened landscape elements with an importance level of “High” are taken as the initially selected landscape elements at each scale (Table 1).

Table 1 Alternative landscape elements

Landscape elements	Scale		
	National	Regional	Local
Elevation	High	High	Low
Undulation	High	High	High
Landscape Patterns	High	High	Medium
Landforms	High	High	Low
Hydrology	High	High	Medium
Climate	High	Medium	Low
Animals	Low	Low	Low
Vegetation	High	High	High
Soil	High	Medium	Low
Land Cover	High	High	High
Land Use	Medium	High	High
Agricultural Industry	Low	Medium	High
Forestry Industry	Low	Medium	High
Social (demographic, religious, etc.)	Low	Medium	High
Infrastructure	Low	Medium	High
Settlement	Low	Medium	High
Constructions	Low	Low	High
Local names	Low	Low	Low
Tangible culture heritage	Medium	Medium	High
Intangible culture heritage	Low	Medium	High

Selected Landscape Elements

The scaling characteristics of landscape elements are similar to that in landscape ecology, where a too large scale can lead to the neglect of a large number of details, while a too small scale can cause stuck in the local and ignoring the overall pattern (Simon A Levin 1992). Therefore, it is extremely important to select appropriate granularity of landscape element data at different scales. Landscape elements should be added more detail from the level of the classification system or the resolution of the mapping data as the scale shrinks.

Our study is based on the independence characteristics of landscape elements, which are reduced from macro- to micro-scales. For example, abiotic landscape elements with a high degree of independence should be selected at the macroscopic scale, such as climate and topography (Mücher et al. 2003). Biotic landscape elements should be selected at the mesoscopic scale, such as vegetation. Cultural landscape elements with a low degree of independence should be selected at the microscopic scale, such as settlement. It is clear that the scaling characteristics of landscape elements differ from the scale effect in landscape ecology in that it may migrate from natural ecosystems to socio-cultural ecosystems. In addition, the resolution of the data carriers for the landscape elements gradually increases with decreasing scale from macro to micro.

The European Landscape Convention (ELC) defines landscape as "an area that is perceived by humans" (Swanwick 2002), and from the perspective of landscape perception, the scaling effect is related to both the extent to which humans perceive the landscape at different scales and how they perceive it. At the macroscopic scale, where people perceive landscape differences through modern technologies such as remote-sensing satellite imagery, China's built-up land area accounts for only 2% of the country's land area. Particularly, the built-up land area in the countryside is even smaller, and human settlement is concentrated on this 2% of land area. The characteristics of economic production and cultural life are negligible at the national scale and regional scale. At the local scale, people perceive the surrounding landscape through low-altitude flight such as drones, which gradually presents three-dimensional characteristics, and the local and recognizable characters of the rural landscape can be revealed through elements of agroforestry production.

By integrating the grey relational analysis based on the questionnaire survey with the scaling characteristics, we selected landscape elements at different scales (Table 2), where the national scale contains climate, topography and landform; the regional scale contains topography, landform, land cover, and vegetation; and the local scale contains topography, land use, vegetation, settlement, time dimension, and landscape morphology.

Datasets

The granularity of data on landscape elements at different scales is an important issue to consider, because the diversity of the landscape varies with the scale of the analysis. In addition, boundaries, patches, and corridors at one scale may disappear or become completely different structures at another scale (Ulrich Walz 2015). We performed repeated experiments with different data granularities based on our practice to determine multi-scale data of landscape elements (Table 2).

Classification Method

To answer Q2, we employed three different classification methods.

National Scale

The union tool in ArcGIS Pro 2.7.0 was used to overlay the two landscape elements to form landscape regions at the national scale.

Regional Scale

Cluster analysis is a commonly used objective classification method without entirely relying on expert judgement and reducing the influence of human subjective factors (Li and Zhang 2017).

First, a fishnet of landscape cells was created, and the size of landscape cells varies according to data precision, study scale size, and operational efficiency. Considering data precision, we ensured that the chosen grid size effectively balances capturing landscape details and maintaining analysis of heterogeneity at a larger scale. This grid size not only preserves sensitivity to small-scale landscape structures, enabling smaller landscape element patches to be interrelated and effectively participate in clustering, but also allows each grid to sufficiently cover types of landscape elements, reflecting the spatial heterogeneity of landscape character and effectively preserving the state of the landscape mosaic. Referring to previous studies, a grid size of 2000 m × 2000 m has been used for landscape classification at a regional scale (Ornetsmüller et al. 2018). Hence, at the regional scale, a fishnet with 27,490 cells, each measuring 2000 m × 2000 m, was produced.

Tabulate Intersection Analysis in ArcGIS Pro 2.7.0 was used to account for the proportion of landscape elements in each cell. Each cell will store information about the area ratio of each landscape element within it, forming a matrix of landscape cells (Fig. 2) that stores the information.

The clustering method was then used to group landscape cells with similar information. We used IBM SPSS Statistics 27 to perform the two-step clustering algorithm (Chiu et al. 2001) to process the landscape cell matrix, thus clustering landscape cells to determine the landscape type. The greatest advantage of two-step clustering is its ability to analyze large datasets and automatically determine the type of clusters (Bacher et al. 2004).

Finally, the clustering results are visualized. We assign a number to each landscape cell based on the clustering results and mark each number with a unique color. ArcGIS Pro 2.7.0 then associates all landscape cells of the same number with the assigned color. In this way, it is possible to see the spatial distribution of landscape cells of the same color and thus visualize the distribution of landscape types.

Local Scale

Due to significant differences in the area of regional and local scale studies, a grid size of 2000 m × 2000 m is overly coarse for local scales, rendering land use and forestry data too generalized at this grid size. Therefore, drawing on studies with similar research scopes (Anees et al. 2020), we have adopted a grid size of 500 m × 500 m for local scale studies. Hence, at the local scale, a fishnet with 40,078 cells, each

Table 2 Landscape elements and datasets

Scale	Landscape element	Mapping data	Source of data	Accuracy (the granularity of data; method of data acquisition)
National scale	Climate	Climate zoning map	The China climate zoning Program Dataset 1981–2010 (Zheng et al. 2013, pp. 1981–2010)	Map scale 1:150, 0000
	Topography and landform	Geomorphological zoning map	The Geographical Atlas of China (Wang and Zuo 2009)	Map scale 1:150, 0000
Regional scale	Topography	Altitude and undulation	Digital Elevation Model (DEM)- Shuttle Radar Topography Mission (SRTM)	Calculation altitude and undulation based on original DEM raster data (grid-precision of 500 m)
	Landform	Geomorphological origin type	The digitally integrated 1: 100,0000 Chinese digital geomorphological datasets (National Earth System Science Data Center)	Map scale 1:100,0000; Extracting geomorphological origin type from the attribute table of the original vector data
Local scale	Land cover	Land-cover raster data	The GlobeLand30 dataset (Jun et al. 2014)	Grid-precision of 30 m
	Vegetation	Vegetation type group	<i>The 1: 100,0000 China Vegetation Atlas</i> (Hou 2019)	Map scale 1:100,0000; Extracting vegetation type group from the attribute table of the original vector data
Local scale	Topography	Topographic form	The digitally integrated 1: 100,0000 Chinese digital geomorphological datasets (National Earth System Science Data Center)	Map scale 1:100,0000; Extracting topographic form from the attribute table of the original vector data
	Land use	Land-use raster data	The Chinese land use remote sensing monitoring data (Resource and Environment Science and Data Center)	Grid-precision of 30 m
Regional scale	Vegetation	The forest species	The National Forest Resources Type II Survey data (Natural Resources Directorates)	Map scale 1:100,0000; Extracting the forest species from the attribute table of the original vector data
	Time dimension	The national cultural relics protection units (NCRPU) retention time	<i>The 1: 100,0000 China Vegetation Atlas</i> (Hou 2019) NCRPU list (Comprehensive Administrative Management Platform of State Administration of Cultural Heritage)	Extracting the specific vegetation name from the Create point spatial data from a table containing NCRPUs latitude–longitude coordinates using ArcGIS Pro 2.7.0
Local scale	Settlement	The Chinese traditional villages (CTV)	CTV List (Ministry of Housing and Urban–Rural Development)	Create point spatial data from a table containing CTVs latitude–longitude coordinates using ArcGIS Pro 2.7.0
	Landscape morphology	Landscape openness	Field survey	Artificially scored values for landscape openness from field survey

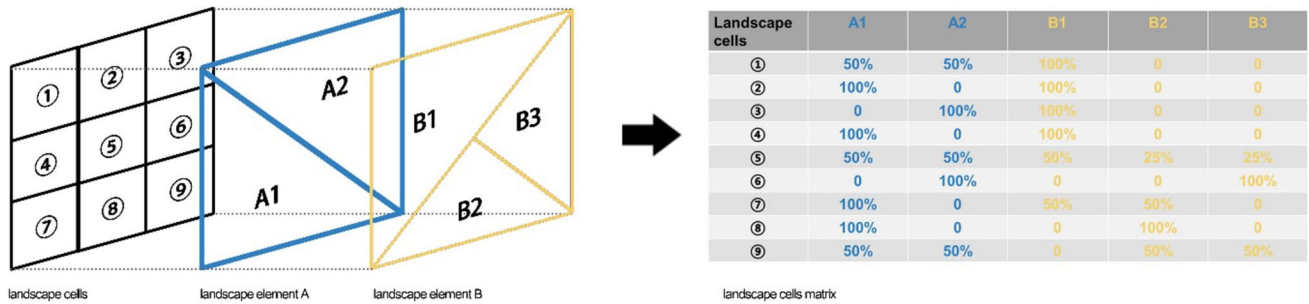


Fig. 2 Construction process of the landscape cell matrix

measuring 500 m × 500 m, was initially produced. And then, we employed a two-step cluster analysis. In addition, the two landscape elements of settlement and time dimension are displayed as point vector data, giving a binary judgment to the landscape subtype. For example, if there are settlement points on the landscape type, the landscape type is judged to be "Settlement: Yes", while the opposite is judged to be "Settlement: No". Thus, the landscape type containing traditional CTVs or NCRPUs will be classified as a new landscape subtype. The landscape morphology element is based on a sample field survey, and each landscape sample site is given a score of openness. Natural neighbor interpolation was used to interpolate the landscape sample sites, which can indicate the areas with high and low openness. The landscapes with extremely high or low openness value will be classified as a new subtype.

