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ORIGINAL ARTICLE

Suitability analysis for an agricultural complex development in Huangma township, Nanchang County, Jiangxi province, China

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Abstract

Existing suitability assessments for agricultural complexes lack fine-scale, objective, and integrated spatial analysis. For this suitability analysis, Huangma township in Nanchang, Jiangxi, was selected as the research area. A total of 13 villages and 2 communities under its jurisdiction were used as the basic units. A multidimensional evaluation index system was constructed, encompassing four dimensions—landscape suitability, rural suitability, facility convenience, and construction suitability—and incorporating 19 evaluation factors, including terrain features, proximity to water bodies, normalized difference vegetation index, historical and cultural resources, public service facilities, economic vitality, and population density. The study employed the hierarchical entropy weight method, which combines the analytic hierarchy process and the entropy weight method for index weighting. The weighted sum method and spatial overlay analysis, utilizing a geographic information system, were employed to derive the comprehensive suitability score. Results indicate that construction suitability is the primary factor influencing the site selection of the agricultural complex in Huangma, with economic vitality and power supply coverage having the highest weights. From the spatial pattern analysis, it was found that the areas with high suitability are concentrated in the northern and central parts of the township, while the southern area has low suitability due to weak infrastructure. Based on the comprehensive score, this study categorizes the research area into three types of regions: high-quality, potential, and weak, providing a scientific basis for future zoned development and differentiated guidance of the agricultural complex. This study not only provides methodological support for location selection and spatial planning in Huangma but also serves as a reference for other rural areas in China exploring sustainable development paths.

Keywords: Agricultural complex; Suitability evaluation; Hierarchical entropy weight method; Spatial analysis; Rural sustainable development

1. Introduction

With the continuous promotion of the rural revitalization strategy, agricultural complexes are gradually becoming important carriers for promoting urban–rural integration and agricultural modernization, serving as a new model for rural development that integrates agricultural production, rural tourism, leisure and recreation, and cultural heritage (Liu, 2018). Scientific and rational site selection and suitability evaluation for the construction of agricultural complexes not only enhance the efficiency of rural space utilization but also provide a basis for informed decision-making in subsequent policy formulation and resource allocation (Xiang *et al*., 2019). However, as rural revitalization moves from conceptual advocacy to concrete spatial implementation, there is an urgent need for fine-scale, evidence-based planning tools that can translate national strategies into operable spatial decisions.

Agritourism, formed by the integration of tourism and agriculture (W. Zhang, 2011), offers advantages such as promoting sustainable agricultural development, increasing farmers' income, and reducing farm operational risks. This may become a key strategy for revitalizing agriculture and achieving high-quality development (Cai *et al*., 2017). Regional factors such as available resources and economic development levels influence agritourism site selection, visitor flow, and project planning. Existing research has examined key determinants of agritourism spatial distribution, including proximity to urban areas, major transportation routes, and rivers, as explored by Bagi & Reeder (2012), Baskerville (2022), Sun & Hou (2021), Gong *et al*. (2020), and Xu (2016). While these studies provide valuable insights into agritourism distribution patterns, they fall short in offering comprehensive suitability evaluation frameworks that can guide site selection decisions in specific regional contexts. This gap is particularly pronounced for agricultural complexes, which require a multi-criteria assessment that integrates ecological, economic, and social dimensions.

Geographic information systems (GIS) are emerging as vital decision support tools for addressing complex spatial challenges in tourism studies. Some scholars employ GIS software as the core spatial analysis method, complemented by mathematical models to conduct factor analysis, correlation studies, spatial site selection, evaluation system development, and potential assessment. Examples include the works of Jiang and Wang (2018), Van Der Merwe *et al*. (2013), and Moore *et al*. (2018). Relevant research in China has primarily focused on Grade A scenic spots, rural leisure resources, and tourism infrastructure, with limited attention to agritourism site selection at the county scale. Most GIS-based studies emphasize the description of spatial patterns rather than comprehensive suitability evaluation, typically using coarse resolutions (100–1,000 m) and relying on subjective weighting schemes (M. Li *et al*., 2020; Z. Liu & Li, 2017; Y. Wang & Zhu, 2019; Q. Wu *et al*., 2017). In addition, existing analyses of family farms and pastoral landscapes are mostly conducted at provincial or municipal levels (Ju *et al*., 2018; Xia *et al*., 2018; Xiong *et al*., 2021; Yuan *et al*., 2016), making it difficult to capture the heterogeneity of township-scale spatial dynamics, where policy implementation and land-use decisions actually occur. This scale mismatch between research and practice underscores the need for a fine-resolution, multi-criteria framework tailored to county-level contexts.

However, several critical research gaps remain. While comprehensive evaluation frameworks exist, their direct application to county-level agricultural complexes in urban–rural integration zones remains limited; yet, this is precisely the spatial scale at which rural revitalization policies are implemented, and investment decisions are made. Moreover, systematic integration of objective weighting methods (analytic hierarchy process [AHP]–entropy) with high-resolution GIS analysis remains limited at the township scale, resulting in frameworks that either overemphasize expert judgment or neglect data-driven consistency. Furthermore, empirical evidence on the suitability of agricultural complexes in inland peri-urban contexts of China is sparse, hindering cross-regional generalization and calibration of existing coastal-based findings.

To address these gaps, Huangma township, located in Nanchang, Jiangxi, serves as an exemplary peri-urban area where ecological, cultural, and infrastructural attributes coexist. To accurately identify the suitable development areas of the agricultural complex in the region, this study uses the 13 administrative villages and two communities under the jurisdiction of Huangma township as the basic evaluation unit, and constructs a multi-indicator evaluation system that includes four dimensions: landscape suitability, rural suitability, facility convenience, and construction suitability. The selected indicators encompass the natural environment, cultural resources, public services, and development potential, reflecting the comprehensive characteristics of integrating production and village functions, as well as the integration of production, living, and ecological spaces within agricultural complexes (Long *et al*., 2018) (Figure 1). In terms of methodology, this study introduces the AHP–entropy method to objectively assign index weights. This method combines the logical modeling capabilities of subjective hierarchical analysis on a structural level with the objective data discrimination advantage of the entropy method, effectively reducing human bias and enhancing the scientific rigor and practical applicability of the evaluation system (Niu *et al*., 2022;

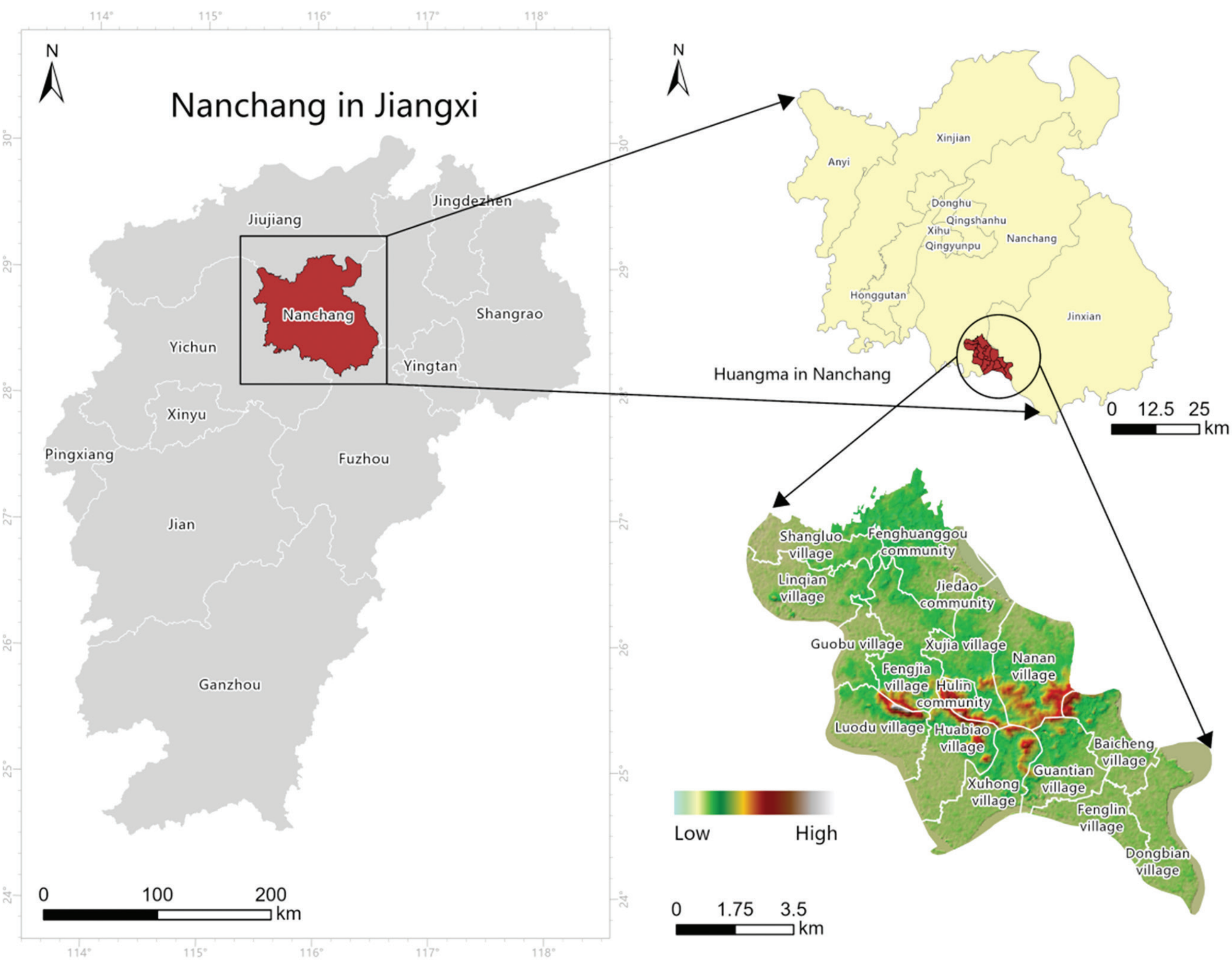

Figure 1. Map of the study area
Source: Map by the authors

Zhou *et al*., 2007). The suitability scores are weighted and summed, and the results are visualized using GIS-based spatial analysis. This study not only provides a basis for planning and site selection of the agricultural complex in Huangma township, Nanchang, but also offers a theoretical and technical path for other similar regions to follow when conducting suitability analyses for agricultural complex construction. This study makes three key contributions to the literature:

