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Review

Classification Schemes and Identification Methods for Urban Functional Zone: A Review of Recent Papers

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Abstract: Urbanization is accelerating due to economic and societal development. The accurate identification of urban functional zones is significant for urban structure optimization, urban planning, and resource allocation. This paper reviews the scholarly literature on urban functional zone identification. Based on the retrieval results of databases, we analyzed the overview and current status. The identification methods and classification schemes are summarized from the existing research. The following results were obtained: (1) point of interest (POI) data are widely used for functional zone identification; (2) the block is the most common unit for functional zone identification; (3) cluster analysis is the main approach for urban functional zone identification; (4) most of the classification schemes are based on the dominant land use and characteristics of data sources. We predict future trends of urban functional zone identification based on the reviewed literature. Our findings are expected to be valuable for urban studies.

Keywords: urban functional zone; classification scheme; identification method

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1. Introduction

City is concentrated by non-agricultural industries and non-agricultural population [1]. It is an organic complex formed by the interaction of multiple functional groups. Urban area can be divided into the structure of spatial, social, cultural, economic, population, and function [2]. The fourth Congrès International d'Architecture Modern held in 1993 proposed a theme of "functional city". Scholars raised an idea of "urban functional districts" including the function of dwelling, work, transportation, and recreation, according to the relationship between architecture and urban planning. Later, the "*Machu Picchu Charter*" promulgated in 1977 stated that urban planning must strive to create an integrated and multi-functional environment in the city [3]. In the "*Urban land intensive utilization potential evaluation regulation (Trial)*", urban functional zones are defined as areas with similar land uses, intensity, directions, benchmark land prices, land-use intensive, and land-use potential [4].

Natural resources and social services are concentrating in a region, constructing a specific urban functional zone. As a vital part of urban economic and social functions, the urban functional zone enables people to understand a city's spatial structure and reflects urban expansion [5,6]. The identification and analysis of urban functional zones is significant in urban structure optimization, urban resource allocation, urban land use, the protection of cultivated land, the selection of commercial sites, the monitoring of geographical conditions, disaster assessment, and urban planning [7–10].

As a unified integrated organism, urban land should be designed based on different functions to meet the needs of working, recreation, commuting, and communication [3], mainly including residential areas, commercial areas, industrial areas, etc. These areas are designed by city planners and can be changed due to people's lifestyles [11]. Due to the different socioeconomic attributes of urban functional zones, their spatial distribution patterns exhibit differences. Residential areas are relatively uniform. Environmental quality, the transportation system, and living facilities are the main factors affecting the location of residential areas [12]. The commercial areas are generally located in urban centers or golden areas with convenient transportation and a dense flow of people [13]. The layout of industrial areas is closely related to the type of dominant industries, which require high accessibility and a good infrastructure. In addition, environmental constraints, costs, and policies have to be considered [14]. The coordinated layout of urban functional zones can have a positive impact on the life and work of urban residents. Conversely, unreasonable development of urban functional zones may cause great harm to urban sustainable development [15]. Therefore, the demand for analysis and monitoring of urban functional zones is increasing.

The existing systematic reviews on urban functional zone are generally based on a single perspective. For example, for a type of method or data [16,17], it is difficult to provide researchers with a comprehensive reference. For helping readers to gain a better insight into the present research and application situation of urban functional zone, we reviewed the recent relevant literature. This paper briefly introduces the development process of urban functional zones in this section. Section 2 describes the research overview and current status and compares the main data sources and units in the urban functional zone studies. Section 3 analyzes and summarizes the methods/models of urban functional zone identification. Section 4 organizes the classification schemes of urban functional zones according to the general classification scheme and basis. Section 5 discusses the limitations of existing studies on urban functional zone identification and future trends. Finally, we summarize the findings and limitations of the review. This paper is expected to be valuable for urban studies.

2. Overview and Current Status for Urban Functional Zones

In order to provide a convincing overview of the research landscape in urban functional zone studies, we indexed it in the Web of Science (WOS) (http://isiknowledge.com) database. The WOS data were retrieved using the search string (TS = urban functional zone) with a time range from 2000 to September 2021, and 1667 results were obtained. Through visual analysis, it is found that the research of urban functional zones mainly involves environmental science, ecology, biodiversity conservation, ecology, geography, agriculture, and other fields, and most of them are ecological research based on functional zones. This paper mainly reviews the research on the classification and identification of urban functional zones. Therefore, we added two databases, Scopus (http://www.scopus.com) and CNKI (https://www.cnki.net), and reset the search strings for literature retrieval. The publications were retrieved using the search string (TS = urban functional zone identification) OR (TS = urban functional zone classification) AND "Article" [Document Type], and 306 results were obtained (Appendix A, Tables A1–A3). The statistics of the publication year of obtained papers are shown in Figure 1, showing an overall upward trend, with a sharp increase in 2018. After manual screening and removing duplication, a total of 102 articles (Appendix A, Table A4) that focus on the identification of urban functional zones are retained. The results are used to analyze the data sources and basic units of urban functional zone classification and identification.

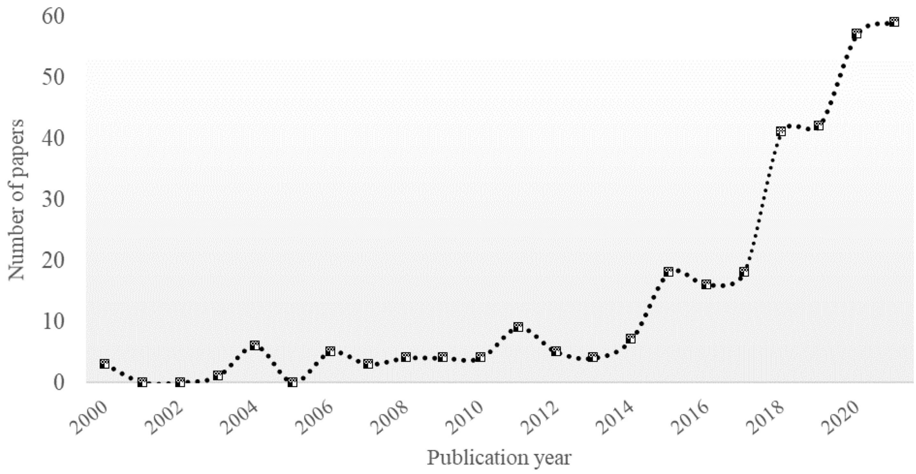

Figure 1. The statistics of the publication year of 306 papers.

2.1. Data Sources of Urban Functional Zone Research

Land use and land cover data [18], urban cadastral data [19], and thematic maps can be used for analyzing urban functional zones. However, it may be difficult to obtain these data, and the limitations of these data lead to low processing efficiency and a long research period. Remote sensing images are efficient data for analyzing urban space, especially in the research of extracting urban land cover by using the spectral, shape, and texture information of ground objects in the image. However, the division of urban functional zones mainly reflects the socio-economic of the region [20,21]. While the social and economic functions of the region cannot be obtained directly from the physical features of remote sensing images. It is difficult to meet the realistic needs of urban planning. Nighttime light data can reflect economic activities in urban areas, but its wide suitability is affected by acquisition costs, spatial resolution, and data processing complexity [22]. With increasing use of big data, cell phone data [23,24], social media data [25,26], traffic travel data [27,28], point of interest (POI) data [29,30], and other location-based data have provided new opportunities for the study of urban internal functions. These data have the advantages of the low acquisition cost, comprehensive data coverage, high temporal and spatial resolution, and high sensitivity to social functional attributes [31].

There were 102 articles analyzed (Figure 2). The literature using a single data source accounted for 50.98%, of which 35 articles only used POI data as the data source, accounting for 34.31% of all articles, followed by only image data as the data source. Meanwhile, 49.02% of the articles used multi-source data, in which the conjunction of POI and image data and the combination of POI and traffic travel data accounting for 13.73%, respectively. POI data, used by 74.51% of articles, was the most widely used data. We used the keywords from 102 articles and imported the information into WordArt (https://wordart.com) to obtain a word cloud image (Figure 3). The image of the word cloud also proves it.

The main reason is that POI data are closely related to the land-use type, with few privacy issues and relatively easy data processing [32]. POI data can reflect the spatial distribution of industries and public institutions. However, it cannot directly describe the spatial scale of industries [4,33–35]. Cell phone data can objectively reflect the real-time distribution of urban populations without functional semantic information [36]. Social media data have plenty of semantic information with the disadvantage of feature sparseness and processing difficulties [37,38]. Traffic travel data can indicate the activity characteristics of citizens, but the analysis accuracy depends largely on the built-in algorithm of Internet map service providers [39]. The acquisition of these socio-economic data includes web crawlers, open API interfaces, and purchases from service providers. Since possible privacy issues limit wide applicability, the above are seldom used as the single data source [40,41]. The identification of urban functional zones based on multi-source data increases the semantic information, improves the spatial and temporal resolution, and provides more accurate results for urban functional zone identification [29,40,42].

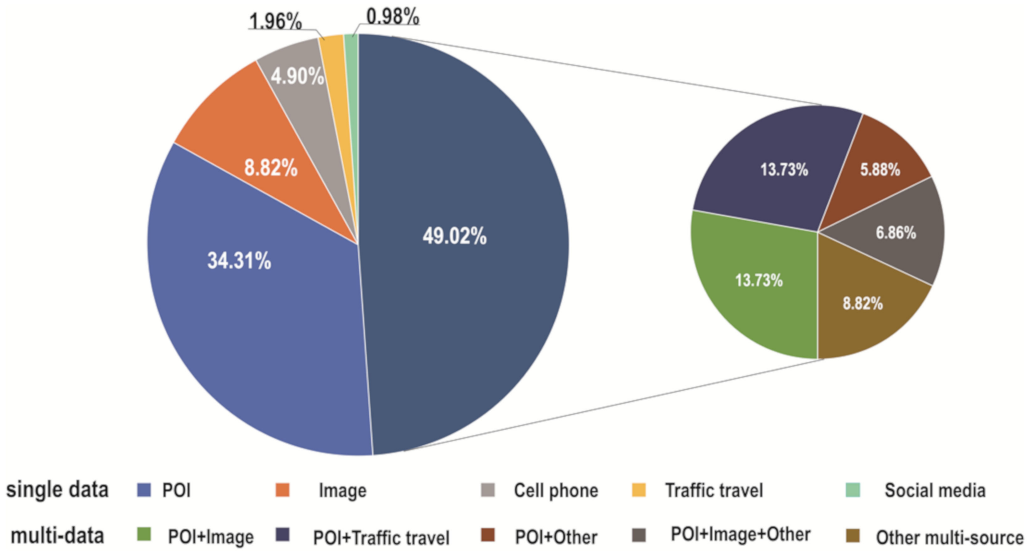

Figure 2. The statistics of the data sources of 102 papers.

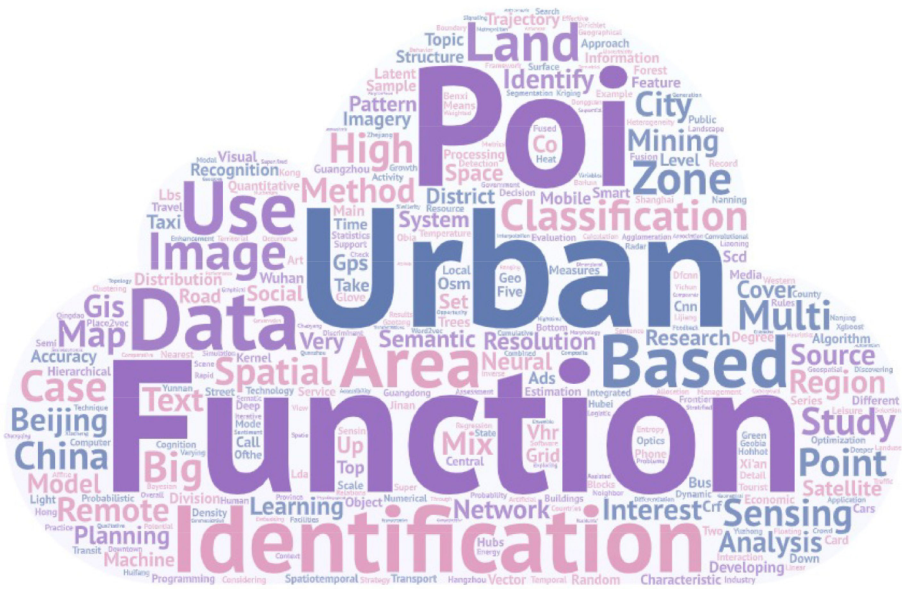

Figure 3. The word cloud of the keywords from 102 articles.

2.2. The Basic Unit of Urban Functional Zone Identification

The basic unit of urban functional zone identification mainly includes the grid, block, traffic analysis zone (TAZ), clustering unit, geoscene, and building unit (Figure 4). (1) Grid: the image is divided into a grid with square cells [43,44]; (2) block: the research area is divided into blocks with irregular geometric size using urban road network data [45,46]; (3) TAZ: the area is divided based on the urban traffic flow, considering the landform, road distribution, administrative division, and sampling convenience [2,47]; (4) clustering unit: the unit, such as Voronoi cell, is formed by clustering location-based service data [4,48]; (5) geoscene: the optimal boundary of the functional zone is obtained by multi-scale segmentation, resulting in the geoscene (image object) used as the basic unit [49,50]; (6) building unit: taking buildings as the basic object of urban space cognition, the identification of functional zones can be completed by identifying the functions of buildings [51].

In addition, a few studies using administrative district or cadastral parcel as basic units on urban functional zone classification [52,53].