Landscape Diversity Index

In response to Q3, we provide a method for estimating the landscape diversity index (LDI).

Indices commonly used to measure landscape diversity often combine two distinct aspects of diversity: richness and evenness (Nagendra 2002). The most commonly used diversity indices are Shannon diversity index (SHDI) and Simpson diversity index (SIDI), both of which allow combined assessments of richness diversity and evenness diversity. SHDI and SIDI will increase whether the richness and/or evenness of the land-cover type increase. It has been demonstrated that the two indices have different sensitivities to rare land-cover types and major land-cover types (McGarigal and Marks 1995). SHDI is sensitive to the presence of rare landscape element types as it contains a log function, while SIDI contains an exponential function and is therefore more sensitive to the presence of major landscape element types (Nagendra 2002). Rare landscape elements should be valued as they provide habitat for sensitive species and contribute to key ecological processes (Dale et al. 2000). In addition, it is necessary to identify and protect the

unique and rare landscape elements of the rural landscape. Therefore, this study chose SHDI to measure the diversity of rural landscapes.

The landscape diversity here is similar to how geodiversity and environmental diversity are calculated. Geodiversity (Pereira et al. 2013; Murray Gray 2004) is the diversity of environmental conditions defined by geological, geomorphological, and soil features. Environmental diversity is a combination of biotic and abiotic factors. Landscape diversity in this study is a combination of various natural and cultural landscape elements.

To assess the diversity of rural landscape types, we need to use Eqs. 5 and 6 to initially calculate the diversity of each landscape element. And then, we need to use Eqs. 7 and 8 to finally calculate the diversity of each landscape type

$$SHDI_n = 1 - \sum_{i=1}^N p_i \times \ln p_i. \tag{5}$$

SHDI_n is the SHDI of landscape element *n* in any grid cell, *N* is the number of *n* types in the grid cell, and *p_i* is the percentage of the area of type *i* of *n* in the grid cell. Theoretically, this index ranges from 0 to infinity

$$NormValue_n = \frac{SHDI_n \times 5}{V_{nmax}}. \tag{6}$$

NormValue_{*i*} is the normalized value of the diversity of landscape element *n* in any one grid cell. *V_{nmax}* is the maximum value of the SHDI of landscape element *n* for the whole study area.

Here, we present a demo (Fig. 3) to rank the diversity index of the vegetation landscape element by two methods, natural breaks (NB) and normalization-based NB, respectively. Figure 4 shows that the two methods produce different results for vegetation. Then, we attempted to compare the two results. The Jenks' NB method is a standard grading method in ArcGIS that groups similar values and maximizes differences between groups (Jenks 1967). When comparing the results obtained by NB and normalization-based NB, the

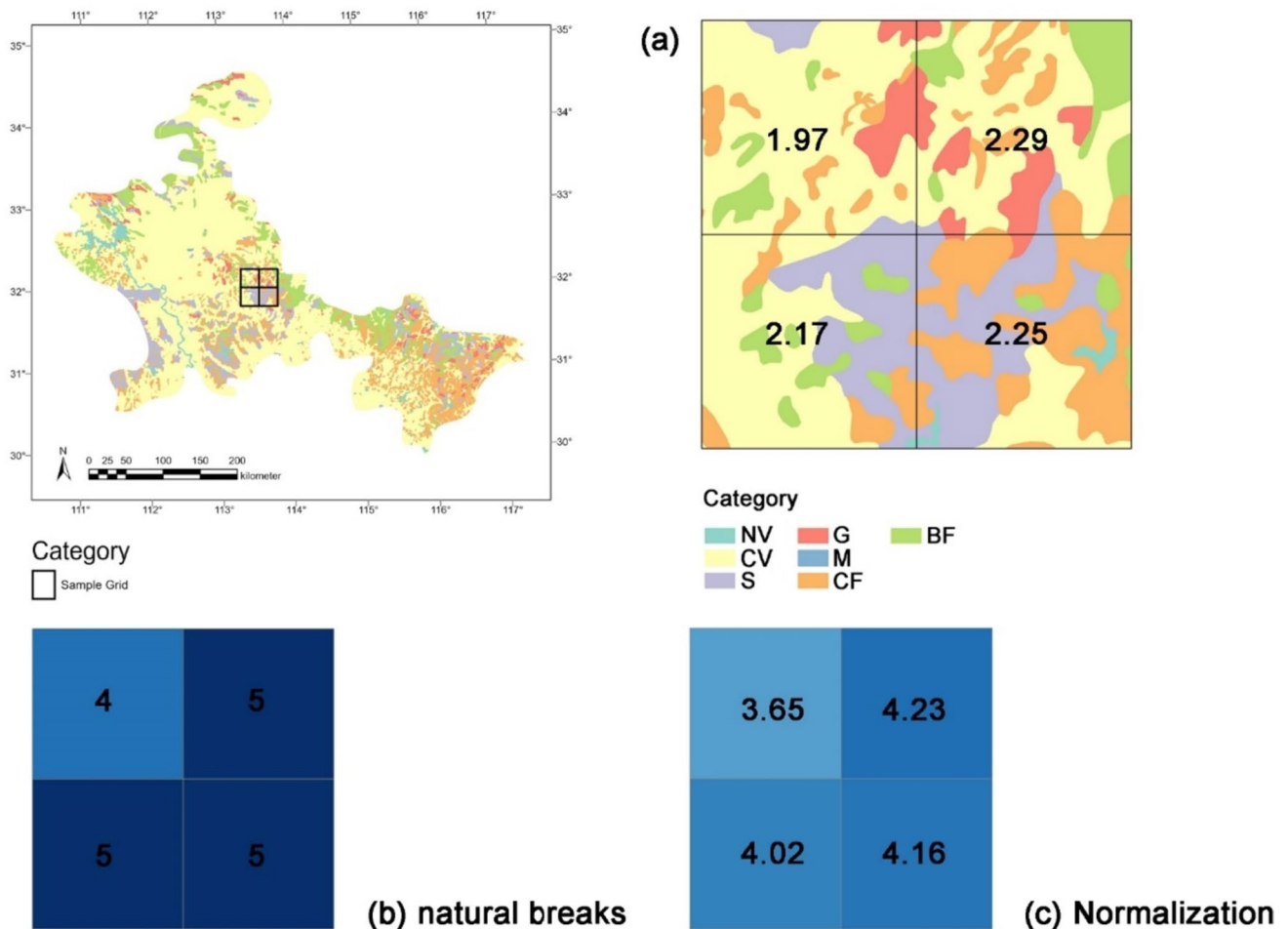


Fig. 3 Example of vegetation diversity index assessment in a 25 km×25 km grid size. **a** Each color represents a vegetation type. *NV* no vegetation (such as water bodies and bare ground); *CV* culti-

vated vegetation; *S* shrub; *G* grass; *M* meadows; *CF* coniferous forest; **b** natural breaks; **c** natural breaks based on normalization

histogram shows that the results obtained by both methods are consistent and comparable. The distribution trends of grades do not differ much, but there are some differences in the specific number of graded areas, especially in grade 5, which has a higher proportion in Fig. 4a and a lower proportion in Fig. 4b. Normalization may lead to an increase in differences between levels and reveal information that needs further study. Thus, locations with special strategic needs can be identified (Carrión-Mero et al. 2022).

To identify the optimal grid size for landscape diversity calculations, we conducted computational experiments (Supplementary A Figure A1, A2) with various grid sizes. At the regional scale, we used grids of 2 km×2 km, 10 km×10 km, and 25 km×25 km; at the local scale, grids of 2 km×2 km, 5 km×5 km, and 10 km×10 km were employed. The results indicated that a 2 km×2 km grid at the regional scale was too small, leading to an over-simplification of landscape elements within the grid cells, such as elevation, undulation, and landforms. Similarly, at the local scale, a 2 km×2 km

grid resulted in a high degree of homogeneity for elements like terrain and crops.

The inherent high degree of uncertainty in the semantic descriptions (Dehn et al. 2001) of land elements and the descriptor variables used makes it impossible to classify land elements in a unique and nonambiguous manner (Schmidt and Hewitt 2004). Consequently, this implies that the boundaries between different types of landscape elements are not clear and distinct, but rather represent fuzzy boundaries. Spatially, landscape element types do not undergo abrupt changes; instead, they exhibit a continuous process of variation. Therefore, using overly small grid cells significantly underestimates the diversity values for these elements. However, choosing larger grids for diversity calculations, such as 25 km×25 km at the regional scale and 10 km×10 km at the local scale, does not significantly overestimate or underestimate the results, nor does it affect the trend of spatial distribution. The only effect is that the results displayed spatially appear coarser. Utilizing the Spatial Analyst tool, we

