

Step-by-Step Intelligent Identification of Urban Inefficient Land from a "Human-Land-Industry" Synergy Perspective

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Keywords

Inefficient urban land; "human-land-industry" synergy perspective; step-by-step intelligent identification; planning response

Abstract

In the current era of stock-based urban redevelopment, large amounts of inefficient urban land waste scarce land resources. Scientifically identifying, planning and governing mixed-function inefficient land has therefore become a major issue in urban planning research and practice. From a "human-land-industry" synergy perspective, this study clarifies the connotation of inefficient urban land identification and proposes a step-by-step intelligent identification method. The first round, preliminary identification based on hierarchical feature combinations, reveals the spatial-location hierarchy of inefficient urban land. The second round, optimized identification based on multidimensional feature clustering, identifies four types of "human-land-industry" feature clusters. The third round, fine-grained identification based on graph-structure deep learning, uncovers contradictions and conflicts in the allocation of resource elements within inefficient land units. The results show that step-by-step intelligent identification can finely identify and deeply explain the characteristics and mechanisms of inefficient land, providing a new pathway for refined governance and planning response in the new era.

Introduction

As China enters a new stage of urbanization dominated by stock-based planning, the identification and reuse of inefficient urban land have become an important pathway for urban renewal, upgrading and redevelopment, as well as a major measure for transforming the mode of urban economic growth. Yet identifying inefficient urban land remains difficult in planning practice [1]. In 2023, the Ministry of Natural Resources issued the *Notice on Carrying Out Pilot Work on the Redevelopment of Inefficient Land*, proposing pilots in 43 cities. This stimulated in-depth research and governance policies for inefficient land in major cities across China. How to accurately and finely identify diverse and complex inefficient land in cities, and how to formulate scientific and reasonable planning responses, have thus become important issues in urban spatial planning.

1 Rethinking the Connotation of Urban Inefficient Land and the Identification Challenge

1.1 The Dilemma: A Shift in the Connotation of Urban Inefficient Land

The focus of urban development in China has gradually shifted toward renewal and quality improvement within high-density mixed spaces in central urban areas [2]. This means that the connotation of urban inefficient land urgently needs to be upgraded and extended at the strategic level. The understanding is moving away from a top-down, single-dimensional emphasis on the input-output ratio of land, toward a bottom-up perspective that pays greater attention to people-oriented performance and evaluates land development quality more through the comprehensive benefits

generated by urban users. This shift can help cities convert existing assets into new cash flows and is also important for improving urban vitality and sustainable development [3].

Accordingly, the object of inefficient land identification is no longer limited to peripheral industrial land or urban villages with high fiscal and economic return potential. It is increasingly shifting toward large amounts of high-density mixed land in central urban areas with low comprehensive benefits. The complexity of such inefficient land is reflected first in its strong dependence on location, second in the fact that it carries multiple elements such as population activities, spatial economy and functional industries, together with their intertwined interactions [4], and third in the mixed composition of fine-grained internal land units. In the new era, the identification of urban inefficient land therefore needs a more people-oriented, refined and intelligent method as a supplement.

1.2 Previous Identification Methods and Their Characteristics

Previous planning practice has often used surface features such as "old, disorderly and poor" as keywords for identifying inefficient urban land [5-6]. A "systems science" approach is commonly adopted: evaluation indicator systems are established by land-use function, with indicators emphasizing economic metrics such as output per unit of land; multiple types of data are then collected for complex integrated calculation, and the final results are checked and confirmed [7]. At the same time, these methods often treat urban land in different locations equally and overlook the effect of locational externalities on land-use efficiency [8]. The required data are slow to update and incomplete in coverage. Because identification is conducted by land-use function, the process can easily become project-based and real-estate-led, resulting in localized outcomes and a narrow target orientation [9].

In essence, the current understanding of urban inefficient land remains limited and no unified connotation or extension has yet been formed. Existing identification methods are essentially a top-down "accounting" mode of work, led by government land finance, taxation and local assessment targets. They evaluate three-dimensional spatial use through two-dimensional economic indicators, rather than taking the people-oriented comprehensive use benefits of urban land as the core criterion.

1.3 Key Technical Difficulties Under the Shift in Connotation

A change in connotation implies a change in method. In recent years, more studies in China and abroad have begun to identify inefficient urban land through more micro-level and dynamic big data. For example, Lin Haiyuan et al. [10] used night-time light and air-quality data to characterize the socioeconomic features of land and examine the effect of socioeconomic factors on inefficient land. Liu Shengjun et al. [11] constructed an identification model with 16 evaluation factors based on four value orientations and used it to overlay and identify inefficient land. Jin et al. [12] proposed an integrated method combining multi-source data on buildings, points of interest, transport and environment to identify inefficient residential, commercial and industrial urban land. Koroso et al. [13] used high-resolution remote-sensing data to analyze spatiotemporal changes in urban land-use efficiency.

Overall, current methods have begun to use more micro-scale, multi-source urban big data, which accords with the trend toward increasingly refined and dynamic urban spatial governance. However, most methods remain confined to single-function land and cannot identify inefficient land with mixed functions. Their results also depend strongly on indicator weights, which reduces the validity and applicability of identification outcomes. Three technical deficiencies therefore deserve focused attention. First, insufficient attention is paid to differences in locational conditions. The development quality of land in different urban locations should not be measured by a fixed set of indicator standards. If two

commercial sites have similar indicator values, the one located on the urban periphery may be highly efficient, whereas a site located in the urban center should be judged inefficient if its comprehensive benefits are lower than those of neighboring commercial land.

Second, the coupling and coordination among internal elements of inefficient land are often ignored. Urban land contains synergistic effects among internal systems. Current methods generally integrate indicators and then apply a one-size-fits-all judgment, without considering the interactions and coordination among different element systems within land parcels or among the smallest land units. The cause of urban inefficient land is in fact the mismatch among internal resource elements, which generates conflicts and contradictions in system operation.