(i) Methodologically, it demonstrates a systematic integration of AHP–entropy weighting with GIS-based spatial analysis, offering a replicable template for township-scale assessments in data-constrained contexts where sample sizes are necessarily limited by administrative units.

(ii) Empirically, it provides county-level evidence from an inland peri-urban context (Jiangxi), complementing existing studies predominantly focused on coastal or developed regions, and documents how infrastructure constraints may dominate suitability patterns in transitional zones.

(iii) Practically, it establishes an operational assessment workflow balancing methodological rigor with practical feasibility, enabling rapid preliminary screening for subsequent detailed planning in similar urban–rural integration areas.

Unlike previous studies that primarily focused on descriptive spatial patterns or single-dimension analysis, this research advances the field by (i) developing an integrated four-dimensional evaluation system specifically designed for agricultural complexes; (ii) introducing objective weight determination through the AHP–entropy method to minimize human bias; and (iii) demonstrating the applicability of this framework in urban–rural integration contexts. The findings offer both immediate practical value for Huangma township's planning decisions and a generalizable methodological template for assessing the development of regional agricultural complexes.

2. Related work

In recent years, with the continuous promotion of the concept of agricultural complexes, the academic and practical sectors have conducted in-depth research on site selection and suitability analysis, gradually forming a more mature research framework. This study primarily discusses the construction of the evaluation index system, the suitability evaluation method, and their practical applications.

2.1. Selection of indicators for suitability evaluation

As a spatial complex for the integrated development of "agriculture + tourism + culture + community," the evaluation of its suitability involves multidimensional factors. Existing studies have generally constructed indicator systems from four dimensions: natural ecological conditions, socioeconomic foundation, infrastructure level, and cultural tourism resources (He *et al*., 2018; Xiang *et al*., 2019). Commonly used indicators include topographic relief, vegetation cover, and water body proximity in the ecological category, population density, nighttime light intensity, and Gross Domestic Product in the economic category, road density and distribution of public service facilities in the facility category, and historical and cultural resources, as well as the distribution of tourist attractions in the cultural category.

2.2. Evaluation methods

In terms of suitability evaluation methods, the mainstream methods can be categorized into subjective and objective assignment methods, as well as combined weighting methods that integrate both. These methods include AHP, entropy weight method, gray correlation method, the Technique for Order of Preference by Similarity to Ideal Solution, fuzzy comprehensive evaluation method, cloud modeling, and multi-criteria decision-making (Guo, 2007; Zhou *et al*., 2007). Among them, the hierarchical entropy weight method has been widely used in the comprehensive evaluation of agricultural complexes, multifunctional agricultural spaces, and rural development, as it can balance structural logic and data objectivity. For example, in the study on the suitability of agricultural complexes conducted by Z. Wang *et al*. (2022) in Chengjiang town, Chongqing, the combination of AHP and entropy weight method was used to determine the weights, which improved the scientific validity and reliability of the results.

2.3. Practical application and case study

Several studies have applied suitability evaluation to spatial planning, construction site selection, and policy formulation, and achieved remarkable results. For example, Feng *et al*. (2020) combined a backpropagation neural network and a hierarchical clustering method to study the spatial zoning of suitability levels in different regions of Jiangsu, providing a visual basis for decision-making in the construction of an agricultural complex. In addition, some studies have combined local characteristics and proposed various development paths for agricultural complexes, such as "landscape idyllic," "cultural tourism," and "leisure and recreation," which have promoted classified guidance and differentiated development (W. Li *et al*., 2021).

In summary, current suitability analyses of agricultural complexes have established evaluation systems supported by multidimensional indicators, empowered by composite methods, and integrated with GIS platforms. However, most studies still face challenges related to coarse evaluation granularity and insufficient consideration of spatio-temporal dynamic changes. Consequently, refined suitability evaluations based on high-resolution data and geospatial analysis hold substantial potential for further development.

3. Methods

The methodological flowchart is shown in Figure 2.

As shown in Figure 2, the indicator system was designed and classified according to three main steps: (i) design and grading of the indicator system, (ii) hierarchical entropy analysis, and (iii) application of the weighted summation method.

3.1. Data source

The data, preprocessing methods, and application metrics used for the experiments are presented in Table 1, where all metric rasters were harmonized to a 10 m resolution.

The point of interest (POI) data for this study were sourced from the Gaode Open Platform (https://lbs.amap.com/), which provides geographical location data for various public facilities, such as restaurants, commercial outlets, and medical services. The data encompassed the year 2023 for Huangma township. To ensure the accuracy and reliability of the dataset, the following steps were taken: duplicate records were removed based on geographic coordinates, and a sample of key facilities was manually verified against high-resolution satellite imagery and local government directories. This verification process ensured the credibility of the data. Additionally, the POI data were processed at a 10-m spatial resolution to align with the study's analysis framework.

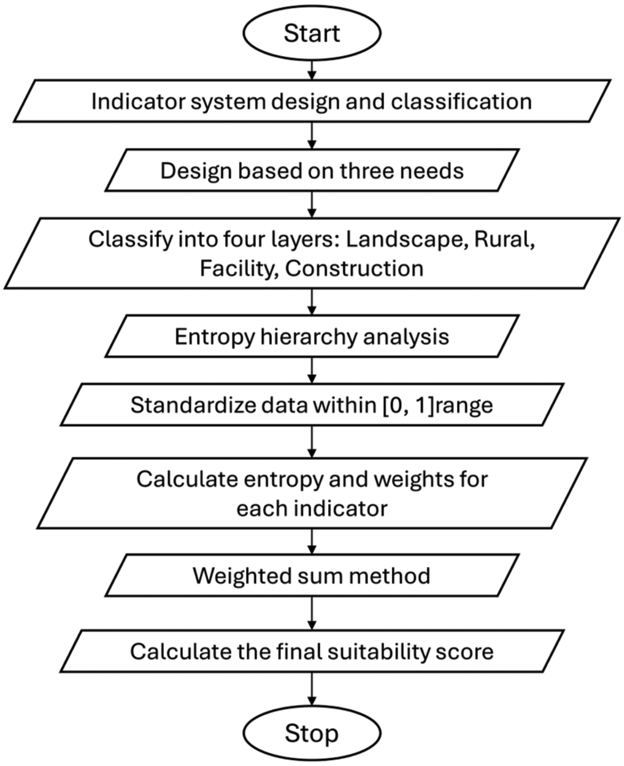

Figure 2. Technical flowchart of the suitability evaluation framework
Source: Flowchart by the authors

3.2. Design and grading of the indicator system

To assess the construction suitability of the Huangma agricultural complex, this study developed a comprehensive indicator system based on the key characteristics of the agricultural complex's construction, drawing on relevant literature and considering landscape, countryside, facility convenience, and construction suitability. The index system is divided into four levels: landscape suitability, rural suitability, facility convenience, and construction suitability (Bian *et al*., 2025). Landscape suitability, as one of the core factors in the construction of agricultural complexes, encompasses a range of aspects, including mountain height characteristics, proximity to water, scenic beauty, vegetation coverage, and terrain diversity. In this township-scale screening, we introduced satellite-derived photosynthetically active radiation (PAR) as a meso-scale ecological energy proxy that complements landscape and construction constraints.

While PAR cannot capture tree-level irradiance or microclimate conditions essential for garden-scale design (Clementi *et al*., 2024), it provides a spatially complete and temporally consistent screening layer for identifying areas with favorable light conditions. At the township scale, PAR primarily serves to distinguish heavily shaded built-up areas from open agricultural or natural landscapes, adding an ecological energy dimension that complements traditional vegetation indices.

