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Mapping urban functional zones with remote sensing and geospatial big data: a systematic review

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ABSTRACT

Urban functional zones (UFZs) serve as the spatial carriers embodying urban economic and social activities, thus making the accurate mapping of UFZs imperative for urban planning, management, and sustainable development. Traditional remote sensing-based methods for mapping UFZs primarily capture the physical attributes of ground objects (such as land cover and spatial patterns) while overlooking the inherent social and economic characteristics, as well as the comprehensiveness, heterogeneity, and scale-dependency. With the rapid development of intelligent sensors, the available geospatial big data, reflecting individual human activities, have greatly increased and enable users to analyze UFZs from both physical and socioeconomic aspects. In this study, we provide a comprehensive review of the existing literature on UFZ mapping using remote sensing and geospatial big data. Specifically, this study summarizes the state of the art from three perspectives: spatial analysis units, representation features derived from multi-source data, and the function classification methods of UFZs. Spatial analysis units encompass regular grids, road blocks, image segmentation units, traffic analysis zones, and buildings. Data features consist of the remote sensing image-derived features (such as visual, spatial pattern, and abstract features) and the geospatial big data-derived features (such as spatial, attribute, and temporal features). For function classification, kernel density estimation, cluster analysis, supervised machine learning, probabilistic topic models, and deep learning methods have been applied. Finally, this study discusses the challenges and limitations of UFZ mapping units, the bias issues of geospatial big data, and the integration of remote sensing and geospatial big data. Meanwhile, future opportunities to these issues and the expansion of functions from 2D to 3D are discussed, in order to formulate an enhanced UFZ mapping framework.

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Urban functional zones; remote sensing; geospatial big data; multimodal fusion; review

1. Introduction

According to the outlook study of demography, global urbanization is projected to continue its upward trajectory over the next three decades, and it is expected to increase from 56% in 2021 to 68% in 2050, implying that urban areas will absorb almost all the future growth of the world's population (about 2 billion people) (Habitat 2022). The significant influx of individuals has accelerated urbanization, posing substantial challenges to urban planning, management, and the pursuit of sustainable urban development. During the urbanization process, similar socioeconomic activities tend to congregate in shared urban spaces, thus giving rise to distinct urban functional divisions that cater to diverse socioeconomic demands (such as commercial zones, residential zones, and industrial zones) (Du et al. 2020). Affected by frequent economic/human activities, cities are constantly evolving, and urban functional zones (UFZs) will change their territory and functions accordingly (Yuan et al. 2014). UFZ maps disclose the distribution and layout of different UFZs within a city, providing insights into the spatial structure of the urban environment. The continuous development of the social economy has rendered human activities increasingly intricate and diverse, which further underscores the growing need for fine-grained urban management. As a result, timely and fine-grained UFZ data are urgently required by many applications, such as housing planning, urban transportation planning, and factory location, as well as numerous urban studies, such as those on urban air quality (Halim et al. 2020), urban public health (Jia et al. 2021), and urban heat island (Huang and Wang

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2019). However, fine-grained UFZ data covering large spatial areas remain limited, especially in developing countries (Hu et al. 2016). Therefore, it is imperative to rapidly and automatically extract UFZ data that can be updated in time and present the fine function spatial structure of a city.

On the one hand, it is convenient to obtain a large amount of remote sensing data, which provides an excellent opportunity for mapping urban land use and land cover (LULC) (Georganos et al. 2018). The continuous progress in deep learning has significantly elevated the accuracy of image interpretation, providing a robust foundation for the automated mapping of UFZs from remote sensing images (Anwer et al. 2018). However, remote sensing images usually excel in depicting the physical layout of geographical objects rather than identifying their specific functions related to human activities. UFZs often represent a blend of physical and social elements, posing the challenge of achieving high-precision UFZ mapping solely based on the physical information present in remote sensing images. This challenge is particularly pronounced in those areas characterized by frequent human activities, such as commercial zones (Hu et al. 2016).

On the other hand, with the rapid advancement of information and communication technology, various smart devices and wireless sensors in cities continuously generate substantial volumes of real-time and reliable geo-related data-in other words, geospatial big data. This kind of data encompasses a variety of sources, such as points of interest (POI), social media data, vehicle trajectories, and mobile phone positioning data (Robinson et al. 2017). These data, which originate from individual human activities, excel in depicting the spatiotemporal dynamics of human behavior. Given the strong correlation between urban functions and human activities, leveraging this emerging geospatial big data becomes instrumental in capturing increasingly intricate urban function patterns and gaining a more profound understanding of UFZs (Wu et al. 2020; Yin et al. 2021). Consequently, geospatial big data serve as a valuable complement to remote sensing images for UFZ mapping. Nevertheless, multi-source data have different structural forms; thus, unifying the data modes, data attributes, and spatial scales is the main challenge in terms of fusing multi-source remote sensing and geospatial big data for the fine mapping of UFZs.

Certainly, it is imperative to assess the advantages and disadvantages of existing studies and present fresh perspectives and insights to guide future UFZ mapping endeavors. This review systematically scrutinizes the body of literature related to UFZ mapping employing remote sensing and geospatial big data, encapsulating a comprehensive analysis of the challenges encountered in the existing studies. Recent advancements in this domain are thoroughly examined, focusing on 1) spatial analysis units, 2) representation features derived from multi-source data, and 3) function classification methods. This paper concludes by delving into the challenges and potential opportunities inherent in current studies.

2. Conceptualizing UFZs

UFZs refer to geographical complexes composed of diverse ground objects, which are spatially continuous and non-overlapping within a city (Zhang et al. 2018). Each UFZ exhibits a relatively consistent built environment and human socioeconomic activities, while different UFZs have different built environments and socioeconomic activities (Tyler and Ward 2010). Currently, there is no unified system for categorizing UFZs. Different studies have adopted similar but not entirely consistent classification systems, which may take into account the specific circumstances of the country, region, and city being studied. For example, due to the mature urban development of large cities, such as Beijing and Shanghai, in China, such areas often use more comprehensive classification systems for UFZs. As shown in Figure 1, a typical UFZ classification system encompasses commercial zones, industrial zones, residential zones, institutional zones, shantytowns, and public open spaces. It is adapted from the "Code for the classification of urban and rural land use and planning standards of development land (GB50137)" of China (Du et al. 2021). This classification system has been widely applied, especially in China (Bao et al. 2020; Y. Chen et al. 2023; Du et al. 2021; Feng et al. 2021; Gong et al. 2020), and has also been adopted in cities outside of China (Sanlang et al. 2021).

In order to undertake UFZ mapping, it is essential to first understand the fundamental characteristics of UFZs and the challenges associated with their mapping tasks. UFZs comprise diverse ground objects. For instance,

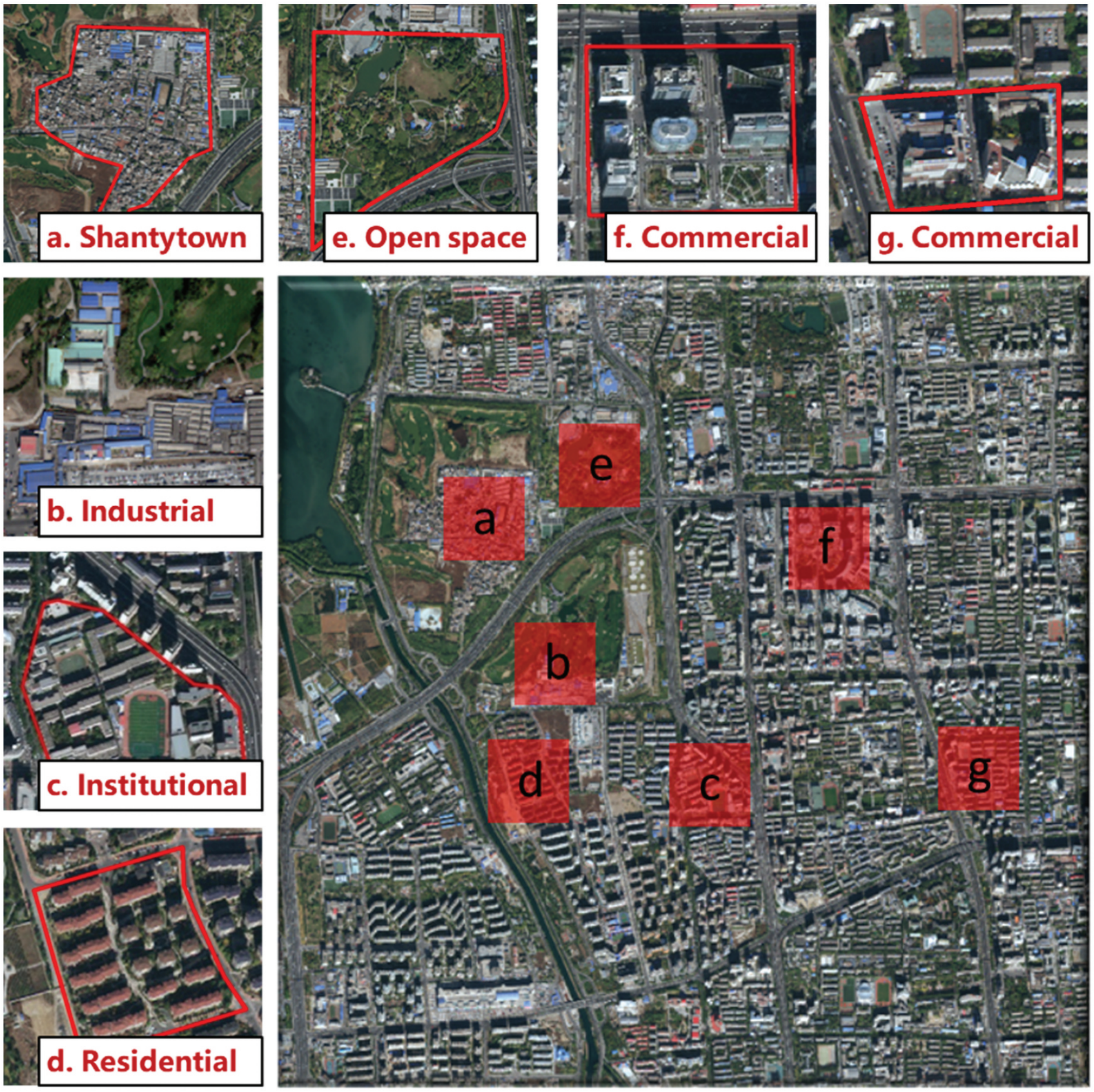


Figure 1. A city area (Haidian District, Beijing) and a typical UFZ classification system. It encompasses commercial zones, industrial zones, residential zones, institutional zones, shantytowns, and public open spaces.

a residential zone is typically composed of buildings, roads, vegetation, and even water bodies. The compositions and spatial configurations of ground objects vary significantly among different types of UFZs and even within the same type of UFZ (see Figure 1(f,g)). Consequently, UFZs exhibit pronounced heterogeneity, scale-dependency, and a comprehensive blend of the physical environment and social systems.