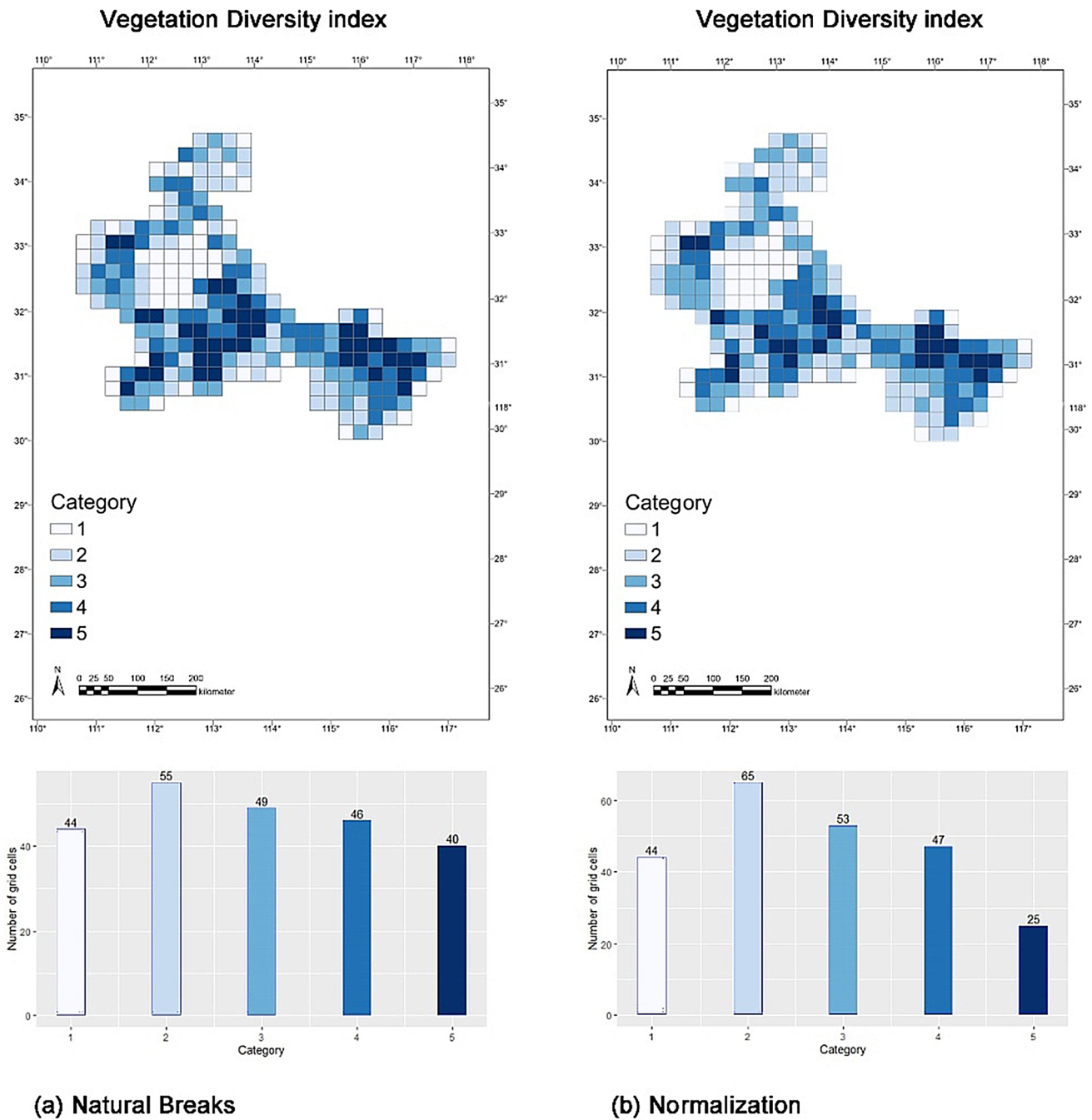


Fig. 4 Comparison of the calculation results of Natural Breaks (NB) and normalization-based NB methods

assigned diversity values to each landscape type, categorizing them as very low, low, medium, high, or very high. The assignment results indicated that at the regional scale, the outcomes using 10 km × 10 km and 25 km × 25 km grids were identical. Similarly, at the local scale, the results for 5 km × 5 km and 10 km × 10 km grids were the same. Hence, we ultimately selected a 10 km × 10 km grid for the regional scale and a 5 km × 5 km grid for the local scale to perform landscape diversity calculations.

Regional Scale

First, we used the "create fishnet tool" of ArcGIS Pro 2.7.0 to create fishnets. A grid cell size of 10 km × 10 km was used for the calculation of the regional scale R8 (Pereira et al. 2013). A total of 1235 grid cells were used in R8, and for each grid cell, the SHDI of each landscape element was calculated with Eq. 5. Finally, the diversity index was broken into five categories using the normalization-based

NB methods: very low (1), low (2), medium (3), high (4), and very high (5). Finally, using Eq. 7, we calculated the R8 LDI at the regional scale.

$$\begin{aligned} & \text{LandscapeDiversity}_{\text{regional}}_{\text{index}} \\ &= \text{ElevationDiversity}_{\text{index}} \\ &+ \text{TerrainDiversity}_{\text{index}} + \text{LandformsDiversity}_{\text{index}} \\ &+ \text{VegetationDiversity}_{\text{index}} + \text{LandCoverDiversity}_{\text{index}}, \end{aligned} \quad (7)$$

where $\text{LandscapeDiversity}_{\text{regional}}_{\text{index}}$ is the total landscape diversity at regional scale. $\text{ElevationDiversity}_{\text{index}}$, $\text{TerrainDiversity}_{\text{index}}$, $\text{LandformsDiversity}_{\text{index}}$, $\text{VegetationDiversity}_{\text{index}}$ and $\text{LandCoverDiversity}_{\text{index}}$ are elevation, topography, landform, vegetation and land cover SHDI, respectively.

Local Scale

In the local scale calculations, DM comprises 475 grid cells of 5 km × 5 km size. We used the same technical procedure (Eqs. 5 and 6) as at the regional scale to calculate landscape diversity of each landscape element. And we used Eq. 8 to calculate the LDI of each landscape type

$$\begin{aligned} & \text{LandscapeDiversity}_{\text{local}}_{\text{index}} \\ &= \text{TerrainDiversity}_{\text{index}} \\ &+ \text{ForestManagementDiversity}_{\text{index}} \\ &+ \text{CropDiversity}_{\text{index}} + \text{LandUseDiversity}_{\text{index}}, \end{aligned} \quad (8)$$

where $\text{LandscapeDiversity}_{\text{local}}_{\text{index}}$ is the diversity of the landscape at the local scale. $\text{TerrainDiversity}_{\text{index}}$, $\text{ForestManagementDiversity}_{\text{index}}$, $\text{CropDiversity}_{\text{index}}$ and $\text{LandUseDiversity}_{\text{index}}$ are terrain, forest management, crop, and land-use SHDI, respectively.

Regression Model

To answer Q3, we explored the relationship between LDI and recreation services (RS). A distribution kernel density map was initially created utilizing scenic spots as a measurement of RS. The mean scenic spots kernel density in each 25 km × 25 km grid was then counted. Then, we measured the Moran's I for LDI and RS separately and determined that both of them have spatial autocorrelation. Finally, we used regression analysis with the Geographically Weighted Regression (GWR) model, utilizing RS as the dependent variable and LDI as the explanatory variable. GWR may take into account variations of geographical data and address the issue of spatial non-smoothness in the conventional OLS regression analysis. The formula is as follows:

$$y_i = \beta_0(u_i, v_i) + \sum_{k=0}^m \beta_k(u_i, v_i)x_{ik} + \varepsilon_i, \quad (9)$$

where i is the intercept of the spatial coordinate, y_i is the response variable, (u_i, v_i) is the sample, $\beta_k(u_i, v_i)$ is the first k coefficient, x_{ik} is the k th explanatory variable, and ε_i is the error term.

Results and Discussion

Classification Results

We proposed a naming method to make the classification results more understandable. Each landscape element type's share of each landscape type's total area was calculated. After that, landscape types were named (Yang et al. 2020). The rules are (1) when $X > 60\%$, code A; (2) when $30\% < X < 60\%$, code {A}; (3) when $10\% < X < 30\%$, code (A); (4) when $X < 10\%$, ignore, where A is the type of landscape element and X is the ratio of A to the area of the landscape type. Each landscape element type is given a unique code. For example, P represents the landscape element of vegetation and P1 represents the landscape element type of coniferous forest. Supplementary A Table A2 and Table A3 provide a code list of all landscape element types at the regional and local scales.

Rural Landscape Regions at the National Scale

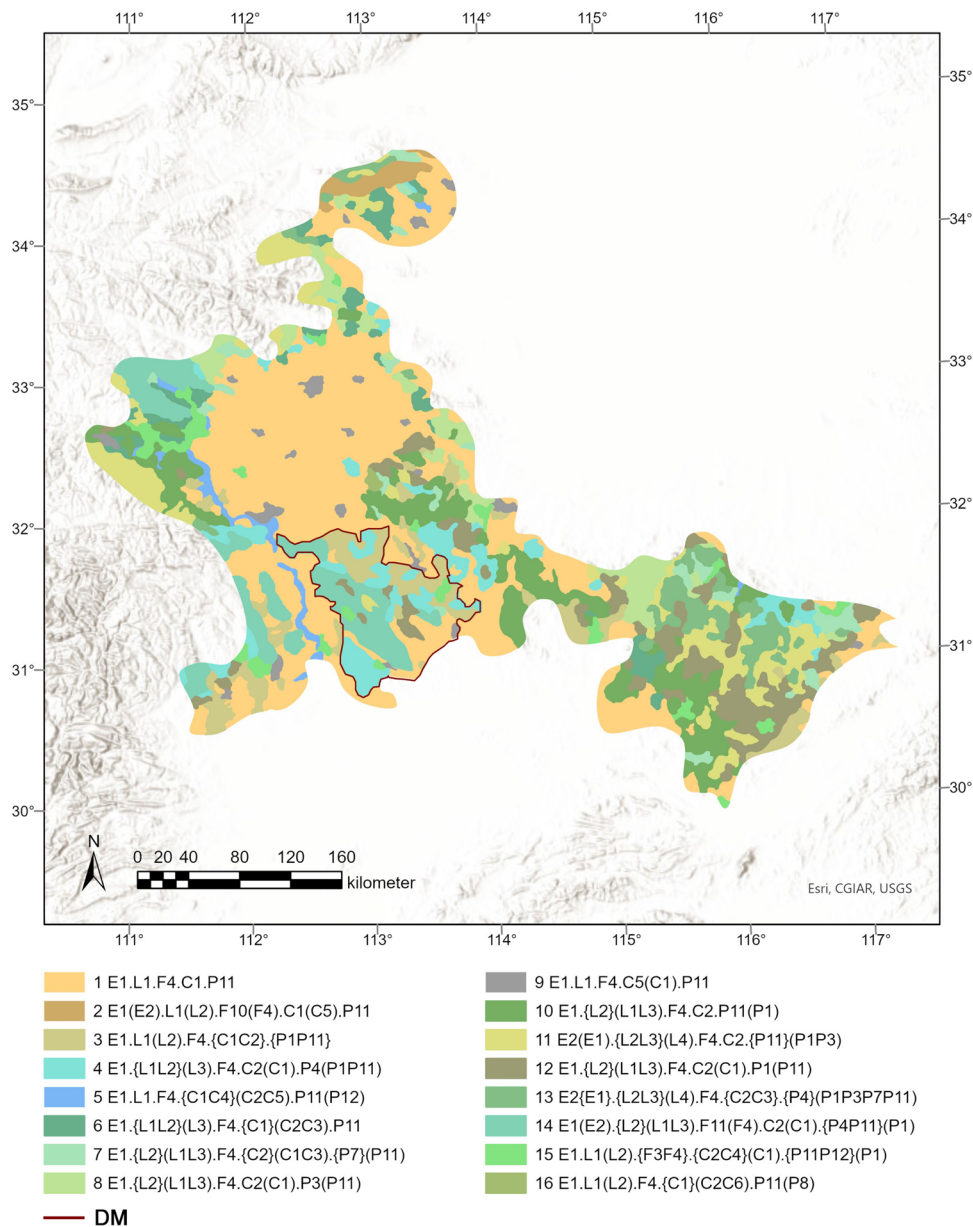
The two landscape variables, climate and topography, were superimposed to form 47 landscape regions (Fig. 1a) (Details can be found in Supplementary A Table A4).