These factors can reflect the advantages of a region in terms of natural landscape, ecological environment, and tourism development potential. For example, mountain height characteristics and proximity to water have a direct impact on the natural landscape and ecological environment of a region. Vegetation cover reflects the ecological quality of a region, while terrain diversity provides diversified land use and agricultural production possibilities. In terms of rural suitability, proximity to historical monuments, proximity to folk squares, climatic environmental quality, and water environmental quality were the main indicators selected. The proximity of historical monuments and folk plazas reflects Hungama's advantages in cultural and tourism resources. Meanwhile, the climate and water environment quality directly affect the region's agricultural production and ecological environment, which are the basic conditions for the sustainable development of agricultural complexes. In terms of facility convenience, the five indicators of road proximity, public facility proximity, medical facility proximity, dining facility proximity, and commercial facility proximity are able to effectively measure the state of infrastructure construction in the region. The development and quality of transportation and public service facilities directly affect the quality of life for residents and tourists' experiences. Meanwhile, the accessibility to medical, catering, and commercial facilities can promote the organic integration of agriculture and tourism, thereby improving the comprehensive attractiveness of agricultural complexes.

Finally, the construction suitability layer focused on factors such as economic vitality, power supply coverage, degree of congestion, and degree of view obstruction, evaluating the region's advantages for building infrastructure and economic development. Regions with high economic vitality can provide the necessary financial support and market demand for agricultural complexes, while ensuring adequate electricity supply coverage is crucial to support agricultural production and the quality of life for residents. Lower levels of crowding and view obstruction can help improve the ecological quality of the region and create a good living and working space. In summary, the index system designed in this study encompasses multiple dimensions, including landscape resources, rural culture, infrastructure, and economic development, and is capable of providing a comprehensive evaluation of the suitability for constructing an agricultural complex in Huangma township. Through the comprehensive analysis of these factors, planners can be provided with a scientific basis for informed decision-making, promoting the sustainable development of the township's agricultural complex. Specific indicators are shown in Table 2.

Table 1. Data preprocessing methods and application indicators

Data	Indicator	Data description	Time period	Preprocessing method	Resolution
DEM (ASF/JAXA ALOS-1 12.5 m)	Mountain	Global 12.5 m DEM (except Antarctica, Greenland, Iceland, North Eurasia)	2006–2011	Reproject to project CRS; resample to 10 m (bilinear)	12.5 m
Lakes and rivers (NGIRCS 1:250,000)	Proximity to water bodies	National basic geographic database—water polygons and lines	2015	Computed the Euclidean distance to the nearest water within the township and exported a 10 m raster	10 m
Scenic spots (Gaode POI)	Distance to scenic spot	POI crawled for Huangma township	2023	Clean duplicates; compute Euclidean distance to the nearest scenic spot using a 10 m raster	10 m
Photosynthetically active radiation index	Photosynthetically active radiation	MCD18A1 (Daily, 500 m)	2023	Aggregate data on the Google Earth Engine platform daily, then calculate the 2023 average	500 m
NDVI (Sentinel-2 L2A)	Vegetation cover	Sentinel-2 multispectral; NDVI=(B8−B4)/(B8+B4)	2023	Cloud and shadow mask (S2_ CLOUD_PROBABILITY); annual median composite; resample to 10 m	10 m
ALOS topo diversity (Theobald *et al.*, 2015)	Topographic diversity	270 m proxy for the diversity of geomorphic–climatic niches	2015	Reproject; resample to 10 m (bilinear); used as continuous covariate	270 m
Historic monuments (Gaode POI)	Proximity of historical monuments	POI crawled for Huangma township	2023	De-duplicate; Euclidean distance to nearest monument; 10 m raster	10 m
Folk square (Gaode POI)	Proximity of the folk square	POI crawled for Huangma township	2023	De-duplicate; Euclidean distance to nearest plaza; 10 m raster	10 m
Aerosol optical depth (Lyapustin & Wang, 2022)	Air quality	MAIAC aerosol optical depth over land (blue band). Larger values=worse air quality	2023	Resampling to 10 m resolution	1 km
NDTI (USGS Landsat 8 L2)	Water quality	NDTI = (Red−Green)/(Red+Green) (B4, B3).	2023	Cloud/water mask; annual median; output 10 m (resampled from 30 m, bilinear)	10 m
Roads (NGIRCS 1:250,000)	Road proximity	National basic geographic database—roads layer	2015	Euclidean distance to nearest road within township; 10 m raster	10 m
Public facilities (Gaode POI)	Proximity to public facilities	POI crawled for Huangma township	2023	De-duplicate; Euclidean distance; 10 m raster	10 m
Medical facilities (Gaode POI)	Proximity to medical facilities	POI crawled for Huangma township	2023	De-duplicate; Euclidean distance; 10 m raster	10 m
Drinking facilities (Gaode POI)	Proximity of dining facilities	POI crawled for Huangma township	2023	De-duplicate; Euclidean distance; 10 m raster	-
Commercial facilities (Gaode POI)	Proximity of commercial facilities	POI crawled for Huangma township	2023	De-duplicate; Euclidean distance; 10 m raster	-
GDP (Zhao *et al.*, 2017)	Economic vitality	1 km GDP raster disaggregated via VIIRS+LandScan	2020	Reproject; resample to 10 m (bilinear) for overlay/normalization	1 km
Nighttime lights (VIIRS VNL V2)	Power supply coverage	VIIRS nighttime lights (~500 m)	2023	Annual mean; reproject and resample to 10 m (bilinear)	500 m
Population count (Bondarenko *et al.*, 2020)	Crowding	Estimated total number of people per grid cell, in people per pixel	2020	Choose constrained/unconstrained version; reproject; resample to 10 m (bilinear)	100 m
Building height (Che *et al.*, 2024)	Visual obstruction	Global three-dimensional building footprint/height	2023	Convert footprints to raster by max height; clip to township; output 10 m raster	10 m

Abbreviations: ALOS: Advanced land observing satellite; ASF: Alaska satellite facility; CRS: Coordinate reference system; DEM: Digital elevation model; GDP: Gross Domestic Product; NDTI: Normalized difference tillage index; NGIRCS: National Geographic Information Resources Census System; POI: Point of interest

Table 2. Design of the suitability index system for the construction of agricultural complexes

Criteria	Factor
Landscape suitability (B1)	Mountain height characterization (C1+)
	Water body proximity (C2+)
	Scenic spot proximity (C3+)
	Vegetation cover (C4+)
	Topographic diversity (C5+)
	Photosynthetically active radiation (C6+)
Rural suitability (B2)	Proximity of historical monuments (C7+)
	Proximity to folk plazas (C8+)
	Climatic quality (C9−)
	Quality of water environment (C10−)
Facility convenience (B3)	Road proximity (C11+)
	Proximity to public facilities (C12+)
	Proximity to medical facilities (C13+)
	Proximity to dining facilities (C14+)
	Proximity to commercial facilities (C15+)
Construction suitability (B4)	Economic vitality (C16+)
	Electricity supply coverage (C17+)
	Congestion (C18−)
	Degree of visual field obstruction (C19−)

Note: +/− indicates that the factor is either a positive or a negative indicator

3.3. Analytic hierarchy process–entropy method

The selection of the AHP–entropy method for this study was based on several conceptual and practical considerations specific to assessing the suitability of an agricultural complex. First, the agricultural complex evaluation involved a hierarchical multi-criteria decision-making problem with a limited sample size (13 administrative villages and two communities), where both expert knowledge about indicator structure and objective data characteristics must be considered. Second, the method must strike a balance between incorporating domain expertise regarding indicator relationships and minimizing subjective bias in weight assignment.

Compared to alternative multi-criteria decision-making approaches, AHP–entropy offers distinct advantages for this context. Unlike the Technique for Order of Preference by Similarity to Ideal Solution, which excels at alternative ranking but lacks explicit consideration of hierarchical structure, AHP–entropy naturally accommodates the nested indicator framework inherent in agricultural complex evaluation. While fuzzy logic approaches effectively handle uncertainty, they introduce computational complexity that is unnecessary in our deterministic, small-sample context, where data quality is relatively high. Moreover, machine learning methods require substantial training datasets to establish reliable patterns, whereas our study involved only 15 evaluation units, which is insufficient for robust model training and validation. Additionally, pure AHP methods, although structurally appropriate, suffer from excessive subjectivity that can compromise the credibility of the evaluation. Pure entropy methods, conversely, ignore the logical relationships among indicators and expert domain knowledge.

The AHP–entropy integration specifically addresses these limitations by (i) utilizing AHP's hierarchical decomposition capability to structure the complex evaluation system systematically, (ii) employing entropy weighting to objectively calibrate indicator importance based on data variability, thereby reducing human bias, (iii) maintaining methodological transparency and replicability essential for policy application, and (iv) achieving computational efficiency suitable for small-sample regional assessments. This hybrid approach is particularly well-suited for urban–rural integration zone planning where scientific rigor must be balanced with practical applicability.

Overall, the AHP–entropy approach is a widely used objective weighting method that can effectively reflect the importance of each index within the system (R. Wu *et al.*, 2022). Using hierarchical entropy analysis to determine the weight of each indicator can not only reduce the subjective arbitrariness inherent in assigning indicator weights for agricultural complex suitability evaluations, but also effectively address the problem of overlapping information among multiple indicator variables.