- **Comprehensiveness**. This means that UFZs are geographic complexes with a certain built environment or landscape pattern comprising various ground objects (Figure 2). The spatial distributions and arrangements of these ground objects are influenced by human socioeconomic activities and present certain rules. Comprehensiveness clarifies the distribution and arrangement of ground objects inside UFZs, serving as a clue for mapping UFZs. At the same time, comprehensiveness stands as the fundamental characteristic of UFZs in terms of geographical manifestation, directly leading to the heterogeneity and scale-dependency of UFZs.
- **Heterogeneity**. First, cities consist of diverse types of UFZs (Figure 1) that are spatially distributed in a staggered and uneven manner. Second, UFZs exhibit significant heterogeneity in their internal composition and structure. For example,

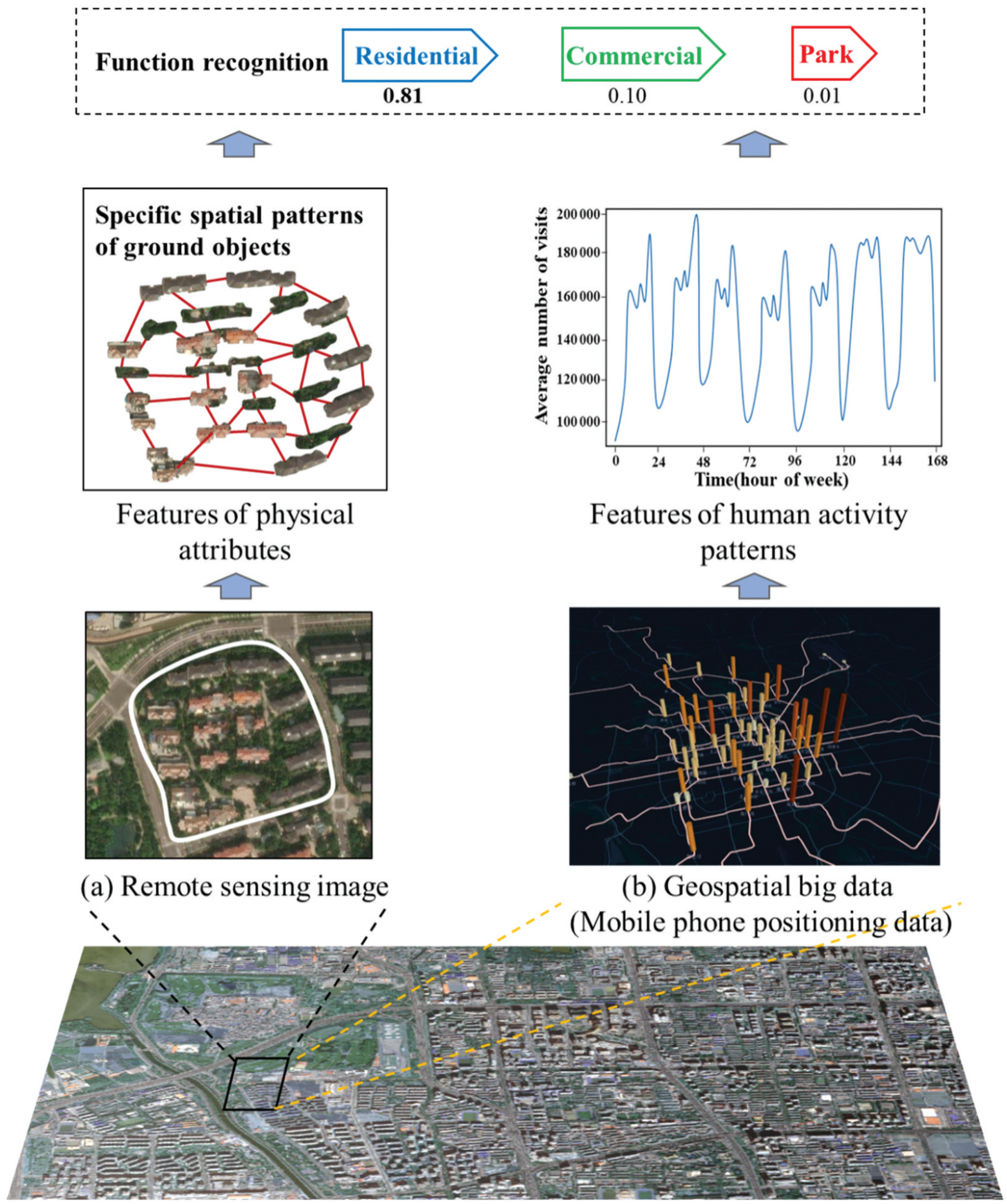


Figure 2. A UFZ exhibits the comprehensive characteristics of a built environment and human activity. It is affected by human socioeconomic activities and formed by various ground objects following specific spatial distribution patterns. (a) The spatial distribution and arrangement of ground objects within UFZs adhere to distinct patterns; (b) the weekly average number of visitors per hour in the residential zone follows a regular pattern (Data source: https://aistudio.baidu.com/aistudio/projectdetail/186492).

residential zones (Figure 1(d)) consist of buildings, vegetation, bare soil, and roads, and the land cover elements present different spatial structures among different types of UFZs and even the same category of UFZ. This characteristic underscores the need for designing features with robust expressive power to effectively discern diverse urban functions.

- **Scale-dependency**. UFZs exhibit considerable variations in size, making them amenable to analysis across multiple scales. This variability stems from the fact that urban functions and ground objects are correlated at different scales, and, thus, multiple scales are appropriate to investigate different granularities of function types. For instance, Zhang et al. (2018) suggested that a campus UFZ may necessitate analysis at a larger scale, while at a smaller scale, a campus tends to be subdivided into residential, teaching, and even commercial and park areas (Figure 3).

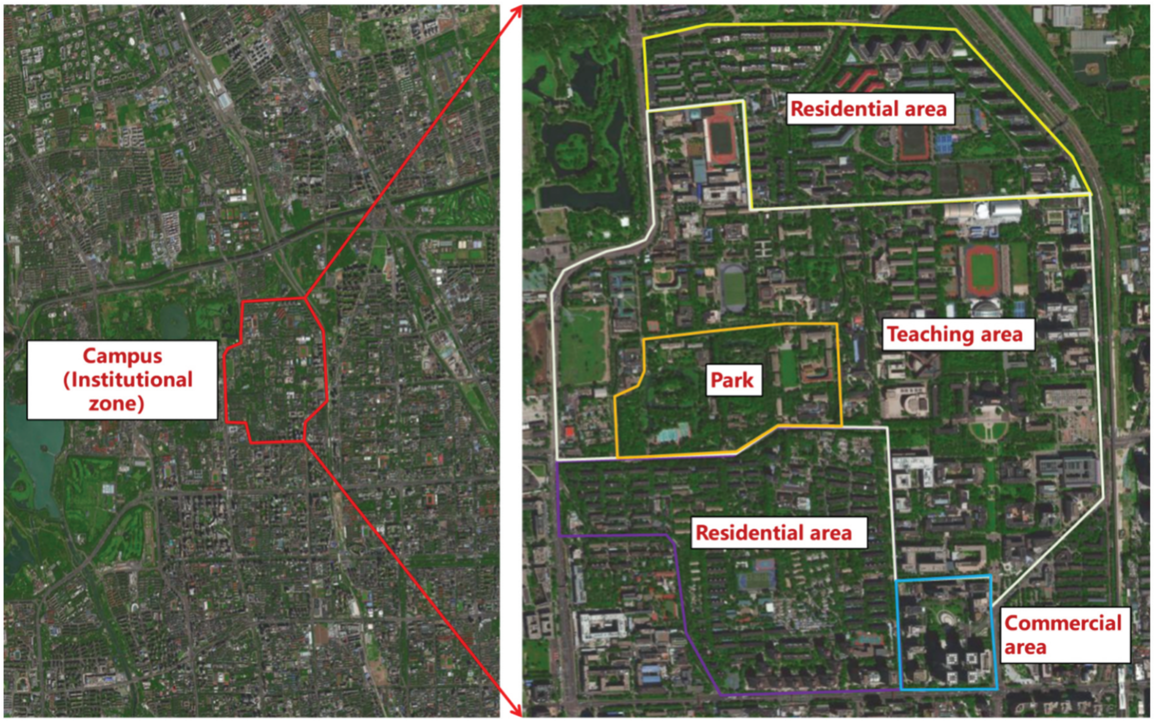


Figure 3. UFZs demonstrate scale-dependency. For instance, a campus falls under the institutional zone category if it is analyzed as a whole and investigated at a large scale; however, at a small scale, the campus reveals subdivisions into residential areas, teaching spaces, and even commercial areas and parks.

The above three characteristics are the key issues in analyzing UFZs, rendering UFZ mapping more intricate compared with object recognition and analysis in the field of remote sensing and geospatial big data. Consequently, they necessitate careful consideration and resolution in the context of UFZ mapping.

3. Method review

3.1. Overview

The purpose of UFZ mapping is to obtain the delineation of different functional zones and the identification of functional types within a city. It is a region-based mapping result where each region typically represents a functional zone. These regions are spatially continuous and non-overlapping. The observation of existing studies reveals that prevalent methods for UFZ mapping generally hinge on three pivotal processes: 1) mapping unit generation, 2) feature representation, and 3) function classification (Figure 4). Similar socioeconomic activities tend to aggregate within specific spatial extents in urban areas, forming UFZs (Tyler and Ward 2010; Zhang et al. 2018). As a result, mapping unit generation aims to spatially generate the UFZ boundary extent. Each type of UFZ possesses inherent representative features (Figure 2), underscoring the significance of these features in identifying the function types. In feature representation, remote sensing images or geospatial big data prove invaluable in extracting distinctive features for function classification from the perspectives of physical attributes (such as the spatial patterns of ground objects) or human activities (such as human daily travel patterns). Finally, function classification employs supervised or unsupervised techniques to categorize urban functions based on feature representation. This paper will delve into and review the existing research through the lens of these three key processes. In the context of UFZ mapping, it is indeed challenging to compare the accuracy of different studies due to variations in classification systems, methodologies, and study areas. These differences make it difficult to establish a standardized accuracy metric across studies. Therefore, we have approached the evaluation of different spatial

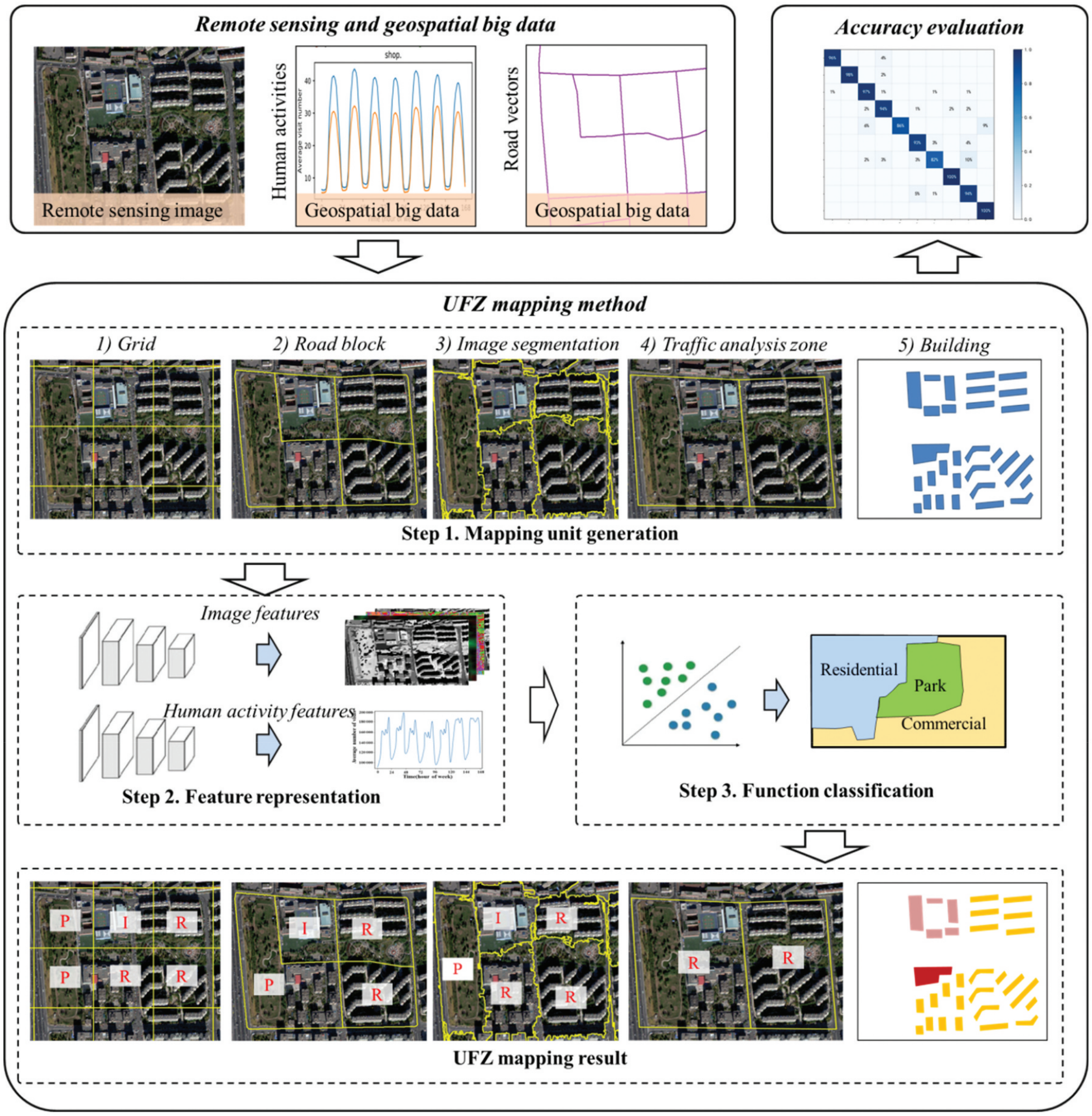


Figure 4. The UFZ mapping paradigm commonly employed in existing studies (R: residential zones; I: institutional zones; P: parks). It relies on remote sensing or geospatial big data and involves three steps: 1) mapping unit generation, 2) feature representation, and 3) function classification.

units, features, and classification methods in a qualitative manner. This allows us to assess their strengths and weaknesses based on the context and findings in the existing literature rather than relying on specific accuracy metrics. In addition, some studies may focus on the identification of specific UFZ types, such as commercial zones (Hou and Chen 2021; Yang et al. 2019) and shantytowns (Fan et al. 2022). These studies often follow or adopt a general classification scheme but may utilize more specialized methods tailored to their unique characteristics.