Rural Landscape Types at the Regional Scale

We finally defined 16 landscape types of R8 (Fig. 5). The landscape type R8-1 has the largest area, covering 40,359 km², and consists of low-altitude plain, flow landform, and farmland.

Supplementary B Table B2 provides the percentage of area for each landscape type and the proportion of landscape elements (Fig. 6). For example, we can clarify from the dataset that elevation of R8-1 consists of almost 99.9% of low altitude (E1), terrain consists of 95.06% of plain (L1) and 4.29% of low hills (L2), and landform consists of almost all flow landform (F4). There are more types of land cover, including 81.57% of arable land (C1), 7.66% of forest (C2), 6.77% of artificial surface (C5), 1.43% of grassland (C3), and 2.56% of water body (C4). Vegetation mainly consists of cultivated vegetation (P11) 93.9%, followed by a small number of other types, including 2.76% of coniferous forest

Fig. 5 Landscape types of R8 Subtropical Humid Climate Huaiyang Low Mountain Region



(P1), 1.42% of broad-leaved forest (P3), 1.25% of bush (P4), and landscape element types with very small proportions are neglected, such as high hills (less than 1%).

We defined the landscape types of 47 landscape regions, covering the entire mainland of China. Supplementary B Table B1 presents the data of all landscape types of 47 landscape regions. A total of 448 different landscape types were identified nationwide at the regional scale.

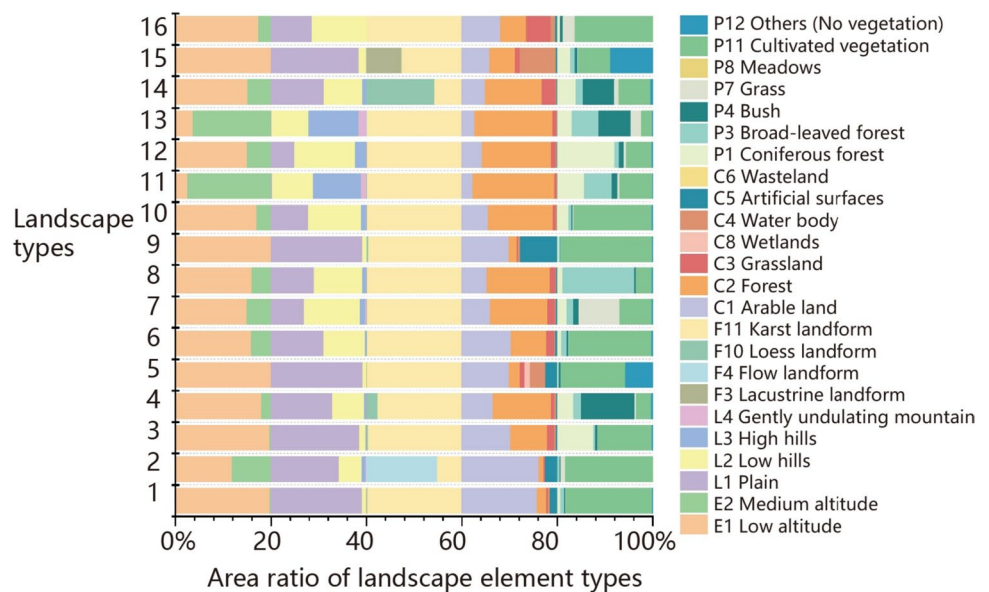
Rural Landscape Subtypes at the Local Scale

At the local scale, DM was identified as 21 landscape subtypes through cluster analysis. Then, by adding the time

dimension landscape elements (Fig. 7), there are 35 landscape subtypes are defined. In our empirical study, the landscape element of settlement is ignored, because there is no distribution of traditional villages in DM.

Finally, 298 sample sites were randomly selected for scoring openness. A field survey was then conducted at each sample site, and three landscape professionals scored the degree of openness of the landscape from 1 to 10, with 1 being closed and 10 being open. A value was assigned to each sample point based on the average of the three scorers. In ArcGIS Pro 2.7.0, the points assigned with openness scores were interpolated as raster surfaces using Natural Neighbor (Fig. 8). Patches with very high and very low openness were marked, and supplemented with the attribute of open or closed. As a result, there

Fig. 6 Area ratio of landscape element types of each landscape types



are 44 landscape subtypes defined in DM (Fig. 9). Supplementary B Table B3 shows the percentage of area for each landscape subtype and the proportion of landscape elements (Fig. 10).

L(DM)-9 is the dominant landscape subtype in DM, with an area of 1,169 km². It is evenly distributed throughout the DM and mainly reflects the rural landscape characters of a mixture of rice, wheat, cotton, and other crops in gently rolling hills and shrub sparse forest around the farmland.

Multi-scale Rural Landscape Diversity

Rural Landscape Diversity at the Regional Scale

We calculated the diversity indices of five landscape elements in R8 according to Eq. 7, including elevation diversity, terrain diversity, landform diversity, land-cover diversity, and vegetation diversity. From Fig. 11a, b, it can be seen that the highest value of topographic relief diversity is in the eastern part of the R8 area due to the higher elevation and greater variation in relief, transitioning from low hills and high hills to small rolling hills. As shown in Fig. 11c, the highest value of geomorphic diversity is in the southwestern part of the R8 area, which is due to the non-continuous distribution of karstic and flow landform in the southwestern part. Figure 11d shows that the overall land cover diversity is higher than that of all other landscape elements, with the highest value in the west, which contains almost all land-cover types of R8, including cropland, forest, grassland, wetland, water body, and artificial surface. As shown in Fig. 11e, the

overall distribution of high vegetation diversity is mainly in the eastern and central parts of R8, both involving rich vegetation types such as coniferous forest, cultivated vegetation, broadleaf forest, scrub, and grass.

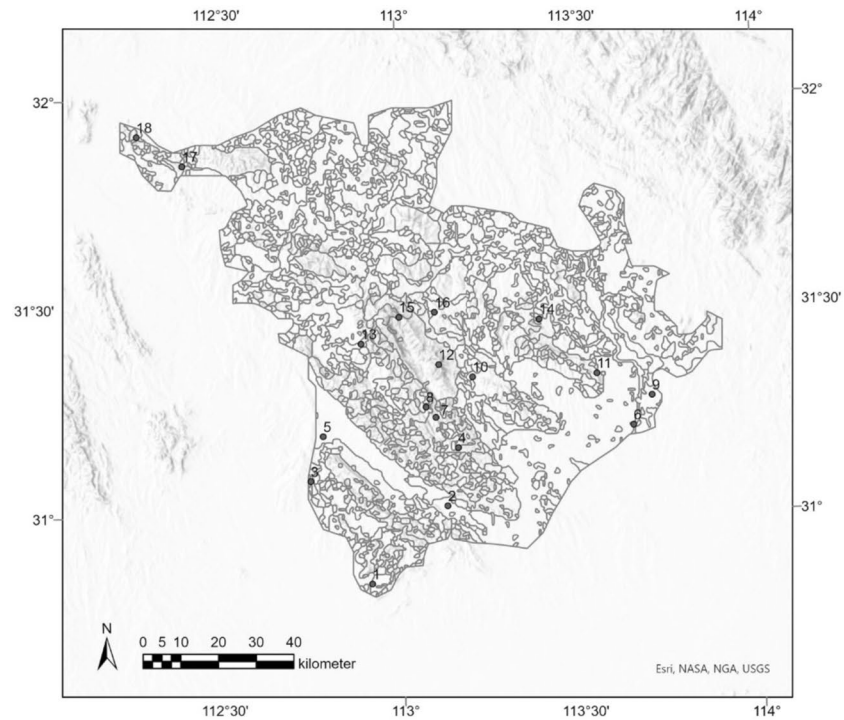
Finally, the LDI map of R8 (Fig. 11f) was obtained. And we calculated the LDI for each landscape type (Fig. 11g). R8-7, R8-13, R8-14, and R8-15 have very high LDI. R8-1 has a very low LDI. Supplementary B Table B2 provides the results of the diversity degree for each landscape type of R8.

Rural Landscape Diversity at the Local Scale

We calculated the diversity index of the four landscape elements of DM according to Eq. 5, including terrain diversity, land use diversity, forest management diversity, and crop diversity. Figure 12a shows that the overall topographic diversity is not high. As shown in Fig. 12b, the overall land-use diversity is high, with low values occurring only in a limited area in the east of DM. Figure 12c shows that the high value of forest management diversity is mainly located in the middle of DM. Figure 12d shows that crop diversity in DM is generally low due to the more homogeneous type of cultivation.

