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**Abstract:** Scientific functional zone planning is the key to achieving long-term development goals for cities. The rapid development of remote sensing technology allows for the identification of urban functional zones, which is important since they serve as basic spatial units for urban planning and functioning. The accuracy of three methods—kernel density estimation, term frequency-inverse document frequency, and deep learning—for detecting urban functional zones was investigated using the Gaode points of interest, high-resolution satellite images, and OpenStreetMap. Kuancheng District was divided into twenty-one functional types (five single functional types and twenty mixed ones). The results showed that an approach using deep learning had a higher accuracy than the other two methods for delineating four out of five functions (excluding the commercial function) when compared with a field survey. The field survey showed that Kuancheng District was progressing towards completing the goals of the Land-Use Plan of the Central City of Changchun (2011–2020). Based on these findings, we illustrate the feasibility of identifying urban functional areas and lay out a framework for transforming them. Our results can guide the adjustment of the urban spatial structure and provide a reference basis for the scientific and reasonable development of urban land-use planning.

Keywords: urban functional zone; U-Net; spatial distribution; Kuancheng District

## 1. Introduction

Urban spaces are places where urban residents live, work, and relax. According to the place-based theory [1], an urban space comprises multiple functional zones that serve different purposes. Urban functional zones were first proposed in the Athens Charter [2] and are important space carriers for realizing urban socioeconomic functions. They provide precise boundaries for urban planning and management that can support infrastructure construction, coordinated regional development [3], and the environmental governance of projects (e.g., highway construction and other essential public services) [3,4]. In addition to influencing the urban process [5], urban functional zones can also be considered a suitable monitoring unit of urban sustainability [6]. The scientific delimitation of urban functional zones is conducive to the rational control of urban sprawl and the formulation of urban planning—which can provide ideas, strategies, frameworks, and guidelines to the government for urban development—as well as being important for supporting sustainable urban development, efficient planning, and accurate industrial distribution.

Research related to the urban functional zone focused on identifying said zones and their related applications. Urban functional zones are widely used in urban studies, such as heavy metal pollution [7], population density [8], urban heat island [9], air pollution [10], and traffic congestion [11].

Rapid urbanization has made the identification of urban functional zones a popular research topic. Traditional methods have relied on field surveys and remote-sensing



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images [12,13]. However, crowdsourced geographic information (e.g., point-of-interest, mobile, and traffic-flow data) provides a new channel for describing and understanding urban spatial structures [4,14–21]. Combining these two types of methods can make the identification of urban functional areas more accurate [22-25]. Identification methods include probability estimation approaches (e.g., kernel density estimation), as well as machine learning methods, such as Latent Dirichlet allocation (LDA) [18,20], support vector machines (SVM) [26], clustering algorithms [20,27], and neural networks [28]. An AI-based approach in the field of machine learning [29], deep learning uses a deep neural network (DNN) to learn object features from massive datasets, enabling it to recognize objects [30]. Deep learning has advanced research in many fields, including object classification [31], target detection [32,33], and semantic segmentation [34,35]. A major advantage of deep learning is that it automatically learns feature information from a large amount of image data [23], which can provide new avenues for research on the semantic segmentation of remote-sensing images. Among these, the most widely used models are convolutional neural networks [23,28,31,36]. Despite this, only a few studies have used deep learning to recognize urban-function areas. This is because it is time-consuming to manually select segmentation parameters and extract object features; moreover, the formation of urban functional areas is influenced by many factors, such as nature, the economy, history, and society.

Related studies have typically focused on economically developed cities, such as Beijing [19,26,27,37], Shenzhen [25,36,38], Guangzhou [14,39], Wuxi [40], and New York [41]. While Klapka and Halás [17,42] studied urban functional zones in the Czech Republic, few studies have focused on old industrial cities (except for Wuhan [20]) and Rust Belt cities. In particular, Changchun, the central city of the Northeast Asia economic circle, is a leading area for industrial transformation in Northeast China and strategic cooperation with Northeast Asia; there, rapid urban expansion has led to the disordered distribution of urban functional areas [43]. As such, there is an urgent need to improve the functional zoning of Changchun.