3.2. Remote sensing and geospatial big data used for UFZ mapping

3.2.1. Remote sensing data

Remote sensing images offer the most immediate representation of ground surfaces, presenting unique opportunities for the quantitative analysis and dynamic monitoring of cities (Treitz and Rogan 2004). The comprehensiveness of UFZs implies a specific built environment, such as the distinct two-dimensional (2D) and three-dimensional (3D) spatial structure of ground objects, the particular spatiotemporal feature of night lights, and the specific spectral and polarization features of ground objects. Fortunately, this information can be captured using present-day remote sensing data, including high- and medium-resolution multispectral images, multi-angle images, night light images, SAR images, etc. Table 1 summarizes the types of remote sensing data that have been employed in existing UFZ mapping studies.

(1) **High resolution remote sensing images**. This is the most frequently used type of data for UFZ mapping, comprising satellite or aerial images with spatial resolutions ranging from meters to sub-meters (Du et al. 2021; Zhang et al. 2017). These images offer detailed views of urban surfaces in a single temporal phase, enabling a closer look at object boundaries and spatial structures that reflect the built environment of cities. However, their relatively low spectral and temporal resolutions limit their capacity to extract specific information about object categories and changes, such as parks with green vegetation. Nonetheless, their high spatial resolution provides a clear analysis of the spatial structure of ground objects, making them the most essential data source for UFZ mapping.

(2) **Medium resolution remote sensing images**. These refer to satellite images with a resolution at the 10-meter level (e.g. Landsat images), striking a balance of a lower spatial resolution with better temporal and spectral resolutions. Since a single image covers a wider area, it facilitates UFZ extraction over larger spatial ranges (Du et al. 2020; Hu et al. 2016). While the land cover information derived from medium resolution satellite images may not offer extensive internal structure details and clear distinctions between UFZs, the presence of multispectral bands proves invaluable for extracting specific land covers, such as water bodies and vegetation, serving the identification of specific UFZs, such as parks. (Kopecká, Szatmári, and Rosina 2017).

(3) **SAR images**. Microwave remote sensing is also applied in UFZ analysis due to its advantages in obtaining the texture and vertical structure information of ground objects (Cai and Chen 2022; Chen, Xu, and Gong 2021; Gamba and Aldrighi 2012; Zhao et al. 2020). The various scattering and texture features in SAR images contribute to the classification of specific targets and building height extraction (Frantz et al. 2021). Building height information is beneficial for identifying urban functions because it provides the 3D spatial structure of ground objects within UFZs (Huang, Chen, and Gong 2018; Tu et al. 2022; Zhao et al. 2020).

Table 1. Remote sensing data employed in the task of UFZ mapping. It includes high resolution, medium resolution, SAR, multi-angle and night light remote sensing images.

Remote sensing data type	Spatial resolution	Information provided	Data Sources	References
High resolution remote sensing images	meter-level, sub-meter-level	Providing fine-grained ground object details and their spatial patterns	SPOT-5, QuickBird, Worldview, GaoFen-1, GaoFen-2, GaoFen-6	Du et al. (2021); Huang, Zhao, and Song (2018); Zhang et al. (2017)
Medium resolution remote sensing images	10-meter-level	Providing time-series multispectral features	Sentinel-2 (https://dataspace.copernicus.eu/explore-data/data-collections.), Landsat (https://earthexplorer.usgs.gov/.)	Hu et al. (2016); Kopecká, Szatmári, and Rosina (2017)
SAR images	10-meter-level	Providing active remote sensing polarization features	Sentinel-1 (https://dataspace.copernicus.eu/explore-data/data-collections.)	Cai and Chen (2022); Frantz et al. (2021); Gamba and Aldrighi (2012); Zhao et al. (2020)
Multi-angle remote sensing images	meter-level, sub-meter-level	Providing 3D spatial structure	Ziyuan-3	Feng et al. (2018); Huang, Chen, and Gong (2018); Huang et al. (2020); Huang et al. (2021)
Night light remote sensing images	meter-level, 10-meter-level	Providing spatiotemporal features of night lights and indirectly characterizes human socioeconomic activities	Jilin1-07 (https://www.jl1mall.com/.), SDGSAT-1 (https://data.sdgsat.ac.cn/.)	Chen et al. (2023); Huang et al. (2021)

Additionally, due to the scattering and texture characteristics of SAR data, they can be used to classify specific types of land cover, such as large water bodies, which is advantageous for identifying public open spaces (Gamba and Aldrighi 2012).

(4) **Multi-angle remote sensing images**. Several studies leverage the 3D features derived from multi-angle imaging to analyze urban functions (Huang, Chen, and Gong 2018; Huang et al. 2020, 2021). In fact, in addition to the 2D spatial structures, UFZs also exhibit obvious 3D features, such as high-rise commercial zones, mid-rise residential zones, and low-rise shantytowns (Chen et al. 2020). Therefore, multi-angle satellite images are valuable for capturing urban vertical information, aiding in UFZ mapping. Additionally, images from different angles and sensors have also been applied to enhance the description of observations from multiple perspectives (Feng et al. 2018).

(5) **Night light remote sensing images**. Night light data not only directly present the nighttime environment on the surface but also indirectly measure human activities and socioeconomic conditions, offering new opportunities for UFZ mapping (Chen, Zhang, and Yang 2021; Levin et al. 2020; Sharma et al. 2016). Recent satellites, such as Jilin 1-07 with a resolution of 0.92 m and SDGSAT-1 with a resolution of 40 m, provide fine-scale nighttime light data, contributing to urban function identification (Chen et al. 2023; Huang et al. 2021).

3.2.2. *Geospatial big data*

Urban functions are closely related to human socioeconomic activities (Barton 2009). Geospatial big data, characterized by a large sample size, diverse types, and strong openness, prove instrumental in describing the socioeconomic activities within cities, thereby providing abundant information for the identification of UFZs (Yin et al. 2021). Table 2 lists the geospatial big data used for UFZ analysis.

(1) **Data reflecting human activity patterns**. With the advancement of mobile internet technology, social media data (Twitter, WeChat, Weibo, etc.) are employed to analyze urban functions, as they provide geographically tagged information that mirrors human activities (Crooks et al. 2015; Wang et al. 2016). For example, as one of the most popular social media platforms in China, WeChat allows users to post messages and record real-time locations. The recorded information on active population density provides dynamic insights into human activity from both spatial and temporal perspectives (Gao et al. 2021). Mobile phone positioning data (Tu et al. 2018) and traffic trajectory data (Hu et al. 2021) are two commonly utilized datasets reflecting users' travel patterns. These periodic datasets allow for the

Table 2. Geospatial big data employed in the task of UFZ mapping. It includes data reflecting human activity patterns and data reflecting scene semantics.

Data type	Data category	Data source	References
Data reflecting human activity patterns	Social media data	Twitter (https://www.statista.com/statistics/303681/twitter-users-worldwide/.)	Crooks et al. (2015); Häberle, Hoffmann, and Zhu (2022)
		Sina-Weibo (https://data.weibo.com/report.)	Wang et al. (2016)
	Mobile phone positioning data	Mobile communication operator (https://alpercinar.com/open-cell-id/.)	Tu et al. (2018); Chen et al. (2024)
		Tencent real-time user data (https://heat.qq.com.)	Gao et al. (2021); Liu et al. (2017)
	Traffic trajectory data	Smart card data (https://vip.chelaile.net.cn/.)	Qi et al. (2018)
		Floating car data (http://traffichut.net.)	Hu et al. (2021); Yuan et al. (2014)
Data reflecting scene semantics	POI	OSM (https://welcome.openstreetmap.org.)	Lu et al. (2022)
		Facebook Places (https://www.plotprojects.com/blog/introducing-your-poi-database-powered-by-facebook-places/.)	Andrade, Alves, and Bento (2020)
		Sina-Weibo (https://open.weibo.com/wiki/Pois/get_poi.)	Miao, Wang, and Li (2021)
		Baidu Map (https://lbs.baidu.com/products/search.)	Yao et al. (2017)
		Gaode Map (https://lbs.amap.com/api/webservice/guide/api/search/)	Wang et al. (2021)
	VGI	OSM (https://welcome.openstreetmap.org)	Zhao et al. (2019)
	Street views	Baidu Street View (https://lbs.baidu.com/products/panoramic)	Chang et al. (2020)
		Tencent Street View (https://lbs.qq.com/tool/streetview/index.htm)	Ye et al. (2021)
		Google Street View (https://lbs.amap.com/api/webservice/guide/api/staticmaps)	Srivastava, Vargas-Munoz, and Tuia (2019)

inference of the spatiotemporal trajectories of human movement, which vary among different types of UFZs (Chen, Xu, and Gong 2021).

(2) **Data reflecting scene semantics**. Volunteered Geographic Information (VGI) data often contain scene semantic information that is voluntarily contributed and uploaded by the public with geographic reference information. OpenStreetMap (OSM) is the most frequently used VGI data, containing information such as POIs, Areas of Interest (AOIs), building vectors, and road vectors (Zhao et al. 2019). AOI data provide valuable information, including closed vector areas and associated attributes such as names and classifications. This type of data can be particularly useful for defining and analyzing specific UFZs due to detailed spatial and attribute information (Zhou et al. 2019). POI data embody regional function semantics dominated by human activities, mainly encompassing the social functions of places (Andrade, Alves, and Bento 2020). Due to their wide coverage, timely updates, easy accessibility, and rich semantic information, POI data have become the most widely used data source for urban function identification (Liu et al. 2021). In contrast to satellite images looking down, street view image data from platforms such as Google (Srivastava, Vargas-Munoz, and Tuia 2019), Baidu (Chang et al. 2020), and Tencent (Ye et al. 2021) provide street-level observations along the road network route. These images offer visual depictions of urban streetscapes, allowing for the inference of the function semantics of places.

3.3. Mapping units

The generation of mapping units represents the initial challenge encountered in UFZ mapping endeavors. It faces the following challenges: 1) exhibit multi-scale characteristics, and 2) possess irregular shapes and sizes. While existing research has utilized various spatial units, there still exists a gap in their adaptability for analyzing UFZs (Du et al. 2021; Lin et al. 2024). This paper will provide an overview of the spatial units utilized in existing studies and discuss the advantages and disadvantages of each type of unit (Table 3 and Figure 5).

(1) **Regular grids**. This approach represents the urban function structure through a set of uniform, continuous, and non-overlapping grid cells, considering each grid cell as a functional unit (Tu et al. 2018). The grid size is predetermined based on the study area's dimensions and the classification system (Zhao and Du 2016), and the division of the grid is straightforward. However, UFZ units typically exhibit diverse sizes and irregular shapes, rendering this method unable to conform to the real boundaries of UFZs and compromising their integrity. In one word, they are suitable for large-scale analyses but may not accurately represent irregular UFZs (Du et al. 2021).

(2) **Road blocks**. With the increase of open road vector data (such as OSM), more and more studies adopt road blocks as spatial units for UFZ mapping (Su et al. 2021; Zhang, Du, and Wang 2015). Although their variable size and shape can present challenges, road blocks closely align with the actual urban infrastructure, making them a promising and widely used UFZ

Table 3. Spatial units used for UFZ mapping. It includes regular grids, road blocks, image segmentation units, TAZs and building units.