Third, it is difficult to identify inefficient land at the smallest land-unit scale. Mixed-use blocks in central urban areas are usually composed of several smallest land units. After preliminary identification of inefficient land, how to further identify inefficient units within the land parcel and explain their internal inefficiency mechanisms remains a question requiring deeper research.

2 Connotation and Method Optimization for Step-by-Step Intelligent Identification

2.1 Connotation of Urban Inefficient Land Identification from a "Human-Land-Industry" Synergy Perspective

Evaluating the development quality of high-density mixed land in central urban areas first requires attention to the spatial externality of location. The relative efficiency of urban land is strongly affected by objective locational conditions, including transport location, land-price location and structural location. The assessment of inefficient land should therefore be based on differentiated hierarchies of objective location. On this basis, the comprehensive benefits of urban land should be examined from a people-oriented use perspective through three systems: population activities, spatial economy and functional industries.

It should be emphasized that high-quality development of land-use benefits from a "human-land-industry" synergy perspective means not only that the comprehensive value of each internal subsystem reaches a relatively high level, but also that the resource elements among subsystems are rationally allocated and coupled in a coordinated way [14]. Only then can land-use efficiency reach the system optimum, that is, high-quality coordinated development among the "human", "land" and "industry" systems (Fig. 1).

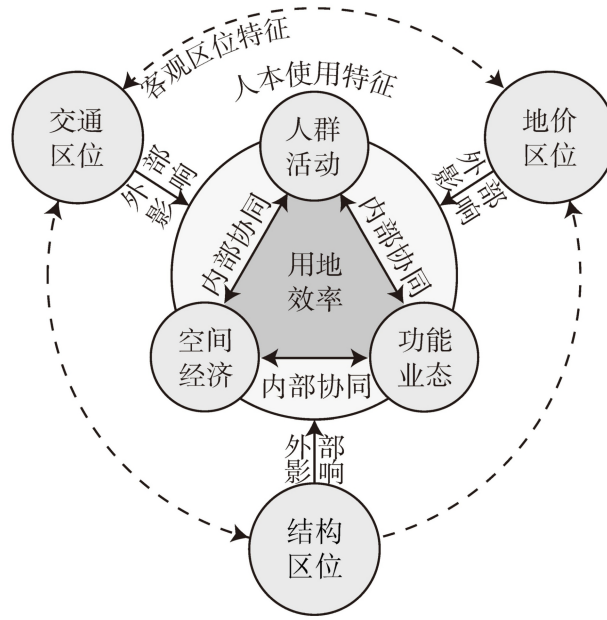


Fig. 1 Connotation of Identifying Urban Inefficient Land from a "Human-Land-Industry" Coordination Perspective

From this perspective, urban inefficient land can be defined as land which, under the same location grade, contains resource mismatches among its internal "human-land-industry" subsystems, producing conflicts that lead to low overall land efficiency [15]. For example, a mixed-use site dominated by residential functions in the urban center may have high surrounding pedestrian flow, but if its overall floor area ratio is low and its functional industry configuration is insufficient, it can easily become a depressed "shadow area" in the urban center [16]. Similarly, contradictions among internal "human-land-industry" subsystems also reflect unreasonable spatial and functional layouts among internal land units, reducing overall system efficiency. For instance, a commercial site may be inefficient because an internal primary or secondary school parcel interferes with the commercial function. The measurable locational features and "human-land-industry" system features of urban land, the clear boundaries of the smallest property-right land units, and the precision support of "human-land-industry" big data provide the objective basis for refined identification of inefficient urban land.

2.2 Step-by-Step Intelligent Identification as an Optimized Methodological Path

Based on the theoretical and objective foundations of inefficient land identification, this study proposes a step-by-step intelligent identification method from a "human-land-industry" synergy perspective. "Step-by-step intelligent identification" refers to three levels of urban inefficient land identification. As the identification level advances, both precision and explanatory depth improve progressively (Fig. 2). First, a location hierarchy model and a "human-land-industry" coupling coordination model are constructed. They measure the location hierarchy of urban land, the characteristics of the three subsystems, and the degree of coupling coordination among them. Through threshold classification and feature combinations across indicators, inefficient urban land is preliminarily identified at the overall level.

Second, based on the calculation of "human-land-industry" feature indicators, intelligent algorithms are used to cluster and screen land-use sub-features. These results are integrated with the first-round results to construct a digital feature spectrum of inefficient land. The feature clusters selected through sub-feature clustering can mine new features from "human-land-industry" data and optimize the boundary of identification thresholds, making the second round more refined while maintaining interpretability.

Third, for the smallest land units inside inefficient land parcels, their "human-land-industry" features are extracted and transformed into graph-structured data. A graph neural network model then classifies internal subdivided land units and finely identifies inefficient land at the smallest unit scale. At this scale, the method pays greater attention to the functional and spatial synergies among units, which is particularly important for explaining the internal mechanisms of inefficient land.