There are several assessment units, each with multiple evaluation indicators, and a matrix of rating indicator characteristics, the calculation of which is presented in Equation (1):

$$x = \left(x_{ij}\right)_{mn} = \begin{bmatrix} x_{11} & \cdots & x_{1n} \\ \vdots & \vdots & \vdots \\ x_{m1} & \cdots & x_{mn} \end{bmatrix} \# \quad (1)$$

The raw data were standardized to be within the intervals to be comparable, and the standardization calculations are shown in Equations (2) and (3):

$$x_{ij} = \frac{\left(x_{ij} - \min\left(x_{ij}\right)\right)}{\left(\max\left(x_{ij}\right) - \min\left(x_{ij}\right)\right)} \# \quad (2)$$

$$x_{ij}^{'} = \frac{\left(\max\left(x_{ij}\right) - \left(x_{ij}\right)\right)}{\left(\max\left(x_{ij}\right) - \min\left(x_{ij}\right)\right)} \# \quad (3)$$

In the formulas, max (x_{ij}) and min (x_{ij}) are the maximum and minimum values of the first indicator value of the first unit to be evaluated, respectively. The obtained matrix is shown in Equation (4):

$$x_{ij}^{'} = \begin{bmatrix} x_{ij}^{'} & \dots & x_{\ln}^{'} \\ \vdots & \vdots & \vdots \\ x_{ml}^{'} & \dots & x_{mn}^{'} \end{bmatrix} \# \quad (4)$$

In Equation (5), e_i is the entropy of the ith evaluation indicator, and p_{ij} is the weight of the eigenvalue of the first indicator in the unit to be evaluated.

$$e_i = -\frac{1}{\ln n}\sum_{j=1}^{1} p_{ij} \ln p_{ij} \# \quad (5)$$

The calculation of the entropy weight of the first evaluation indicator is shown in Equation (6):

$$w_i = \frac{\left(1-e_i\right)}{\sum_{i=1}^{1}\left(1-e_i\right)} \# \quad (6)$$

3.4. Weighted sum method

We employed a two-level weighted sum consistent with the guideline-indicator hierarchy. For each analysis unit p, the composite suitability score is computed as shown in Equation (7):

$$S(p) = \sum_{j=1}^{m} v_j \left(\sum_{i=1}^{n_j} w_{j,i} z_{j,i}(p) \right) \# \quad (7)$$

where $m = 4$ denotes the four guideline layers (landscape, rural, facility, and construction) with outer weights v_j satisfying $\sum_j v_j = 1$. Within each guideline j, there are n_j indicators (in total $\sum_j n_j = n = 14$) with within-guideline weights $W_{j,i}$ normalized such that $\sum_{i=1}^{n_j} w_{j,i} = 1$. The term $z_{j,i}(p)$ is the standardized (0−1) value of the indicator i under guideline j for unit p after benefit/cost transformation and min–max scaling.

Thus, the inner sum produces a guideline-specific subscore as a convex combination of its indicators, and the outer sum aggregates these subscores using the guideline weights. For clarity, if for unit p the landscape guideline has $v_L = 0.30$ and two indicators with $w_{L,1} = 0.60$ and $w_{L,2} = 0.40$, as well as standardized values of $z_{L,1}(p) = 0.80$ and $z_{L,2}(p) = 0.50$, then the landscape contribution equals to $0.30 \times (0.60 \times 0.80 + 0.40 \times 0.50) = 0.204$. The remaining three guidelines are computed analogously and summed to obtain $S(p)$. This formulation explicitly distinguishes the guideline-level weights v_j from the indicator-level weights $w_{j,i}$, resolving the ambiguity in the earlier notation.

3.5. Sensitivity and validation analysis

To evaluate the robustness and validity of the suitability results, we performed both deterministic sensitivity tests and comparative validations. Robustness to weight uncertainty was assessed through weight-perturbation experiments on the four normative layers (B1: landscape, B2: rural, B3: facility, and B4: construction). For each layer in turn, we applied ±10% multiplicative shocks to its weight, while renormalizing all weights to sum to one, yielding a total of eight perturbation scenarios. For every scenario, we recomputed the composite suitability surface on the full study grid and performed two complementary validations against the baseline: (i) rank stability, measured by Spearman's ρ between baseline and perturbed pixel-wise scores, and (ii) spatial stability, measured by the Jaccard index of the top-10% high-suitability zones. Across all scenarios, Spearman's ρ remained above 0.998, and Jaccard indices exceeded 0.95, indicating exceptionally high robustness of the ranking and spatial prioritization.

Beyond weight perturbations, three additional consistency checks were conducted to approximate expert validation and to ensure that the findings are not artifacts of particular modeling choices. First, the hierarchical structure and indicator relationships were derived from established frameworks in agritourism and rural suitability assessment, providing conceptual alignment with domain knowledge. Second, the internal validity of the hybrid AHP–entropy weighting was confirmed by the strong agreement between the subjective (AHP) and objective (Entropy) weight sets (mean cosine similarity >0.96), comparable to expert consensus levels reported in previous AHP–entropy applications. Third, cross-study comparison showed that the spatial ranking of top-suitability villages (e.g., northern core clusters) coincided with empirical development priorities documented in official county planning and in prior agritourism cases across Jiangxi, constituting an indirect but meaningful external validation.

Additionally, conceptual sensitivity checks were conducted for alternative standardization functions, classification rules, and spatial resolutions. Replacing min–max normalization with z-score or quantile normalization preserved ordinal rankings. Substituting Jenks' natural breaks with equal-interval classification marginally shifted class boundaries without altering the identity of top-ranked zones, and resampling tests (10 m ↔ 30 m) yielded consistent pattern structures. These combined results demonstrate that the model's outputs are theoretically grounded, internally consistent, and externally plausible, thereby providing a reliable empirical basis for subsequent spatial and policy analyses.

4. Results

4.1. Weight analysis of system indicators

Based on the calculation results of entropy weighting (Table 3), it can be seen that in the guideline layer, the weight distribution of each indicator reflects the evaluation system's focus on the suitability of constructing agricultural complexes in Huangma township. Among them, the weight of construction suitability (B4) was the highest, at 0.3441, indicating that in the process of constructing an agricultural complex, construction conditions such as infrastructure and economic vitality play a crucial role. Huangma township is located in the urban–rural junction zone, and the development of its agricultural complex relies on a stable power supply, economic and industrial support, and a reasonable land layout to ensure the sustainable operation of the complex. Therefore, in this study, the construction suitability factor becomes a key factor influencing the overall suitability. Secondly, the weight of landscape suitability (B1) was 0.3047. Facility convenience (B3) ranked third with a weight of 0.2382, indicating that convenient public service facilities make a tangible contribution to rural quality of life and tourism reception capacity. Rural suitability (B2) showed a lower weight (0.1130), implying that while cultural heritage and rural ambience remain important, they play a relatively smaller role than infrastructure- and service-related conditions in this case.

Table 3. Hierarchical entropy analysis method for evaluating the suitability of the construction of agricultural complexes

Normative layer	Weights	Factorial	Weights
Landscape suitability (B1)	0.3047	Mountain height characterization (C1+)	0.0139
		Water body proximity (C2+)	0.0773
		Scenic spot proximity (C3+)	0.0548
		Vegetation cover (C4+)	0.0158
		Topographic diversity (C5+)	0.0674
		Photosynthetically active radiation (C6+)	0.0755
Rural suitability (B2)	0.1130	Proximity of historical monuments (C7+)	0.0545
		Proximity to folk plazas (C8+)	0.0584
		Climatic quality (C9−)	0.0232
		Quality of water environment (C10−)	0.0018
Facility convenience (B3)	0.2382	Road proximity (C11+)	0.0697
		Proximity to public facilities (C12+)	0.0475
		Proximity to medical facilities (C13+)	0.0370
		Proximity to dining facilities (C14+)	0.0397
		Proximity to commercial facilities (C15+)	0.0443
Construction suitability (B4)	0.3441	Economic vitality (C16+)	0.1458
		Electricity supply coverage (C17+)	0.1480
		Congestion (C18−)	0.0046
		Degree of visual field obstruction (C19−)	0.0207

Note: +/− indicates that the factor is either a positive or a negative indicator

In the factor layer, after ranking the weights of the 19 specific evaluation indicators, it was evident that electricity supply coverage (0.1480) and economic vitality (0.1458) were the two most significant influential indicators. The construction of agricultural complexes requires not only a beautiful natural environment, but more importantly, a solid economic foundation and reliable energy coverage. The level of economic development and industrial support capacity of Huangma township directly affects the operational suitability of the complex, while the stability of the power supply determines the efficiency of the modern facilities in the park. Hence, these two indicators carried the highest weight in the evaluation system, which aligns with the demand for the integrated development of "industry + ecology + countryside" in the agricultural complex. Secondly, proximity to water bodies (0.0773), road proximity (0.0697), and topographic diversity (0.0674) exhibited higher weights, indicating that the natural landscape and accessibility to transportation have a significant impact on the location and development of agricultural complexes. PAR (0.0755) also showed a notable contribution within the landscape dimension, highlighting the relevance of vegetation-level light conditions to garden performance.

The weights of proximity to scenic spots (0.0548) and proximity to historical monuments (0.0545) suggest that cultural and tourism resources play a significant role in the development of agricultural complexes. As a traditional rural area, Huangma township is rich in surrounding historical relics and scenic spots. If these cultural resources can be reasonably utilized, they can enhance the characteristics and attractiveness of the agricultural complex, thereby strengthening the sustainable development of rural tourism.