Mapping units	Advantages	Disadvantages	Typical references
Regular grids	Simpleness to generate grids	Impreciseness to represent the sizes, shapes, and boundaries of UFZs	Häberle, Hoffmann, and Zhu (2022); Tu et al. (2018); Zhao et al. (2015)
Road blocks	Free availability and partly coincide with UFZ boundaries	Single scale, and incompleteness and scarceness in some areas	Huang, Zhao, and Song (2018); Su et al. (2021)
Image segmentation units	Capability of expressing multi-scale spatial units	Inaccurate conformity with UFZ boundaries	Nielsen (2015); Zhang et al. (2018)
TAZs	Better coincide with real UFZ boundaries	Difficulty to obtain and update in time	Liu et al. (2017); Yao et al. (2017)
Building units	Suitability for fine-grained urban function analysis	Discontinuous function zones	Bandam et al. (2022); Chen et al. (2017); Chen et al. (2023); Häberle, Hoffmann, and Zhu (2022); Lin et al. (2021)

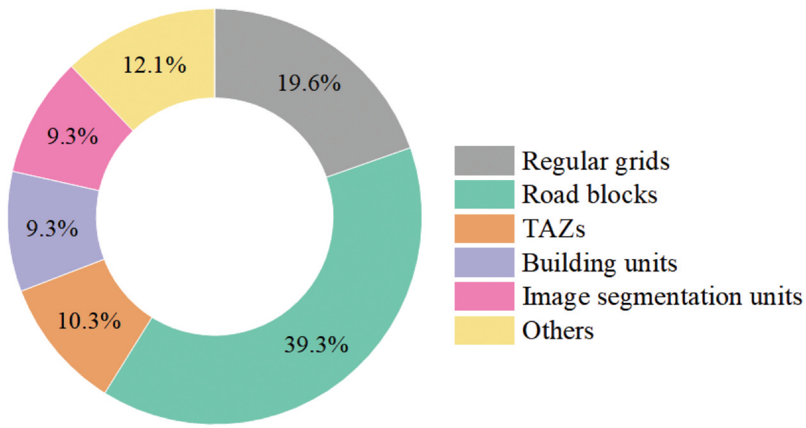


Figure 5. The proportions of different spatial units used in existing studies. These conclusions are drawn from the analysis of 107 papers, with searches conducted on Google Scholar covering the time span from 2011 to 2024.

unit. However, cities feature a vast network of roads with varying hierarchical levels (such as high-level highways, arterial roads, low-level internal roads, and sidewalks). The utilization of low-level roads may lead to fragmented segmentation units, while the utilization of high-level roads can result in road blocks comprising different function types, a phenomenon known as a mixed function (Zhang et al. 2017). On the other hand, roads are unevenly distributed, and it is difficult to achieve satisfactory segmentation results in road-sparse areas. In addition, block segmentation can only extract single-scale UFZs and ignores the multi-scale properties of UFZs (Kirchhoff, Trepl, and Vicenzotti 2013; Zhang et al. 2017). Therefore, while road blocks are the most commonly used choice, the aforementioned issues need to be carefully considered when delineating UFZs. The most comprehensive and appropriately scaled road vector data should be selected based on the study area and objectives.

(3) **Image segmentation units**. Image segmentation aims to divide an image into a series of non-overlapping regions, making the pixels in each region uniform in color and texture (object segmentation) (Blaschke 2010) or having consistent semantics (semantic segmentation) (Du et al. 2021). UFZs represent units with the specific functional semantics and spatial patterns of ground objects, making the automatic segmentation of UFZs through image segmentation methods a viable approach (Zhou et al. 2020). However, UFZs consist of diverse and heterogeneous ground objects. The comprehensiveness and heterogeneity of UFZs pose challenges for existing image segmentation methods to generate accurate UFZ units that align with the true boundaries of UFZs.

(4) **Traffic Analysis Zones (TAZs)**. These zones are usually delineated by the transport department for transport planning and management, comprehensively considering factors such as terrain, road distribution, administrative division, and sampling convenience (Liu et al. 2017; Long and Shen 2015; Yao et al. 2017). They are typically applied to analyzing the commuting patterns of urban populations. Although TAZs are also used for urban function analysis, they may not always align with UFZs (Yao et al. 2017). The limitation of using TAZs for UFZ mapping lies in the scarcity and difficulty in collecting data, thus restricting the applicability of this spatial unit (Liu et al. 2021; Xu et al. 2021).

(5) **Building units**. Buildings serve as fundamental elements within a UFZ. Once the function type of each building is determined, buildings with similar functions can be spatially clustered to form larger functional zones using clustering algorithms such as hierarchical clustering (Chen et al. 2017; Lin et al. 2021, 2024). Building footprint data can be collected from open platforms (Lin et al. 2021) or remote sensing image classification (Frantz et al. 2021). As the basic elements of UFZs, buildings can be

considered as the minimum analysis scale for UFZs, and through scale conversion, they can accommodate multi-scale UFZ analysis tasks. However, footprint data from open platforms may not encompass the entire urban area, and buildings identified through image classification are subject to extraction accuracy concerns (Lin et al. 2021).

3.4. Feature representation

Based on generating UFZ units, extracting diverse features from the remote sensing and geospatial big data used for representing UFZs is a fundamental step because the accuracy of function classification highly relies on the ability to express these features for urban functions. Illustrated in Figure 6, this section will provide an overview of the frequently employed representation features derived from remote sensing and geospatial big data for the purpose of urban function classification.

3.4.1. Feature representation derived from remote sensing data

Different types of remote sensing data bring a variety of urban surface observations, providing features for identifying urban functions from different perspectives. These extracted features can fall into three types: visual features, spatial pattern features, and abstract features. Visual features refer to a series of quantitative descriptors (spectral, texture, geometric, etc.) directly extracted from images to characterize UFZ units, which are defined based on human visual perception experience (Popescu, Gavat, and Datcu 2011). Given the diverse spatial patterns among objects in different UFZs, spatial pattern features are introduced as supplementary indicators for identifying function types (Zhang, Du, and Wang 2017). Abstract features consist of theme semantic features and deep learning features, which can be considered as high-level abstract expressions of UFZs (Huang, Zhao, and Song 2018).

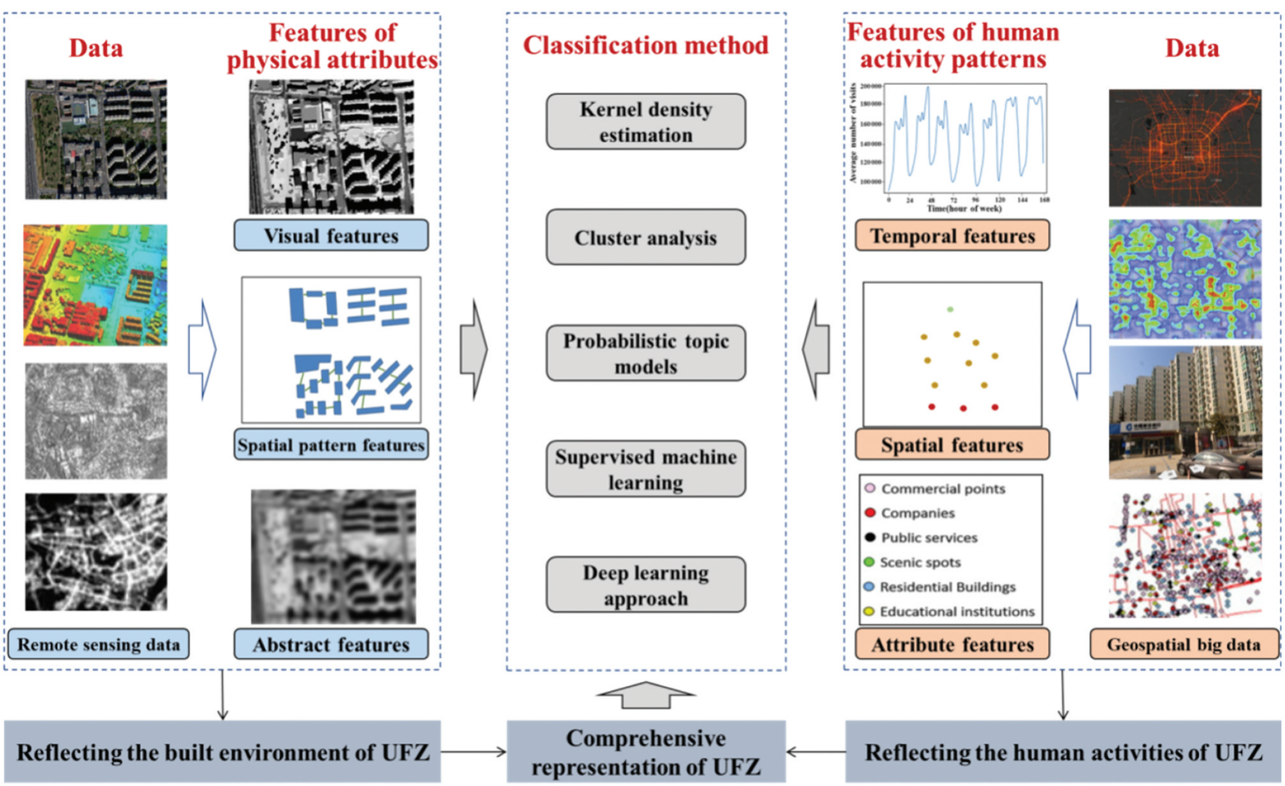


Figure 6. Feature representation and function classification among different data sources for UFZ mapping. Remote sensing data provide physical attribute features, while geospatial big data offer patterns of human activities. These features can be utilized individually for function classification using various machine learning methods, or they can be combined to construct a comprehensive representation of UFZs for classification.

(1) **Visual features**. Visual features serve as fundamental measurements for capturing heterogeneous spectral and texture changes, endowing them with the capability to differentiate between various function types. The spectral band mean (Jia et al. 2018), spectral indices (such as the Normalized Difference Vegetation Index and the Normalized Difference Water Index) (Sanlang et al. 2021), texture features (Zhang, Du, and Wang 2015), geometric features (Sanlang et al. 2021), morphological features (Li et al. 2016), and the brightness features of nighttime light images (Chen et al. 2023) have been explored for urban function classification in existing studies. However, effectively expressing UFZ differences proves challenging for visual features due to the comprehensive and heterogeneous nature of UFZs, which weakens the recognition ability of visual features (Comber, Brunsdon, and Farmer 2012).
(2) **Spatial pattern features**. The comprehensiveness of UFZs implies that the diverse ground objects constituting UFZs exhibit specific spatial patterns (Figure 2). As a result, the spatial patterns between ground objects are introduced as a feature parameter for urban function classification, including object co-occurrence (Zhang, Du, and Zhang 2018), geometric metrics (Zhang et al. 2018), and neighborhood graphs (Walde et al. 2014). In addition to the 2D spatial relationships of ground objects, the structural information in the vertical dimension, especially the height information of buildings, proves valuable for urban function analysis (Huang, Chen, and Gong 2018; Tu et al. 2022). Spatial pattern features improve the expression ability of UFZs, but the highly heterogeneous nature of urban scenes in real cities poses challenges to their comprehensive representation for UFZ recognition.
(3) **Abstract features**. They are more expressive features obtained by abstracting and transforming images or visual features through machine learning or statistical learning methods. Theme semantic features are considered abstract as they estimate the probability distribution of function topics in each UFZ, enhancing UFZ analysis accuracy. However, thematic semantic features are easily affected by semantic ambiguity, leading to uncertainty in understanding the classification of urban functions (Zhao, Zhong, and Zhang 2016; Zhao et al. 2015). The features learned by deep learning have more powerful expressive capabilities, which can better address the challenges posed by the comprehensiveness and heterogeneity of UFZs (Huang, Zhao, and Song 2018; Lu et al. 2022; Wu et al. 2023). Nonetheless, deep features lack clear semantics, so the expression of UFZs by deep features typically lacks interpretability.

3.4.2. Feature representation derived from geospatial big data

The analysis of urban functions and human activities using geospatial big data has emerged as a prominent research focus in recent years (Li et al. 2016). Although the information derived from geospatial big data is diverse, they can still be measured by their spatial (Su et al. 2021), attribute (Ye et al. 2021), and temporal features (Cao et al. 2020) for urban function analysis.