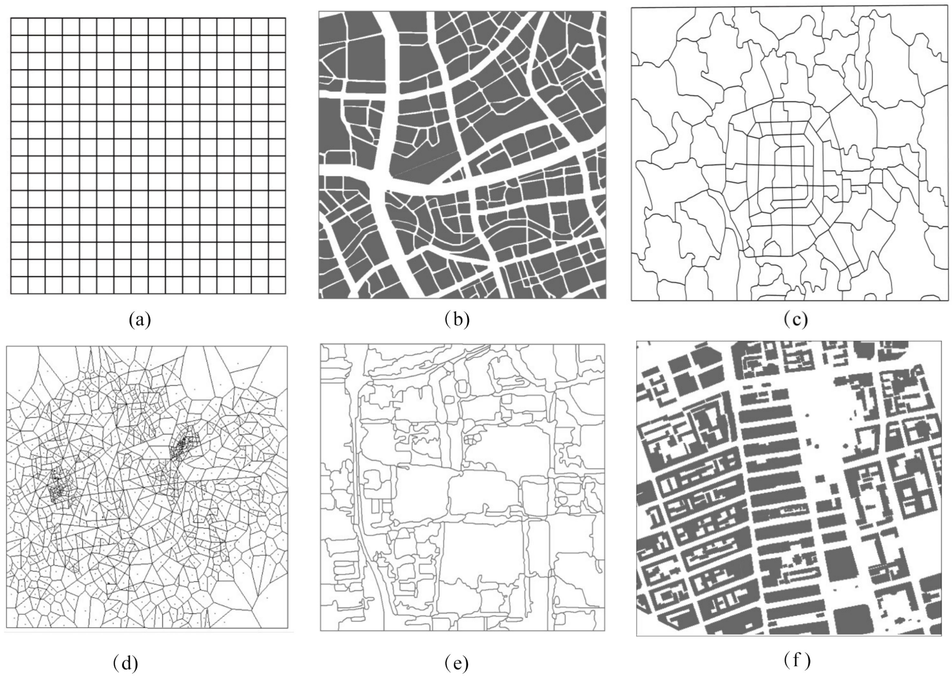

Figure 4. Different units of urban functional zone (**a**) grid, (**b**) block, (**c**) traffic analysis zone (TAZ), (**d**) clustering unit, (**e**) geoscene, (**f**) building unit.

The statistics for the number of articles that used 6-unit types are shown in Figure 5. Among these articles, 25 articles used the grid, 30 adopted the block, 12 used the TAZ, 11 adopted the clustering unit, 13 used the geoscene, and 4 adopted the building unit. Besides, articles that take macro administrative district and others as the basic unit and use multi-unit for comparative analysis were not considered in the statistical analysis [54,55].

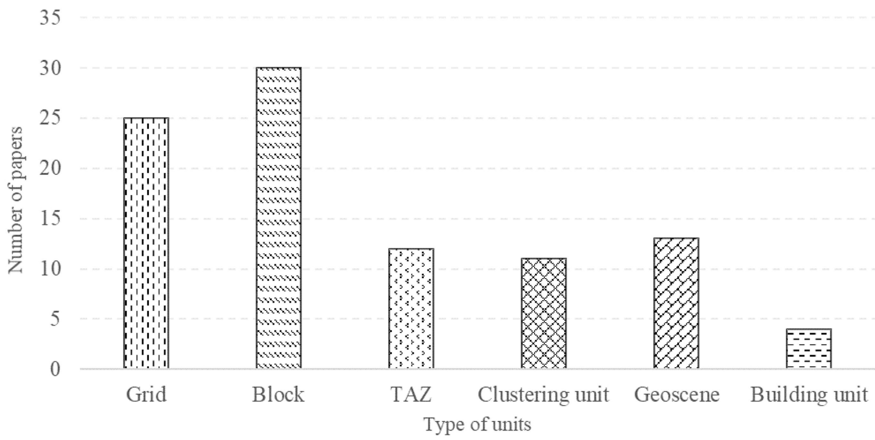

Figure 5. Statistics of the publications using the six units of the urban functional zone.

The grid unit is a straightforward basic unit. However, the shape and size of the units differ from the real boundaries of the functional zones, reducing the accuracy of urban functional zone identification [43,56]. A block is a homogeneous unit, but under-segmentation may occur. A block may contain multiple functional zones, which cannot be determined [46,57]. The TAZ is a unit based on geographic information or mobile data. Due to the limitation of data sources, the application scope of this unit is limited [41,58].

The clustering unit is determined by the radiation range of location-based data. In underdeveloped areas, the density of location-based data is low, and there are only one or several clustering units in a large area of land, reducing the identification accuracy [48,59]. The geoscene represents actual objects. It has the advantages of describing heterogeneous areas, automatic segmentation of functional areas, the extraction of functional zones at multiple scales, and providing highly accurate functional zone boundaries. However, this method requires the selection of multi-scale parameters, and the segmentation process is relatively complex [49,60]. The building unit is a more detailed space unit. However, its outline cannot cover the whole urban area and the functional type of the building is easy to be misclassified or cannot be identified when the data support is weak [61].

3. Identification and Division of Urban Functional Zones

The methods of classification and identification for urban functional zone are the focus of scholars. According to the chronological order and difficulty, it is divided into the following five categories. Traditional methods: the division of urban functional zones is based on statistical data, expert knowledge, and land use/land cover extracted from remote sensing images. Density analysis: the classification of urban functional zones is based on the density of data in the unit. Cluster analysis: the identification of urban functional zones is realized by clustering and classifying the shallow features of the data. Advanced framework: the urban functional zones are identified by mining potential information or multi-level features of data. Deep learning: the urban functional zones are classified and identified by using deep learning models to extract deep features.

3.1. Urban Functional Zone Division Based on Traditional Methods

Initially, urban functional zone division was performed using qualitative methods, such as statistical surveys and expert knowledge. Huang, et al. [62] analyzed the questionnaire survey information of the public and experts, and finally realized the division of urban functional zones based on public will. Gu, et al. [19] made the function-oriented zone on NET and Geomedia platforms using cadastral data and Delaunay triangulation and Graham methods. Methods based on expert knowledge are limited by statistical data and may be time-consuming and labor-intensive, strong subjectivity, and difficult to prove the accuracy of results.

The use of remote sensing image data can provide detailed information on ground objects [63,64], and dynamic monitoring of urban land-use change can be achieved by analyzing remote sensing images in different periods [65]. A remote sensing intelligent geo-interpretation model (RSIGIM) that includes multi-source remotely sensed data and ancillary geographic data were used to perform land-cover/land-use classification in Hong Kong [66]. In addition, some scholars used object-oriented segmentation and hierarchical classification to extract information on intra-urban land use, detect urban land-use change, and classify intra-urban land based on the functional characteristics using visual interpretation [67]. Remote sensing images provide rich information on the physical features of cities but lack information on functional interaction patterns and the socioeconomic environment. In addition, the timeliness of the images may not be adequate.

3.2. Urban Functional Zone Division Based on Density Analysis

Some scholars identified urban functional zones using density analysis based on urban static data (such as road network data and POI data) since remote sensing data do not adequately reflect urban socioeconomic functions. Chi, et al. [33] quantitatively analyzed urban functional zones by calculating the density of POI data in the grid, and mixed functional zones were visually described. Other scholars used this method to determine the influence of the number of grids on the identification of urban functional zones. The results showed that the classification of mixed functional zones in the Xicheng District of Beijing was more accurate when a 25×25 spatial grid was used than a 50×50 spatial grid [68]. Kang, et al. [34] assigned scores to different levels of POI data and identified urban functional districts by calculating the POI density scores of block units. Wang, et al. [45] considered the spatial autocorrelation of POI data and used kernel density estimation (KDE) to weaken the discretization phenomenon of the POI data (Figure 6). The authors calculated the quadrat density of the POI data in the block to improve the identification accuracy of mixed functional zones. On this basis, some studies conducted comparative experiments of different kernel density bandwidths. A larger kernel density bandwidth increased the influence range of the POI points and the mixing degree of the functional zones [69].

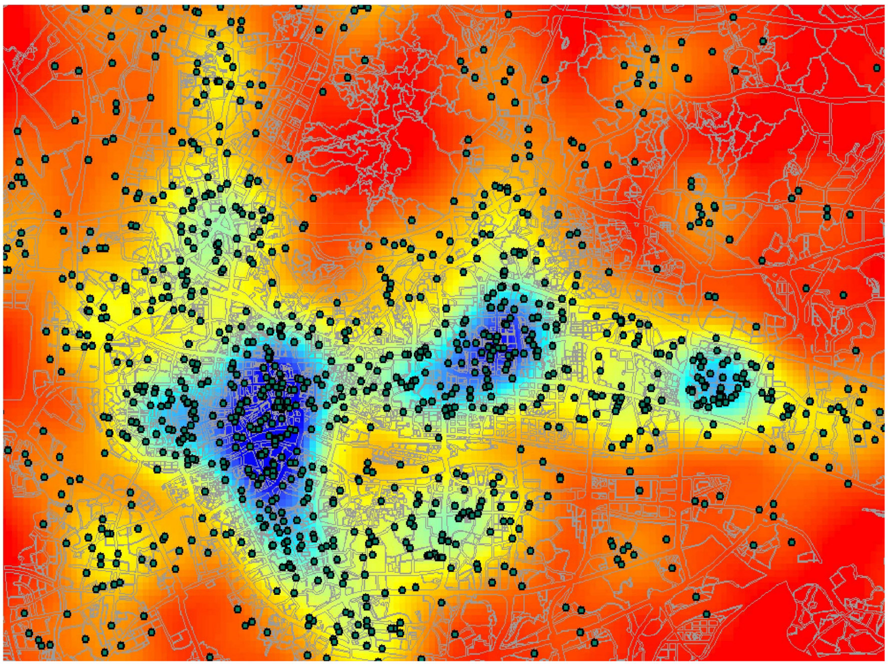

Figure 6. Diagram of kernel density estimation for POI data. (The figure was drawn by the author).

Yu, et al. [70] used POI data to analyze and delineate the central business district (CBD) using network KDE. Gu, et al. [71] used KDE and head/tail breaks to analyze POI data and identify the spatial distribution and interaction of different functional districts. Huang, et al. [72] used urban road network data and POI data and divided the urban functional zones using kriging interpolation and network KDE. Wang and Dai [73] calculated the density of POI data in each block and used SPSS software to perform principal component analysis (PCA) on the standardized block density. Comprehensive indicators were selected to describe the characteristics of the functional zones and visualize the results. Zhao, et al. [74] used the term frequency-inverse document frequency (TF–IDF) statistical method to identify urban functional regions based on POI data. Cao, et al. [75] performed automatic classification of a large number of buildings into different functional types using the weighted frequency density ratio of each POI data type inside and within a distance to a building, improving the traditional quantitative identification of urban functional zones. The classification method based on density analysis is easy to understand. It mainly relies on processing platforms such as ArcGIS or SPSS to realize fast and efficient classification of urban functional zones [56]. However, since most of them only consider single data (POI), there is room for improvement in the accuracy of these division methods [38,58].

3.3. Urban Functional Zone Division Based on Cluster Analysis

Cluster analysis refers to feature extraction of static or dynamic urban data (such as cell phone data, traffic travel data, and check-in data) to partition urban functional land and identify functional zones according to the functional characteristics of the region or the temporal and spatial characteristics of human mobility. K-means algorithm is a common clustering method in urban functional zone identification. Many studies use different data based on this method to classify urban functional zones, such as mobile phone data [23,76], taxi GPS data [77], and check-in data [78], etc. The advantages of this method are fast speed, simple calculation, and excellent clustering effect, but the number of clusters (K) needs to be manually determined and the initial cluster center has a great influence on the clustering effect [79]. The K-medoids method is different from the central point selection of K-means, which involves lower data requirements than K-means. Chen, et al. [80] proposed a dynamic time warping (DTW) distance-based k-medoids method to delineate urban functional zones with building-level social media data. Partition around medoids (PAM) is the basic algorithm of K-medoids. The results show that the PAM algorithm can be applied to the identification of urban functional areas, and the identification accuracy of functional areas is up to 86% [81]. Fuzzy c-means clustering (FCM) is the extension of K-means. Besides the number of clusters, the selection of weighted index also has a certain influence on the clustering result. Jiang, et al. [4] and Xiao, et al. [82] used fuzzy c-means clustering to identify urban regions with different functions from POI data and successfully divided and analyzed urban areas. Spectral clustering is generally superior to K-means. Frias-Martinez and Frias-Martinez [83] used a spectral clustering algorithm and self-organizing map (SOM) to classify land use in urban areas by clustering geographical regions with similar tweeting activity patterns. Gaussian mixture model (GMM) can provide stronger description ability than K-means. Song, et al. [84] distinguished urban functional zones by integrating GPS movement trajectories and an unsupervised Gaussian mixture model (GMM). Jiang, et al. [31] improved this method and designed a multi-feature weighted decision algorithm based on call detail records (CDR) data to identify urban functional zones with a supervised GMM. When the dataset is dense, the density-based spatial clustering of applications with noise (DBSCAN) algorithm can be considered. It does not need to input the number of clusters and can find outliers while clustering [79]. Pan, et al. [28] used the iterative DBSCAN algorithm to extract functional zones and manually labeled the features of taxi GPS traces to classify land use. A support vector machine (SVM) was used, achieving a recognition accuracy of 95%. Ordering points to identify the clustering structure (OPTICS) clustering is similar to DBSCAN, but in particular, it can obtain clusters of different densities. Ning, et al. [26] combined the spatial correlation and semantic information of POI data with location-based check-in data and proposed a feature model of POI data that considered human activity characteristics by OPTICS. Zhong, et al. [85] used an ant colony clustering algorithm to divide urban block functions based on the activity characteristics of smart card data (SCD) and the POI category information. This method has high optimization performance, but a slow convergence speed.

The classifier classifies the source data based on the class knowledge formed by the training samples. K-nearest neighbor (KNN) algorithm is one of the simplest classification algorithms. Jin, et al. [86] used the MapReduce framework from the Hadoop platform to realize the KNN parallel algorithm by writing java language and classified urban land use types in the travel zone based on the time sequence characteristics of the residents' call volume reflected in the CDR data. Logistic regression is a common algorithm model for binary classification. Feng, et al. [87] used a logistic regression model to determine urban functional zones based on the category proportions of the POIs after autocorrelation processing. This approach avoided the limitation of identifying functional zones only based on the POI ranking and yielded high identification accuracy. Liu and Long [88] considered the properties of adjacent parcels, such as the size and compactness and the point density of POI data and determined the model parameters through logistic regression. A cellular automata (CA) model was used to identify the parcels automatically. Classification tree is robust and extensible to abnormal data. Liu, et al. [27] used a classification tree method and verified that the characteristics of taxi trajectory data are closely associated with various land-use types and intensities. When the depth of the decision tree is too large, over-fitting phenomenon may occur. In order to solve it, random forest (RF) can be used. Toole, et al. [24] used the random forest algorithm to identify clusters of locations with similar zones and mobile phone activity patterns to understand the land-use pattern in Boston. Xu and Yang [89] proposed a word vector model that integrated POI and check-in data and used the co-location quotient method and KDE to obtain weighted feature vectors to identify urban functional zones. Some studies used SQL Server to process travel data and matched the functional zones with the actual land use utilizing the expectation maximization (EM) algorithm [2,90,91]. The efficiency and quality of most clustering algorithms are well performed when they are implemented based on C/C++, java, MATLAB, and Python, which can provide good identification accuracy for urban functional zones [92]. However, for some complex and heterogeneous urban areas, these methods using shallow features of data may have poor classification accuracy.