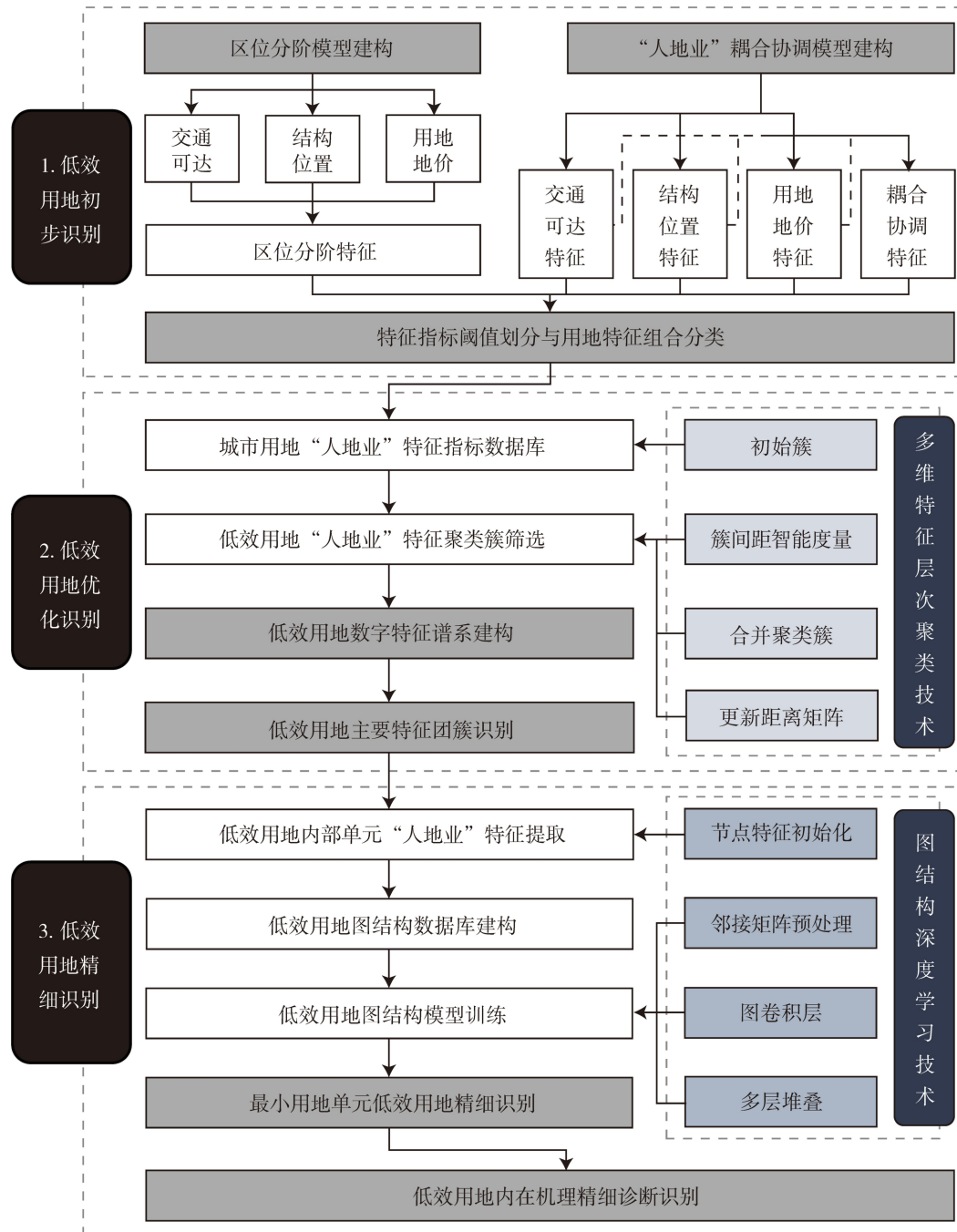


Fig. 2 Methodological Framework for the Hierarchical Intelligent Identification of Inefficient Urban Land from a "Human-Land-Industry" Synergy Perspective

In essence, step-by-step intelligent identification is a people-oriented approach to refined allocation of urban element resources. By progressively improving identification precision and depth, it intelligently detects resource-element mismatch and fine-scale mechanisms of inefficiency. On the one hand, identifying inefficient urban land must consider multidimensional and multiscale features. Step-by-step intelligent identification decomposes this complex problem hierarchically, facilitating feedback and correction across levels and gradually improving accuracy and precision. On the other hand, under the

new connotation, inefficient urban land is characterized by complex interweaving among multiple elements. The introduction of intelligent techniques can uncover features that are difficult for humans to identify directly.

3 Data and Methodological Model Construction

3.1 Study Area and Data

This study takes the central urban area of Nanjing as the research object. The area covers 312.5 km² and mainly includes Gulou, Qinhuai, Xuanwu and Jianye districts, as well as parts of Yuhuatai, Qixia and Jiangning districts within the ring road [17]. As an important provincial-level megacity in the Yangtze River Delta, Nanjing has a relatively mature central urban area. Under the background of stock-based quality improvement, however, a large amount of inefficient urban land within this area urgently needs to be identified and renewed. Choosing Nanjing's central urban area as the study area is therefore practically necessary and offers reference value (Fig. 3).

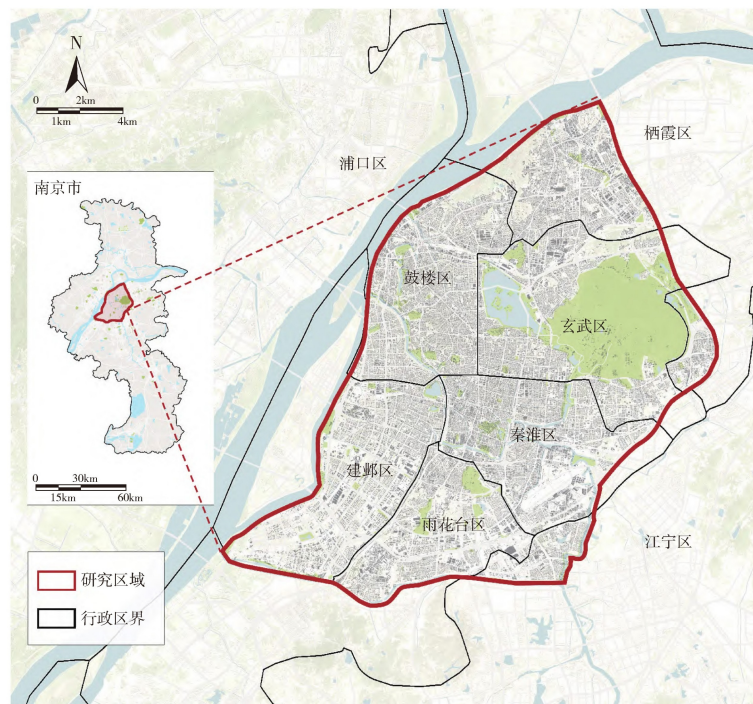


Fig. 3 Study Area and Scope

The research data include mobile location service (LBS) data for one working day in 2023 within the central urban area of Nanjing, building vector data, POI data, road data, housing-price data and land-use data. LBS data were purchased from operators and include anonymized mobile-phone user IDs as well as temporal and spatial location information. Building vector, road and land-use data were obtained from OpenStreetMap. POI data were crawled from Amap, and housing-price data were crawled from Lianjia. All data are from 2023.