It is worth noting that the weights of climatic environmental quality (0.0232) and water environmental quality (0.0018) were relatively low, suggesting that although these environmental factors are important in evaluating agricultural complexes, they exerted a smaller influence in the present study area compared with economic and infrastructural factors. This may be because the overall environmental quality of Huangma township is good and ecological conditions are relatively stable; therefore, these variables are not binding constraints for siting at the current scale.

In addition, the lower weights of crowding degree (0.0046) and visual obstruction degree (0.0207) indicated that, in this low-density rural context, the influence of perceived crowding and viewshed blockage is limited; the broader rural landscape already meets visitors' landscape expectations, making these factors secondary relative to accessibility and construction conditions.

4.2. Spatial analysis of integrated evaluation findings

The normalized individual factors are shown in Figures 3-6, where all factor scores are standardized to a unitless 0–1 scale through the normalization procedure. The legend gradients represent relative suitability levels, ranging from low (approaching 0) to high (approaching 1), rather than absolute physical measurements. All the factor layers were weighted according to the weights computed in Section 4.1 to obtain Figure 7. In the following, we expanded the discussion on the single factors as well as the weighted composite suitability.

4.2.1. Analysis of single-factor spatial distribution pattern

From the single-factor distribution maps in Figures 3-6, it is evident that there are significant differences among Huangma township's sub-areas in each of the landscape suitability, rural suitability, facility convenience, and construction suitability factors. Figure 3 shows the spatial distribution of mountain height characteristics, water proximity, landscape proximity, vegetation cover, topographic diversity, and the PAR index. The mountainous and low-mountain areas in the northern part of Huangma township scored higher in landscape suitability, especially

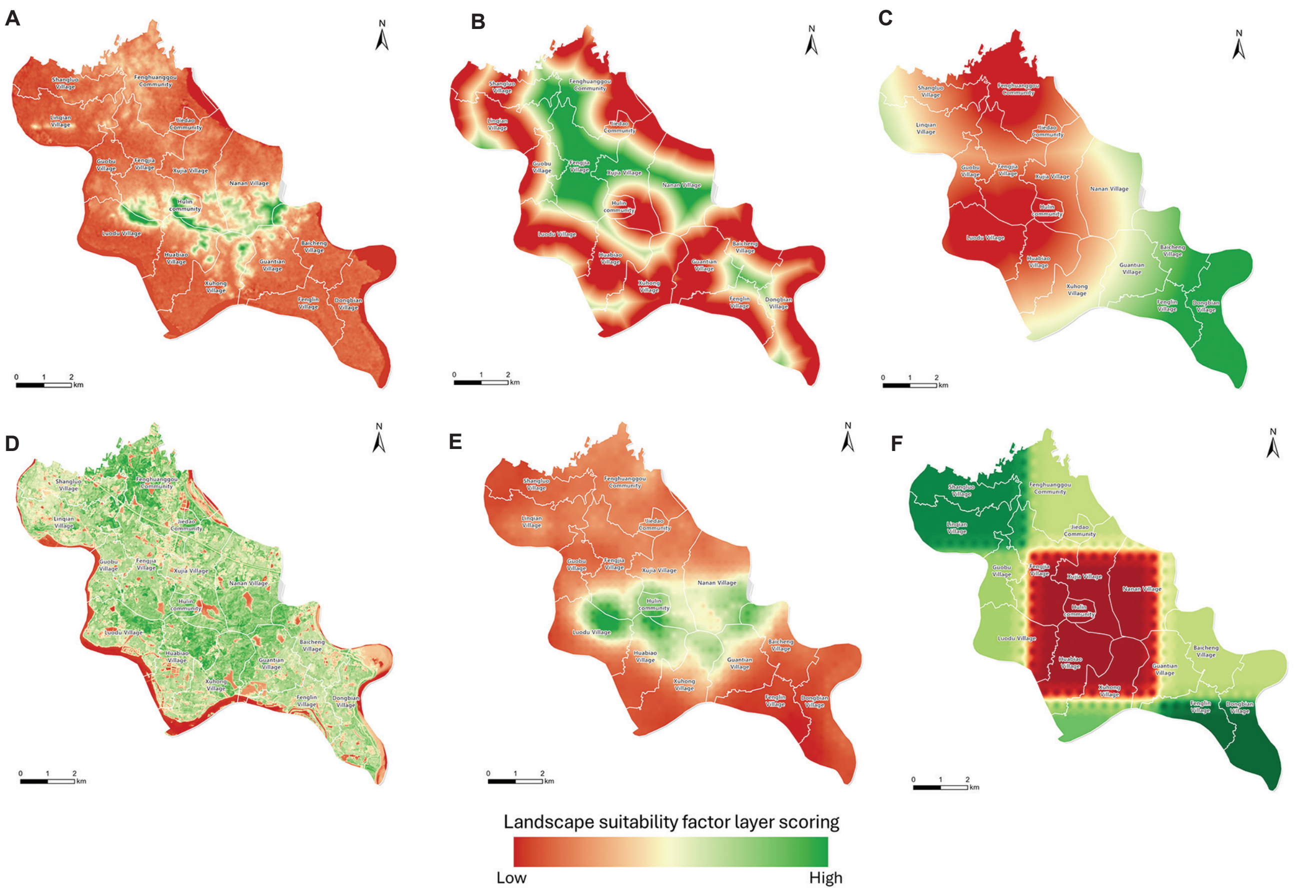

Figure 3. One-way analysis of landscape suitability for agricultural complexes. (A) Mountain height characteristics; (B) proximity to water body; (C) proximity to scenic spots; (D) vegetation cover; (E) topographic diversity; and (F) photosynthetically active radiation index
Source: Maps by the authors

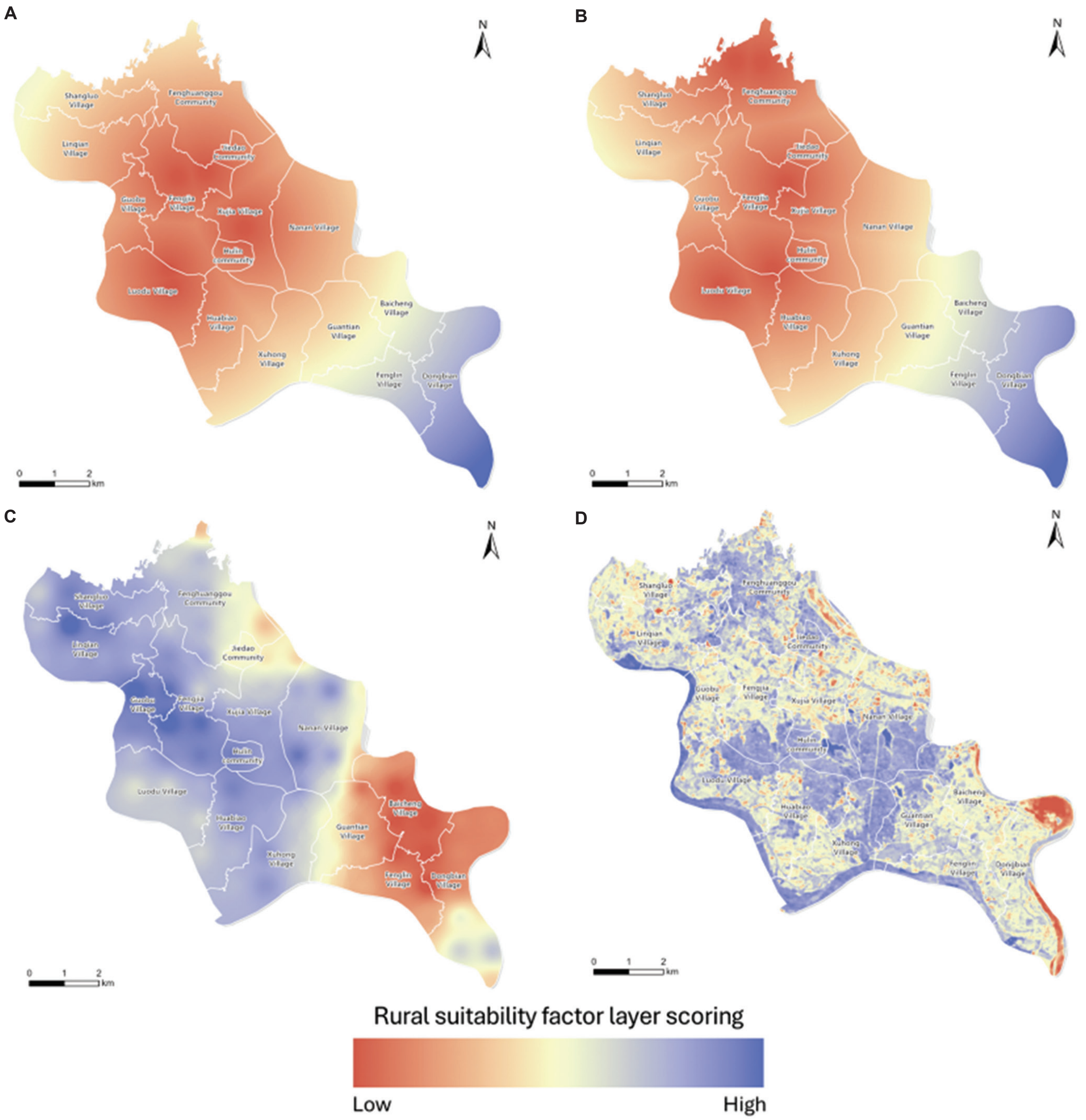

Figure 4. One-way analysis of the rural suitability of agricultural complexes. (A) Proximity to historical monuments; (B) proximity to folk square; (C) quality of the climate environment; and (D) quality of the water environment
Source: Maps by the authors

in terms of proximity to scenic spots and vegetation cover, which are concentrated in zones with better ecology and rich landscape resources. The PAR map (Figure 3F) further reveals clear light-environment heterogeneity: relatively higher PAR values occur along open terrains and river/field corridors, whereas lower PAR values appear in more shaded or built-up blocks, highlighting the importance of tree- and garden-level light conditions in the landscape dimension. Figure 4 illustrates the rural suitability factor layer, where the distributions for proximity to historical monuments and proximity to folk squares exhibited strong regional patterns, with higher scores concentrated in clusters of cultural-historic resources. Figure 5 shows the spatial distribution of proximity to transport, public