3.4. Urban Functional Zone Division Based on an Advanced Framework

Since classical methods do not provide sufficient accuracy for identifying urban functional zones in heterogeneous scenes, some scholars used data mining methods to extract the semantics of the data. For example, topic models, such as probabilistic latent semantic analysis (pLSA) and latent Dirichlet allocation (LDA), have been used to generate latent semantics for scene classification and describe urban functional zones according to object features and functional categories. Yuan, et al. [29] used LDA to establish a discovers regions of different functions (DRoF) framework and implemented their method on a 64-bit server with a Quad-Core 2.67 G CPU and 16 GB RAM with a total of 1394 min. Chen, et al. [93] established LDA and Dirichlet polynomial regression (DMR) based on the Mallet platform to process the mobility pattern. The OPTICS clustering method was employed to process the results of the LDA and DMR and identify different functional regions. Some scholars found that the uncertain parameters in the LDA affected the final classification results of urban functional zones [94], and the object bank based on object semantics had strong robustness and interpretability [95]. Zhang, et al. [96] proposed a novel cognitive structure of urban functional zone recognition called hierarchical semantic cognition (HSC), which relies on geographic cognition and considers four semantic layers and the hierarchical relationship between the semantic layers. Experimental results showed that this method produced more accurate results than the SVM and LDA. If a bottom-up classification is used in HSC, the identification results of the urban functional zones are affected by the inaccurate information in the bottom layers. Therefore, an innovative framework that uses iterative optimization by integrating bottom-up and top-down processes was proposed to improve the classification accuracy of urban functional zones and land cover types [97].

3.5. Urban Functional Zone Division Based on Deep Learning

Deep learning can effectively extract high-level feature information from remote sensing images. Yao, et al. [47] used the greedy algorithm and Google Word2Vec to extract high-dimensional characteristic vectors from the POI data and TAZs to classify urban land use. Some scholars found that it is important to consider the linear relationship between POIs and the nonlinear spatial relationship between a given POI and the surrounding POIs. Yan, et al. [98] took into account the spatial relationship between POI data and extended the Word2Vac model to the Place2Vac model. Zhai, et al. [99] used the Place2Vac model to identify urban functional regions and implemented the model in Tensor-Flow based on the Mini-Batch Gradient Descent. However, this method had a high acquisition cost and was time-consuming. Zheng, et al. [100] improved the method and achieved low-cost, efficient, and accurate functional zone identification. Chen, et al. [101] used the spatial co-location model method to determine the nonlinear spatial relationship of POIs. The comparative experimental results proved that the recognition accuracy of the functional regions was higher for this method than the Place2Vec method. Xu, et al. [102] used the deep semantic segmentation network D-Link Net to extract buildings to calculate the building level metrics based on the Baidu PaddlePaddle open-source framework and Senta sentiment analysis system. Multisource heterogeneous data were integrated to identify the categories of functional zones, and sentiment analysis was conducted to characterize typical functional zones.

Convolutional neural networks (CNNs) have been widely used recently for urban functional zone identification due to their strong ability to extract image features and excellent performance in image segmentation and geographic object-based image analysis (GEOBIA). Deep learning methods require massive amounts of training data to determine the network parameters and perform automatic learning of the features. Zhong, et al. [103] proposed the large-patch CNN (LPCNN) model to address the problem of insufficient markers in remote sensing images (Fan et al., 2015). This model expands the training data of small-scale remote sensing image data set. Castelluccio, et al. [104] used CNN and remote sensing images to classify land use. Ma, et al. [105] compared three CNN training methods for land use and land cover classification, i.e., full training, fine-tuning, and pre-training, and concluded that fine-tuning of the pre-trained CNN network model provided the best results. Zhou, et al. [49] used the AlexNet model and Dropout technology to avoid over-fitting and reduce the scale effect and realized fine classification of urban functional zones by Super Object (SO). Bao, et al. [51] used the deep-feature convolutional neural network (DFCNN) to mine building physical semantics and social function semantics, which selected TensorFlow1.7 as the deep learning framework on the Ubuntu 16.04 operating system. The proposed model detected urban functional zones more effectively and accurately, compared with Alex Net and random forest. Deep learning is well suitable for extracting high-level information, and its migration and scalability have unlimited potential for urban functional zone identification and analysis. Thus, this method is worthy of further exploration.

The identification and division methods of urban functional zones in the above articles are summarized in Table 1.

Table 1. Methods of identifying and dividing urban functional zones.

Type	Method	Data	Accuracy	Reference
Urban functional zone division based on traditional methods	expert knowledge	Statistical data	/	[62]
	Remote sensing image information + GIS technology	Image data	Classification accuracy = 95.08%	[67]
Urban functional zone division based on density analysis	Quadrate density method	POI data	/	[33]
	Point level score assignment + Quadrate density	POI data	Conformity accuracy = 88%	[34]
	Kernel density estimation (KDE) + Quadrate density	POI data	Mixed accuracy = 93.3% Single accuracy = 82.02%	[45]
	Kernel density estimation + Head/tail breaks	POI data	/	[71]
	Network kernel density estimation + Kriging interpolation	POI data	Average F1-score = 0.582	[72]
	Quadrate density + Principal component analysis	POI data	/	[73]
	Term frequency-inverse document frequency	POI data	/	[74]

Table 1. *Cont.*

Type	Method	Data	Accuracy	Reference
Urban functional zone division based on cluster analysis	K-means algorithm	Cell phone data	Overall accuracy = 76.75%	[76]
	K-medoids algorithm	Social media data		[80]
	Partition around medoids (PAM)	Traffic travel data	Recognition accuracy = 86%	[81]
	Fuzzy c-means clustering	Cell phone data, POI data	Overall accuracy = 73%	[82]
	Spectral clustering algorithm + Self-organizing map (SOM)	Social media data, Cell phone data, POI data	/	[83]
	Gaussian mixture model (GMM)	Cell phone data, traffic travel data	Recall ratio = 51.08%	[31]
	Iterative DBSCAN clustering algorithm + Support vector machine (SVM)	Traffic travel data	Recognition accuracy = 95%	[28]
	Ordering points to identify the clustering structure (OPTICS) + Hierarchical clustering	Social media data, POI data	Conformity accuracy = 77.7%	[26]
	Ant colony clustering	Traffic travel data, POI data	/	[85]
	K-nearest neighbor (KNN)	Cell phone data	Recognition accuracy = 72%	[86]
	Logistic regression + Analysis of Variance (ANOVA)	POI data	/	[87]
Urban functional zone division based on an advanced framework	Logistic regression + Cellular Automata (CA)	POI data, Image data	/	[88]
	Classification tree	Traffic travel data	Total accuracy = 83.5%	[27]
	random forest (RF)	Cell phone data	Total accuracy = 54%	[24]
	expectation maximization (EM) algorithm	Traffic travel data, POI data	Average accurate rate = 60.83%	[2]
	Discovers regions of different functions (DRoF)	POI data, traffic travel data	/	[29]
	LDA + DMR + OPTICS clustering	POI data, traffic travel data	/	[93]
	Hierarchical semantic cognition (HSC)	POI data, image data	Overall accuracy = 90.8%	[96]
	Hierarchical semantic cognition + Inverse hierarchical semantic cognition (HSC + IHSC)	Image data	Overall accuracy = 90.9%	[97]
Urban functional zone division based on deep learning	Word2Vec model	POI data	Overall accuracy = 87.28%	[47]
	Place2vec model	POI data	Overall accuracy = 74.24%	[99]
	D-Link Net	POI data, image data, Traffic travel data	Overall accuracy = 82.37%	[102]
	Convolutional neural network (CNN)	Image data	Classification accuracy = 91.8%	[104]
	super object (SO)-CNN model (SO-CNN)	POI data, Image data	Producer's accuracy = 91.09%	[49]
	deep-feature convolutional neural network (DFCNN)	POI data, Image data	Accuracy = 96.65%	[51]

4. Classification Schemes for Urban Functional Zones

According to the review, it is found that there are differences in the classification schemes formed in the study of urban functional zones. The classification schemes related to urban functional zones are summarized in Table 2. There are classification schemes for classifying urban areas in national standards. The "*Urban land intensive utilization* *potential evaluation regulation (Trial)*" defined the following classes of urban land: specific function land, residential land, commercial land, industrial land, and land with educational institutions based on the dominant function [106]. Urban planners are focused on land use and typically adopt the classification scheme in the "*Standard for Basic Terminology of Urban Planning*". This scheme includes residential land, industrial land, public facilities, municipal utilities, road and squares, intercity transportation land, warehouse land, specially-designated land, green space, water, and miscellaneous [107]. In addition, some urban planning also has classification schemes for zoning urban areas, such as the regulatory plan [108], the constructive-detailed plan [109], and the main functional area planning [110].

In recent studies, many classification schemes of urban functional zones were defined by the main nature of land use, and then adjusted according to the characteristics of data sources. It can be divided into using functional characteristics, trajectory characteristics, image characteristics, and mixing characteristics (including the combination of functional characteristics and other characteristics) (Figure 7). (1) Functional characteristics: residential areas, industrial areas, commercial areas, public management and public service areas, green space and squares, road and traffic facility areas [33,34,45,74,87]. (2) Trajectory characteristics: residential areas, industrial parks and office areas, commercial and leisure areas, and nightlife areas [23,24,85]. (3) Image characteristics: commercial office zones, urban green zones, industrial warehouse zones, and residential zones [49,57]. (4) Functional and trajectory characteristics: developed residential areas, emerging residential areas, scenic areas, commercial and entertainment areas, science/education/technology areas, and areas designated for development [2,29,90]. (5) Functional and image characteristics: urban green zones, industrial districts, public services, shanty towns, residential districts, schools, commercial districts, and hospitals [51,96,97].

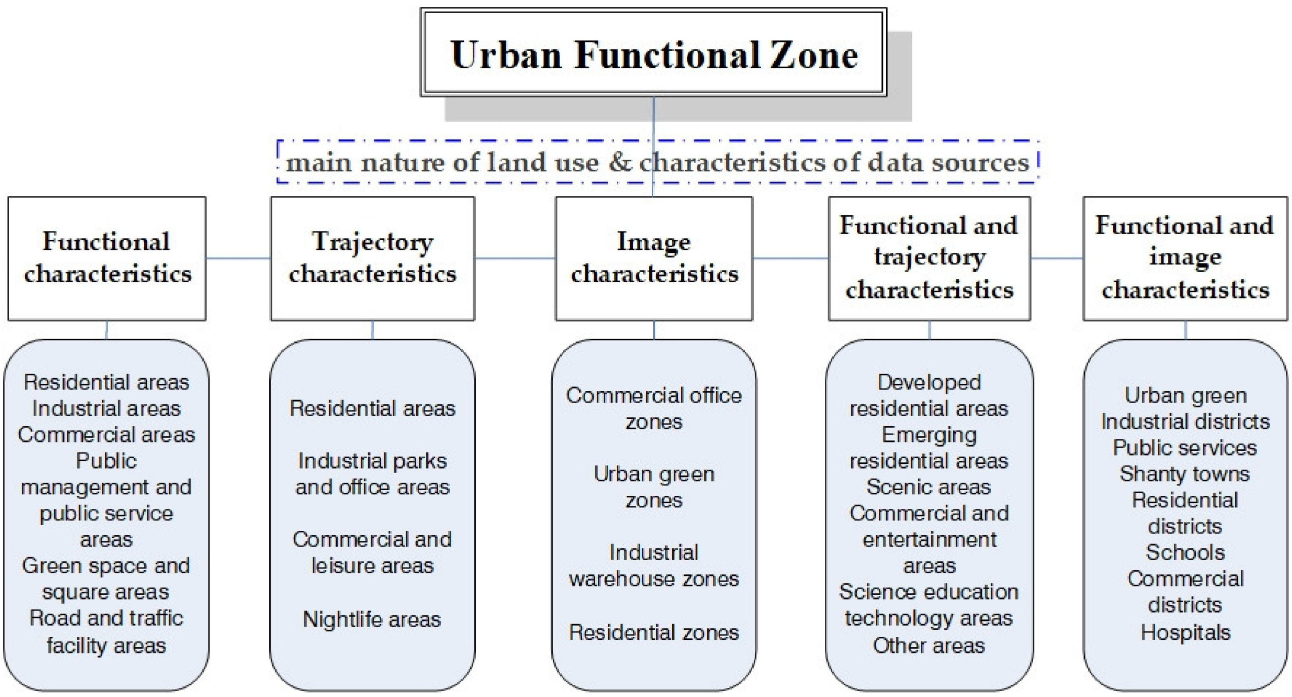

Figure 7. The classification of urban functional zones based on the main nature of land use and data sources.

In addition, some scholars classified the functional zones from the perspectives of the social environment. Yan [13] separated urban areas into economic and non-economic functional areas according to regional economic differences. The latter refers to areas not directly related to economic activities, such as residential areas and administrative areas. Economic functional zones include commercial areas, business areas, industrial areas, and tourist areas. Some cities, such as the capital, have special urban functions. Liu and Peng [111] divided Beijing's urban areas into 10 functional zones, including capital administrative areas, central commercial areas, financial and business areas, historical preservation areas, transportation hub areas, cultural and entertainment areas, hospitals, schools and other crowded areas, public leisure areas, and residential areas. Zhang [112] divided the city into four zones: ecological conservation development areas, new urban development areas, urban function expansion areas, and capital functional core areas.