3.2 Construction of the Location Hierarchy Model

The objective location characteristics of urban land are mainly determined by transport accessibility, structural centrality and land-price distribution within the urban structural network [18]. These three types of indicators are therefore used to measure objective locational features. Transport accessibility

and structural centrality are calculated with space syntax software and assigned to land units through inverse distance weighting interpolation. Land-price features are calculated from the average housing price of properties within each land unit (Table 1). After normalization of the three indicators, the comprehensive location feature of each urban land unit is measured as:

$$Li = (Ti + Ni + Pi) / 3$$

where `Ti` is the transport accessibility feature of land unit `i`, `Ni` is the structural position feature, `Pi` is the land-price feature, and `Li` is the comprehensive location feature. Because the three indicators are considered equally important for urban land location, each coefficient is set to 1/3. The natural breaks method is then used to divide `L` into four location tiers: core area, sub-core area, general area and fringe area.

特征指标	计算公式	说明
交通可达特征 T	$\sum_{y \in R_i} \frac{p(y)}{d(x,y)}$	$p(y)$ 为搜索半径 R 内节点 y 的权重, $d(x,y)$ 为节点 y 到 x 的最短拓扑
结构位置特征 N	$\sum_{y \in N} \sum_{z \in R_i} OD(y,z,x) \frac{p(z)}{Links(x)}$	$OD(y,z,x)$ 为搜索半径 R 内通过节点 y 与节点 z 之间的最短拓扑距离
用地地价特征 P	$\frac{\sum p_i}{n}$	p_i 为房价兴趣点的价格, n 为用地内房价兴趣点的数量

Table 1 Location Characteristics of Urban Land-Use Areas

3.3 Construction of the "Human-Land-Industry" Coupling Coordination Model

From a people-oriented use perspective, this study constructs a "human-land-industry" feature indicator system consisting of three systems: population activities, spatial economy and functional industries [19]. These are measured with multi-source big data (Table 2). For the population activity system, point density of population flow in the morning, afternoon and evening of a working day is calculated to represent all-day activity. For the spatial economy system, building development characteristics are used, including floor area ratio, building density and average building height. For the functional industry system, indicators are set from the perspectives of production, commercial and public-service functions provided by urban land, thereby making up for the limitation of traditional inefficient land identification, which emphasizes only economic production functions.

It should be noted that because urban system elements are strongly spatially related on land, the "human-land-industry" coupling coordination model uses urban land blocks enclosed by roads on all sides as its research units. The step-by-step identification model first constructs a digital feature spectrum of inefficient land at the urban block scale and then further identifies inefficient land within the smallest internal land units.

Through normalization of system indicators and entropy-weight integration, the dimensions of multi-source data are unified. Comprehensive indicators are obtained for the population activity, spatial economy and functional industry systems, and the coupling degree of the land-use system is then measured:

$$Ci = 3 * (Vi * Si * Fi)^{(1/3)} / (Vi + Si + Fi)$$

According to existing literature, the coupling degree `C` is divided into four intervals: `(0, 0.3]` for low-level coupling, `(0.3, 0.5]` for antagonism, `(0.5, 0.8]` for adjustment, and `(0.8, 1]` for high-level coupling [20].

Coupling degree mainly emphasizes the linkage and dependence among systems, whereas coupling coordination degree adds a comprehensive evaluation of the quality of synergy among systems. The

improvement of urban land efficiency therefore depends more on enhanced coupling coordination [21]. The coupling coordination degree among "human-land-industry" systems is further measured as:

$$Di = (Ci * Ti)^{(1/2)}$$

where $Ti = \alpha Vi + \beta Si + \gamma Fi$. Because the three subsystems are considered equally important for the urban land-use system, the coefficients α , β and γ are all set to 1/3. With reference to related literature, the coupling coordination degree Di is divided into five intervals: $[0, 0.4]$ for severe disorder, $(0.4, 0.5]$ for moderate disorder, $(0.5, 0.6]$ for basic coordination, $(0.6, 0.7]$ for moderate coordination, and $(0.7, 1]$ for high coordination [22]. Measuring coupling coordination among the three subsystems quantifies the degree of synergy, conflict and contradiction among systems and preliminarily explains the internal mechanism by which inefficient urban land forms.

特征维度	特征指标	计算公式	说明
人群活动系统 V	上午人群活力 V_1	$Sum_{T_{1i}}/A$	T_{1i} 、 T_{2i} 、 T_{3i} 分别为工作日 6—12 时、12—18 时、18—24 时用地单元内的手机信令点， A 为用地单元的面积
	下午人群活力 V_2	$Sum_{T_{2i}}/A$	
	夜晚人群活力 V_3	$Sum_{T_{3i}}/A$	
空间经济系统 S	容积率 S_1	$\frac{\sum_{i=1}^n A_i}{A}$	A_i 为用地单元内建筑单体的建筑面积， S_i 为用地单元内建筑单体的占地面积， H_i 为用地单元内建筑单体的高度， A 为用地单元的面积， n 为用地单元内建筑单体的数量
	建筑密度 S_2	$\frac{\sum_{i=1}^n S_i}{A}$	
	建筑平均高度 S_3	$\frac{\sum_{i=1}^n H_i}{n}$	
功能业态系统 F	生产功能密度 F_1	Sum_{S_i}/A	S_i 为用地单元内的生产功能兴趣点， O_i 为用地单元内的商业功能兴趣点， P_i 为用地单元内的公服功能兴趣点， A 为用地单元的面积
	商业功能密度 F_2	Sum_{O_i}/A	
	公服功能密度 F_3	Sum_{P_i}/A	