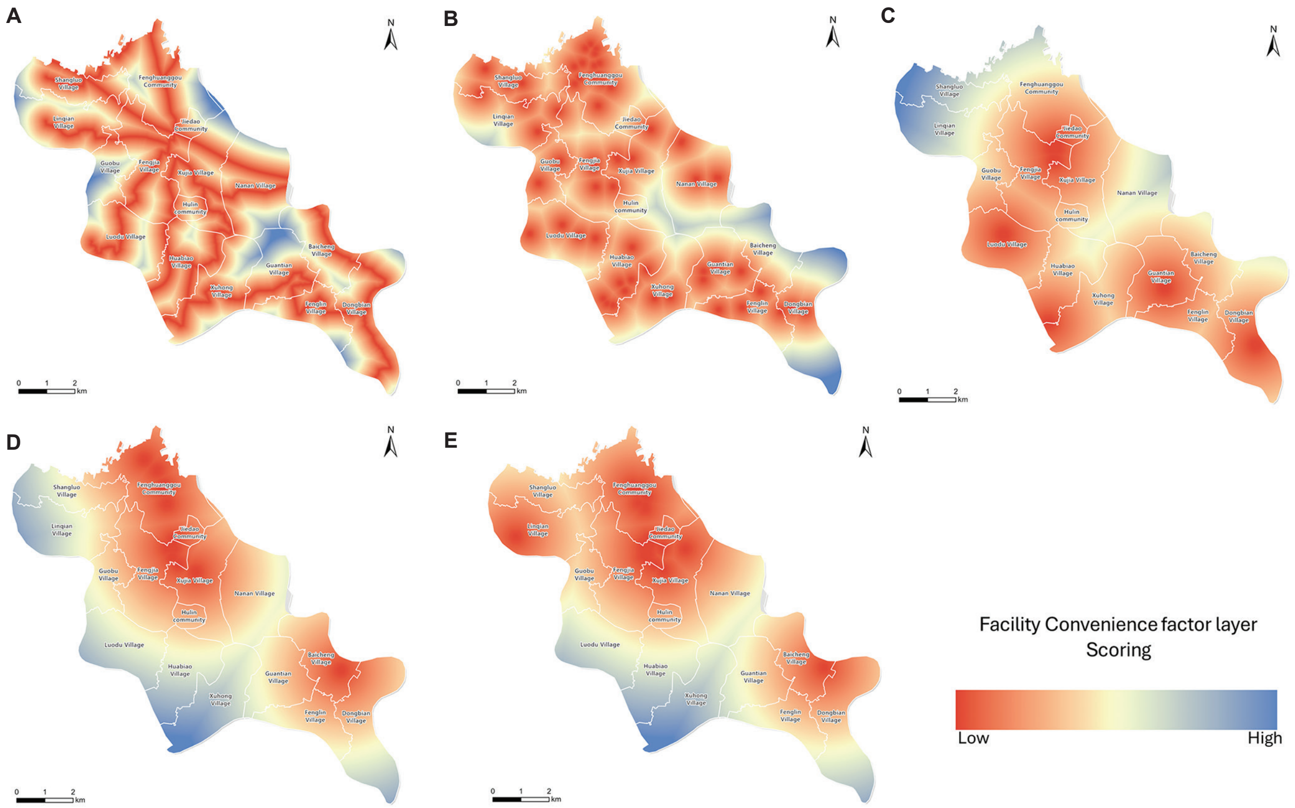

Figure 5. One-way analysis of the convenience of facilities in agricultural complexes. (A) Proximity to road; (B) utility accessibility; (C) proximity to medical facilities; (D) proximity to dining facilities; and (E) proximity to commercial facilities
Source: Maps by the authors

facilities, medical facilities, dining facilities, and commercial facilities; areas with a higher density of transport and public services clearly showed better convenience, especially in the township center and around the urban fringe. Figure 6 shows the spatial patterns of economic vitality, electricity supply coverage, congestion level, and view occlusion. Overall, areas with stronger commerce and infrastructure showed higher economic vitality and electricity coverage, while low-congestion sectors provided additional siting advantages for agricultural complexes.

4.2.2. Overall field-complex suitability analysis

Figure 7 shows the spatial distribution of comprehensive suitability scores after weighting all factors. The overall scores ranged approximately from 0.161 to 0.452 (class breaks updated in the legend), forming a clear gradient that peaks in a central belt and other pockets where multiple factors jointly perform well (economic vitality, electricity coverage, landscape resources, road accessibility, vegetation coverage, and PAR). In contrast, several peripheral sectors showed lower overall scores—typically those with weaker economic vitality and sparser infrastructure—although some still possess ecological or cultural advantages. The spatial pattern reflects both geographical constraints and historical policy priorities: northern areas benefit from mountainous terrain providing superior landscape resources (high C2, C5 scores) and proximity to county urban centers enabling better infrastructure investment, while southern peripheral villages suffer from remote locations that limit both road accessibility (low C11) and electricity grid expansion (low C17), compounded by historically lower policy resource allocation in these areas. The strong correlation between high-scoring zones and the confluence of infrastructure factors (C11, C17) with landscape factors (C2, C5, C6) demonstrates that comprehensive suitability emerges not from single-factor advantages but from synergistic combinations where accessibility enables effective utilization of ecological and cultural resources. Overall, Huangma township retains high potential for agricultural complex construction. Priority areas are those that combine strong infrastructure/energy support with high-quality landscape and PAR conditions, while lower-scoring areas could be improved through targeted enhancements in facilities, transportation, and associated rural cultural and industrial development.

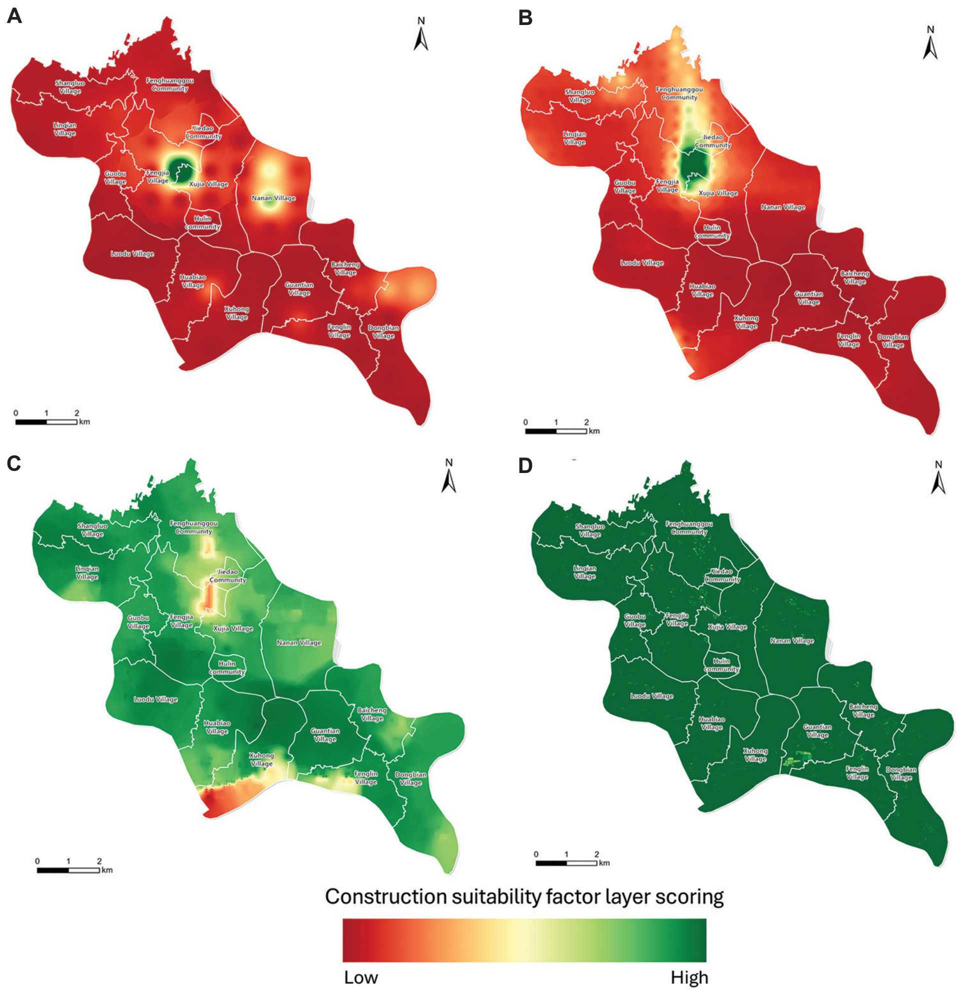

Figure 6. One-way analysis of the suitability of the construction of agricultural complexes. (A) Economic viability; (B) electricity supply coverage; (C) congestion; and (D) degree of visual field obstruction
Source: Maps by the authors