Table 2. General classification schemes of urban functional zones.

Classification	Basis	Amount	Category	Reference
National standards	Urban land intensive utilization potential evaluation regulation (Trial)	5 categories	Special function land, residential function land, commercial function land, industrial function land, educational function land	[106]
Urban planning	Standard for Basic Terminology of Urban Planning	11 categories	Residential land, industrial land, public facilities, municipal utilities, road and squares, intercity transportation land, warehouse land, specially-designated land, green space, waters, and miscellaneous	[107]
	Regulatory plan	4 categories	Residential, living, and commercial areas, production areas, leisure and green areas, urban supporting functional areas	[108]
	Constructive-detailed plan	3 main categories	Production service functional area, infrastructure type functional area, special function area	[109]
		16 categories	Administrative office, financial business district, commercial service area, tourism and entertainment area, scientific research industry zone, cultural education district, industrial R&D zone Transportation hub, city facility service area (water, electricity, heating and other facilities), historical sites, logistics park, residential area, green ring environmental area (rivers and lakes) Military facility area, civil air defense construction area	
	Main functional area planning	4 categories	Prohibited zones, restricted development zones, key development zones, optimized development zones	[110]
Main nature of land use	Functional characteristics	6 categories	Residential areas, industrial areas, commercial areas, public management and public service areas, green space and square areas, road and traffic facility areas	[33,34,45]
	Trajectory characteristics	4 categories	Residential areas, industrial parks and office areas, commercial and leisure areas, nightlife areas	[23,24,85]
	Image characteristics	4 categories	Commercial office zones, urban green zones, industrial warehouse zones, residential zones	[49,57]
	Functional and trajectory characteristics	7 categories	Developed residential areas, emerging residential areas, scenic areas, commercial and entertainment areas, science/education/technology areas, and other areas to be developed	[2,29,90]
	Functional and image characteristics	8 categories	Urban green, industrial districts, public services, shanty towns, residential districts, schools, commercial districts, hospitals	[51,96,97]
Social environment	Regional economy	2 main categories	Economic functional areas Non-economic functional areas	[13]
		6 categories	Commercial areas, business areas, industrial areas, tourist areas residential areas, administrative areas	
	Urban functions (culture)	10 categories	Capital administrative areas, commercial central areas, financial and business areas, historical preservation areas, transportation hub areas, cultural and entertainment areas, hospitals, schools and other crowded areas, public leisure areas, and residential areas	[111]
	Urban functions (ecology)	4 categories	Ecological conservation development areas, new urban development areas, urban function expansion areas, capital functional core areas	[112]

5. Discussion

The rational allocation of urban space can improve the urban land use efficiency, resulting in promoting the harmonious development of regional economy and environment.

Many studies have discussed the classification, distribution, and driving factors of urban functional zones, which provides references for urban spatial structure examination, land use planning verification, and urban functional form optimization. Although there are some achievements in urban functional zones studies, limitations still existing.

(1) Because of inhomogeneous data in urban areas, it is difficult to identify functional zones in some areas with poor data, which affects the accuracy of functional zone identification. Moreover, the processing of block is insufficient refinement. Due to the different road network densities within the area, it is necessary to explore the method of block processing that is adaptive for distinct regions.
(2) Due to the structural and functional similarities with residential buildings, campus dormitories are easily misclassified. Furthermore, the existing identification methods of urban functional zones are not highly automated, and the accuracy verification of identification results is not scientific enough.
(3) No classification criteria can better meet the research needs. On the one hand, there is no unified standard for urban functional zone classification. On the other hand, the indicators of existing relevant standards and regulations are not advanced, the emerging data such as POI data are ignored.

The analysis of this paper shows that the adaptive division of research units and the integration of multisource data are required for the effective and accurate classification of urban functional zones. More 3D data should also be considered with high precision and accessibility, which could contribute to the division of urban functional zones. It is necessary to explore the identification methods for urban functional zones with better versatility and interpretability. The classification scheme of urban functional zones including mixed functional zones is closer to real life. How to make the indicators that would be used to determine the mixing degree more diversified and standardized is the focus of future research.

6. Conclusions

An in-depth study of urban functional zones is of great significance for improving urban planning and layout and alleviating urban problems. This paper reviews important studies on urban functional zone classification and identification in detail. Firstly, we describe the overview and current status of urban functional zone studies. Block is a popular unit in the application of the functional zone. Point of interest (POI) data are widely used in the identification of a functional zone. Then, the methods of urban functional zone identification are analyzed. Clustering is a mainstream method that can identify urban functional zones rapidly and effectively. Topic model and deep learning are more advantageous for complex and heterogeneous urban scenes. Finally, we summarize the classification schemes of urban functional zones and find that most of them are designed according to land use and the characteristics of data sources.

This review provides a quick overview of urban functional zone studies and some practical references for application. However, there are some disadvantages. Due to manual screening and classification, which is time-consuming and labor-intensive, the number of papers screened is limited. Meanwhile, the results may be affected by the subjective influence of statisticians leading to low repeatability. We hope that there will be a high-accuracy algorithm or literature statistical tool in the future that can identify the applied information in the article instead of the manual screening.

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Appendix A

Table A1. List of papers obtained from Scopus database.

Number	Title
1	Delineating functional urban areas using a multi-step analysis of artificial light-at-night data
2	Integrating aerial lidar and very-high-resolution images for urban functional zone mapping
3	A novel semantic recognition framework of urban functional zones supporting urban land structure analytics based on open-source data
4	A glove-based poi type embedding model for extracting and identifying urban functional regions
5	Spatial structure of Zhengzhou Airport Economy Zone: its evolution and drivers
6	Estimating building-scale population using multi-source spatial data
7	The influence of spatial grid division on the layout analysis of urban functional areas
8	A taxonomy of driving errors and violations: Evidence from the naturalistic driving study
9	Identification and portrait of urban functional zones based on multisource heterogeneous data and ensemble learning
10	A new urban functional zone-based climate zoning system for urban temperature study
11	An SOE-Based Learning Framework Using Multisource Big Data for Identifying Urban Functional Zones
12	Cartographic modeling of the Russian steppe-zone urban landscapes with the use of neural networks
13	Bounding Boxes Are All We Need: Street View Image Classification via Context Encoding of Detected Buildings
14	Spatial and vertical distribution, composition profiles, sources, and ecological risk assessment of polycyclic aromatic hydrocarbon residues in the sediments of an urban tributary: A case study of the Songgang River, Shenzhen, China
15	Recognizing urban functional zones by a hierarchical fusion method considering landscape features and human activities
16	A multi-faceted, location-specific assessment of land degradation threats to peri-urban agriculture at a traditional grain base in northeastern China
17	Large-scale urban functional zone mapping by integrating remote sensing images and open social data
18	DFCNN-based semantic recognition of urban functional zones by integrating remote sensing data and POI data
19	Heavy metal pollution and comprehensive ecological risk assessment of surface soil in different functional areas of Shenzhen, China
20	Heuristic sample learning for complex urban scenes: Application to urban functional-zone mapping with VHR images and POI data
21	A multi-modal transportation data-driven approach to identify urban functional zones: An exploration based on Hangzhou City, China
22	A novel method of division major function oriented zoning using multi-source data in Guangzhou, China
23	Recognition and zoning optimization of geographical spatial conflict in Wuhan metropolitan area based on multi-functional perspective

Table A1. *Cont.*

Number	Title
24	Recognition of Functional Areas Based on Call Detail Records and Point of Interest Data
25	SO–CNN based urban functional zone fine division with VHR remote sensing image
26	Identification and location of a transitional zone between an urban and a rural area using fuzzy set theory, CLC, and HRL data
27	Identification of urban functional regions based on floating car track data and POI data
28	Exploring resources and environmental carrying capacities at the county level: A case study of China's Fengxian County
29	Multifunctional characteristics and revitalization strategies of different types of rural development at village scale
30	Characterizing and measuring transportation infrastructure diversity through linkages with ecological stability theory
31	Identification of urban functional zones using network kernel density estimation and kriging interpolation
32	Hierarchical community detection and functional area identification with OSM roads and complex graph theory
33	Residential land extraction from high spatial resolution optical images using multifeature hierarchical method
34	Identification of urban functional areas based on POI Data: A case study of the guangzhou economic and technological development zone
35	Beyond Word2vec: An approach for urban functional region extraction and identification by combining Place2vec and POIs
36	Comparison of approaches for urban functional zones classification based on multi-source geospatial data: A case study in Yuzhong District, Chongqing, China
37	The phenological responses of plants to the heat island effect in the main urban area of Chongqing
38	Identification, classification, and mapping of coastal ecosystem services of the Guangdong, Hong Kong, and Macao Great Bay Area
39	Monitoring changes in the impervious surfaces of urban functional zones using multisource remote sensing data: a case study of Tianjin, China
40	Potential of thirteen urban greening plants to capture particulate matter on leaf surfaces across three levels of ambient atmospheric pollution
41	Children from a rural region in the chiapas highlands, Mexico, show an increased risk of stunting and intestinal parasitoses when compared with urban children [Alto riesgo de desmedro y parasitosis intestinal en niños de una región rural de los altos de chiapas, méxico, en comparación con niños de una región urbana]
42	Influence factors on injury severity of traffic accidents and differences in urban functional zones: The empirical analysis of Beijing
43	Mapping urban functional zones by integrating very high spatial resolution remote sensing imagery and points of interest: A case study of Xiamen, China
44	Ecological network analysis on intra-city metabolism of functional urban areas in England and Wales
45	Urban landscape extraction and analysis in the mega-city of China's coastal regions using high-resolution satellite imagery: A case of Shanghai, China
46	Semantic and Spatial Co-Occurrence Analysis on Object Pairs for Urban Scene Classification
47	Status, sources, and risk assessment of polycyclic aromatic hydrocarbons in urban soils of Xi'an, China
48	A solution to the conflicts of multiple planning boundaries: Landscape functional zoning in a resource-based city in China
49	Integrating bottom-up classification and top-down feedback for improving urban land-cover and functional-zone mapping
50	Delineation and classification of rural–urban fringe using geospatial technique and onboard DMSP–Operational Linescan System
51	Multiscale geoscene segmentation for extracting urban functional zones from VHR satellite images

Table A1. *Cont.*

Number	Title
52	Evolution of the criteria for delimiting metropolitan settlement systems in poland [Ewolucja kryteriów delimitacji wielkomiejskich układów osadniczych w polsce]
53	Hierarchical semantic cognition for urban functional zones with VHR satellite images and POI data
54	Classifying urban land use by integrating remote sensing and social media data
55	Pollution characteristics and potential ecological risks of heavy metals in topsoil of Beijing
56	Use of soil biota in the assessment of the ecological potential of urban soils
57	Physical properties of soils in Rostov agglomeration
58	Functional classification of poland's communes (gminas) for the needs of the monitoring of spatial planning [Klasyfikacja funkcjonalna gmin polski na potrzeby monitoringu planowania przestrzennego]
59	Identification of technogenic disturbances of urban ecosystems using the methods of bioindication and biotesting
60	Impact of urbanization on aquatic insect assemblages in the coastal zone of Cameroon: the use of biotraits and indicator taxa to assess environmental pollution
61	Urban Land Use Classification Using LiDAR Geometric, Spatial Autocorrelation and Lacunarity Features Combined with Postclassification Processing Method
62	Design challenges of multifunctional flood defences: A comparative approach to assess spatial and structural integration
63	Analysis of green infrastructure in Lodz, Poland
64	Application of fuzzy evaluation model based on GIS to urban sound functional division
65	Discrimination of residential and industrial buildings using LiDAR data and an effective spatial-neighbor algorithm in a typical urban industrial park
66	From "urban form" to "metropolitan structure": A typology of spatial configuration of density within urban audit's "larger urban zones" [De la forme urbaine à la structure métropolitaine: Une typologie de la configuration interne des densités pour les principales métropoles européennes de l'Audit Urbain]
67	Highly time- and size-resolved fingerprint analysis and risk assessment of airborne elements in a megacity in the Yangtze River Delta, China
68	Relationships between environmental variables and seasonal succession inphytoplankton functional groups in the Hulan River Wetland
69	Analysis of intra-urban traffic accidents using spatiotemporal visualization techniques
70	Spatial distribution of prime farmland based on cultivated land quality comprehensive evaluation at county scale
71	Functional zoning for air quality
72	A study of functional planning of groundwater nitrate content using GIS and fuzzy clustering analysis
73	Assessing the flow regime in a contaminated fractured and karstic dolostone aquifer supplying municipal water
74	A functional classification method for examining landscape pattern of urban wetland park: A case study on Xixi Wetland Park, China
75	A data mining based approach to predict spatiotemporal changes in satellite images
76	Less invasive plate osteosynthesis in humeral shaft fractures
77	Spatiality and zoning of urban functions in the north-eastern part of Kolkata Metropolitan area
78	Using widely available geospatial data sets to assess the influence of roads and buffers on habitat core areas and connectivity
79	Establishing green roof infrastructure through environmental policy instruments
80	Estimation of numbers and disrtibution of workers in a large city: Warsaw case study [Szacowanie liczby i rozmieszczenia pracujacych w dużym mieście na przykładzie Warszawy]
81	A study on the soil properties of urban green space in Guangzhou and the impact of human activities on them

Table A1. *Cont.*

Number	Title
82	Research methodology for the investigation of rural surgical services.
83	Prevalence and associated factors of depressive simptomatology in elderly residents in the Northeast of Brazil [Prevalência e fatores associados à sintomatologia depressiva em idosos residentes no Nordeste do Brasil]
84	Cumulative environmental impacts and integrated coastal management: The case of Xiamen, China
85	The transitive image of the town and its intra-urban structures in the era of post-communist transformation and globalisation [Tranzitívna podoba mesta a jeho intraurbánnych štruktúr v ére postkomunistickej transformácie a globalizácie]
86	Identification of anthropogenic organic contamination associated with the sediments of a hypereutropic tropical lake, Venezuela

Table A2. List of papers obtained from WOS database.