Table 2 Indicator Framework for "Human-Land-Industry" Systems in Urban Land

3.4 Construction of the "Human-Land-Industry" Digital Feature Spectrum

The primary function of the "human-land-industry" digital feature spectrum is to reconstruct the multidimensional characteristics of urban land in the central urban area into a digital spectrum, forming a systematic digital classification of "human-land-industry" features. Methodologically, the hierarchical clustering algorithm in Python's Scikit-learn is used to cluster the smallest sub-features of urban land blocks across the location hierarchy, people-oriented performance and coupling coordination layers. Taking each land block as a unit, the method iteratively merges clusters from the bottom up to construct a clustering tree [24], outputting a digital spectrum of "human-land-industry" feature types for urban land (Fig. 4).

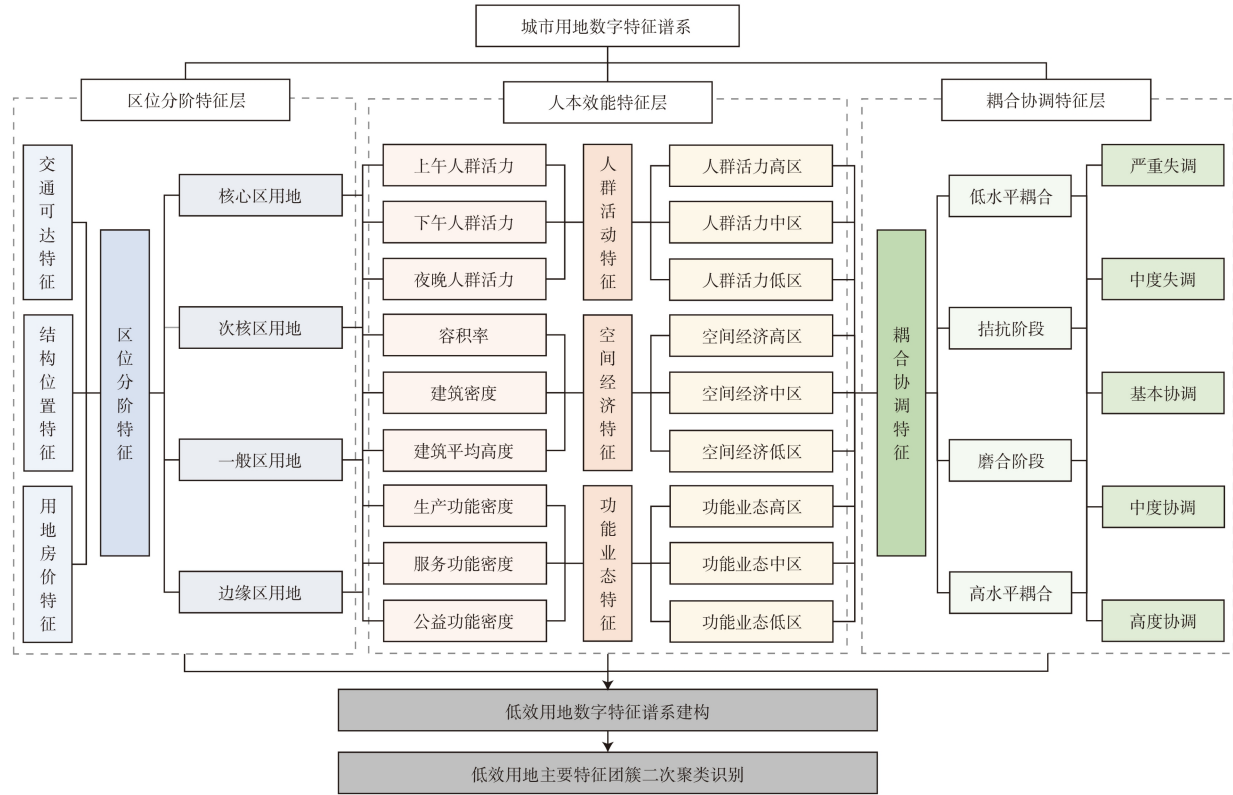


Fig. 4 Constructing a Digital Feature Spectrum for Inefficient Land Uses from a "Human-Land-Industry" Synergy Perspective

The core function of this digital feature spectrum is to screen inefficient land clusters and integrate them with the preliminary identification results, thereby realizing the second round of optimized identification. Identifying inefficient urban land is essentially a scientific problem of refined classification. The second-round optimized identification based on the digital feature spectrum uses hierarchical clustering of the smallest classification indicators and spectrum construction to re-understand inefficient land as a whole and in parts. It also mines potential feature associations among inefficient land parcels, enabling a more refined optimized identification than the preliminary results.

3.5 Construction of the Fine-Grained Identification Model for Inefficient Land Units

The smallest identification unit of urban inefficient land is the independent land unit within mixed urban land. In central urban areas, inefficient land often forms because of contradictions among internal land units, including unreasonable "human-land-industry" elements within each unit and unreasonable layout structures among units. Graph neural network (GNN) models can mine high-level features from irregular graph-structured data composed of nodes and edges, and can automatically classify graph nodes. Their potential has been demonstrated in various classification tasks [25-26]. This study therefore transfers a GNN model to the classification and identification of inefficient land at the smallest land-unit scale.