This study adopted a U-Net model and used high-resolution remote-sensing images to identify specific urban functional zones, including residential zones (RN), commercial and commercial services facilities zones (CN), public administration and public service zones (PN), industrial and mining storage zones (IN), and ecological zones (EN). Using kernel density estimation based on point-of-interest data, we aimed to discover the overlay of urban functional zones. Finally, a confusion matrix was used to verify accuracy. This study introduced the U-Net model of deep learning to investigate urban functional zones, which can effectively identify them and avoid the problem of reduced accuracy caused by the absence of POI in old industrial cities, especially suburbs. The results can guide the adjustment of the urban spatial structure from the macro and are beneficial to the layout, coordination, and matching of the city's overall function, which can provide an effective reference for sustainable urban planning and development. Further, the method appears to be practical for mapping urban functional zones for application in other cities with similar socioeconomic attributes. It could even be used to map urban functional zones for earlier years if early remote-sensing images are available.

# 2. Materials and Methods

# 2.1. Study Area

This study used the Kuancheng District of Changchun, China, which spreads from rural–urban fringe areas to urban areas (Figure 1). Kuancheng District is located in the north of Changchun, with an urban area of 245 km<sup>2</sup>. It is in the transition zone between the eastern mountainous humid region and the western-plain semiarid region, belonging to the temperate continental subhumid monsoon climate type. The terrain in the area is relatively flat, with a large distribution of typical black soil resources. As one of the main districts of Changchun, Kuancheng is one of the city's earliest urban districts. It



is recognized by China's Ministry of Civil Affairs as an experimental zone for national community governance and service innovation.

Figure 1. Location of Kuancheng District.

# 2.2. Data Processing

Data for administrative divisions were obtained from the National Bureau of Statistics of China. We employed a GaoFen-2 (GF-2) image covering the study area that was acquired in September 2019. Using ENVI 5.3, images with a resolution of 3.24 m in the multispectral GF-2 image were merged with images with a panchromatic resolution of 0.8 m to produce a pan-sharpened image of 1 m resolution with four bands. Field survey data were obtained from the GF-2 image by visual interpretation manually and field investigation.

Road-network data for Kuancheng District were collected from OpenStreetMap (OSM), a popular volunteer geographic information (VGI) source that provides free, open geographical data. The data are in vector format and contain different classes of streets, consisting of the following: motorway, motorway\_link, primary, primary\_link, tertiary, tertiary\_link, secondary, pedestrian, residential, footway, track, trunk, and service, which form the boundary of functional zones.

In addition, point-of-interest (POI) data can record the geospatial and attribute information of a single point [21] (e.g., a house, store, or bus stop). After removing duplicate samples, we obtained a dataset of 17,665 POI data points indicating the functional and locational properties of sites as of 30 September 2020. These were generated from Gaode Map Services (https://ditu.amap.com/ (accessed on 30 September 2020)), a well-known map service provider in China. In the POI dataset, there were 23 labels in the top-level category, 264 in the second-level category, and 869 in the third-level category. Based on the Code for Classification of Urban Land Use and Planning Standards of Development Land (GB 50137-2011), the POI dataset was divided into five labels at the first level (i.e., RN, CN, PN, IN, and EN) and twenty-two at the second level (see Appendix A), where roads and traffic facilities were abandoned since the elementary unit was divided by roads.

## 2.3. Method

Figure 2 shows the study framework. A traffic network is the skeleton of the urban functional area; thus, the OSM road network was first used to segment the study area. Next, hotspot analysis was conducted based on POI data, and we then compared the results derived from the U-Net deep learning (UDL), kernel density estimation (KDE), and term frequency-inverse document frequency (TF-IDF) methods.



Figure 2. Flowchart of the study.

## 2.3.1. Unit Division of Urban Functional Zones

An urban functional zone is a fundamental unit carrying socioeconomic functions in urban planning and management. The parcel formed by a road network is the basic unit of urban planning and management, and it serves the socioeconomic functions of a city [44]. In this study, road vectors obtained from OSM were used to delineate functional zones, and each zone was spatially represented by a block. First, motorway, motorway\_link, primary, primary\_link, tertiary, tertiary\_link, cycleway, residential, track, and trunk roads

were selected and topology-processed; this involved extending roads by 100 m to process unconnected road networks and trimming road networks in suspension roads and separate roads. Then, the road space was created by establishing 20 m buffer zones for the roads. The space was used to generate a binary road grid image, and then the centerline extraction function under the ArcScan module in ArcGIS 10.4 was used to extract the centerline of the road. After manual correction, urban functional zone units were generated and, after deleting smaller land units, 707 zones were finally generated.