Number	Title
1	Sensing spatial distribution of urban land use by integrating points-of-interest and Google Word2Vec model
2	Classifying urban land use by integrating remote sensing and social media data
3	Establishing green roof infrastructure through environmental policy instruments
4	Neural networks and landslide susceptibility: a case study of the urban area of Potenza
5	Cumulative environmental impacts and integrated coastal management: the case of Xiamen, China
6	Hierarchical semantic cognition for urban functional zones with VHR satellite images and POI data
7	Development of a macrophyte-based index of biotic integrity for Minnesota lakes
8	Beyond Word2vec: An approach for urban functional region extraction and identification by combining Place2vec and POIs
9	Highly time- and size-resolved fingerprint analysis and risk assessment of airborne elements in a megacity in the Yangtze River Delta, China
10	Mapping Urban Functional Zones by Integrating Very High Spatial Resolution Remote Sensing Imagery and Points of Interest: A Case Study of Xiamen, China
11	A data mining based approach to predict spatiotemporal changes in satellite images
12	Status, sources, and risk assessment of polycyclic aromatic hydrocarbons in urban soils of Xi'an, China
13	How to map soil organic carbon stocks in highly urbanized regions?
14	Spatial identification of land use functions and their tradeoffs/synergies in China: Implications for sustainable land management
15	SO-CNN based urban functional zone fine division with VHR remote sensing image
16	The impact of urban planning on land use and land cover in Pudong of Shanghai, China
17	Monitoring finer-scale population density in urban functional zones: A remote sensing data fusion approach
18	Development priority zoning in China and its impact on urban growth management strategy
19	Seasonal and spatial variations of PM10-bounded PAHs in a coal mining city, China: Distributions, sources, and health risks
20	Multiscale Geoscene Segmentation for Extracting Urban Functional Zones from VHR Satellite Images
21	Identification and monitoring of Ulmus americana transcripts during in vitro interactions with the Dutch elm disease pathogen Ophiostoma novo-ulmi
22	Ecological and human health risk assessments in the context of soil heavy metal pollution in a typical industrial area of Shanghai, China
23	Integrating bottom-up classification and top-down feedback for improving urban land-cover and functional-zone mapping
24	Ecological network analysis on intra-city metabolism of functional urban areas in England and Wales

Table A2. *Cont.*

Number	Title
25	The transitive image of the town and its intra-urban structures in the era of post-communist transformation and globalisation
26	A framework for mixed-use decomposition based on temporal activity signatures extracted from big geo-data
27	Using hydro-geomorphological typologies in functional ecology: Preliminary results in contrasted hydrosystems
28	Identification of NOx and Ozone Episodes and Estimation of Ozone by Statistical Analysis
29	Hierarchical community detection and functional area identification with OSM roads and complex graph theory
30	Delineation and classification of rural-urban fringe using geospatial technique and onboard DMSP-Operational Linescan System
31	Carbon stocks and CO_2 emissions of urban and natural soils in Central Chernozemic region of Russia
32	Impact of urbanization on aquatic insect assemblages in the coastal zone of Cameroon: the use of biotraits and indicator taxa to assess environmental pollution
33	Heuristic sample learning for complex urban scenes: Application to urban functional-zone mapping with VHR images and POI data
34	Release risk assessment of trace metals in urban soils using in-situ DGT and DIFS model
35	Characteristics and landcover of estuarine boundaries: implications for the delineation of the South African estuarine functional zone
36	Large-scale urban functional zone mapping by integrating remote sensing images and open social data
37	A solution to the conflicts of multiple planning boundaries: Landscape functional zoning in a resource-based city in China
38	Geostatistical assessment for the regional zonation of seismic site effects in a coastal urban area using a GIS framework
39	Identification of Urban Functional Areas Based on POI Data: A Case Study of the Guangzhou Economic and Technological Development Zone
40	Influence Factors on Injury Severity of Traffic Accidents and Differences in Urban Functional Zones: The Empirical Analysis of Beijing
41	Use of soil biota in the assessment of the ecological potential of urban soils
42	Physical Properties of Soils in Rostov Agglomeration
43	Analysis of Green Infrastructure in Lodz, Poland
44	Short-term dynamics and spatial heterogeneity of CO_2 emission from the soils of natural and urban ecosystems in the Central Chernozemic Region
45	Semantic and Spatial Co-Occurrence Analysis on Object Pairs for Urban Scene Classification
46	From "urban form" to "metropolitan structure": a typology of spatial configuration of density within Urban Audit's "Larger Urban Zones"
47	DFCNN-Based Semantic Recognition of Urban Functional Zones by Integrating Remote Sensing Data and POI Data
48	Identification of Urban Functional Regions Based on Floating Car Track Data and POI Data
49	A multi-modal transportation data-driven approach to identify urban functional zones: An exploration based on Hangzhou City, China
50	Context-Enabled Extraction of Large-Scale Urban Functional Zones from Very-High-Resolution Images: A Multiscale Segmentation Approach
51	Monitoring changes in the impervious surfaces of urban functional zones using multisource remote sensing data: a case study of Tianjin, China
52	Discrimination of residential and industrial buildings using LiDAR data and an effective spatial-neighbor algorithm in a typical urban industrial park

Table A2. *Cont.*

Number	Title
53	Assessing multiscale visual appearance characteristics of neighbourhoods using geographically weighted principal component analysis in Shenzhen, China
54	Recognizing urban functional zones by a hierarchical fusion method considering landscape features and human activities
55	Spatio-Temporal Coordination and Conflict of Production-Living-Ecology Land Functions in the Beijing-Tianjin-Hebei Region, China
56	Identification and Location of a Transitional Zone between an Urban and a Rural Area Using Fuzzy Set Theory, CLC, and HRL Data
57	Characterizing and measuring transportation infrastructure diversity through linkages with ecological stability theory
58	Comparison of Approaches for Urban Functional Zones Classification Based on Multi-Source Geospatial Data: A Case Study in Yuzhong District, Chongqing, China
59	Indicators for Assessing Habitat Values and Pressures for Protected Areas-An Integrated Habitat and Land Cover Change Approach for the Udzungwa Mountains National Park in Tanzania
60	Delineation of Urban Agglomeration Boundary Based on Multisource Big Data Fusion-A Case Study of Guangdong-Hong Kong-Macao Greater Bay Area (GBA)
61	A multi-faceted, location-specific assessment of land degradation threats to peri-urban agriculture at a traditional grain base in northeastern China
62	POI Mining for Land Use Classification: A Case Study
63	Automatic Identification of the Social Functions of Areas of Interest (AOIs) Using the Standard Hour-Day-Spectrum Approach
64	Urban landscape extraction and analysis in the mega-city of China's coastal regions using high-resolution satellite imagery: A case of Shanghai, China
65	Stable hydrogen isotope composition of n-alkanes in urban atmospheric aerosols in Taiyuan, China
66	Identifying Region-Wide Functions Using Urban Taxicab Trajectories
67	Urban functional zone mapping by integrating high spatial resolution nighttime light and daytime multi-view imagery
68	Identification of Urban Functional Areas by Coupling Satellite Images and Taxi GPS Trajectories
69	Source identification of heavy metals and stable carbon isotope in indoor dust from different functional areas in Hefei, China
70	Land use classification from social media data and satellite imagery
71	Land Use Changes with Particular Focus on Industrial Lands in Polish Major Cities and Their Surroundings in the Years 2005, 2009 to 2014
72	PCE point source apportionment using a GIS-based statistical technique combined with stochastic modelling
73	A New Urban Functional Zone-Based Climate Zoning System for Urban Temperature Study
74	Analyzing Urban Agriculture's Contribution to a Southern City's Resilience through Land Cover Mapping: The Case of Antananarivo, Capital of Madagascar
75	Land-use conflict identification in urban fringe areas using the theory of leading functional space partition
76	Exploring the Relationship between Urbanization and the Eco-Environment: A Case Study of Beijing
77	Humus Horizons of Soils in Urban Ecosystems
78	Prospecting soil bacteria from subtropical Brazil for hydrolases production
79	Identification of anthropogenic organic contamination associated with the sediments of a hypereutropic tropical lake, Venezuela
80	Decision-Level and Feature-Level Integration of Remote Sensing and Geospatial Big Data for Urban Land Use Mapping
81	A taxonomy of driving errors and violations: Evidence from the naturalistic driving study

Table A2. *Cont.*

Number	Title
82	Spatial and vertical distribution, composition profiles, sources, and ecological risk assessment of polycyclic aromatic hydrocarbon residues in the sediments of an urban tributary: A case study of the Songgang River, Shenzhen, China
83	Spatial development planning in peri-urban space of Burdwan City, West Bengal, India: statutory infrastructure as mediating factors
84	Recognition of Functional Areas Based on Call Detail Records and Point of Interest Data
85	Urban Land Use Classification Using LiDAR Geometric, Spatial Autocorrelation and Lacunarity Features Combined with Postclassification Processing Method
86	Mapping large-scale and fine-grained urban functional zones from VHR images using a multi-scale semantic segmentation network and object based approach
87	Estimating building-scale population using multi-source spatial data
88	Quantify city-level dynamic functions across China using social media and POIs data
89	Exploring Impact of Spatial Unit on Urban Land Use Mapping with Multisource Data
90	Evaluation of the Index of Atmospheric Purity in an American tropical valley through the sampling of corticulous lichens in different
91	Experimental research on trade-offs in ecosystem services: The agro-ecosystem functional spectrum
92	Residential land extraction from high spatial resolution optical images using multifeature hierarchical method
93	Ecosystem Base for Land-Use Planning in the Coastal Plain of Rio Grande do Sul
94	A Study of Functional Planning of Groundwater Nitrate Content Using GIS and Fuzzy Clustering Analysis
95	Construction of a Territorial Space Classification System Based on Spatiotemporal Heterogeneity of Land Use and Its Superior Territorial Space Functions and Their Dynamic Coupling: Case Study on Qionglai City of Sichuan Province, China
96	How Do Two- and Three-Dimensional Urban Structures Impact Seasonal Land Surface Temperatures at Various Spatial Scales? A Case Study for the Northern Part of Brooklyn, New York, USA
97	Assessment of Crash Occurrence Using Historical Crash Data and a Random Effect Negative Binomial Model: A Case Study for a Rural State
98	Integrating Aerial LiDAR and Very-High-Resolution Images for Urban Functional Zone Mapping
99	A novel semantic recognition framework of urban functional zones supporting urban land structure analytics based on open-source data
100	A GloVe-Based POI Type Embedding Model for Extracting and Identifying Urban Functional Regions
101	Accumulation and health implications of metals in topsoil of an urban riparian zone adjacent to different functional areas in a subtropical city
102	Spatial structure of Zhengzhou Airport Economy Zone: its evolution and drivers
103	Block2vec: An Approach for Identifying Urban Functional Regions by Integrating Sentence Embedding Model and Points of Interest
104	Sociocultural basis of urban planning regulation for public open spaces
105	The Influence of Spatial Grid Division on the Layout Analysis of Urban Functional Areas
106	Identification and Portrait of Urban Functional Zones Based on Multisource Heterogeneous Data and Ensemble Learning
107	Cartographic modeling of the Russian steppe-zone urban landscapes with the use of neural networks
108	An SOE-Based Learning Framework Using Multisource Big Data for Identifying Urban Functional Zones
109	Contamination, Spatial Distribution and Source Analysis of Heavy Metals in Surface Soil of Anhui Chaohu Economic Development Zone, China
110	Spatial Patterns of Neighborhoods in the Historic City of Yazd
111	Chicago, Illinois, smart growth study

Table A3. List of papers obtained from CNKI database.

Number	Title
1	Research on Urban Function Recognition Based on Multi-modal and Multi-level Data Fusion Method
2	Boundary Identification and Spatial Pattern Optimization of Central Urban Areas Based on POI Data:Taking Gaotang County for Example
3	Identify Urban Functional Zones Using Multi Feature Latent Semantic Fused Information of High-spatial Resolution Remote Sensing Image and POI Data
4	Urban Functional Area Identification Based on Remote Sensing Images
5	Division and Identification of Urban Functional Areas Based on POI Data—A Case Study of Nanning Downtown Area
6	Making good use of planning and Control System to Improve territorial space governance ability: Thinking on Beijing Block Level Regulatory detailed planning
7	Identification of urban function mixing degree in Nanjing metropolitan area based on multi-source data
8	Urban Functional Area Division Considering POI and Land Use Data
9	Identification of Urban Street Function Based on POI Data—A Case of Xi'an Huifang
10	Research on Identification and Optimization Strategy of Qingdao Urban Leisure Space Distribution Based on POI Data
11	Urban land use classification based on remote sensing images and neural network
12	Division and Identification of Urban Functional Areas based on POI-take Main Urban Area of Quanzhou as an Example
13	Spatial Agglomeration Mode of Urban Functional Areas in Western Frontier Tourist City: A Case Study of Lijiang City, Yunnan Province
14	Urban Functional Area Identification Based on Similarity of Time Series
15	Identification of urban functional areas based on POI data: A case study of Hohhot
16	Urban Functional Area Identification Method and Its Application Combined OSM Road Network Data with POI Data
17	Study on the Comprehensive Identification of Urban Functional Areas in Hong Kong Based on Multi-Source Data
18	Quantitative identification of urban functional areas based on spatial grid
19	A poi data-based study on urban functional areas of the resources-based city:a case study of benxi, liaoning
20	Identification of Urban Functional Areas Based on GPS Trajectory and POI Data with Association Rules
21	Identification of the urban functional regions considering the potential context of interest points
22	Identification of Urban Functional Regions Based on POI Data and Place2vec Model
23	Research on Urban Functional Area Recognition Integrating OSM Road Network and POI Data
24	The identification of urban functional areas as a service for territorial space planning
25	A comparative study of urban functional structure based on POI data: A case study of Beijing and Shanghai
26	Identify of Urban Functional Areas and Function Composite Calculation of the Central City Based on POI Data: A Case of Dongguan
27	Urban Planning Based on Multi-source Spatiotemporal Big Data:A Case Study of Xiacheng District of Hangzhou City
28	Conceptual Analysis and Functional Identification of Urban Green Space in the Context of Park City
29	Geoscene-Based Modeling and Analysis of Urban Functional Zoning
30	Identifying Urban Functional Regions Based on POI Data and Spatial Analysis of Main Transit Hubs
31	Academic writing on "Spatial Development and Planning Innovation"
32	Urban Functional Zone Recognition and Green Space Evaluation of Shanghai Based on POI Data
33	Study on functional Classification and urban functional Orientation of Hunan Cities