Based on the inefficient land obtained in the second round, the "human-land-industry" features of the smallest internal land units are extracted. Each unit's own features are used as node features, and spatial connections between land units are used as edges, producing a graph-structured database of urban land units. A spatial-domain convolution model, GraphSAGE, which is well suited for classification

learning, is selected to train the data [27], enabling the model to automatically classify inefficient nodes in urban land graph structures. Model performance is expressed through accuracy and F1-score, calculated as:

$$Accuracy = TP / (TP + FP)$$

$$F1 = 2TP / (2TP + FP + FN)$$

where 'TP' is the number of correctly predicted inefficient plots, 'FP' is the number of negative samples incorrectly predicted as inefficient plots, and 'FN' is the number of omitted inefficient plots. The model's classification output can further identify combinations of relatively inefficient land units, supporting deeper explanation of internal mechanisms (Fig. 5).

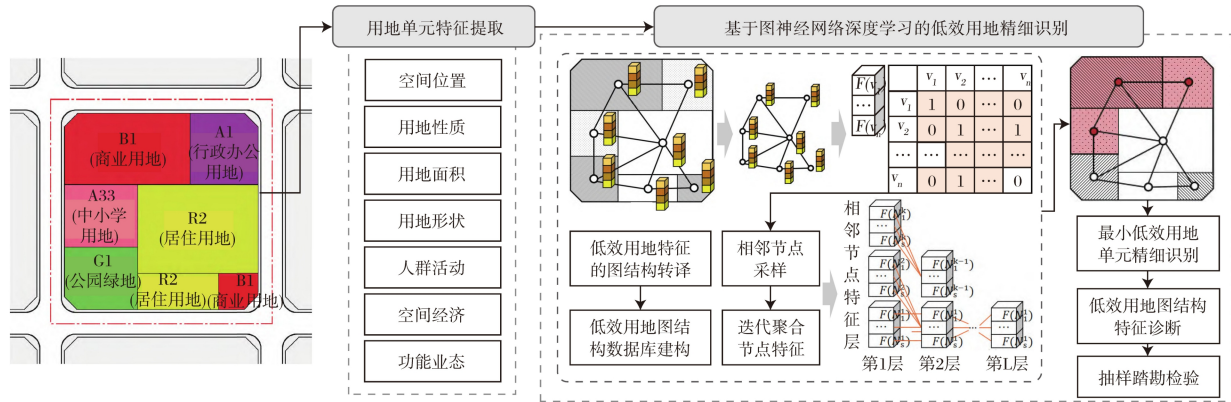


Fig. 5 Fine-Grained Identification Model for the Smallest Unit of Inefficient Land Uses

4 Step-by-Step Intelligent Identification of Urban Inefficient Land and Mechanism Analysis

4.1 First-Round Preliminary Identification Based on Hierarchical Feature Combinations

The first round of urban inefficient land identification is based on feature-indicator calculation from the location hierarchy model and the "human-land-industry" coupling coordination model. Inefficient land is preliminarily identified through feature combinations after hierarchical classification of land-use indicators. Specifically, the locational features of urban land in Nanjing's central urban area are first measured. Because development and use levels differ greatly across locations, the location hierarchy threshold is set according to four tiers: core area, sub-core area, general area and fringe area [Fig. 6(a)]. Because land-use efficiency under different location tiers is not directly comparable, preliminary identification must compare "human-land-industry" features horizontally within the same location tier. The population activity, spatial economy and functional industry features of urban land are measured, and the quantified "human-land-industry" features are divided into high, medium and low thresholds under different location tiers. Coupling coordination among the systems is then measured. According to the actual data distribution, land parcels with basic coordination, moderate coordination and high coordination are classified as high coupling coordination types. Based on hierarchical feature combinations of "human-land-industry" indicators, 267 inefficient urban land parcels of 16 types are preliminarily identified under different location tiers [Fig. 6(a) and Fig. 6(b)]. Because Nanjing has not yet issued an official document for identifying inefficient land, the results can provide a reference for related work. Comparing the identification results with the renewal units designated in the *Nanjing*

Urban Renewal Action Plan (2024-2026) shows a high degree of spatial overlap, which verifies the validity of the results to a certain extent.

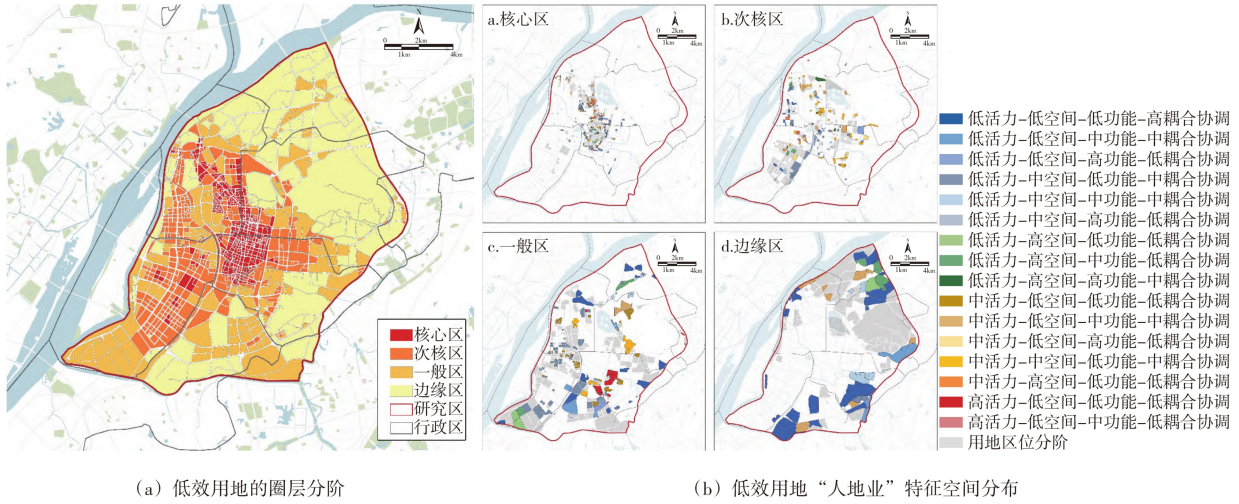


Fig. 6 Preliminary Identification of Inefficient Land Uses in the First Round of Hierarchical Feature Combination

4.2 Second-Round Optimized Identification Based on Multidimensional Feature Clustering

The second round differs from the first in that it performs hierarchical clustering on the smallest sub-feature layers of urban land blocks, and uses these clustering results as a supplement and optimization of the first-round threshold classification. Hierarchical clustering by intelligent algorithms compensates for the first round's neglect of the hierarchical structure and internal connections among inefficient land categories. At the same time, distance height in the clustering tree helps optimize the threshold for classifying inefficient land.