#### 2.3.2. Classification System

A city-function zoning system is a division of zones in a city based on dominant functions. It forms a coherent functional aggregation, establishes relatively independent and interconnected functional zones, and forms an organic whole through rational planning. As the base map for territorial spatial planning, the main functional zones provide a common basis for all manner of spatial governance policies, planning, and evaluation [45]. Thus, functional zones, based on the agglomeration of urban elements, are important for the urban functional layout, facilitating the macroscopic specification, coordination, and matching of urban functions.

Researchers have offered various classifications (Table 1) for the urban functional zone, including residential, commercial, ecological, industrial, public, and transport classifications. According to the Code for Classification of Urban Land Use and Planning Standards of Development Land (GB 50137-2011), urban development land includes the following types: residential, administration and public services, commercial and business facilities, industrial, manufacturing, logistics and warehouse, road, street and transportation, municipal utilities, and green space and square. Thus, this study used the following functional classifications, as mentioned previously: RN, CN, PN, IN, and EN. There is no transport zone since zones were divided based on the central line of the roads.

Order	Functional Classifications	Authors
1	Diplomatic and political zone, science and education zone, mature residential zone, new residential zone, commercial and entertainment zone, tourist attraction zone, area to be developed, unclassified area	Miao et al. [19]
2	Commercial zone, campuses, parks and greenbelts, industrial zone, residential districts, shantytowns	Zhang et al. [26]
3	Corporate business area or factory, shopping mall, tourism attraction place, public facility, transportation facility, science and education place, medical service place, food and beverage place and daily life service place, governmental and public organizations	Hu et al. [20]
4	Residential, education and training, recreation and entertainment, medical and public health, commercial and finance, incorporated and business, party and government organization, scenic areas	Luo et al. [46]
5	Office building/space, financial services, medical/education, entertainment, life services, residence communities, government	Hong and Yao [21]
6	Ecological area, transit region, urban buffer, suburbs, subcenter, urban center	Tu et al. [25]
7	Urban green, industrial districts, public services, residential districts, commercial districts, hospitals, schools, shantytowns	Bao et al. [36]
8	Developed working and industrial regions, developed public service region, emerging working and industrial regions, emerging residential region, developed residential region, nature park, developing rural region, undefined region	Zhai et al. [40]
9	Mixed use, residential, industry, business, conservation	Malik and Dewancker [47]

**Table 1.** Functional zoning classifications by different researchers.

### 2.3.3. U-Net Deep Learning

U-Net was first proposed for biomedical image segmentation [48]. Given the advantages of its simple, effective symmetrical encoder–decoder structure, U-Net has been widely used for various remote-sensing tasks, such as semantic segmentation. Most researchers use the U-Net framework or an improved version of it. ResUNet-a is a U-Net-based deep learning architecture that can improve the semantic segmentation of high-resolution remote-sensing images [35]. Peng et al. [49] proposed UNet++ for semantic segmentation based on the encoder-decoder architecture. He et al. [50] proposed HFSA-Unet to explore the correlations among the immediate layers for automatic building segmentation in remote-sensing images.

Therefore, we chose U-Net to classify urban functional zones. The architecture of U-Net can be thought of as an encoder network followed by a decoder network. Unlike a classification, where the end result of the deep network is the only important thing, semantic segmentation requires not only pixel-level discrimination but also a mechanism to project the discriminative features learned at different stages of the encoder onto the pixel space.

The encoder is the first half of the architecture diagram (Figure 3). It is usually a pre-trained classification network, such as VGG/ResNet, where convolution blocks are applied, followed by max pool downsampling to encode the input image into feature representations at multiple levels. The decoder is the second half of the architecture. The goal is to semantically project the discriminative features (lower resolution) learned by the encoder onto the pixel space (higher resolution) to get a dense classification. The decoder consists of upsampling and concatenation, followed by regular convolution operations.



Figure 3. U-Net architecture.

U-Net is a classification method with supervised learning; thus, the samples, which are fundamental for recognizing zone functions, should be selected first. We used fieldwork information for 25 km<sup>2</sup> of urban area in the Kuancheng District for sampling. This area stretches from rural-urban fringe areas to urban areas and includes all urban functional types. The function "Label Objects for Deep Learning" under "Classification Tools" in ArcGIS Pro 2.7 was used to export the training data. Metadata were formatted as "Classified Tiles" so we could train the U-Net model.