Finally, the LDI map of DM (Fig. 12e) was obtained. And we calculated the LDI for each landscape subtype (Fig. 12f). L(DM)-24, L(DM)-26, L(DM)-28, L(DM)-34, L(DM)-35, L(DM)-37, and L(DM)-40 have very high LDI. And L(DM)-33, L(DM)-36, and L(DM)-42 have very low LDI. Supplementary B Table B3 shows the diversity degrees of each landscape subtype in DM.

Fig. 7 Distribution of national cultural relics protection units and their construction time in DM



● National Cultural Relics Protection Units, NCRPU

- 1 Ancient Culture Site - Neolithic Age
- 2 Ancient architecture - Qing Dynasty
- 3 Ancient Culture Site - Neolithic Age
- 4 Revolutionary Sites and Memorial Buildings - Modern China
- 5 Ancient Culture Site - Neolithic Age
- 6 Ancient Culture Site - Shang Dynasty, Zhou Dynasty
- 7 Revolutionary Sites and Memorial Buildings - Modern China
- 8 Revolutionary Sites and Memorial Buildings - Modern China
- 9 Ancient architecture - Ming Dynasty
- 10 Ancient Culture Site - Neolithic Age, Shang Dynasty, Han Dynasty
- 11 Carvings - Song Dynasty, Ming Dynasty, Qing Dynasty
- 12 Ancient Culture Site - Ming Dynasty, Qing Dynasty
- 13 Ancient Culture Site - Eastern Zhou Dynasty
- 14 Revolutionary Sites and Memorial Buildings - Modern China
- 15 Ancient architecture - Song Dynasty, Yuan Dynasty, Ming Dynasty, Qing Dynasty
- 16 Ancient Culture Site - Neolithic Age
- 17 Revolutionary Sites and Memorial Buildings - Modern China
- 18 Ancient Buildings and Historic Commemorative Buildings - Han Dynasty, Song Dynasty, Qing Dynasty

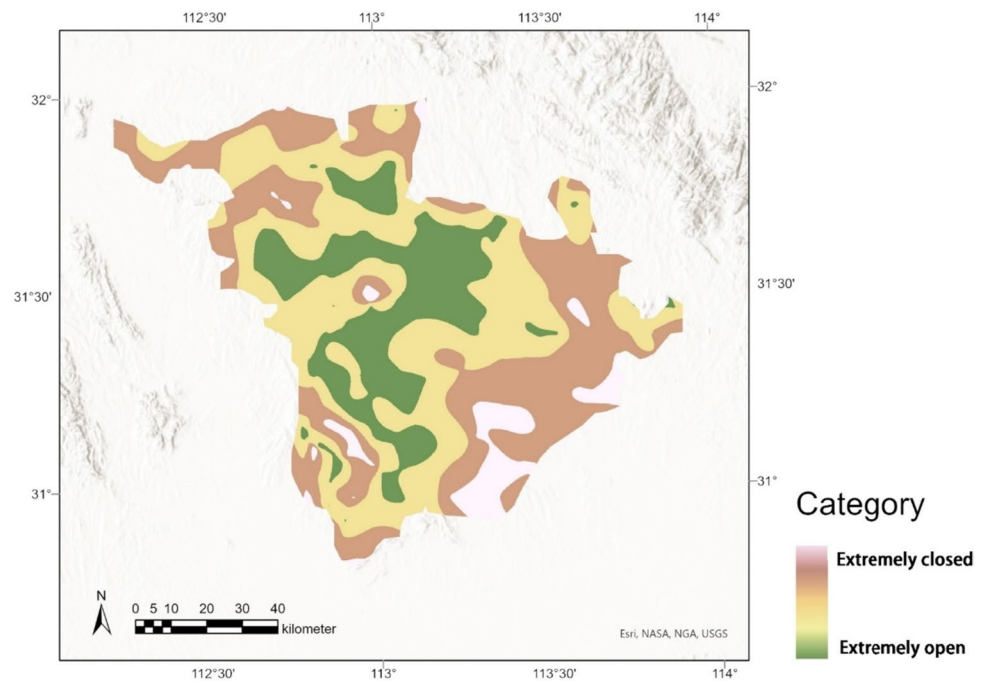
Regression Model Result

The results showed that the direction and extent of the effect of LDI on RS varied depending on the spatial distribution. At the regional scale (Fig. 13), it revealed a positive correlation between LDI and RS in the northwestern part of R8, while a negative correlation was observed in the southeastern part. At the local scale (Fig. 14), there was a positive correlation between LDI and RS in southern

and northern part of DM, whereas a negative correlation was found in the central region.

When developing plans at different scales, planners must incorporate targeted planning strategies for landscape types or subtypes that are distributed differently, with a focus on meeting human recreation needs. For landscape types in northwest of R8, it is important to preserve high levels of LDI, while landscape types in the southeast should aim to maintain low levels of LDI.

Fig. 8 Distribution of landscape openness in DM



Application Case

Each of the defined landscape types has a similar composition of landscape elements, which helps to integrate rural natural and cultural landscape resources. Landscape planning can be guided by this result. Furthermore, landscape diversity calculations can show the existing state of the landscape for conservation planning.

Table 3 provides an application case, summarizing the natural and cultural resource characteristics of the various landscape subtypes and providing recommendations for landscape management.

General Discussions

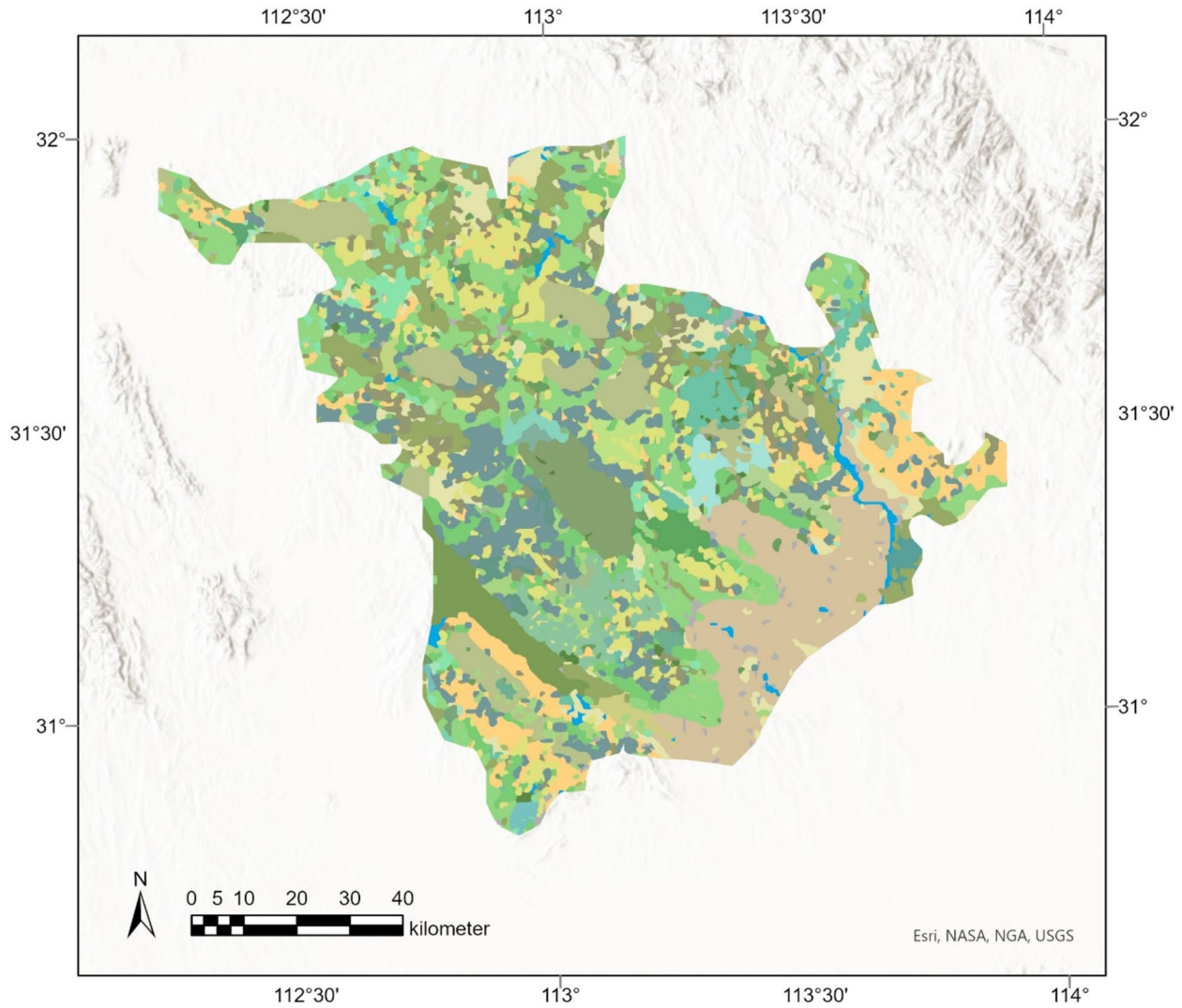
In previous landscape classification studies, the European Landscape Map (LANMAP2), among others, focused primarily on natural landscape elements (Wascher 2005). Subsequent efforts, such as the European Landscape Character Assessment (LCA), began to incorporate cultural landscape elements but relied mainly on land-use data for representation (Mücher et al. 2010). The UK's approach to LCA (Tudor 2014) marked a significant advancement by directly integrating cultural landscape elements into its national-scale classification. However, for countries with extensive territorial areas, the inclusion of cultural landscape elements necessitates a more detailed, micro-scale examination. Although recent advancements in landscape classification have leveraged remote-sensing data (Watmough et al. 2017; Zheng

et al. 2023), these methods frequently neglect the critical cultural components of rural landscapes.