Specifically, land feature data are first preprocessed by expanding hesitation degree. Each land feature datum is then treated as a basic class. Weighted distances among classes are calculated, the classes with the minimum distance are merged into a new class, a new class center is constructed, and weighted distances between the new class and other classes are calculated. The process continues until all classes are merged, producing the clustering result of land-use features.

Combined with the first-round preliminary results, horizontal sections at different positions of the clustering tree are used to extract clusters that match the characteristics of inefficient land. These clusters are integrated with the preliminary results to form a spectrum clustering tree of inefficient land. The size of each node represents the amount of inefficient land, and each node contains the specific value interval for that feature layer. According to the core problem types of "human-land-industry" features at the land-block scale, typical feature clusters in the tree spectrum are further merged and identified to construct a complete digital feature spectrum of urban inefficient land (Fig. 7).

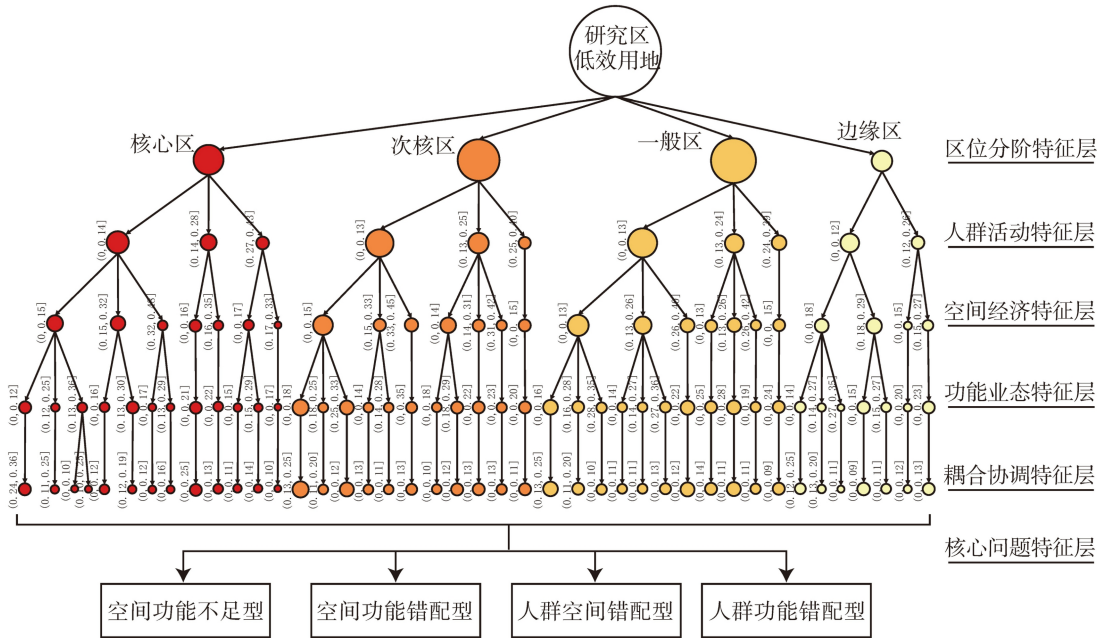


Fig. 7 Second-Round Optimized Identification of Inefficient Land Uses in the Digital Feature Spectrum

4.3 Third-Round Fine-Grained Identification Based on Graph-Structure Deep Learning

The internal mechanism of urban land inefficiency lies in structural mismatch among "human-land-industry" elements between the smallest internal land units. The third round therefore focuses on fine-grained identification of inefficient land with mixed internal composition. First, the "human-land-industry" features of the smallest land units within inefficient land are extracted and translated into point data. The spatial relations among adjacent inefficient land units are then converted into connecting lines between nodes, thereby constructing a graph-structured database of internal features of inefficient land in Nanjing's central urban area.

Thirty percent of the graph-structured data for inefficient land units are randomly selected. Through field investigation combined with diagnosis by professional planners, relatively inefficient internal plots are labeled. The GraphSAGE model is then trained on the database. After training, the model reaches an accuracy of 86.7% and an F1-score of 85.2%. The trained model is used to classify inefficient nodes across the entire dataset, outputting inefficient nodes inside inefficient urban land in Nanjing's central urban area. The results are classified and summarized, and four typical internal mechanism patterns of inefficient land are extracted (Table 3).