Table A3. *Cont.*

Number	Title
34	Application and management analysis of X-ray security inspection equipment with intelligent identification function in urban rail transit
35	Discovering urban functional regions based on sematic mining from spatiotemporal data
36	Semantic information mining and remote sensing classification of urban functional areas
37	Research on the Identification and Relief of Non-Provincial Capital City Function in Provincial Capital Cities: A Case Study of Chengdu
38	Dynamic Identification of Urban Functional Areas and Visual Analysis of Time-varying Patterns Based on Trajectory Data and POIs
39	Mobile Phone Data Based Urban Functional Area Classification Algorithm
40	Identifying City Functional Areas Using Taxi Trajectory Data
41	A study on quantitative identification of urban functional areas in yichun based on point of interest data
42	Functional Classification Method of Urban Road
43	How reliable are cellular positioning data in tourism environments?An exploration of functional regions
44	Research on Classification System of Urban Green Space
45	Identification of Urban Functional Areas Based on Logistic Regression Model
46	Identification and Spatial Interaction of Urban Functional Regions in Beijing Based on the Characteristics of Residents' Traveling
47	Discussion and Analysis on Planning Method of Areal Bridge Landscape Based on Classification of Bridge Landscape
48	Application of spatial and temporal entropy based on multi-source data for measuring the mix degree of urban functions
49	Research on identification method of urban land functional area based on Mobile signaling data
50	Research on identifying urban regions of different functions based on POI data
51	Identification, Spatial Pattern and Service Function of Emergency Shelters in Shenyang City
52	A study of urban functional area identification methods based on big data of social sensing
53	Research on quantitative identification method of urban functional area based on big data
54	Functional Classification of Urban Buildings in High Resolution Remote Sensing Images through POI-assisted Analysis
55	Vegetation allocation of urban green space in wheat area based on SO_2
56	A Primary Study On Urban Land Use Classification From The Perspective Of Ecosystem Services
57	Implementing the Strategy of "Service District" to fulfill the function of "four Services" in the core functional district of the Capital—A Record of the pilot work of comprehensive standardization of classification and classification management of urban environment in Xicheng District, Beijing
58	Analysis of Function Identification of Urban Blocks Based on SCD and POI Data—A Case Study of Chaoyang District
59	Semi-Supervised Urban Land Using Classification Method Based on Uncertainty Sampling
60	Urban functional area identification based on call detail record data
61	Identifying urban functional zones using bus smart card data and points of interest in beijing
62	Quantitative Identification and Visualization of Urban Functional Area Based on POI Data
63	Discovering urban functional regions using latent semantic information:Spatiotemporal data mining of floating cars GPS data of Guangzhou
64	Quantitative function identification and analysis of urban ecological-production-living spaces
65	The Delimitation and Classified Planning and Management of Transformation Function Region:the Experience and Exploration of Urban Renewal in Shenzhen

Table A3. *Cont.*

Number	Title
66	International case studies of free trade zones
67	Study on the classification of urban road traffic management function
68	Measurement and classification of the functions of small and medium-sized cities in The Capital region of China
69	Discussion on functional classification of urban road traffic management
70	Demand Analysis for Urban Rail Transit Systems Based on Function Classification
71	The definition of urban concentrated areas and the relations with the national main function areas of China
72	Function Classification and Setting of Urban Bus Station—A Case Study of Chongqing
73	The Analysis of Sport Image's Function in City Development—In a perspective of image building and recognition
74	Spatial function identification of urban main body and selection of core industry main body: A case study of Heilongjiang Province
75	Research on Functional Classification of Urban Roads
76	Guangzhou; tree canopy coverage; function classification; urban forest
77	Quantitative Analysis to Classified Urban Functions in the Core Area of Huaihai Economic Zone
78	A functional classification method for examining landscape pattern of urban wetland park:a case study on Xixi Wetland Park, China
79	Functional Classification of Lake City and Control of Design and Plan Study of the Functionality of Lake Landscape in Wuhan
80	Urban functional zoning and zoning classification management
81	The Function Classification and Spatial Organizational Structure of Japan's Capital Megapolis
82	The value of Beijing Olympic Games economy and its realization
83	Classification, Ecosystem Service, Protection and Utilization of the Urban Ecological Land—A Case Study of Liaocheng City
84	Research and Classification of Urban Plant Landscape Functions
85	Research on Urban Road Traiffc Management Function ClassiifCation
86	Study on Urban Road Function Classification of "Planning New Town"—Practice of Road function Classification in Lingang New Town
87	One year, one thing, three years, big changes—Shanghai makes every effort to draw a blueprint for environmental protection construction
88	Identifying Functional Urban Regions with POI Data
89	Urban Functional Area Recognition Based on Crowd Travel Behavior Trajectory
90	Classification and extraction of forest land in China based on the perspective of "Production-Living-Ecology"
91	Identify multi-level urban functional structures by using semantic data
92	Research on Identification and Visualization of Nanning City Functional Area Based on POI Data
93	Exploring urban functional areas based on multi-source data: A case study of Beijing
94	Urban Research Using Points of Interest Data in China
95	A POI Data-Based Study ofthe Urban Functional Areas of Chongqing and Their Mix Degree Recognition
96	Urban Green Space Classification and Landscape Pattern Measurement based on GF-2 Image
97	Fine identification and governance of functional areas in the Beijing-Tianjin-Hebei urban agglomeration supported by big data
98	Identification and evaluation of urban functional land based on POI data—A case study of five districts in Jinan
99	A Study on the Method for Functional Classification of Urban Buildings by Using POI Data

Table A3. *Cont.*

Number	Title
100	Identifying Mixed Functions of Urban Public Service Facilities in Beijing by Cumulative Opportunity Accessibility Method
101	Function identification method of urban rail Interchange Station based on factor analysis and cluster analysis
102	Urban Functional Area Identification Method Based on Mobile Big Data
103	Identification of Urban Functional Zones Using Network Kernel Density Estimation and Kriging Interpolation
104	Sensing Multi-level Urban Functional Structures by Using Time Series Taxi Trajectory Data
105	Research on function identification and distribution characteristics of Wuhan supported by big data
106	Urban Land Use Function Recognition Method Using Sequential Mobile Phone Data
107	Identification of Urban Interest Function Region by Using Social Media Check-in Data
108	Spatial Distribution and Interaction Analysis of Urban Functional Areas Based on Multi-source Data
109	Identification and Classification of Wuhan Urban Districts Based on POI

Table A4. List of papers after manually checking.

Number	Title
1	A new urban functional zone-based climate zoning system for urban temperature study
2	A novel method of division major function oriented zoning using multi-source data in Guangzhou, China
3	Sensing spatial distribution of urban land use by integrating points-of-interest and Google Word2Vec model
4	Classifying urban land use by integrating remote sensing and social media data
5	Hierarchical semantic cognition for urban functional zones with VHR satellite images and POI data
6	Beyond Word2vec: An approach for urban functional region extraction and identification by combining Place2vec and POIs
7	Mapping Urban Functional Zones by Integrating Very High Spatial Resolution Remote Sensing Imagery and Points of Interest: A Case Study of Xiamen, China
8	SO-CNN based urban functional zone fine division with VHR remote sensing image
9	Monitoring finer-scale population density in urban functional zones: A remote sensing data fusion approach
10	Multiscale Geoscene Segmentation for Extracting Urban Functional Zones from VHR Satellite Images
11	Integrating bottom-up classification and top-down feedback for improving urban land-cover and functional-zone mapping
12	Hierarchical community detection and functional area identification with OSM roads and complex graph theory
13	Heuristic sample learning for complex urban scenes: Application to urban functional-zone mapping with VHR images and POI data
14	Large-scale urban functional zone mapping by integrating remote sensing images and open social data
15	Identification of Urban Functional Areas Based on POI Data: A Case Study of the Guangzhou Economic and Technological Development Zone
16	Semantic and Spatial Co-Occurrence Analysis on Object Pairs for Urban Scene Classification
17	DFCNN-Based Semantic Recognition of Urban Functional Zones by Integrating Remote Sensing Data and POI Data
18	Identification of Urban Functional Regions Based on Floating Car Track Data and POI Data
19	A multi-modal transportation data-driven approach to identify urban functional zones: An exploration based on Hangzhou City, China
20	Context-Enabled Extraction of Large-Scale Urban Functional Zones from Very-High-Resolution Images: A Multiscale Segmentation Approach
21	Recognizing urban functional zones by a hierarchical fusion method considering landscape features and human activities

Table A4. *Cont.*

Number	Title
22	Comparison of Approaches for Urban Functional Zones Classification Based on Multi-Source Geospatial Data: A Case Study in Yuzhong District, Chongqing, China
23	POI Mining for Land Use Classification: A Case Study
24	Urban functional zone mapping by integrating high spatial resolution nighttime light and daytime multi-view imagery
25	Identification of Urban Functional Areas by Coupling Satellite Images and Taxi GPS Trajectories
26	Land use classification from social media data and satellite imagery
27	Recognition of Functional Areas Based on Call Detail Records and Point of Interest Data
28	Mapping large-scale and fine-grained urban functional zones from VHR images using a multi-scale semantic segmentation network and object based approach
29	Exploring Impact of Spatial Unit on Urban Land Use Mapping with Multisource Data
30	Integrating Aerial LiDAR and Very-High-Resolution Images for Urban Functional Zone Mapping
31	A novel semantic recognition framework of urban functional zones supporting urban land structure analytics based on open-source data
32	A GloVe-Based POI Type Embedding Model for Extracting and Identifying Urban Functional Regions
33	Block2vec: An Approach for Identifying Urban Functional Regions by Integrating Sentence Embedding Model and Points of Interest
34	The Influence of Spatial Grid Division on the Layout Analysis of Urban Functional Areas
35	Identification and Portrait of Urban Functional Zones Based on Multisource Heterogeneous Data and Ensemble Learning
36	An SOE-Based Learning Framework Using Multisource Big Data for Identifying Urban Functional Zones
37	Research on Urban Function Recognition Based on Multi-modal and Multi-level Data Fusion Method
38	Boundary Identification and Spatial Pattern Optimization of Central Urban Areas Based on POI Data:Taking Gaotang County for Example
39	Identify Urban Functional Zones Using Multi Feature Latent Semantic Fused Information of High-spatial Resolution Remote Sensing Image and POI Data
40	Urban Functional Area Identification Based on Remote Sensing Images
41	Division and Identification of Urban Functional Areas Based on POI Data—A Case Study of Nanning Downtown Area
42	Identification of urban function mixing degree in Nanjing metropolitan area based on multi-source data
43	Urban Functional Area Division Considering POI and Land Use Data
44	Identification of Urban Street Function Based on POI Data—A Case of Xi'an Huifang
45	Research on Identification and Optimization Strategy of Qingdao Urban Leisure Space Distribution Based on POI Data
46	Urban land use classification based on remote sensing images and neural network
47	Division and Identification of Urban Functional Areas based on POI-take Main Urban Area of Quanzhou as an Example
48	Spatial Agglomeration Mode of Urban Functional Areas in Western Frontier Tourist City: A Case Study of Lijiang City, Yunnan Province
49	Urban Functional Area Identification Based on Similarity of Time Series
50	Identification of urban functional areas based on POI data: A case study of Hohhot
51	Urban Functional Area Identification Method and Its Application Combined OSM Road Network Data with POI Data
52	Study on the Comprehensive Identification of Urban Functional Areas in Hong Kong Based on Multi-Source Data

Table A4. *Cont.*

Number	Title
53	Quantitative identification of urban functional areas based on spatial grid
54	A poi data-based study on urban functional areas of the resources-based city:a case study of benxi, liaoning
55	Identification of Urban Functional Areas Based on GPS Trajectory and POI Data with Association Rules
56	Identification of the urban functional regions considering the potential context of interest points
57	Identification of Urban Functional Regions Based on POI Data and Place2vec Model
58	Research on Urban Functional Area Recognition Integrating OSM Road Network and POI Data
59	The identification of urban functional areas as a service for territorial space planning
60	A comparative study of urban functional structure based on POI data: A case study of Beijing and Shanghai
61	Identify of Urban Functional Areas and Function Composite Calculation of the Central City Based on POI Data: A Case of Dongguan
62	Urban Planning Based on Multi-source Spatiotemporal Big Data: A Case Study of Xiacheng District of Hangzhou City
63	Geoscene-Based Modeling and Analysis of Urban Functional Zoning
64	Identifying Urban Functional Regions Based on POI Data and Spatial Analysis of Main Transit Hubs
65	Urban Functional Zone Recognition and Green Space Evaluation of Shanghai Based on POI Data
66	Discovering urban functional regions based on sematic mining from spatiotemporal data
67	Semantic information mining and remote sensing classification of urban functional areas
68	Dynamic Identification of Urban Functional Areas and Visual Analysis of Time-varying Patterns Based on Trajectory Data and POIs
69	Mobile Phone Data Based Urban Functional Area Classification Algorithm
70	Identifying City Functional Areas Using Taxi Trajectory Data
71	A study on quantitative identification of urban functional areas in yichun based on point of interest data
72	Identification of Urban Functional Areas Based on Logistic Regression Model
73	Identification and Spatial Interaction of Urban Functional Regions in Beijing Based on the Characteristics of Residents' Traveling
74	Application of spatial and temporal entropy based on multi-source data for measuring the mix degree of urban functions
75	Research on identification method of urban land functional area based on Mobile signaling data
76	Research on identifying urban regions of different functions based on POI data
77	A study of urban functional area identification methods based on big data of social sensing
78	Research on quantitative identification method of urban functional area based on big data
79	Functional Classification of Urban Buildings in High Resolution Remote Sensing Images through POI-assisted Analysis
80	Analysis of Function Identification of Urban Blocks Based on SCD and POI Data—A Case Study of Chaoyang District
81	Semi-Supervised Urban Land Using Classification Method Based on Uncertainty Sampling
82	Urban functional area identification based on call detail record data
83	Identifying urban functional zones using bus smart card data and points of interest in beijing
84	Quantitative Identification and Visualization of Urban Functional Area Based on POI Data
85	Discovering urban functional regions using latent semantic information:Spatiotemporal data mining of floating cars GPS data of Guangzhou
86	Identifying Functional Urban Regions with POI Data
87	Urban Functional Area Recognition Based on Crowd Travel Behavior Trajectory