Given the challenges in quantifying cultural elements, our method innovatively supplements this with binary data at the local level. This approach allows for refined classification across multiple layers, providing a comprehensive and detailed understanding of the landscape. Looking ahead, it will be an interesting topic to simulate the sphere of influence of cultural elements in the future.

While China has already developed a single-scale nationwide natural landscape classification scheme (Pan et al. 2022), there has been no comprehensive study classifying the vast rural landscapes across the country. Most research on rural landscape classification focuses on specific villages or towns (Zhang et al. 2015). Furthermore, classification datasets need to be varied according to different spatial scales (Atik et al. 2015). Our study fills this gap by proposing a comprehensive multi-scale framework for classifying China's rural landscapes, utilizing spatial datasets ranging from large to small scales.

However, although our framework offers a new perspective for the multi-scale classification of rural landscapes, the uniqueness of geographical features may be relatively underestimated in this process. This challenge is not unique; similar to land classification, landscape classification also lacks a unified model, standardized classification indicators, and a "one size fits all" solution (Jin et al. 2022). The selection of indicators can directly affect the accuracy and reliability of classification results (Kuemmerle et al. 2013; Václavík et al. 2013). Too many indicators can lead to a low level of generalization in the classification results and an



- Category
- 1 I4(I3).{u3}(u1u2).a1(a6).{p0}(p16p2)
 - 2 I4(I3I5).(u1u2u4u5).a1(a6).{p0}(p16)
 - 3 {I4}(I5I6).{u3}(u4u5u8).a1(a6).{p0p13p16}
 - 4 I4(I3I5).{u5}(u2u3u4).a1(a6).{p0p16}(p22)
 - 5 I4(I5).{u3u5}(u4).a1.{p15}(p0p16)
 - 6 I4(I5).{u4}(u3u5).a1(a6).{p16}(p0p17p2)
 - 7 I3(I4).(u1u10u15u2u5).a6(a1).p0(p16)
 - 8 I3.(u1)(u2u5).a6.p0(p16)
 - 9 I4.(u1u2u3u4u5).a6.{p0p16}
 - 10 I3(I4).(u1u16u18u2).a6(a1).p0
 - 11 I4.{u1}(u2u4u5).a1.p0(p16)
 - 12 I4(I3).{u5}(u1u2u3).{a1a6}.{p0p21}(p16)
 - 13 I3(I4).(u1u12u2u4u5).a1(a6).p0(p16)
 - 14 I4.u4.a1.p16(p0)
 - 15 I4(I3).u5.a1.p16(p0)
 - 16 I4.u3(u5).a1.p16(p0)
 - 17 I4.{u4}(u3u5).a1(a6).p2(p0p16)
 - 18 I6.{u4}(u3u5).a1.p16p2(p0)
 - 19 I4(I3I6).{u5}(u3u4).a1(a6).{p0p1}
 - 20 I5.{u3}(u4u5).a1.p16(p0p2)
 - 21 I1.(u1)(u2u5).a6(a1).p0.t2I5.o1
 - 22 I4.{u1}(u2u4u5).a1.p0(p16).t2
 - 23 I4(I3).u5.a1.p16(p0).t2
 - 24 I4(I3).{u5}(u1u2u3).{a1a6}.{p0p21}(p16).t2I4I7
 - 25 {I4}(I5I6).{u3}(u4u5u8).a1(a6).{p0p13p16}.t15t19t20t21.o1
 - 26 I5.{u3}(u4u5).a1.p16(p0p2).t15t20t21
 - 27 I3(I4).(u1u16u18u2).a6(a1).p0.t4t5
 - 28 I3(I4).(u1u16u18u2).a6(a1).p0.t21
 - 29 I3(I4).(u1u16u18u2).a6(a1).p0.t20
 - 30 I6.{u4}(u3u5).a1.p16p2(p0).t20t21
 - 31 I4(I5).{u3u5}(u4).a1.{p15}(p0p16).t22
 - 32 I4.u4.a1.p16(p0).t22
 - 33 I4.{u4}(u3u5).a1(a6).p2(p0p16).t22
 - 34 I5.{u3}(u4u5).a1.p16(p0p2).t22
 - 35 {I4}(I5I6).{u3}(u4u5u8).a1(a6).{p0p13p16}. t7t15t21
 - 36 I3.(u1)(u2u5).a6.p0(p16).o1
 - 37 I4.(u1u2u3u4u5).a6.{p0p16}.o2
 - 38 I4.{u1}(u2u4u5).a1.p0(p16).o1
 - 39 I4(I3).{u5}(u1u2u3).{a1a6}.{p0p21}(p16).o1
 - 40 I4.u4.a1.p16(p0).o2
 - 41 I4.u3(u5).a1.p16(p0).o1
 - 42 I4.{u4}(u3u5).a1(a6).p2(p0p16).o2
 - 43 I4(I3I6).{u5}(u3u4).a1(a6).{p0p1}.o2
 - 44 I4(I3I6).{u5}(u3u4).a1(a6).{p0p1}.o1

Fig. 9 DM landscape subtypes

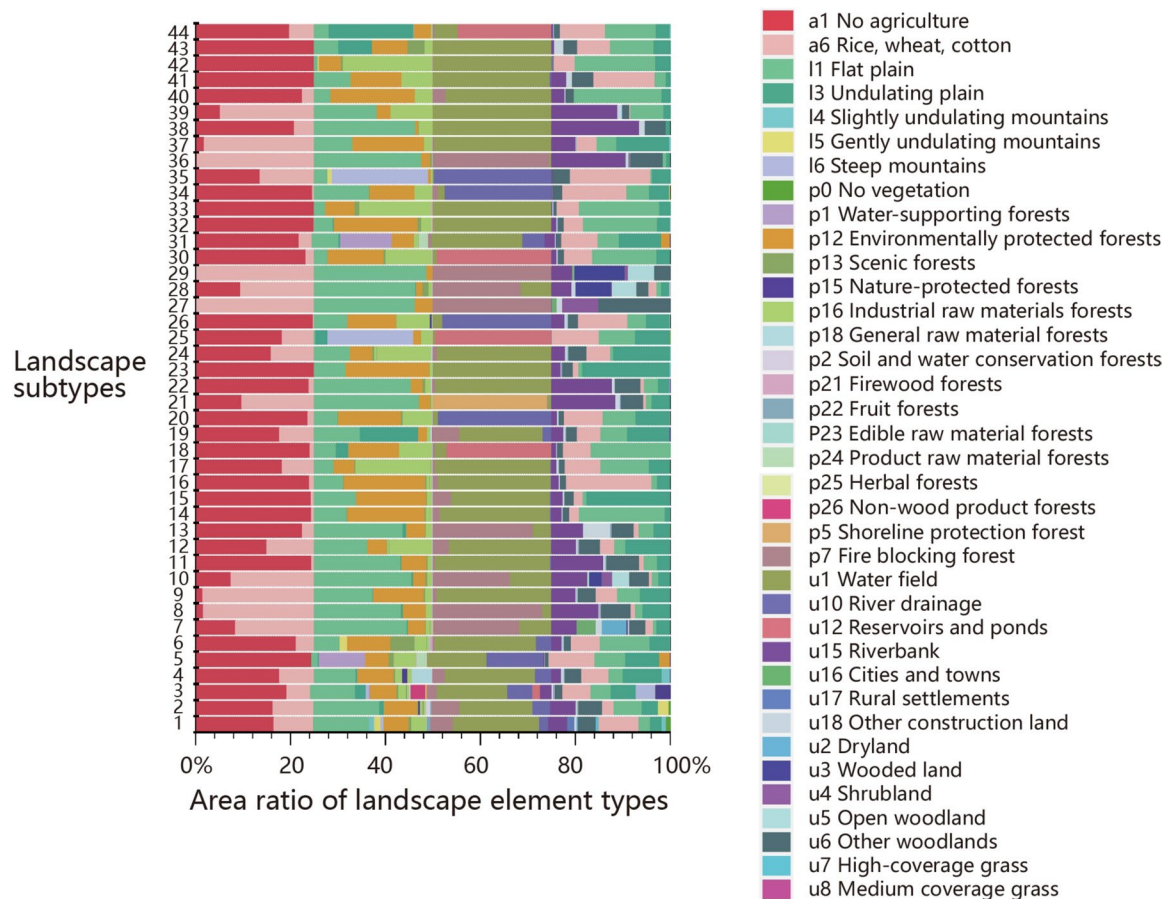


Fig. 10 Area ratio of landscape element types of each landscape subtypes

excessive computational burden. Too few indicators cannot fully reflect the multi-dimensional characteristics of the landscape (Jin et al. 2022). Therefore, it is essential to carefully select appropriate indicators. In addition to considering operability, the indicators should also be dynamically adjusted according to the landscape change to more accurately define rural landscapes.

Furthermore, the inclusion of agroforestry production characteristics as indicators in the rural landscape classification in our study is an important improvement. In previous landscape classification studies, there is a gap in forestry data landscape classification studies (Kuemmerle et al. 2013), and information related to forest management has been rarely included in the classification. This study fills this gap by including the information on forest management at the local scale.

The homogenization of rural landscapes not only leads to a loss of cultural values within ecosystems but also to a decline in the aesthetic quality of these landscapes. As a consequence, this leads to a diminished recognition and appreciation by society of the cultural benefits provided by ecosystem services. In addressing this issue, our study

utilizes landscape elements as connectors, bridging the gap between intangible, non-material services, and the tangible aspects of landscapes. We have calculated the LDI using these landscape elements, applying our findings to inform planning and management practices.

In our study, we delve into rural landscapes based on the scaling characteristics of landscape elements, laying essential groundwork for an analysis that is tailored to the specific contexts of these landscapes. The scaling characteristics provide an effective framework for landscape classification at different spatial scales, facilitating the development of diverse landscape management strategies. Additionally, our constructed classification system presents a comprehensive, stratified, and integrated hierarchical structure. This nested approach allows for a holistic understanding of the landscape system and its structured components. Our multi-scale, multi-level research outcomes transcend administrative boundaries, facilitating the effective quantification and assessment of landscape conditions from a holistic to a local level, promoting stratified management and protection of rural areas across different scales.