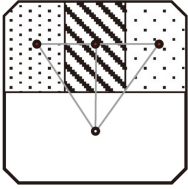
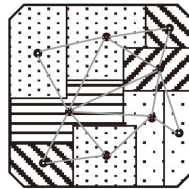
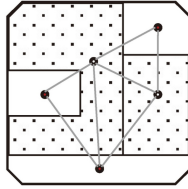
内在机理	空间封闭型			功能抵触型		
案例用地						
图结构机理	低效用地单元通常为图结构中心的居住用地单元,外围用地单元导致其内部封闭			低效用地单元通常为相连的若干不同功能类型的用地单元,耦合协调度低导致整体低效		
机理模式						
内在机理	畸零分割型			闲置短板型		
案例用地						
图结构机理	图结构中大部分节点均为低效用地单元,内部用地单元过多且边界不规则导致整体效率不高			低效用地单元通常为图结构边缘不相邻的节点,用地闲置导致整体利用效率不高		
机理模式						

Table 3 Detailed Identification of the Graph Structure of Four Typical Inefficient Land Uses

The four typical mechanism patterns are: spatial enclosure, in which the inefficient unit is usually a residential unit at the center of the graph structure and peripheral units create internal closure; functional conflict, in which several adjacent units of different functions have low coupling coordination and reduce overall efficiency; irregular fragmentation, in which most nodes in the graph are inefficient units and excessive, irregular land-unit boundaries reduce overall efficiency; and idle-shortboard type, in which inefficient units are usually non-adjacent edge nodes whose idleness lowers overall utilization efficiency.

Through the three rounds of step-by-step intelligent identification, the precision of inefficient land identification ultimately reaches the structural characteristics of the smallest internal land units. The process also reveals internal structural mismatch mechanisms in large amounts of mixed-function inefficient land in Nanjing's central urban area. These include mismatch among internal component elements, which reveals unreasonable allocation of "human-land-industry" elements within inefficient

land, and mismatch in internal spatial layout, which reveals spatial-layout conflicts among the smallest internal land units.

4.4 Characteristics and Mechanisms Revealed by Step-by-Step Intelligent Identification

Based on step-by-step intelligent identification of inefficient urban land in Nanjing's central urban area, this study summarizes three core characteristics and explains their internal mechanisms from three levels: overall spatial distribution, core feature structure and typical internal structure.

First, inefficient land shows ring-like differences in spatial distribution. "Ring-like difference" means that inefficient urban land has different spatial distribution characteristics under different location tiers. In the core area of the central city, inefficient land is mostly located in urban-center "shadow areas". In the sub-core area, it is scattered within the urban land fabric, with no obvious spatial agglomeration. In the general area, it shows clustered characteristics and concentrates around specific urban nodes. In the fringe area, it concentrates contiguously in later-developing areas, producing spatial "block-like" patterns. This phenomenon appears because socioeconomic development levels differ significantly across location tiers.

Second, the digital spectrum of inefficient land shows tree-like clusters. "Tree-like clusters" refers to the tree-like differentiation structure of the digital feature spectrum of inefficient land and to the four major feature clusters formed after integrating feature branches. These four feature clusters indicate that the internal "human-land-industry" subsystems of inefficient land are in a state of low coupling coordination. Yet this inefficient state is difficult to adjust through the renewal motivation of the plot itself, leaving urban land in a relatively static inefficient state across the "human-land-industry" systems.

Third, the internal structure of inefficient land shows mismatch blockage. "Mismatch blockage" means that mismatch in the element composition and spatial layout of the smallest internal land units blocks the flow of resource elements inside the land-use structural network. It includes the four typical types shown in Table 3. This phenomenon arises because urban land-use planning inevitably lags behind reality: conflicts between past land-use plans and current land-use demands have produced many structurally unreasonable and inefficient internal land conditions.

5 Planning Response and Conclusion

5.1 Planning Response

The identification and reuse of inefficient urban land are crucial to sustainable urban development. However, because redevelopment involves multiple authorities and the balancing of interests among different stakeholders, it cannot proceed without the core role of urban planning in coordinating public urban resources. This study therefore discusses planning responses to inefficient land reuse at three levels: overall guidance, spatial optimization and institutional design.

First, differentiated zoning, grading and classification guidance should be provided at the overall level. According to the different location tiers identified for inefficient urban land, redevelopment guidance should be formulated separately for inefficient land in core areas, sub-core areas, general areas and fringe areas [28]. In more specific grading and classification, a database of inefficient land should be established based on the digital feature spectrum. Improvement potential should be rated and graded, while differentiated improvement methods should be guided by feature type [29].

Second, fine-grained structural adjustment should be carried out at the micro level. The third-round fine-grained identification results can directly guide structural adjustment of the smallest land units

inside inefficient land blocks. This includes adjustment of functional structure and adjustment of the spatial layout of land units through boundary modification, subdivision, consolidation and other methods [30]. At the same time, urban design should play a key role in micro-scale spatial shaping, promoting spatial revitalization and quality improvement of inefficient land [31].

Third, a diversified and flexible mechanism for inefficient land renewal should be established. Implementing inefficient land reuse also requires solving financial issues in the renewal process [32]. Through institutional design that innovates financing mechanisms and diversifies investment channels, cities can generate new cash flows and land value appreciation. For example, Guiyang has explored an "urban three transformations" approach for inefficient land, allowing social capital and citizens to participate deeply, so that social investors, citizens and government jointly become the renewers, operators and managers of inefficient land.

5.2 Summary and Reflection

This paper proposes a step-by-step intelligent identification method from a "human-land-industry" synergy perspective to realize multiscale, intelligent and refined identification of inefficient urban land. Through three rounds of progressive identification, the study deepens understanding of current urban inefficient land from the overall system to micro-level mechanisms, providing a decision-making basis for planning response and refined governance.

However, uneven urban development and internal interest games inevitably produce relatively inefficient land. As the level of urban development rises, increasingly high requirements will be placed on the comprehensive benefits of land in core areas, and land-use modes will need to transform and upgrade continuously. Identification of inefficient urban land must therefore be dynamically adjusted in accordance with urban development changes. Efficiently and scientifically integrating multidimensional big and small data on socioeconomic conditions and other aspects of high-density urban land is also a major challenge. In addition, more scientific and practical planning governance methods for inefficient land require further study. The step-by-step intelligent identification method proposed here is therefore intended not only to explore identification of inefficient land within high-density mixed land in central urban areas, but also to offer ideas and reference for future methodological innovation in urban inefficient land identification, thereby promoting high-quality development of urban land.

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