(1) **Spatial features**. Geospatial big data are generated by individuals within specific time and spatial contexts. Spatial features encompass positioning features (Bao et al. 2020), geometric features (Zhao et al. 2019), and trajectory features (Yuan et al. 2014). For instance, POI data are frequently utilized to offer rich category information about a spatial location (Bao et al. 2020). The trajectory features of humans or taxis can be employed to quantify the spatio-temporal aspects of human activities, aiding in the exploration of urban functions (Yuan et al. 2014).
(2) **Attribute features**. Beyond spatial locations, geospatial big data encompass qualitative or quantitative descriptions of the natural or human attributes of ground objects. For example, in the case of POI, the location coordinates *(x, y)* are accompanied by attributes such as name and category. Similarly, mobile phone positioning data not only provide spatial information but also include user details such as age, occupation, and gender. In addition, attribute features can be conveyed through visual or textual formats. For example, street view

images, social media photos, and text data usually contain attribute information, which helps to recognize urban functions (Srivastava, Vargas-Munoz, and Tuia 2019; Zhao et al. 2019).

(3) **Temporal features**. The human activities reflected in geospatial big data exhibit dynamic changes over time, capturing the temporal dimension of human socioeconomic activities. For example, mobile phone positioning data, taxi trajectory data, and social media data often contain trends, periodicities, and random characteristics. These temporal patterns unveil the ebb and flow of human activities, contributing to the inference of urban functions (Cao et al. 2020; Pei et al. 2014). As an illustration, consider a residential zone where, during working hours, the population is lower, whereas it increases during non-working hours. In contrast, commercial zones exhibit an opposite trend to residential zones throughout the day.

3.5. Function classification

Classifying urban functions is crucial for mapping UFZs and ensuring mapping accuracy. Despite the availability of advanced methods for urban function classification, the comprehensiveness, heterogeneity, and scale-dependency of UFZs significantly impact the success of the classification process (Chen, Xu, and Gong 2021). As depicted in Figure 6, according to the data sources used, classification strategies can fall into two categories: single data methods and data fusion methods. Various classification methods have been employed in existing studies, including kernel density estimation, cluster analysis, probabilistic topic model (PTM), supervised machine learning methods (encompassing traditional approaches such as Random Forest and Support Vector Machine), and deep learning methods (Table 4). Data fusion methods integrate remote sensing and geospatial big data to recognize UFZs based on physical attributes and socioeconomic characteristics. The fusion strategy can be categorized into data-level, feature-level, decision-level, and hybrid-level fusion.

3.5.1. Function classification methods

This section provides a description and analysis of the function classification methods employed in existing studies on UFZ mapping.

(1) **Kernel density estimation**. This method intuitively reflects the aggregation and distribution characteristics of specific types of geospatial data through density analysis to determine the urban function type of mapping units, such as grids and road blocks (Hou and Chen 2021; Lin et al. 2021; Wang et al. 2021; Yang et al. 2019; Yuan et al. 2014). For instance, POIs encompass the locations and attribute information of various facilities in a city; thus, the density and agglomeration trends of POIs analyzed via kernel density estimation aid in identifying urban functions (Bao et al. 2020; Yuan et al. 2014). However, kernel density estimation is designed to assess the aggregation intensity of a single geospatial datum, limiting its ability to capture the comprehensiveness of UFZs and determine the spatial range information of UFZs (Liu et al. 2021).

(2) **Cluster analysis**. This method groups units with similar features derived from remote sensing or geospatial big data into the same function category (Lee et al. 2016). Commonly used clustering methods include K-means (Gao, Janowicz, and Couclelis 2017; Miao, Wang, and Li 2021; Wang et al. 2016; Zhi et al. 2016), K-medoids (Chen et al. 2017; Liu et al. 2020), fuzzy c-means clustering (Qi et al. 2018; Xiao, Zhang, and Hu 2019), Gaussian mixture models (Deng et al. 2022; Gao et al. 2019; Jiang, Hu, and Shi 2016), and spatial clustering applications (DBSCAN) (Hao et al. 2020; Pan et al. 2012; Tu et al. 2022; Xiao et al. 2022). However, cluster analysis primarily discerns the category of UFZs, lacking the ability to capture the spatial scope. Moreover, cluster algorithms heavily depend on the function separability of derived features from diverse data, facing challenges in overcoming the comprehensiveness and heterogeneity of UFZs, especially in complex urban environments (Tyler and Ward 2010).

(3) **Probabilistic Topic Model (PTM)**. PTM methods facilitate the theme mining of remote sensing and geospatial big data or their derived features, revealing the functional themes within specific spatial areas (Crooks et al. 2015; McKenzie and Janowicz 2017). Various PTM methods, such as bag of visual words (BoVW) (Zhao and Du 2016), probabilistic Latent Semantic Analysis (pLSA) (Hofmann

Table 4. Function classification method regarding different data sources. It includes kernel density estimation, cluster analysis, probabilistic topic model, supervised machine learning and deep learning.

Method		Remote sensing data	Geospatial big data	Data fusion
Kernel density estimation		/	Bao et al. (2020); Hou and Chen (2021); Lin et al. (2021); Wang et al. (2021); Yang et al. (2019); Yuan et al. (2014)	/
Cluster analysis	K-means	Nielsen (2015)	Gao, Janowicz, and Couclelis (2017); Miao, Wang, and Li (2021); Wang et al. (2016); Zhi et al. (2016)	/
	K-medoids	/	Chen et al. (2017); Liu et al. (2020)	/
	Fuzzy c-means clustering	/	Qi et al. (2018); Xiao, Zhang, and Hu (2019)	/
	Gaussian mixture models	/	Deng et al. (2022); Gao et al. (2019); Jiang, Hu, and Shi (2016)	/
	Spatial clustering applications (DBSCAN)	/	Hao et al. (2020); Pan et al. (2012); Tu et al. (2022); Xiao et al. (2022)	/
Probabilistic topic model	BoVW	Zhao and Du (2016)	/	Chen, Zhang, and Yang (2021)
	pLSA	Zhao et al. (2015); Zhong, Zhu, and Zhang (2015)	Tao et al. (2019)	Liu et al. (2017)
	LDA	Zhao et al. (2015); Zhao, Zhong, and Zhang (2016); Zhong, Zhu, and Zhang (2015); Zhu et al. (2017)	Gao, Janowicz, and Couclelis (2017)	X. Liu et al. (2017); Du et al. (2020)
Supervised machine learning	K-NN	Zhang, Du, and Wang (2015)	Liu et al. (2020)	Qian et al. (2020)
	Random Forest	Ruiz Hernandez and Shi (2018)	Toole et al. (2012); Yao et al. (2017)	Chang et al. (2020); Du, Zhang, and Zhang (2015); Lin et al. (2024); Mao et al. (2020); Zhang et al. (2017)
	Support Vector Machine	/	Deng et al. (2022)	Du et al. (2020); Liu et al. (2017); Mao et al. (2020); Zhang, Du, and Wang (2017)
	Decision Tree	Hua et al. (2012)	/	/
	Artificial Neural Network	/	/	Mao et al. (2020)
	XGBoost	/	/	Cao, Guo, and Zhang (2019); Chen, Zhang, and Yang (2021); Feng et al. (2021)
Deep learning	CNN	Anwer et al. (2018); Du et al. (2021); Huang, Zhao, and Song (2018)	/	Bao et al. (2020); Lu et al. (2022); Shen et al. (2022); Wu et al. (2023)
	Natural language processing	/	L. Cai et al. (2022); Huang et al. (2022); Niu and Silva (2021); Qin et al. (2022); Sun et al. (2021); Yao et al. (2017); Zhai et al. (2019); Zhang et al. (2021)	/
	Graph neural network	Gai et al. (2024)	Hu et al. (2021); Huang et al. (2023); Xu et al. (2022)	Yang et al. (2022)
	Transformer	/	/	Shi et al. (2024); Zhou et al. (2023)

2001; Liu et al. 2017; Zhao et al. 2015; Zhong, Zhu, and Zhang 2015; Zhu et al. 2017) and Latent Dirichlet Allocation (LDA) (Gao, Janowicz, and Couclelis 2017; Liu et al. 2017; Zhao, Zhong, and Zhang 2016; Zhao et al. 2015; Zhong, Zhu, and Zhang 2015), have been employed for urban function discovery. Although PTM has enhanced the accuracy of urban function classification, such models nevertheless face challenges in terms of interpreting topics and sensitivity to model parameters. Simultaneously, they encounter difficulty in accurately capturing the practical implications of urban functions within an unsupervised learning framework (Hu et al. 2020).

(4) **Supervised machine learning method**. These methods rely on features extracted from remote sensing or geospatial big data. They involve the collection of manually labeled training samples to train an optimal model, which is subsequently applied to classify functions in new data, incorporating the prior knowledge of the samples to enhance classification accuracy (Zhang and Du 2015). For remote sensing data, methods such as K-NN (Qian et al. 2020; Zhang, Du, and Wang 2015), Random Forest (Chang et al. 2020; Du, Zhang, and Zhang 2015; Mao et al. 2020; Ruiz Hernandez and Shi 2018), Support Vector Machine (Du et al. 2020; Mao et al. 2020; Zhang, Du, and Wang 2017), Decision Tree (Hua

et al. 2012), and Artificial Neural Network (Mao et al. 2020) have been employed. With regard to geospatial big data, K-NN (Liu et al. 2020; Qian et al. 2020), Random Forest (Chang et al. 2020; Toole et al. 2012; Xing and Meng 2018; Yao et al. 2017; Zhang et al. 2017), Support Vector Machine (Deng et al. 2022; Du et al. 2020; Liu et al. 2017), and XGBoost (Cao, Guo, and Zhang 2019; Chen, Zhang, and Yang 2021) have also been applied. The performance of these methods is heavily contingent on the spatial separability of the features used and the quality of samples. Given the comprehensiveness and heterogeneity of UFZs, features with robust expressive capabilities are essential for the effectiveness of these supervised machine learning methods (Cao, Guo, and Zhang 2019; Oquab et al. 2014).

(5) **Deep learning method**. For urban function classification, the essence of deep learning methods lies in feature learning, with the goal of acquiring robust feature representations through hierarchical networks. This approach aims to conquer the classification challenges posed by the comprehensiveness and heterogeneity of UFZs. For remote sensing and geospatial big data, studies have proposed different network models for their analysis. Concerning remote sensing images, these models extract deep features and subsequently employ either end-to-end methods (Anwer et al. 2018; Du et al. 2021; Huang, Zhao, and Song 2018) or traditional supervised machine learning classifiers (Wu et al. 2023; Zhao and Du 2016) for function classification. For geospatial big data, three types of approaches have emerged: 1) NLP (Natural Language Processing)-based methods leverage the idea of understanding text to capture and recognize the characteristics of urban functions (Cai et al. 2022; Huang et al. 2022; Niu and Silva 2021; Qin et al. 2022; Sun et al. 2021; Yao et al. 2017; Zhai et al. 2019; Zhang et al. 2021); 2) graph neural network methods deal with the contextual and topological information of POIs, taxi trajectory data, etc., to classify urban functions (Hu et al. 2021; Huang et al. 2023; Xu et al. 2022); and 3) geospatial big data can be converted into 2D images, followed by inputting these images into deep learning model for feature extraction and classification (Bao et al. 2020; Lu et al. 2022; Shen et al. 2022; Wu et al. 2023). In addition, renowned for its powerful representational capabilities and excellent handling of sequential data, the Transformer has emerged as an ideal choice for processing multimodal data. In the realm of UFZ recognition, researchers have leveraged the characteristics of the Transformer to propose a series of algorithms based on multimodal data fusion, enabling more accurate and comprehensive representation and classification of urban functions (Shi et al. 2024; Zhou et al. 2023). The potent feature learning capability of deep learning enhances the expression of UFZ heterogeneity and improves the accuracy of urban function recognition, making it the most commonly used and promising method for current UFZ mapping tasks. However, deep learning methods heavily rely on sample data and lack interpretability. The heterogeneity of UFZs means that sample data are diverse, making deep learning more sensitive to the input data for UFZ mapping (Izzo et al. 2022).