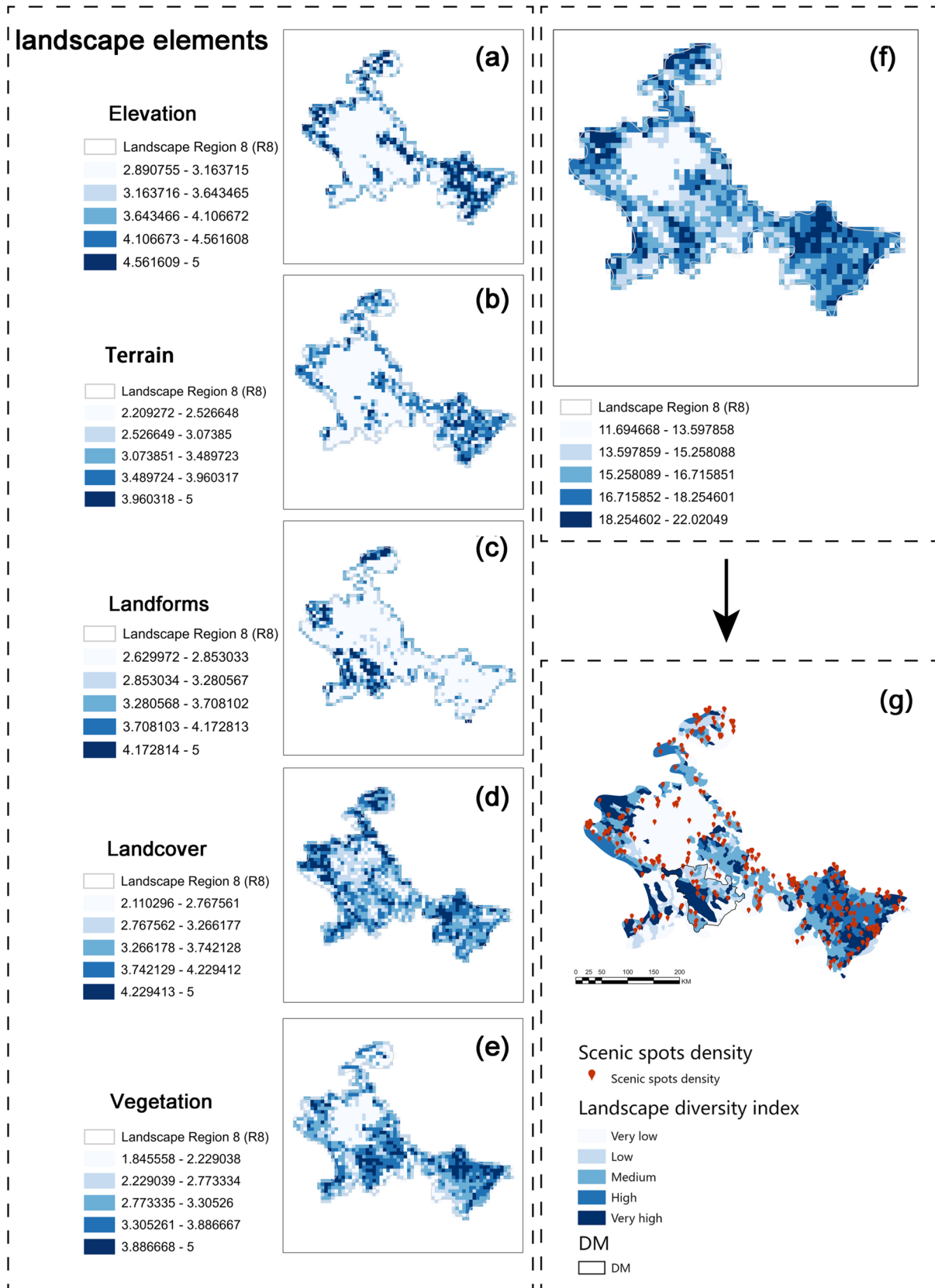


Fig. 11 Rural landscape diversity at the regional scale. **a** Elevation diversity index; **b** Terrain diversity index; **c** landform diversity index; **d** land cover diversity index; **e** vegetation diversity index; **f** landscape diversity index of R8; **e** diversity degree of each landscape type

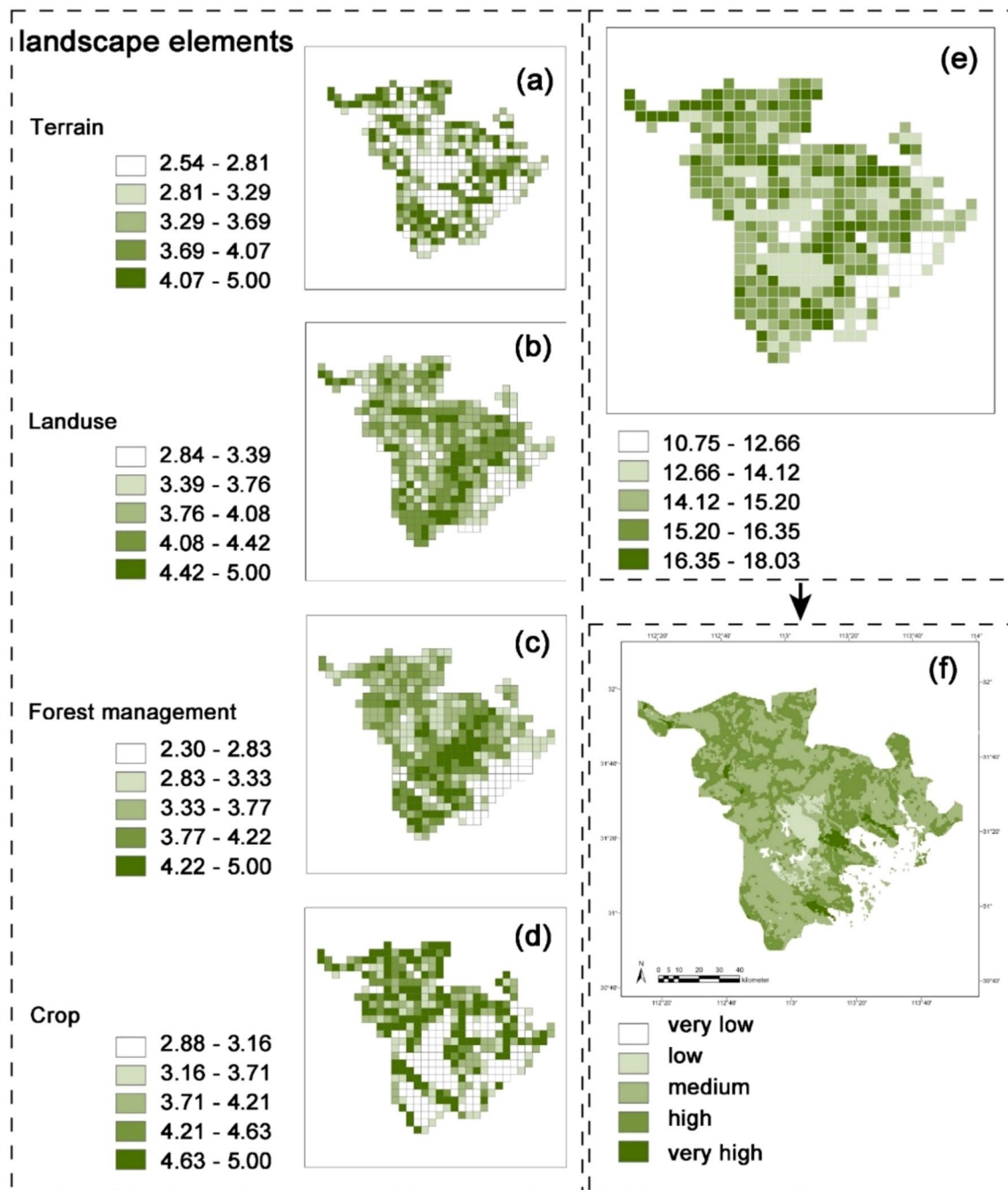


Fig. 12 Rural landscape diversity at the local scale. **a** Terrain diversity; **b** land use diversity; **c** forest management diversity; **d** crop diversity; **e** landscape diversity of DM; **f** diversity degrees of each landscape subtype

In future research, rural landscape typologies can serve as a database for studies on rural landscapes (Simensen et al. 2021). This resource can assist decision-makers at various levels to become familiar with the characteristic attributes of rural landscapes in different regions, thereby identifying hotspots for landscape resource utilization or conservation. Furthermore, the LDI, derived from calculating the diversity

of each landscape type and subtype, can serve as an auxiliary tool for conservation planning (Beier et al. 2015).