4.3. Comprehensive evaluation classification ranking

To more clearly and intuitively evaluate the suitability of each community and village in Huangma township for agricultural complexes, this study adopted a three-type classification based on the average scores of the 15 sub-administrative areas (Pan *et al*., 2025). A village was classified as high-quality if its total indicator score exceeded the overall mean across all units and at least two of the four guideline scores were above their respective means. Areas in this category exhibited overall advantages across indicators and were more suitable for agricultural complex development. Conversely, a village was classified as weak if its total score fell below the column average and at least three of the four indicators were below their respective averages. Such areas performed poorly on the indicators and may face greater construction and development challenges, resulting in lower suitability. Villages that do not meet either criterion were categorized as a potential type. These areas showed some development potential and, despite certain deficiencies, offered room for improvement and upgrading. Results are shown in Table 4.

High-quality units are units with total scores above the township mean and at least two guideline scores above their respective means. Examples include Fenglin village, Dongbian village, Nanan village, Baicheng village, Shangluo village, Linqian village, Guobu village, and Xuhong village. These areas paired stronger ecological/landscape endowments with better facilities and construction conditions, providing a solid foundation for agricultural complex development.

Weak units are units with total scores below the mean and at least three guideline scores below their means—e.g., Xujia village, Huabiao village, Luodu village, Fenghuanggou

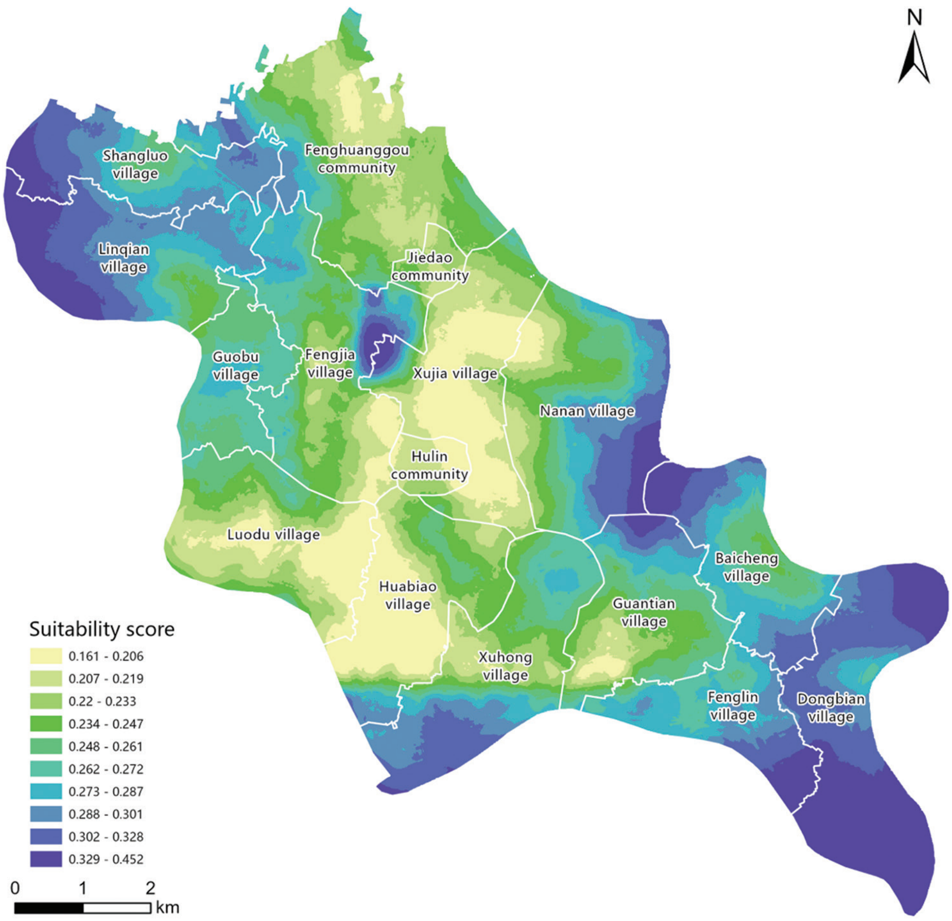

Figure 7. Distribution map of the suitability of the Huangma township for an agricultural complex
Source: Map by the authors

Table 4. Rural suitability scores for communities in Huangma township

Name	Landscape suitability score	Rural suitability score	Appropriateness of facilities	Appropriateness of construction	Total score	Type
Guantian village	0.3245	0.4154	0.2937	0.0877	0.2542	Potential
Fenglin village	0.4166	0.5406	0.2582	0.0916	0.2923	High quality
Dongbian village	0.4494	0.7041	0.3219	0.1040	0.3438	High quality
Baicheng village	0.4061	0.4554	0.2895	0.0934	0.2855	High quality
Nanan village	0.3207	0.3291	0.3188	0.1356	0.2664	High quality
Shangluo village	0.3994	0.3912	0.3340	0.1202	0.2937	High quality
Linqian village	0.4090	0.3994	0.3478	0.1163	0.2997	High quality
Guobu village	0.3540	0.2932	0.3325	0.1109	0.2630	High quality
Xujia village	0.2707	0.2314	0.2062	0.1590	0.2142	Weak
Fengjia village	0.3822	0.2206	0.1813	0.1861	0.2495	Potential
Xuhong village	0.2765	0.4015	0.4000	0.0934	0.2645	High quality
Huabiao village	0.2230	0.2965	0.3219	0.0978	0.2168	Weak
Luodu village	0.2786	0.2015	0.3234	0.0911	0.2188	Weak
Fenghuanggou community	0.3342	0.2482	0.2074	0.1604	0.2381	Weak
Hulin community	0.2648	0.2326	0.2652	0.0966	0.2068	Weak

community, and Hulin community. Deficits were concentrated in infrastructure and service accessibility, as well as, in some cases, landscape quality, thereby constraining the potential for near-term implementation.

Potential units are those between the two thresholds that showed strengths on some dimensions but not enough to qualify as high-quality, such as Guantian village and Fengjia village. With targeted upgrades (transport, public services, and site planning), their comprehensive suitability can be enhanced to support phased development.

4.4. Sensitivity analysis

To assess the influence of weight uncertainty, we performed ±10% perturbations of each normative layer weight (B1: landscape, B2: rural, B3: facility, and B4: construction), renormalizing the remaining weights to sum to one. The detailed results of the perturbation experiments are summarized in Table 5. As shown, all values remained above 0.95, confirming high consistency between the baseline and perturbed scenarios. Robustness was evaluated at the pixel level using Spearman's rank correlation (ρ) between baseline and perturbed suitability surfaces and the Jaccard overlap of top-10% high-suitability areas. Across all eight scenarios, the overall suitability ranking was essentially unchanged (ρ = 0.9988–0.9999), and the spatial extent of high-suitability areas remained highly consistent (Jaccard = 0.956–0.975). Among the guideline layers, B1 and B2 produced slightly larger—but still small—spatial shifts, whereas B4 (construction suitability) was the least sensitive (Jaccard ≈ 0.971–0.975). These results demonstrate that the composite suitability and the high-quality/potential/weak typology were robust to reasonable variations in guideline-layer weights, providing confidence in the substantive findings reported.

5. Discussion

5.1. Alignment and divergence with existing theories

The results reveal structural patterns that both reinforce and refine established theoretical perspectives in agritourism and rural spatial development. The strong influence of facility convenience—particularly road proximity and service convenience—closely aligns with Hansen's (1959) accessibility model, which argues that spatial opportunities expand as transport and service access improve. In our case, accessibility consistently amplified the developmental value of landscape and cultural resources, operating as a functional multiplier in peri-urban contexts. However, the findings also revealed a conditional effect not fully captured by classical linear interpretations of accessibility theory. When accessibility remained below a moderate functional threshold, improvements in landscape or cultural suitability failed to increase overall development potential. This suggests that accessibility operates as a minimum enabling condition, rather than a uniformly incremental factor, refining long-standing assumptions in accessibility-based rural development models. The results also diverge from traditional landscape suitability theory, which typically positions natural endowments—such as vegetation, topography, and scenic qualities—as primary determinants of site quality. Although landscape suitability remained influential in our township-scale evaluation, its contribution was clearly mediated by construction-related dimensions. Villages with high ecological potential but insufficient infrastructure ranked lower than those with moderate landscapes but strong functional conditions. This pattern indicates that, in inland peri-urban settings, landscape advantages become developmentally productive only when paired with adequate infrastructure, contrasting with conservation-oriented or scenic regions where natural attributes dominate suitability assessments. Furthermore, the observed village typology echoed—but also subtly modified—Butler's (1980) Tourism Area Life Cycle (TALC). Progression from the "exploration" to the "involvement" and "development" stages appeared to be constrained not only by resource endowment, as TALC traditionally suggests, but also by infrastructural readiness. In peri-urban townships, advancement along the TALC curve is thus gated by foundational accessibility and service thresholds, offering a refined interpretation of tourism area evolution specific to transitional rural–urban interfaces.