Table A4. *Cont.*

Number	Title
88	Identify multi-level urban functional structures by using semantic data
89	Research on Identification and Visualization of Nanning City Functional Area Based on POI Data
90	Exploring urban functional areas based on multi-source data: A case study of Beijing
91	A POI Data-Based Study ofthe Urban Functional Areas of Chongqing and Their Mix Degree Recognition
92	Identification and evaluation of urban functional land based on POI data—A case study of five districts in Jinan
93	A Study on the Method for Functional Classification of Urban Buildings by Using POI Data
94	Identifying Mixed Functions of Urban Public Service Facilities in Beijing by Cumulative Opportunity Accessibility Method
95	Urban Functional Area Identification Method Based on Mobile Big Data
96	Identification of Urban Functional Zones Using Network Kernel Density Estimation and Kriging Interpolation
97	Sensing Multi-level Urban Functional Structures by Using Time Series Taxi Trajectory Data
98	Research on function identification and distribution characteristics of Wuhan supported by big data
99	Urban Land Use Function Recognition Method Using Sequential Mobile Phone Data
100	Identification of Urban Interest Function Region by Using Social Media Check-in Data
101	Spatial Distribution and Interaction Analysis of Urban Functional Areas Based on Multi-source Data
102	Identification and Classification of Wuhan Urban Districts Based on POI

References

1. Fan, J.; Tian, M. Relative analysis and provincial differences of China's urbanization and non-agricultural development. *Sci. Geogr. Sin.* **2003**, *23*, 641–648. [CrossRef]
2. Han, H.; Yu, X.; Long, Y. Identifying urban functional zones using bus smart card data and points of interest in Beijing. *City Plan. Rev.* **2016**, *40*, 52–60. [CrossRef]
3. Chen, Z. Review of Athens Charter and Charter of Miachu Picchu. *Int. Urban Plan.* **2009**, *24*, 41–42. [CrossRef]
4. Jiang, Y.; Dong, M.; Fan, J.; Gao, S.; Liu, Y.; Ma, X. Research on identifying urban regions of different functions based on POI data. *J. Zhejiang Norm. Univ.* **2017**, *40*, 398–405. [CrossRef]
5. Yao, Y.; Zhang, Y.; Guan, Q.; Mai, K.; Zhang, J. Sensing Multi-level Urban Functional Structures by Using Time Series Taxi Trajectory Data. *Geomat. Inf. Sci. Wuhan Univ.* **2019**, *44*, 875–884. [CrossRef]
6. Shen, Q.; Li, C.; Zhou, G.; Ma, Z. The coupling of functional urban spaces: A case study of Changchun from 2002 to 2012. *Geogr. Res.* **2015**, *34*, 1897–1910. [CrossRef]
7. Deng, Y.; Liu, J.; Liu, Y.; Luo, A. Detecting Urban Polycentric Structure from POI Data. *Int. J. Geo-Inf.* **2019**, *8*, 283. [CrossRef]
8. Hu, T.; Yang, J.; Li, X.; Gong, P. Mapping Urban Land Use by Using Landsat Images and Open Social Data. *Remote Sens.* **2016**, *8*, 151. [CrossRef]
9. Li, Y.; Liu, Y.; Ren, Y.; Wang, Z.; Qu, C. Semantic information mining and remote sensing classification of urban functional areas. *J. Univ. Chin. Acad. Sci.* **2019**, *36*, 56–63. [CrossRef]
10. Batty, M. The Size, Scale, and Shape of Cities. *Science* **2008**, *319*, 769–771. [CrossRef]
11. Deng, Y.; Luo, A.; Liu, J.; Wang, Y. Point of interest matching between different geospatial datasets. *ISPRS Int. J. Geo-Inf.* **2019**, *8*, 435. [CrossRef]
12. Luo, Z.; Lei, D.; Li, X.; Yuan, Y. Identification and influencing factors of residential environment deprivation in a river valley city: A case study of Lanzhou city. *Geogr. Res.* **2021**, *40*, 1949–1962. [CrossRef]
13. Yan, F. Research on the development pattern of urban functional areas. *Econ. Res. Guide* **2010**, *12*, 134–136.
14. Gao, J.; Chen, J.; Yang, D. Spatial distribution of urban land prices in Nanjing. *Prog. Geogr.* **2013**, *32*, 361–371. [CrossRef]
15. Liu, J. Reference of Planning and Construction of New Town Area in Typical Metropolitan in Foreign Countries to the Construction of Xiongan New Area. *Econ. Rev. J.* **2018**, *1*, 114–122. [CrossRef]
16. Renato, A.; Ana, A.; Carlos, B. POI Mining for Land Use Classification: A Case Study. *ISPRS Int. J. Geo-Inf.* **2020**, *9*, 493. [CrossRef]
17. Ding, L.; Niu, X.; Song, X. Urban Spatial Studies with Big Data of Mobile Location: A Progress Review. *Urban Plan. Int.* **2015**, *30*, 53–58.
18. Zeng, Q.; Yin, B.; Cai, M.; Cai, C.; Zhang, Z.; Lin, D. Multi-temporal land use/land cover remote sensing data processing and accuracy assement—A case of Wuhan Metropolitan. *J. East China Norm. Univ.* **2009**, *43*, 314–318. [CrossRef]
19. Gu, J.; Chen, X.; Yang, H. Spatial clustering algorithm on urban function oriented zone. *Sci. Surv. Mapp.* **2011**, *36*, 64–67. [CrossRef]

20. Li, Y.; Zhang, M. Object-oriented construction land change detection from high-resolution remote sensing image. *Bull. Surv. Mapp.* **2021**, *2*, 54–58. [CrossRef]
21. Xiao, J.; Shen, Y.; Ge, J.; Tateishi, R.; Tang, C.; Liang, Y.; Huang, Z. Evaluating urban expansion and land use change in Shijiazhuang, China, by using GIS and remote sensing. *Landsc. Urban Plan.* **2006**, *75*, 69–80. [CrossRef]
22. Huang, X.; Yang, J.; Li, J.; Wen, D. Urban functional zone mapping by integrating high spatial resolution nighttime light and daytime multi-view imagery. *ISPRS J. Photogramm. Remote Sens.* **2021**, *175*, 403–415. [CrossRef]
23. Soto, V.; Frías-Martínez, E. Automated land use identification using cell-phone records. In Proceedings of the 3rd ACM international workshop on MobiArch, Bethesda, MD, USA, 28 June 2011; pp. 17–22. [CrossRef]
24. Toole, J.L.; Ulm, M.; González, M.C.; Bauer, D. Inferring land use from mobile phone activity. In Proceedings of the ACM SIGKDD International Workshop on Urban computing, Beijing, China, 12 August 2012; pp. 1–8. [CrossRef]
25. Wang, B.; Wang, F.; Zhang, H. The Dynamic Changes of Urban Space-timeActivity The Dynamic Changes of Urban Space-timeActivity andActivity Zoning Based on Check-in Data in Sina Web. *Sci. Geogr. Sin.* **2015**, *35*, 151–160. [CrossRef]
26. Ning, P.; Wan, Y.; Shen, Y.; Ren, F. Identification of urban interest function region by using social media check-in data. *J. Geomat.* **2018**, *43*, 110–114. [CrossRef]
27. Liu, Y.; Wang, F.; Xiao, Y.; Gao, S. Urban land uses and traffic 'source-sink areas': Evidence from GPS-enabled taxi data in Shanghai. *Landsc. Urban Plan.* **2012**, *106*, 73–87. [CrossRef]
28. Pan, G.; Qi, G.; Wu, Z.; Zhang, D.; Li, S. Land-Use Classification Using Taxi GPS Traces. *IEEE Trans. Intell. Transp. Syst.* **2013**, *14*, 113–123. [CrossRef]
29. Yuan, J.; Zheng, Y.; Xie, X. Discovering regions of different functions in a city using human mobility and POIs. In Proceedings of the 18th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, Beijing, China, 12–16 August 2012; pp. 186–194. [CrossRef]
30. Mckenzie, G.; Janowicz, K.; Adams, B. A weighted multi-attribute method for matching user-generated Points of Interest. *Cartogr. Geogr. Inf. Sci.* **2014**, *41*, 125–137. [CrossRef]
31. Jiang, G.; Hu, F.; Shi, L. Urban functional area identification based on call detail record data. *J. Comput. Appl.* **2016**, *36*, 2046–2050. [CrossRef]
32. Estima, J.; Painho, M. Investigating the Potential of OpenStreetMap for Land Use/Land Cover Production: A Case Study for Continental Portugal. In *OpenStreetMap in GIScience*; Jokar Arsanjani, J., Zipf, A., Mooney, P., Helbich, M., Eds.; Springer International Publishing: Cham, Switzerland, 2015; pp. 273–293. [CrossRef]
33. Chi, J.; Jiao, L.; Dong, T.; Gu, Y.; Ma, Y. Quantitative Identification and Visualization of Urban Functional Area Based on POI Data. *J. Geomat.* **2016**, *41*, 68–73. [CrossRef]
34. Kang, Y.; Wang, Y.; Xia, Z.; Chi, J.; Jiao, L.; Wei, Z. Identification and Classification of Wuhan Urban Districts Based on POI. *J. Geomat.* **2018**, *43*, 81–85. [CrossRef]
35. Zhao, W.; Li, Q.; Li, B. Extracting hierarchical landmarks from urban POI data. *Natl. Remote Sens. Bull.* **2011**, *15*, 973–988. [CrossRef]
36. Calabrese, F.; Ferrari, L.; Blondel, V.D. Urban Sensing Using Mobile Phone Network Data: A Survey of Research. *Acm Comput. Surv.* **2014**, *47*, 1–20. [CrossRef]
37. Huang, Q.; Wong, D.W.S. Activity patterns, socioeconomic status and urban spatial structure: What can social media data tell us? *Int. J. Geogr. Inf. Sci.* **2016**, *30*, 1873–1898. [CrossRef]
38. Liu, X.; He, J.; Yao, Y.; Zhang, J.; Liang, H.; Wang, H.; Hong, Y. Classifying urban land use by integrating remote sensing and social media data. *Int. J. Geogr. Inf. Sci.* **2017**, *31*, 1675–1696. [CrossRef]
39. Xiao, B. Calculation Method for Transit Accessibility of Urban Rail Transit Planning Scheme Based on Internet Map Data. *Urban Mass Transit* **2021**, *24*, 69–73. [CrossRef]
40. Cao, K.; Guo, H.; Zhang, Y. Comparison of approaches for urban functional zones classification based on multi-source geospatial data: A case study in Yuzhong District, Chongqing, China. *Sustainability* **2019**, *11*, 660. [CrossRef]
41. Yu, B.; Wang, Z.; Mu, H.; Sun, L.; Hu, F. Identification of Urban Functional Regions Based on Floating Car Track Data and POI Data. *Sustainability* **2019**, *11*, 6541. [CrossRef]
42. Steiger, E.; De Albuquerque, J.; Zipf, A. An Advanced Systematic Literature Review on Spatiotemporal Analyses of Twitter Data. *Trans. Gis* **2016**, *19*, 809–834. [CrossRef]
43. Luo, S.; Liu, Y.; Du, M.; Gao, S.; Wang, P.; Liu, X. The Influence of Spatial Grid Division on the Layout Analysis of Urban Functional Areas. *ISPRS Int. J. Geo-Inf.* **2021**, *10*, 189. [CrossRef]
44. Kobayashi, T.; Taguchi, A. A model for urban space allocation to transportation area and residential area. *J. Oper. Res. Soc. Jpn.* **2001**, *44*, 281–296. [CrossRef]
45. Wang, J.; Ye, Y.; Fang, F. A study of urban functional zoning based on kernel density estimation and fusion data. *Geogr. Geo-Inf. Sci.* **2019**, *35*, 66–71. [CrossRef]
46. Du, S.; Du, S.; Liu, B.; Zhang, X.; Zheng, Z. Large-scale urban functional zone mapping by integrating remote sensing images and open social data. *GIScience Remote Sens.* **2020**, *57*, 411–430. [CrossRef]
47. Yao, Y.; Li, X.; Liu, X.; Liu, P.; Mai, K. Sensing spatial distribution of urban land use by integrating points-of-interest and Google Word2Vec model. *Int. J. Geogr. Inf. Syst.* **2016**, *31*, 825–848. [CrossRef]