3.5.2. Data fusion methods

The integration of multi-source data through spatial coupling holds significant promise in mitigating the limitations associated with a single data source. Therefore, this promises to conquer the comprehensiveness of UFZs to enhance classification accuracy (Bao et al. 2020; Du et al. 2020; Lu et al. 2022; Wu et al. 2023). In the context of multi-source data fusion for UFZ analysis, it is essential to acknowledge that different data exhibit variations in data modes, attributes, and spatial scales. These discrepancies pose significant challenges to the design of fusion methods (Baltrušaitis, Ahuja, and Morency 2018). As illustrated in Figure 7, existing fusion methods can be categorized into data-level, feature-level, and decision-level fusion according to the stage of modality fusion. In order to combine the advantages of multiple integration levels, hybrid-level fusion methods have also been proposed (Hong et al. 2021).

(1) **Data-level fusion**. It directly converts multimodal data into same-modal data for unified processing and analysis. A common approach is to

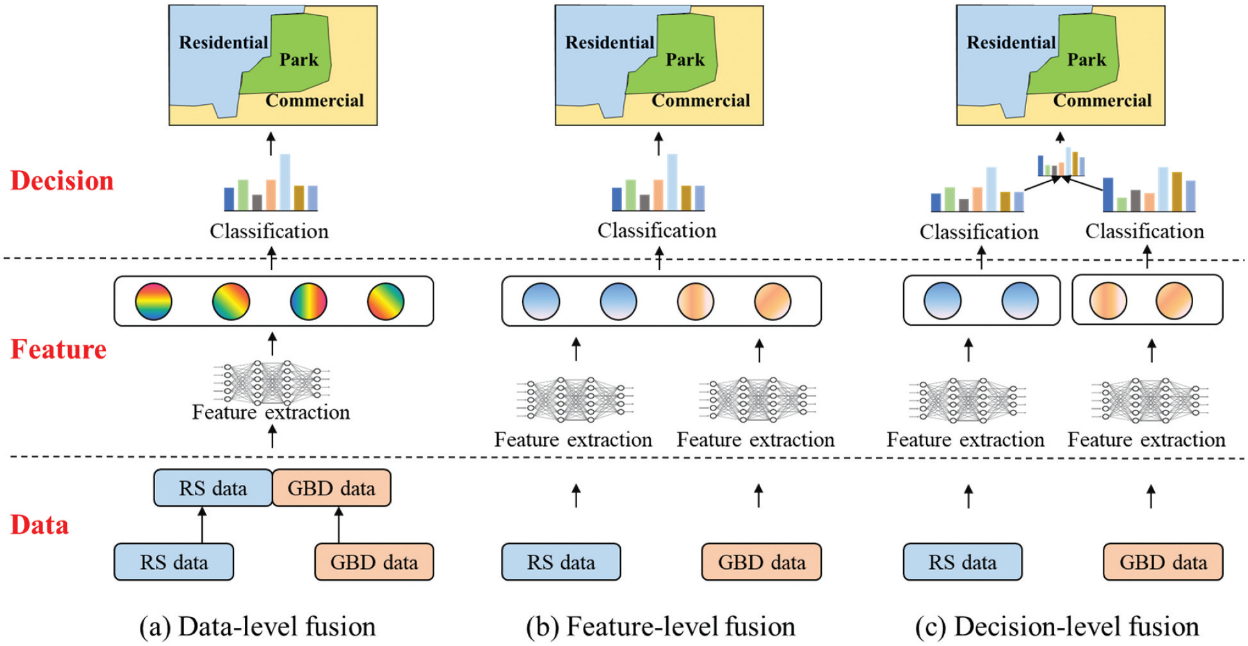


Figure 7. UFZ analysis scheme based on multi-source data fusion. Fusion methods include the data-level, feature-level, and decision-level. Additionally, various combinations of these levels can also be employed.

transform geospatial big data into 2D image data, subsequently overlaying them as a band of remote sensing images (Wu et al. 2023; Xie et al. 2022; Zhang et al. 2020). However, the inherent inconsistencies between different data, such as meaning, dimension, and spatial scale, present substantial challenges in the design of fusion methods (Hong et al. 2020).

(2) **Feature-level fusion**. In order to address inconsistencies between original data in each modality, feature representation is extracted independently from each modality and subsequently fused at the feature level (Bao et al. 2020, Cao et al. 2019, 2020; Du et al. 2020; Hu et al. 2016; Lu et al. 2022; Su et al. 2021; Tu et al. 2021; Zhang et al. 2017). For instance, certain studies employ parallel-branched convolutional network models for feature extraction, combining the extracted features in the network model and ultimately implementing function classification through classifiers (Bao et al. 2020; Cao et al. 2020; Lu et al. 2022). Nevertheless, managing the conflicts between semantic features extracted from different data sources requires careful consideration; otherwise, the concept of multimodal fusion may compromise the accuracy of function classification.

(3) **Decision-level fusion**. This approach comprehensively analyzes the results obtained from multimodal data in the final stage of function classification (Chen et al. 2018; Jia et al. 2018; Tu et al. 2018; Yang et al. 2022). This fusion method is feature-independent, and the classification results from different data sources are typically uncorrelated. The fusion rules and methods applied to fuse the preliminary decision results from different data sources are the key to improving classification accuracy (Jia et al. 2018).

(4) **Hybrid-level fusion**. This approach combines the strengths of individual fusion methods, enhancing fusion robustness while introducing increased structural complexity and training difficulty (He et al. 2023; Zhao et al. 2019; Zhou et al. 2021). Given the diversity and flexibility of deep learning model structures, hybrid-level fusion methods are deemed more suitable (He et al. 2020).

3.5.3. *Accuracy evaluation*

The accuracy evaluation of mapping results is crucial for the extraction and mapping processes. Various types of reference data have been used to assess the accuracy of UFZ mapping results. These include remote sensing image delineation (Du et al. 2021;

Sanlang et al. 2021; Zhang et al. 2018), existing GIS data (Hu et al. 2021), field surveys (Gong et al. 2020), officially published documents (Cao, Guo, and Zhang 2019; Chen et al. 2024; Hu et al. 2016), and validation of standard datasets (Cao et al. 2020; Fan et al. 2022). Each method has its own accuracy, applicability, and pros and cons. Remote sensing images provide high spatial resolution but may require extensive processing. Existing GIS data are readily available and comprehensive, yet they may be outdated. Field surveys offer high accuracy and ground truth validation, though they are time-consuming and resource-intensive. Official documents are authoritative but may not always be up-to-date or accessible. Different studies can determine their reference data based on the availability of data in their specific study area. In comparisons with reference data, quantitative evaluation metrics such as overall accuracy, precision, recall, Kappa and F1-score are used to assess the mapping accuracy. These performance metrics provide a quantitative assessment of the effectiveness of various approaches and highlight their comparative accuracy.

4. Discussions on limitations and challenges

In recent years, UFZ analysis, employing multimodal data fusion, has gained prominence because it allows for a more comprehensive description of urban functions, offering hope for enhanced UFZ mapping accuracy in complex urban environments (Gong et al. 2020; Lu et al. 2022). Despite the notable advancements in data and methodologies, the three essential characteristics of UFZs, comprehensiveness, heterogeneity, and scale-dependency, still pose great challenges to UFZ mapping. Therefore, there are still limitations in finely mapping UFZs that necessitate further exploration (Figure 8).

4.1. Limitations on UFZ mapping units

Generating UFZ units serves as both the prerequisite and a major challenge in UFZ mapping, especially in highly dense urbanized environments (Du et al. 2020; Zhang et al. 2017). UFZs, characterized by various shapes, sizes, and multi-scale properties, necessitate mapping units that can accommodate such diversity. Concurrently, contemporary urban planning often integrates multiple functional uses within confined spaces, encompassing residential, commercial, educational, and other purposes. Distinguishing these functions becomes challenging when the spatial resolutions of input data and features are coarser than the UFZ units, underscoring the importance of utilizing fine-scale spatial units for precise UFZ mapping (B. Chen, Xu, and Gong 2021).

As shown in Figure 5, compared to other units, road blocks are the most commonly used and are most likely to align with the actual functional zones (Liu et al. 2021). However, the accuracy of UFZ units is significantly influenced by the completeness and quality of the road vector data (Du et al. 2020). In Figure 9, publicly available road data in this area can

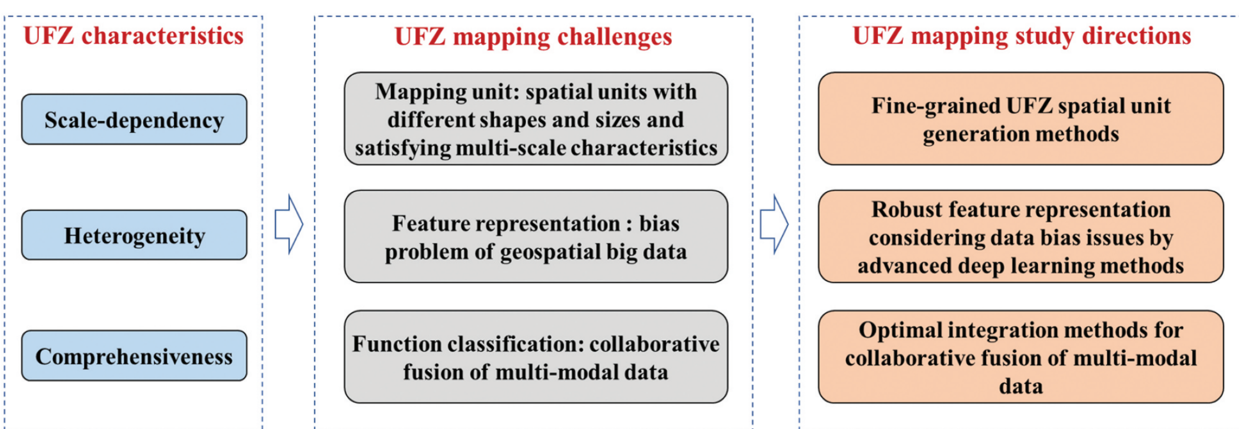


Figure 8. UFZ mapping challenges and potential study directions. Considering the characteristics of UFZs, UFZ mapping faces several challenges. In order to address these challenges, potential research directions have been proposed.

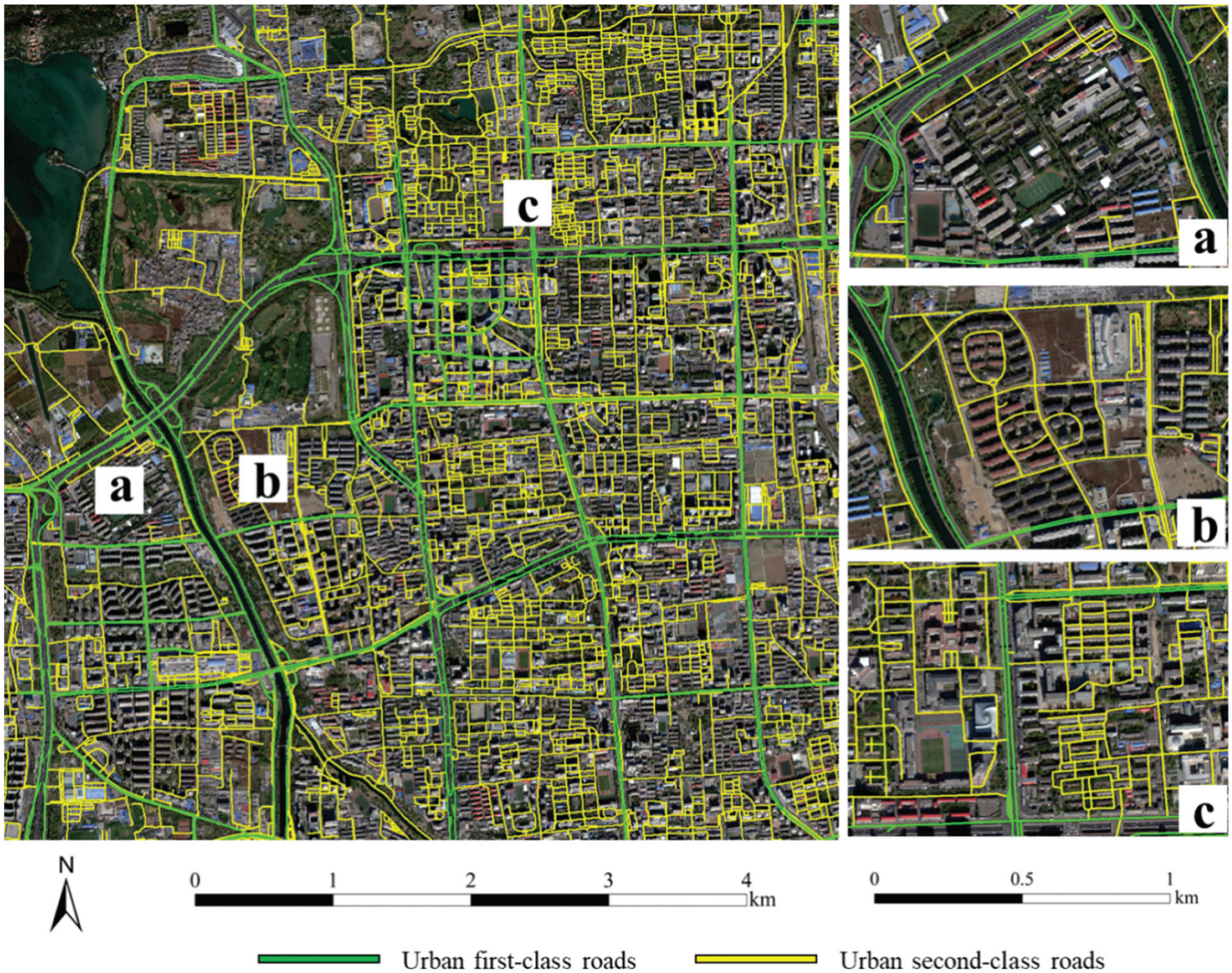


Figure 9. Road vector data within a specific area in Beijing. (a) First-class roads make the segmented units too large; (b) the roads are incomplete; (c) second-class roads make the segmented units too fragmented.