Table 5. Sensitivity analysis

Normative layer	Disturbance (%)	Spearman's rho	Top 10% Jaccard
B1: Landscape	+10	0.999255311	0.973157319
	−10	0.999078831	0.966944326
B2: Rural	+10	0.999382191	0.96261109
	−10	0.999269544	0.961628925
B3: Facility	+10	0.998850088	0.957538984
	−10	0.99876496	0.956122513
B4: Construction	+10	0.999124111	0.971247171
	−10	0.999039712	0.975270226

5.2. Cross-regional divergence and contextual interpretation

Beyond within-study patterns, the weighting structure diverges from agritourism and agricultural complex assessments in other regions in ways that are theoretically meaningful. In coastal and scenic-oriented provinces, prior studies frequently assign dominant weight to landscape and ecological indicators—often exceeding 45%—consistent with landscape-dominant suitability theory and conservation-led planning priorities (J. Zhang *et al*., 2012). In contrast, evaluations in semi-arid northern China emphasize water availability and land productivity (W. Li *et al*., 2021; Zhong *et al*., 2019), reflecting resource-constraint theory, which predicts that ecological scarcity shapes suitability hierarchies. Huangma township displayed a distinctly different structure: infrastructure-centered suitability, where construction suitability and facility convenience jointly account for more than half of the total weight. This pattern aligns with peri-urban transformation theory, which posits that modernization needs, market proximity, and transitional governance arrangements elevate infrastructural readiness as the primary enabling factor. The divergence across regions substantiates a context-dependent suitability paradigm, indicating that no universal hierarchy of indicators governs the suitability of agricultural complexes; instead, regional constraint structures and development stages mediate the relative importance of landscape, infrastructure, and cultural factors. Under this interpretation, our results extend existing empirical research by demonstrating how the hybrid AHP–entropy framework can adapt to distinct contextual pressures, shifting from landscape dominance in scenic regions to infrastructure dominance in peri-urban inland settings. This reinforces the theoretical expectation that agritourism suitability emerges from an interplay of ecological potential and infrastructural conditions shaped by regional development trajectories.

5.3. Mechanistic insights from dominant indicators

The weight distribution further revealed key mechanisms shaping suitability formation in peri-urban agricultural complexes. The dual prominence of economic vitality and electricity coverage indicates a mutually reinforcing dynamic: a stable electricity supply enables agro-processing, digital services, cold-chain logistics, and e-commerce participation, which together strengthen commercial activity. In turn, stronger economic vitality increases the fiscal capacity and demand for infrastructure upgrades. This reciprocal mechanism is characteristic of urban–rural transition belts, where villages are embedded in wider metropolitan economic systems but still constrained by uneven infrastructural provision. Landscape indicators also exhibited a functional orientation. Variables such as water proximity and PAR exerted a stronger influence than purely aesthetic attributes, suggesting that productive ecological functions—supporting cultivation efficiency, microclimatic stability, and mixed-use agriculture—are central to suitability formation at the township scale. This contrasts with remote rural landscapes, where natural scenery dominates, and with urban areas, where service accessibility outweighs ecological conditions. Collectively, these mechanisms illustrate that suitability in peri-urban agricultural complexes emerges from a co-dependence between ecological potential and infrastructural readiness, with neither dimension acting as a sufficient determinant on its own. This helps explain why infrastructure-poor but landscape-rich villages underperform, and why functionally strong villages with moderate landscapes can achieve higher comprehensive suitability.

5.4. Structural trade-offs in peri-urban agricultural complex development

The dominance of construction suitability and accessibility highlights the structural tensions inherent in peri-urban development. Infrastructure upgrades are essential for enabling agricultural–tourism integration, improving mobility, and facilitating market access. Yet, the same processes can increase congestion, intensify environmental pressure, and compromise high-value landscape areas—particularly where carrying capacity is limited. These dynamics mirror classic TALC patterns in which enhanced accessibility triggers economic agglomeration but simultaneously increases ecological and visual stress. The relatively lower contribution of cultural suitability highlights another dimension of trade-off: while cultural resources differentiate village character, they remain under-leveraged without complementary infrastructure. This imbalance suggests a risk that modernization priorities may overshadow cultural preservation unless institutions explicitly integrate cultural stewardship into development planning. These tensions demonstrate that peri-urban agricultural complex development requires balanced governance, recognizing that infrastructural intensification, ecological conservation, and cultural protection must be co-managed rather than pursued independently. Without such balance, development gains may come at the expense of long-term sustainability—an issue especially relevant for rapidly transforming townships.

5.5. Indicator-driven policy recommendations

Linking policy guidance directly to dominant indicators provides actionable pathways for enhancing suitability. The substantial influence of electricity coverage suggests prioritizing upgrades to rural distribution networks, improving voltage stability, and extending service to peripheral settlements. Strengthening economic vitality through support for small agro-processing hubs, rural e-commerce services, and business incubation programs can reinforce the commercial foundations necessary for the development of agritourism. The strong effect of road accessibility highlights the value of targeted "last-mile" transportation improvements, particularly in southern and peripheral areas, where modest enhancements can produce substantial gains in facility convenience and mobility. Landscape suitability considerations—especially in areas of high ecological value—require low-impact development guidelines, ecological buffers, and landscape-sensitive zoning to protect the environmental assets underpinning long-term attractiveness. Although cultural indicators contribute less to the overall weight, their significance for differentiation implies that heritage preservation must be integrated with accessibility improvements to avoid the marginalization of culturally rich but infrastructure-poor villages. These indicator-driven policy directions offer a coherent framework for aligning infrastructural investment, ecological stewardship, and rural revitalization in peri-urban agricultural complex planning.

6. Conclusion

This study developed a GIS-based multi-criteria suitability evaluation framework for agricultural complex development in Huangma township, integrating AHP–entropy weighting with spatial overlay analysis across four dimensions and 19 indicators. The results showed that construction suitability exerted the strongest influence on overall suitability, with economic vitality and electricity coverage jointly accounting for the largest share of the total weight, followed by landscape suitability and facility convenience, while rural cultural factors played a comparatively smaller role. Spatially, high-suitability areas were concentrated in the northern and central parts of the township, where infrastructure and economic conditions were more favorable, whereas the southern areas were constrained by weaker roads and public services. Based on composite scores, the 13 villages and two communities were classified into high-quality, potential, and weak types, providing a clear structure for differentiated development pathways. Sensitivity analysis further indicated that the overall ranking and spatial pattern were robust to reasonable variations in indicator weights.

Beyond these empirical findings, the study contributes to theory, methodology, and practice. Theoretically, it supports and refines accessibility-based explanations of rural development by showing that infrastructure and service accessibility function as enabling conditions that determine whether landscape and cultural resources can be effectively converted into development potential. At the same time, the dominance of construction suitability over landscape suitability, and the relatively high importance of functional landscape indicators, such as proximity to water bodies and PAR, suggests a shift from purely scenic-oriented to more production-oriented understandings of landscape in agricultural complex planning, and echoes the idea that progression through tourism development stages is strongly conditioned by infrastructural thresholds. Methodologically, the integration of AHP–entropy weighting with GIS spatial analysis offers a transparent and replicable approach that balances expert knowledge with data-driven objectivity at the township scale. Practically, the indicator system, weight structure, and three-type classification provide local governments with an operational tool for zoning, prioritizing infrastructure and economic investments, and designing targeted policies that focus on improving electricity coverage, economic vitality, and road accessibility in weak and potential areas while guiding more refined product and experience development in the high-quality areas.

This study has several limitations that also point to fruitful directions for future research. First, the analysis was based on cross-sectional data for 2023–2024, capturing a static snapshot of suitability rather than dynamic trajectories under ongoing policy and infrastructure changes. Second, due to data constraints at the township scale, the indicator system primarily reflected physical, environmental, and infrastructural conditions, while social and institutional dimensions, such as community participation and governance capacity, were only indirectly reflected. Third, the framework was tested in a single peri-urban township, and its transferability to other geographical and institutional contexts remains to be examined. Future research could extend the framework to multi-period datasets to explore how suitability responds to infrastructure investment and land-use change. It could also integrate survey- or interview-based indicators to incorporate local stakeholder perspectives and institutional factors, and conduct comparative applications across multiple townships or regions with different ecological and development backgrounds. In addition, scenario-based simulations building on the current indicator system could be used to test how alternative policy mixes—such as different combinations of transport, energy, and public service investments—might reshape suitability patterns over time, providing more forward-looking support for rural spatial planning.

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Conflict of interest

The authors declare they have no competing interests.

Author contributions

Conceptualization: All authors
Formal analysis: Zaharah Mohd Yusoff

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Methodology: Ling Cai
Writing–original draft: Ling Cai
Writing–review & editing: Zaharah Mohd Yusoff

Ethics approval and consent to participate

Not applicable.

Consent for publication

Not applicable.

Availability of data

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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