48. Zhang, D.; Wan, J.; He, Z.; Zhao, S.; Fan, K.; Park, S.O.; Jiang, Z. Identifying region-wide functions using urban taxicab trajectories. *ACM Trans. Embed. Comput. Syst.* **2016**, *15*, 1–19. [CrossRef]
49. Zhou, W.; Ming, D.; Lv, X.; Zhou, K.; Bao, H. SO–CNN based urban functional zone fine division with VHR remote sensing image. *Remote Sens. Environ.* **2019**, *236*, 11458. [CrossRef]
50. Zhang, X.; Du, S.; Wang, Q.; Zhou, W. Multiscale Geoscene Segmentation for Extracting Urban Functional Zones from VHR Satellite Images. *Remote Sens.* **2018**, *10*, 281. [CrossRef]
51. Bao, H.; Ming, D.; Guo, Y.; Zhang, K.; Zhou, K.; Du, S. DFCNN-Based Semantic Recognition of Urban Functional Zones by Integrating Remote Sensing Data and POI Data. *Remote Sens.* **2020**, *12*, 1088. [CrossRef]
52. Liu, X.; Jiao, P.; Yuan, N.; Wang, W. Identification of multi-attribute functional urban areas under a perspective of community detection: A case study. *Phys. A Stat. Mech. Its Appl.* **2016**, *462*, 827–836. [CrossRef]
53. Guo, Z.; Liu, K.; Li, Y. Identify of Urban Functional Areas and Function Composite Calculation of the Central City Based on POI Data: A Case of Dongguan. *Urban Geotech. Investig. Surv.* **2020**, 40–46. [CrossRef]
54. Dong, X.; Xu, Y.; Huang, L.; Liu, Z.; Xu, Y.; Zhang, K.; Hu, Z.; Wu, G. Exploring Impact of Spatial Unit on Urban Land Use Mapping with Multisource Data. *Remote Sens.* **2020**, *12*, 3597. [CrossRef]
55. Liu, J.; Zhang, J.; Jia, K. Boundary Identification and Spatial Pattern Optimization of Central Urban Areas Based on POI Data:Taking Gaotang County for Example. *Urban Dev. Stud.* **2021**, *28*, 74–83. [CrossRef]
56. Hu, Y.; Han, Y. Identification of Urban Functional Areas Based on POI Data: A Case Study of the Guangzhou Economic and Technological Development Zone. *Sustainability* **2019**, *11*, 1385. [CrossRef]
57. Du, S.; Du, S.; Liu, B.; Zhang, X. Context-Enabled Extraction of Large-Scale Urban Functional Zones from Very-High-Resolution Images: A Multiscale Segmentation Approach. *Remote Sens.* **2019**, *11*, 1902. [CrossRef]
58. Yuan, G.; Chen, Y.; Sun, L.; Lai, J.; Li, T.; Liu, Z. Recognition of Functional Areas Based on Call Detail Records and Point of Interest Data. *J. Adv. Transp.* **2020**, *2020*, 8956910. [CrossRef]
59. Yang, X.; Fang, Z.; Yin, L.; Li, J.; Zhou, Y.; Lu, S. Understanding the Spatial Structure of Urban Commuting Using Mobile Phone Location Data: A Case Study of Shenzhen, China. *Sustainability* **2018**, *10*, 1435. [CrossRef]
60. Zhang, X. Geoscene-Based Modeling and Analysis of urban functional zoning. *Geogr. Geo-Inf. Sci.* **2020**, *36*, 144. [CrossRef]
61. Yu, L.; He, X.; Liu, J. Discovering urban functional regions based on sematic mining from spatiotemporal data. *J. Sichuan Univ.* **2019**, *56*, 246–252. [CrossRef]
62. Huang, N.; Zhang, L.; Liu, Q.; Wang, P. The Research on Approach and Method of Sustainable Development-based Urban Functional Zoning and Application. *Urban Dev. Stud.* **2009**, *16*, 63–70. [CrossRef]
63. Hu, S.; Wang, L. Automated urban land-use classification with remote sensing. *Int. J. Remote Sens.* **2013**, *34*, 790–803. [CrossRef]
64. Barnsley, M.J.; Barr, S.L. Inferring urban land use from satellite sensor images using kernel-based spatial reclassification. *Photogramm. Eng. Remote Sens.* **1996**, *62*, 949–958.
65. Huang, C.; Deng, L.; Fang, C. Satellite Remote Sensing and Dynamic Variation of Urban Land Use Changes—Taking Chengdu City as an Example. *J. Geo-Inf. Sci.* **2007**, *9*, 118–123. [CrossRef]
66. Luo, J.; Zhou, C.; Yang, Y. Land-cover and land-use classification based on remote sensing intelligent Geo-interpreting model. *J. Nat. Resour.* **2001**, *16*, 179–183. [CrossRef]
67. Kuang, W.; Zhang, S.; Liu, J.; Shao, Q. Methodology for classifying and detecting intra-urban land use change: A case study of Changchun city during the last 100 years. *J. Remote. Sens.* **2010**, *14*, 345–355. [CrossRef]
68. Luo, S.; Liu, Y.; Gao, S.; Wang, P. Quantitative identification of urban functional areas based on spatial grid. *Bull. Surv. Mapp.* **2020**, *S1*, 214–217. [CrossRef]
69. Ding, Y.; Xu, H.; Wang, C. Research on urban functional area recognition integrating OSM road network and POI data. *Geogr. Geo-Inf. Sci.* **2020**, *36*, 57–63. [CrossRef]
70. Yu, W.; Ai, T.; Shao, S. The analysis and delimitation of Central Business District using network kernel density estimation. *J. Transp. Geogr.* **2015**, *45*, 32–47. [CrossRef]
71. Gu, Y.; Jiao, L.; Dong, T.; Wang, Y.; Xu, G. Spatial Distribution and Interaction Analysis of Urban Functional Areas Based on Multi-source Data. *Geomat. Inf. Sci. Wuhan Univ.* **2018**, *43*, 1113–1121. [CrossRef]
72. Huang, Y.; Shao, S.; Lei, Y.; Tian, J. Identification of urban functional zones using network kernel density estimation and kriging interpolation. *J. Geomat.* **2019**, *44*, 14–18. [CrossRef]
73. Wang, Q.; Dai, Z.Y. The analysis of urban spatial structure based on POI data and principal component analysis. *Territ. Nat. Resour. Study* **2018**, *6*, 12–16. [CrossRef]
74. Zhao, J.; Li, H.; Deng, S.; Jiang, J. Identifying urban functional regions based on POI data and spatial analysis of main transit hubs. *Geomat. Spat. Inf. Technol.* **2019**, *42*, 38–42.
75. Cao, Y.; Liu, J.; Wang, Y.; Wang, L.; Wu, W.; Su, F. A Study on the Method for Functional Classification of Urban Buildings by Using POI Data. *J. Geo-Inf. Sci.* **2020**, *22*, 1339–1348. [CrossRef]
76. Tang, C.; Liao, H.; Wu, N.; Dong, L.; Zhang, R.; Li, Y.; Gao, X. Mobile Phone Data Based Urban Functional Area Classification Algorithm. *Comput. Knowl. Technol.* **2018**, *14*, 285–289. [CrossRef]
77. Cai, L.; Hui, F.; Ye, M.; Kang, K.; Zhao, X. Semi-Supervised Urban Land Using Classification Method Based on Uncertainty Sampling. *J. Jilin Univ.* **2016**, *34*, 550–555. [CrossRef]

78. Wang, Y.; Wang, T.; Ming-Hsiang, T.; Li, H.; Jiang, W.; Guo, F. Mapping Dynamic Urban Land Use Patterns with Crowdsourced Geo-Tagged Social Media (Sina-Weibo) and Commercial Points of Interest Collections in Beijing, China. *Sustainability* **2016**, *8*, 1202. [CrossRef]
79. Zhang, H.; Wang, R.; Chen, B.; Hou, Y.; Qu, D. Dynamic Identification of Urban Functional Areas and Visual Analysis of Time-varying Patterns Based on Trajectory Data and POIs. *J. Comput.-Aided Des. Comput. Graph.* **2018**, *30*, 1728–1740. [CrossRef]
80. Chen, Y.; Liu, X.; Li, X.; Liu, X.; Yao, Y.; Hu, G.; Xu, X.; Pei, F. Delineating urban functional areas with building-level social media data: A dynamic time warping (DTW) distance based k-medoids method. *Landsc. Urban Plan.* **2017**, *160*, 48–60. [CrossRef]
81. Li, Y.; Tu, Z.; Liu, Y.; Tang, M.; Wang, N. Urban Functional Area Identification Based on Similarity of Time Series. *Geospat. Inf.* **2021**, *19*, 22–29, 47. [CrossRef]
82. Xiao, D.; Zhang, X.; Hu, Y. Urban Functional Area Identification Method Based on Mobile Big Data. *J. Syst. Simul.* **2019**, *31*, 2281–2288. [CrossRef]
83. Frias-Martinez, V.; Frias-Martinez, E. Spectral clustering for sensing urban land use using Twitter activity. *Eng. Appl. Artif. Intell.* **2014**, *35*, 237–245. [CrossRef]
84. Song, X.; Pu, Y.; Liu, D.; Feng, Y. Mining urban functional areas using pedestrians' movement trajectories. *Acta Geod. Et Cartogr. Sin.* **2015**, *44*, 82–88.
85. Zhong, S.; Yue, W.; Zhang, Y. Analysis of function identification of urban blocks base on SCD and POI date—A case study of chaoyang district. *Urban Environ. Stud.* **2016**, *3*, 67–85.
86. Jin, P.; Chen, M.; Sun, Z. Research on Recognition Method of Urban Land Function Area Based on Mobile Phone Signaling Data. *Inf. Commun.* **2018**, *1*, 268–270.
87. Feng, R.; Dong, X.; Liang, T.; Wang, L. Identification of urban functional areas based on logistic regression model. *Geomat. Spat. Inf. Technol.* **2018**, *41*, 109–112. [CrossRef]
88. Liu, X.; Long, Y. Automated identification and characterization of parcels with OpenStreetMap and points of interest. *Environ. Plan. B Plan. Des.* **2016**, *43*, 341–360. [CrossRef]
89. Xu, J.; Yang, F. A study of urban functional area identification methods based on big data of social sensing. *Urban. Archit.* **2017**, *27*, 30–34. [CrossRef]
90. Chen, Z.; Qiao, B.; Zhang, J. Identification and Spatial Interaction of Urban Functional Regions in Beijing Based on the Characteristics of Residents' Traveling. *J. Geo-Inf. Sci.* **2018**, *20*, 291–301. [CrossRef]
91. Long, Y.; Zhang, Y.; Cui, C. Identifying Commuting Pattern of Beijing Using Bus Smart Card Data. *Acta Geogr. Sin.* **2012**, *67*, 1339–1352. [CrossRef]
92. Wang, W. A Review of Large-scale Machine Learning Tools for Big Data Environments. *Softw. Guide* **2021**, *20*, 238–241.
93. Chen, S.; Tao, H.; Li, X.; Zhuo, L. Discovering urban functional regions using latent semantic information: Spatiotemporal data mining of floating cars GPS data of Guangzhou. *Acta Geogr. Sin.* **2016**, *71*, 471–483. [CrossRef]
94. Blei, D.M.; Ng, A.; Jordan, M.I. Latent dirichlet allocation. *J. Mach. Learn. Res.* **2003**, *3*, 993–1022.
95. Li, L.-J.; Su, H.; Lim, Y.; Fei-Fei, L. Object Bank: An Object-Level Image Representation for High-Level Visual Recognition. *Int. J. Comput. Vis.* **2014**, *107*, 20–39. [CrossRef]
96. Zhang, X.; Du, S.; Wang, Q. Hierarchical semantic cognition for urban functional zones with VHR satellite images and POI data. *Isprs J. Photogramm. Remote Sens.* **2017**, *132*, 170–184. [CrossRef]
97. Zhang, X.; Du, S.; Wang, Q. Integrating bottom-up classification and top-down feedback for improving urban land-cover and functional-zone mapping. *Remote Sens. Environ.* **2018**, *212*, 231–248. [CrossRef]
98. Yan, B.; Janowicz, K.; Mai, G.; Song, G. From ITDL to Place2Vec—Reasoning About Place Type Similarity and Relatedness by Learning Embeddings From Augmented Spatial Contexts. In Proceedings of the ACM SIGSPATIAL, Redondo Beach, CA, USA, 7–10 November 2017; pp. 1–10. [CrossRef]
99. Zhai, W.; Bai, X.; Shi, Y.; Han, Y.; Peng, Z.R.; Gu, C. Beyond Word2vec: An approach for urban functional region extraction and identification by combining Place2vec and POIs. *Comput. Environ. Urban Syst.* **2019**, *74*, 1–12. [CrossRef]
100. Zheng, Z.; Zheng, R.; Xu, J.; Wang, J. Identification of urban functional regions based on POI data and Place2vec model. *Geogr. Geo-Inf. Sci.* **2020**, *36*, 48–56. [CrossRef]
101. Chen, Z.; Zhou, L.; Yu, W.; Wu, L.; Xie, Z. Identification of the urban functional regions considering the potential context of interest points. *Acta Geod. Et Cartogr. Sin.* **2020**, *49*, 907–920. [CrossRef]
102. Xu, N.; Luo, J.; Wu, T.; Dong, W.; Zhou, N. Identification and Portrait of Urban Functional Zones Based on Multisource Heterogeneous Data and Ensemble Learning. *Remote Sens.* **2021**, *13*, 373. [CrossRef]
103. Zhong, Y.; Fei, F.; Zhang, L. Large patch convolutional neural networks for the scene classification of high spatial resolution imagery. *J. Appl. Remote Sens.* **2016**, *10*, 025006. [CrossRef]
104. Castelluccio, M.; Poggi, G.; Sansone, C.; Verdoliva, L. Land Use Classification in Remote Sensing Images by Convolutional Neural Networks. *Acta Ecol. Sin.* **2015**, *28*, 627–635. [CrossRef]
105. Ma, J.; Sun, Y.; Deng, G.; Huang, S.; Meng, X. Evaluation of Different Approaches of Convolutional Neural Networks for Land Use and Land Cover Classification Based on High Resolution Remote Sensing Images. In Proceedings of the 2019 IEEE International Conference on Signal, Information and Data Processing (ICSIDP), Chongqing, China, 11–13 December 2019; pp. 1–4. [CrossRef]
106. Li, G.; Fang, C.; Pang, B. Quantitative measuring and influencing mechanism of urban and rural land intensive use in China. *J. Geogr. Sci.* **2014**, *24*, 858–874. [CrossRef]

107. Xu, Y.; Zhao, S.; Fan, J. Urban planning construction land standard and its revision based on climate and topography in China. *J. Geogr. Sci.* **2021**, *31*, 603–620. [CrossRef]
108. Wang, Y.; Ni, S.; Zhang, C.; Wei, L. A Risk Assessment Method for Geological Environment of Functional Region of City. *Acta Geol. Sichuan* **2010**, *30*, 326–329. [CrossRef]
109. Su, Q. Formation Mechanism and Planning Characteristics of Urban Functional Areas. *Urban Rural Dev.* **2012**, 24–25. [CrossRef]
110. Han, Q.; Gu, Z.; Yuan, X. Spatial coupling of the urban master planning and main functional area planning. *City Plan. Rev.* **2011**, *35*, 44–50.
111. Liu, X.; Peng, W. District the City according to Function and Manage the City according to District. *Urban Manag. Sci. Technol.* **2010**, *12*, 20–22. [CrossRef]
112. Zhang, Z. Interpretation of Beijing Municipal Major Function Zone Planning. *Invest. Beijing* **2012**, *10*, 30–32.