be primarily classified into two categories: urban first- and second-class roads. Sometimes, internal fragmented roads within UFZs further complicate matters. The choice of road levels for UFZ division has a profound impact on the final mapping results. In addition, the scarcity of road data in suburban areas precludes their use in generating UFZ units. Zhang et al. (2017) pointed out that the results of road segmentation are greatly affected by road vector data. Consequently, there are inherent limitations associated with using road blocks for UFZ mapping. Furthermore, UFZs exhibit scale dependency; that is, different UFZs usually manifest different analysis scales (Zhang et al. 2018). Moreover, diverse methods for generating units can significantly impact the integration of remote sensing and geospatial big data, resulting in distinct statistical inferences and interpretations (Janelle, Warf, and Hansen 2004).

4.2. The bias problem of geospatial big data

Geospatial big data, characterized by diverse types and a large sample size, contain abundant information about human activities and are accessible on numerous platforms. The extensive utilization of such data facilitates the extraction and analysis of the socioeconomic attributes of UFZs, thereby enhancing UFZ mapping accuracy. However, the pervasive issue of bias in geospatial big data significantly compromises analysis accuracy, warranting careful consideration (Du et al. 2020; Zhang, Du, and Wang 2017). POIs represent a widely employed category of geospatial big data in UFZ analysis (Liu et al. 2021). Nevertheless, the distribution of POI data in terms of category semantics and space exhibits bias. As depicted in Figure 10, since people pay more attention to such things as commercial points and traffic points, the POIs of these types are very dense, while

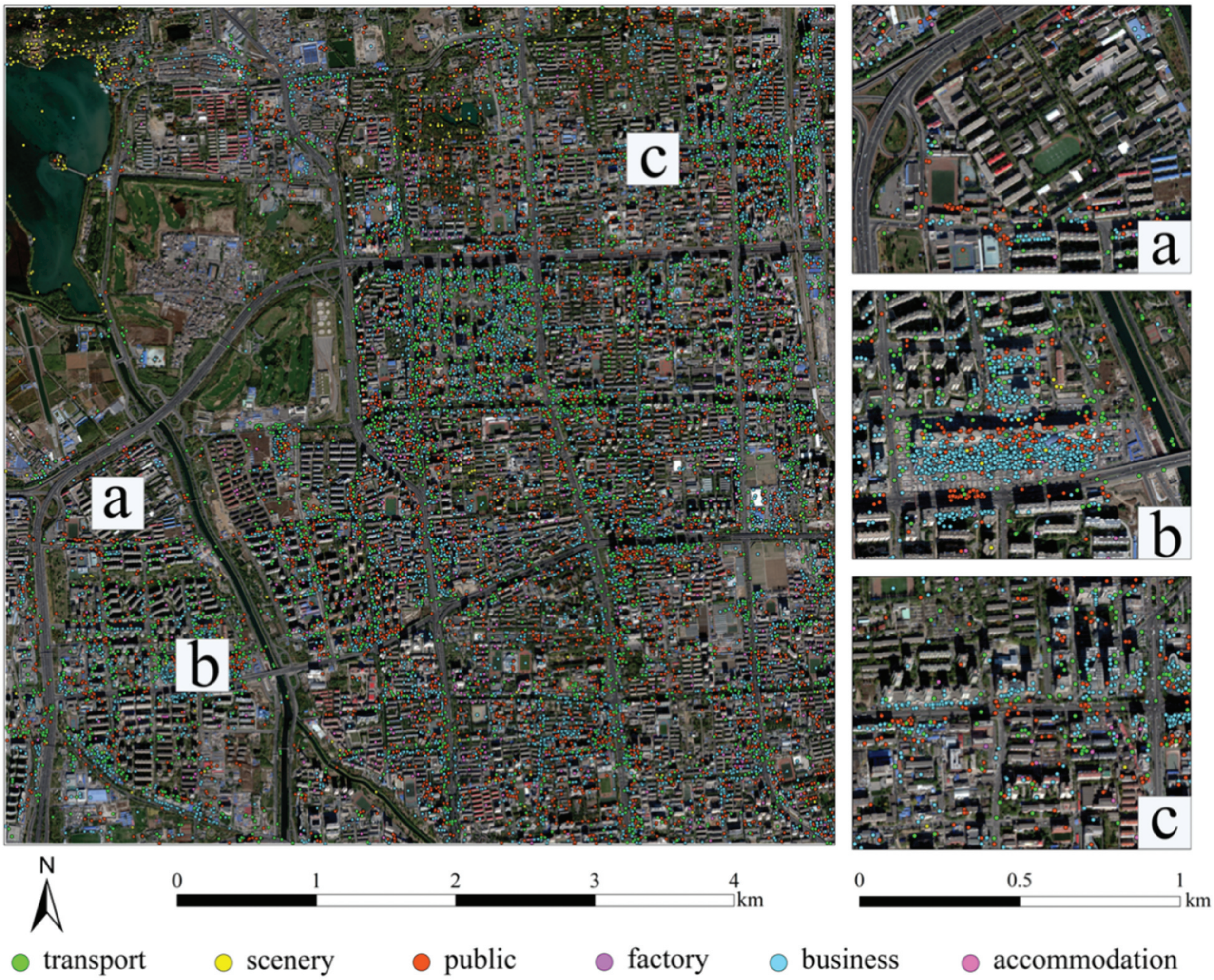


Figure 10. Bias problem in POI data. (a) Some areas do not have POIs; (b) uneven POI categories; (c) uneven distribution of POIs.

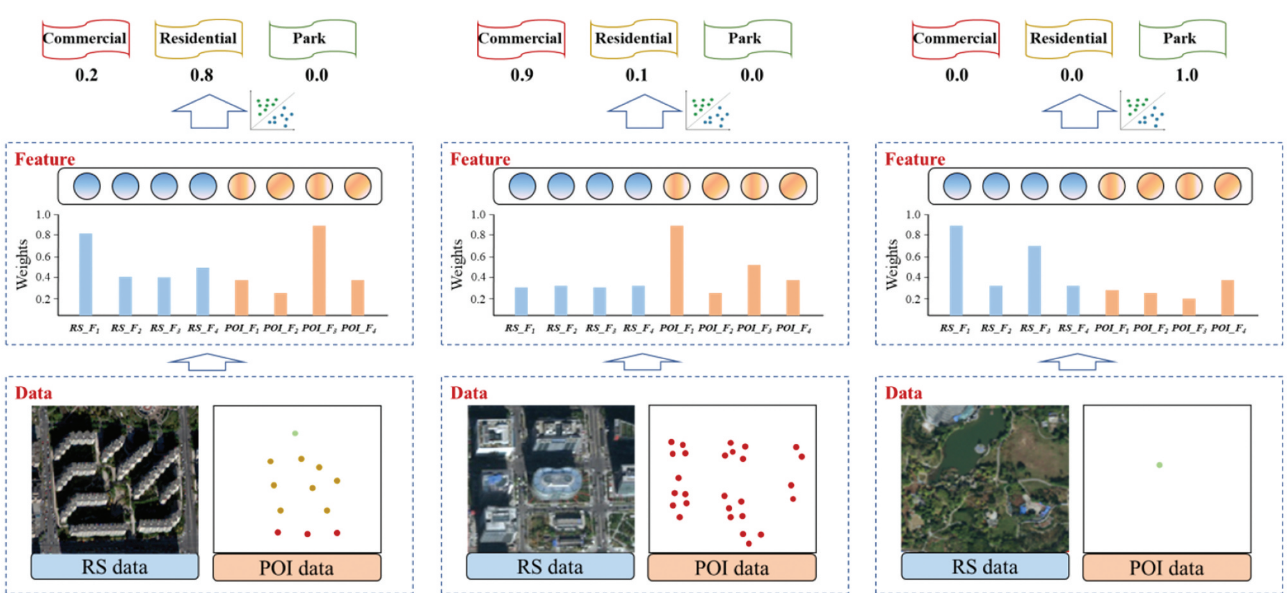
other types of POI remain relatively sparse. Additionally, suburban and rural areas lack sufficient POI data (Bao et al. 2020). Furthermore, POI data lack information about land use patterns, providing only spatial point attribute information. For example, POIs of the bank and residential types correspond to different spatial ranges. This restricts the applicability of POI data in UFZ mapping tasks. Social media data and mobile phone positioning data display substantial individual heterogeneity and bias can arise from the demographic and behavioral characteristics of users, as well as from the spatial and temporal resolution of the data. In addition, bias in traffic trajectory data can result from the distribution of sensors or data collection points, which may not cover all areas uniformly. VGI data are often collected by volunteers, which can lead to bias based on the interests, expertise, and availability of the contributors. This may result in uneven spatial coverage and data quality. Moreover, some geospatial big data (such as mobile phone positioning data) offer insights into the temporal and spatial distribution and flow of specific populations and can only be used to infer the spatial location of socioeconomic activities, such as living and working, rendering them unsuitable for supporting the analysis of urban spatial forms (Crooks et al. 2015). In general, although geospatial big data have improved the UFZ mapping results, existing research still grapples with the limitation of inadequate consideration of data bias. Geospatial big data are inherently diverse, and their application in UFZ mapping is complex. The employment of different data analysis methods often yields disparate function classification results. Consequently, optimizing UFZ mapping through the application of multi-source geospatial big data remains a challenge.

4.3. The challenges of integrating remote sensing and geospatial big data

The comprehensiveness of UFZs requires a dual perspective encompassing both physical and socioeconomic attributes. While the integration of remote sensing and geospatial big data holds significant promise in overcoming the limitations of individual data sources, spatially coupling these two types of data presents challenges related to changes in data quality, inconsistencies, data attributes, and temporal and spatial scales. These factors contribute to variations in the representation and description of UFZs (Yin et al. 2021). If multimodal data are simply and directly fused (such as data-level fusion), the negative impact of data bias may be amplified. However, many existing studies tend to fuse the two types of data directly without adequately addressing the potential differences. Therefore, when the two data types are quite different, careful attention is required in the fusion process. In addition, in this integration, collaboration between the two data sources is crucial to classifying urban functions without compromising the distinct characteristics maintained by each dataset. For instance, as illustrated in Figure 11, the fusion of remote sensing images and POI data for urban function classification necessitates a co-operative approach. Their relative importance varies for different function types. For parks, remote sensing image features outweigh POI data, while for commercial zones, POI data features take precedence over remote sensing images, and residential zones exhibit a balance in the significance of both data types. Thus, achieving the fine-grained analysis of UFZs through the fusion of multimodal remote sensing and geospatial big data presents numerous challenges. Despite these challenges, the multimodal data fusion remains a field with immense potential.