Building on this foundation, future research could delve deeper into the ecological functions of landscape types. Some studies define landscapes as a complex of different natural ecosystems that are interconnected geographically, functionally, and historically. Therefore, it is essential to meticulously determine the interdependent

Fig. 13 GWR results at regional scale

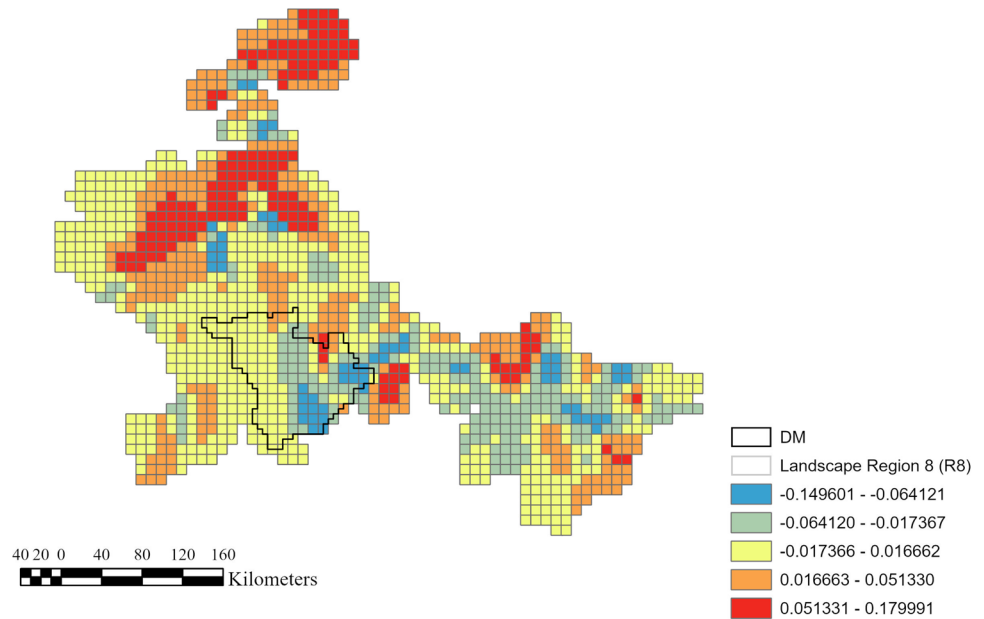
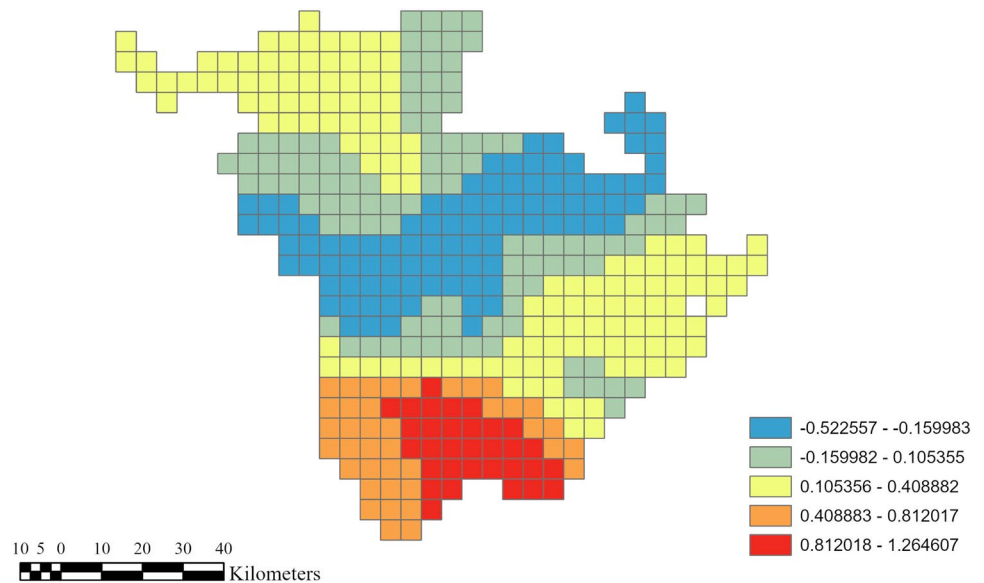


Fig. 14 GWR results at local scale



characteristics of different natural ecosystems within the landscape at macro-, meso-, and micro-scales (Doing 1997). Based on this understanding, subsequent research efforts may focus on further conducting more comprehensive analyses of the biodiversity status of landscape types, based on the interdependent characteristics of natural ecosystems (Halvorsen et al. 2020).

Conclusion

Our study proposes a multi-scale approach to define rural landscape types and their diversity in rural China. On the basis of systematic review and participatory approach,

landscape elements were preliminarily screened through GRA, and then further screened based on the scaling characteristics, resulting in the construction of a multi-scale framework of landscape elements. Based on this framework, we obtained the landscape classification results using overlapping and cluster analysis techniques. Our research complements and optimizes the previous national landscape classification at a single scale in China.

Besides, we proposed an integrated LDI calculation method that incorporates multiple landscape elements. Furthermore, we investigated the relationship between LDI and RS and demonstrated that the direction and magnitude of influence of LDI on RS vary across different spatial contexts.

Table 3 Description example of 16 landscape subtypes in DM





Landscape subtype	Summarize of the landscape subtype	Landscape diversity	Photo
L(DM)-4	The terrain is diverse, from undulating plain to mountainous terrain. Gently mountainous areas, which are mainly covered with open woodland. The type of forest management is mainly timber forest, with a small amount of edible. There is a small amount of low-intensity dryland farmland between the valleys	High	
L(DM)-8	On the undulating plains, paddy and dryland crops are distributed. Some mosaic woods with significant natural value are interspersed between the fields	High	
L(DM)-9	Wheat and cotton fields on gentle hills, with some shrubland and open woodland on the edges of the farmland	High	
L(DM)-11	On the gentle hills, most of the farmland is a mixture of paddy and dryland, with dryland making up the majority, with a small amount of open woodland shrubland mosaic between the fields	Medium	

Table 3 (continued)


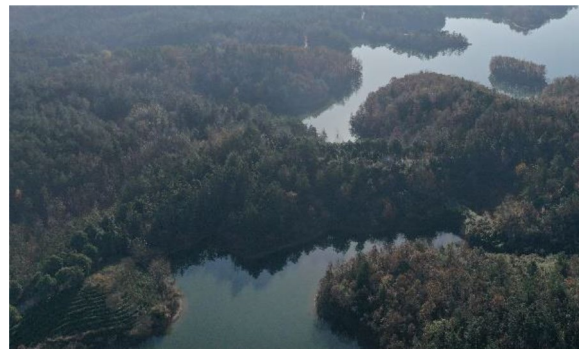

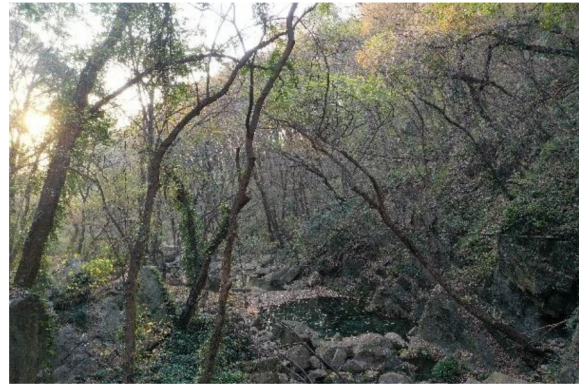



Landscape subtype	Summarize of the landscape subtype	Landscape diversity	Photo
L(DM)-12	<p>The majority of the area, which includes some orchards, is comprised of open forests on the gently sloping hills. The majority of dryland farming is cultivated with wheat and cotton. The landscape diversity is very high. This rural landscape subtype's cropland is distributed according to the hills. They are often created and maintained by several generations of farmers, using locally adapted and unique management practices and techniques. Despite having a little area, they have an exceptionally high natural value</p>	High	
L(DM)-13	<p>On the undulating plain, a varied landscape is created by shrub woodlands, small areas of low-intensity cropland, and ponded reservoirs</p>	Medium	
L(DM)-15	<p>Gently mountainous terrain with open woodland. Forest management type is mainly short rotation forest</p>	Medium	
L(DM)-20	<p>Forests having composite canopy structures that are more natural on mountainous terrain. The steep mountain terrain produces some unique natural landscapes. The main types of forest management are timber forests and soil and water conservation forests. There are some national forest parks that are currently protected by the conservation status</p>	Medium	

Table 3 (continued)

Landscape subtype	Summarize of the landscape subtype	Landscape diversity	Photo
L(DM)-25	The gently sloping mountain terrain offers open views. The forests on the mountain are mainly scenic forests with a few timber forests, including Dahongshan National Scenic Spots and Historical Sites, which contain an ancient structure spanning the Song, Yuan, Ming and Qing dynasties: the Hongshan Temple Pagoda and inscriptions	Medium	
L(DM)-31	More gently rolling hills with forest cover. The forest management type is mainly nature reserve forest. Contains one revolutionary site and revolutionary memorial building: the old revolutionary site of Jiukouyan	High	
L(DM)-36	Intensive agricultural landscape on an extremely open plain, mainly planted with cotton and rice. The landscape diversity is very low. The homogenization of crop landscape elements can pose a threat to natural ecosystems, causing species loss and also threatening soil degradation	Very low	

These findings provide valuable insights for landscape management.

As China increasingly focuses on developing large-scale ecological spatial systems that transcend administrative boundaries, the need for landscape-centric regional planning, coordination, and management has become more pronounced. This strategy aims to offer ecology-based planning solutions, contributing positively to the development of national landscapes. Integrating rural landscape classification into national spatial planning as a targeted project is essential for the sustainable development of landscape resources, thereby aiding rural revitalization.

Our study's classification results at the national scale can be integrated with the national scale overall territorial spatial planning. This integration is instrumental in defining the countrywide rural regional system and providing a foundation for strategies and principles of rural landscape development within the national territorial space. The classification results at the regional scale align with provincial-level territorial spatial planning, serving as an intermediary scale to emphasize coordination and implementation. These results offer guidance for the integration and management of rural landscape resources, as well as for shaping their spatial layout and management patterns. At the local scale, the classification results align with

county-level spatial planning, breaking down to implement objectives set at the regional landscape management level. The high precision of these classification results ensures a robust framework for the precise execution of classified management. The combined multi-scale, hierarchical classification results derived from all three scales create a comprehensive landscape resource management system, which is both divisible and transmissible across different levels.

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Author Contributions Conceptualization, YL, YZ, and XW; data curation, YL, YZ, RC, and CW; formal analysis, YL and RC; funding acquisition, XW; investigation, YL, YZ, CW; methodology, YL, YZ, and XW; project administration, XW; software, RC; supervision, XW; validation, YL and YZ; visualization, YL; writing—original draft, YL; writing—review and editing, YL, YZ, RC, CW, and XW.

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Data Availability All open access data are contained in the manuscript, appendix and supplementary files.

Declarations

Conflict of interests The authors have no relevant financial or non-financial interests to disclose.

Ethics Approval The paper is original unpublished work, and it is not under consideration for publication anywhere else. No data, text, or theories by others are presented, all relevant literature is cited.

Inform Consent All authors consent with the content of the paper. All authors consent with the publication of the paper.

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