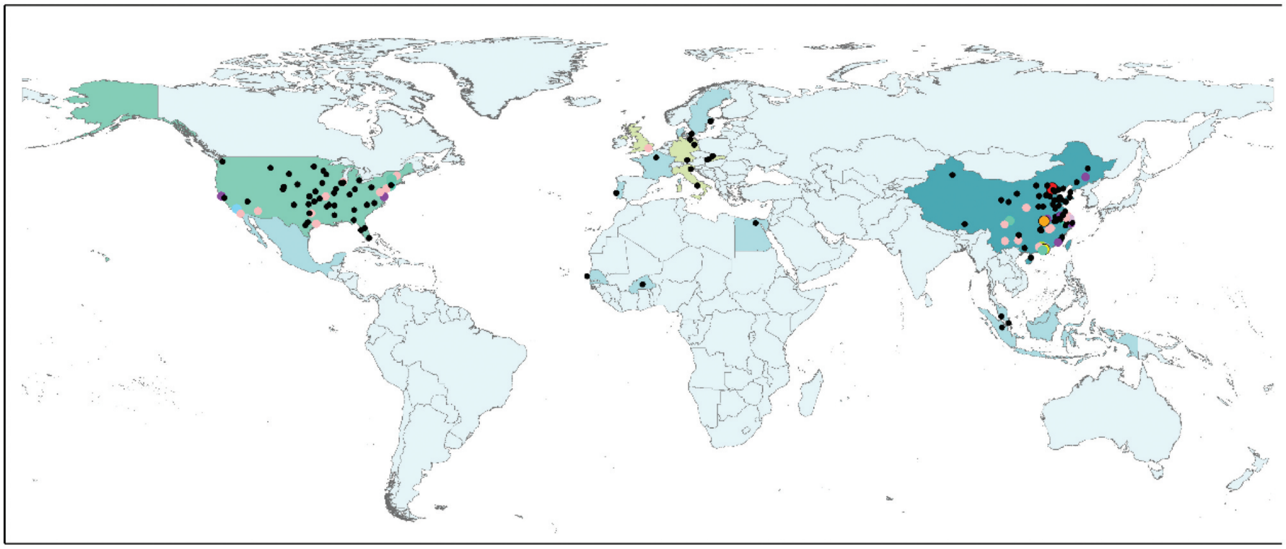
4.4. Mapping UFZs in national and global cities

Although benefiting from the advancement of data and methods, research in UFZ mapping has achieved excellent results, but most of the research and practice is limited to specific places and regions (Chen, Xu, and Gong 2021; Du et al. 2021). As shown in Figure 12(a), most of the literature related to UFZ analysis focuses on specific regions, mainly in China and the United States. Among them, China accounts for 56.5%, and the United States accounts for 41.7%. Additionally, 80.4% of existing studies only focused on a single city, with studies covering two cities making up only 8.4% (Figure 12(b)). Through statistical analysis, it is found that nearly half (48.6%) of the research covers areas of less than 1000 km^2 (Figure 12(c)). Overall,



(a) Identification of residential zone (b) Identification of commercial zone (c) Identification of park

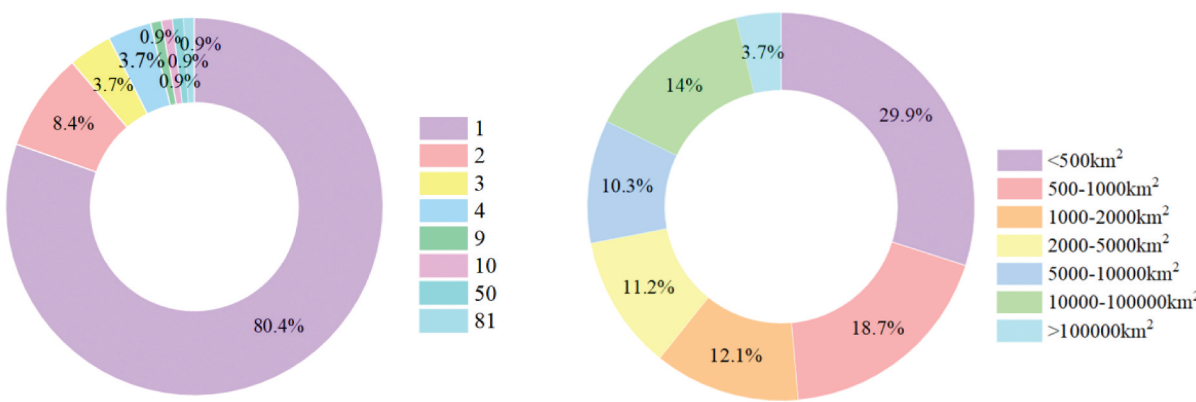
Figure 11. Collaborative fusion of remote sensing and POI data. (a) For residential zones, two data types exhibit similar importance; (b) for commercial zones, POI data features outweigh remote sensing image features; (c) for parks, remote sensing image features outweigh POI data features.



Number of cities studied in each country			
China	95	Sweden	1
USA	70	Singapore	1
UK	3	Egypt	1
Italy	2	Mexico	1
Germany	4	France	1
Slovakia	3	Portugal	1
Denmark	1	Senegal	1
Burkina Faso	1		
Malaysia	1		
Indonesia	1		

Frequency statistics for the cities studied							
Beijing	29	Ningbo	3	Chicago	2	Huizhou	2
Wuhan	14	Changchun	3	Dallas	2	Zhongshan	2
Shenzhen	11	Nanjing	3	Houston	2	Zhaoqing	2
Guangzhou	8	Xiamen	3	Lebanon	2	London	2
Shanghai	7	Foshan	3	Philadelphia	2	Taizhou	2
Zhuhai	5	San Francisco	3	Phoenix	2	Wuxi	2
Chengdu	5	Boston	3	San Diego	2	xian	2
Hangzhou	5	Nantong	2	Washington D.C	2	hefei	2
New York	5	Kunming	2	Nanchang	2		
Los Angeles	4	Chongqing	2	Dongguan	2		

(a)



(b) (c)

Figure 12. Statistics of cities in existing studies on UFZ mapping. (a) Location of study cities, where the colored dots denote the point locations of the study cities; the frequency of cities denotes the number of times a city has been studied, and the number of cities refers to the number of cities studied within a country; (b) the statistical count of the number of cities included in each study; (c) the statistical count of the area size included in each study. These conclusions are drawn from the analysis of 107 papers, with searches conducted on Google Scholar, covering the time span from 2011 to 2024.

existing research tends to concentrate on specific large cities in countries such as China and the United States, with limited geographic diversity. For example, cities such as Beijing, Wuhan, Shenzhen, and Guangzhou from China were studied 29, 14, 11, and 8 times, respectively, far exceeding other cities, especially those outside China (Figure 12(a)). It raises questions about the applicability and transferability of existing methods. Furthermore, the majority of future urban growth is expected to occur in medium-sized and small cities, making this bias toward large cities problematic. Therefore, mapping UFZs for global cities is crucial for sustainable urban development worldwide. In facing the urgent challenges of urban planning and management brought about by the process of urbanization, it is necessary to provide UFZ data with the same standard at national and even global scales. These data need to have a consistent classification system and allow for the assessment of the progress of urbanization in a large-scale context (Gong et al. 2020).

5. Discussions on future opportunities

5.1. Generating fine-scale UFZ mapping units

In the future, automatic multi-scale and fine-grained urban functional zoning holds promise for research. Fine-scale spatial units require features that can intricately describe the spatial characteristics of UFZs. This feature needs to be jointly supported by remote sensing and geospatial big data. On this basis, by taking into account function feature information, a certain segmentation method can be adopted to achieve the delineation of fine-scale UFZ units. For example, based on advanced deep learning methods, a unified feature representation model for multimodal data can be constructed. Subsequently, semantic segmentation networks, graph neural networks, etc., can be employed to achieve the multi-scale segmentation of fine spatial units. Additionally, in this process, the constraint of natural UFZ division boundaries, such as roads, should be overlaid (Du et al. 2021).

5.2. Collaboration of multimodal data

Deep learning techniques offer opportunities for effectively integrating multimodal data. The hierarchical structure of deep learning models allows for the autonomous learning of intricate and robust features, enhancing the representation of UFZs. Compared with low-level manual features, deep features exhibit superior capabilities in function recognition. Despite the success of deep learning in unimodal classification tasks, its performance faces challenges in dealing with the comprehensiveness of UFZs, which requires the integration of both physical and social attribute information. This limitation arises from the constraints of information diversity and data heterogeneity (Hong et al. 2020). The essence of successful data fusion lies in designing collaborative fusion methods that enable the characteristics of both data types to synergize for effective urban function classification. In such models, a data stream from one modality in a deep learning network can not only glean specific characteristics from its own domain but also consider diverse complements from another modality stream, ensuring a more comprehensive information mix (Hong et al. 2020; Lu et al. 2022). Fortunately, recent studies have demonstrated the significant potential of deep learning in integrating remote sensing and geospatial big data for urban function analysis (Cao et al. 2020; Guo et al. 2024; Lu et al. 2022). This integration holds promise for enhancing the expressiveness of UFZs, addressing their comprehensiveness more effectively.

5.3. Large models offer opportunities for multimodal data fusion analysis

It is noteworthy that the advent of key technologies such as the Transformer has propelled significant advancements in large language models and vision models (Hadi et al. 2023). Notable models such as GPT, BERT, SAM, and SegGPT have emerged, substantially enhancing the ability of computers to process text and image data to unprecedented levels. These advancements provide robust technical support for understanding urban functions through multimodal data. Large language models excel at extracting function information from textual data such as POI and human activity data, while large vision models help address the heterogeneity of UFZs in remote sensing images. Together, these models offer more powerful capabilities for the comprehensive representation of UFZs. The continued development of large language models and vision models promises to deliver improved methods for UFZ mapping.

5.4. Expansion of urban functions from 2D to 3D

As urbanization accelerates, the complexity of urban spaces increases, making traditional 2D function zoning inadequate for fine management and planning needs. Recognizing and analyzing urban functions in a 3D spatial environment can improve analytical accuracy, supported by extensive 3D spatial data. First, in a 3D environment, factors such as building height, shape, structure, and the distribution of urban vegetation significantly influence urban function analysis. Therefore, obtaining and utilizing extensive 3D spatial data is crucial. Recent advancements in remote sensing have increased the methods for acquiring high-precision 3D data. Second, urban functions are not merely defined in 2D space; they should be extended and analyzed in 3D space. For instance, in certain UFZs, the lower floors of buildings might be commercial, while the upper floors might be residential. This vertical distribution of functions is difficult to accurately identify in traditional 2D analysis but can be better understood and represented in 3D spatial analysis. We believe that this will be a crucial direction, as 3D spatial analysis can provide more comprehensive and accurate urban function zoning. This relies on the fusion analysis of multiple data sources, which may include satellite images, street-view images, and urban human mobility data. For example, using street-view images can help users better understand the facade features and commercial activities of buildings, while combining human mobility data can help analyze the function distribution and flow characteristics of different floors.

6. Conclusions

Achieving the rapid and automated mapping of fine-grained UFZ data holds promising prospects for widespread applications. UFZs, composed of diverse geographical objects and human activities, exhibit the characteristics of comprehensiveness, heterogeneity, and scale-dependency. These inherent traits render the mapping and analysis of UFZs particularly challenging. Current research on UFZ mapping predominantly adheres to a paradigm involving spatial unit generation, feature representation, and function classification. From an examining of existing studies, it is evident that road blocks are the most commonly used spatial units. The semantic features extracted from high-resolution images and POI data are the most commonly used features for function classification, while deep learning-based methods have gradually become the mainstream approach.

Overall, UFZ research derives its main impetus from two fields. First, within the realm of remote sensing, researchers leverage remote sensing classification principles to map UFZs, with a focus on their physical attributes. The second field lies in geospatial big data, where researchers deduce types of socioeconomic activities among urban residents and aggregate human activity models to characterize urban functions. Currently, spatially coupling remote sensing and geospatial big data allows for a more comprehensive description of UFZ characteristics, and the trend toward fusion analysis of these two data types is gaining prominence.

Despite the success achieved in UFZ research based on remote sensing, geospatial big data, and multimodal data fusion, certain limitations persist. The generation of fine-scale spatial units, optimal data fusion methods, large models, the expansion of urban functions from 2D to 3D, and the mapping of national and global cities will be key areas of focus for future research.

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Data availability statement

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

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