The training model was implemented in the PyCharm development environment using Python so that more details could be identified, and some parameters could be adjusted and optimized. Finally, the function "Classify Pixels Using Deep Learning" under "Image Analyst" in ArcGIS Pro 2.7 was used to identify the urban functional zones.

The function of each zone was determined by the area proportions of different functional areas in the zones. A type ratio of 50% was selected as the functional zone standard. When a type of area proportion reached 50% or more in the unit, it was considered a single functional zone. When all area proportions were less than 50%, it was considered a mixed functional zone, which was determined by the two main types in the unit, whose area proportions were between 30% and 50%. When all area proportions were greater than 0% but less than 30%, it was considered a mixed uniform functional zone. When all area proportions were 0, it was considered a no data zone.

# 2.3.4. Verification

The accuracy of KDE, UDL, and TF-IDF was assessed against the field survey data using confusion matrices, which was summarized to provide further accurate information by computing quantity disagreement, shift disagreement, and exchange disagreement [51]. Quantity disagreement is the difference between the prediction and field survey categories due to an imperfect match in the overall proportions of all mapped categories. Shift and exchange are allocation disagreements which are the difference between the field survey and the prediction due to an imperfect match in the spatial allocations of the mapped categories, given the categorical proportions in the field survey and prediction [52]. Exchange is the disagreement of allocation disagreement that pairwise confusions cause, and shift is the disagreement that non-pairwise confusions cause [52].

## 3. Results

## 3.1. Identification of Functional Zones

# 3.1.1. Single Functional Zone

Kuancheng District can be divided into five single functional zones. Figure 4 shows the distribution of single functional zones in the study area based on the methods of KDE (Figure 4a), UDL (Figure 4b), and TF-IDF (Figure 4c).

KDE, TF-IDF, and UDL identified, respectively, 359, 640, and 635 single functional zones. In the KDE results, IN accounted for the largest number (190 zones). The number of single functional zones gradually increased in the following order: CN, EN, NN, and RN. Except for the southern part of the Kuancheng District, which is close to the city center, most single functional zones were spread out across the region.

In the TF-IDF results, CN accounted for the largest number (295 zones). The number of single functional zones gradually increased in the following order: RN, EN, PN, IN, and NN. Single functional zones were evenly distributed in Kuancheng District.

In the UDL results, RN accounted for the largest number (300 zones). The number of single functional zones gradually increased in the following order: PN, NN, IN, and EN. The single functional zone for CN was zero. This indicates that either CN and others became mixed functional areas or CN was not identified by the UDL method. Single functional zones were evenly distributed in the study area.

## 3.1.2. Mixed Functional Zones

Figure 5 shows the spatial distribution of mixed functional zones in the Kuancheng District; the colors indicate different mixed functional zones. Table 2 shows the results. The horizontal axis is the largest of the functional areas in the zone, and the vertical axis is the second-largest, which determines what kind of mixed functional zones the mixed zone contains.

The KDE results included 16 types of mixed functional zones, among which the number of PN-CN zones (54 zones) was the largest, followed by IN-CN (43 zones), CN-IN (41 zones), and PN-IN (32 zones). The TF-IDF results contained ten types of mixed functional zones, among which the number of CN-PN zones (22 zones) was the largest, followed by PN-CN (16 zones). The UDL results had the fewest types (eight types) of mixed functional zones, among which the largest were EN-IN (16 zones) and IN-EN (15 zones), followed by RN-EN (11 zones) and RN-IN (10 zones).



**Figure 4.** Spatial distribution of single functional zones in Kuancheng District predicted by (**a**) Size KDE, (**b**) UDL, and (**c**) TF-IDF (RN, residential zone; CN, commercial and commercial services facilities zone; PN, public government and public service zone; IN, industrial and mining storage zone; EN, ecological zone; NN, no data zone).

# 3.2. Verification

We evaluated the KDE, TF-IDF, and UDL results as described below. Table 3 shows the results; the horizontal axis is the field survey results, and the vertical axis is the predicted results of three methods.

The overall error for KDE of urban functional zones was 83%, divided between quantity disagreement (66%), exchange (9%), and shift (9%) (Figure 6). MN had the highest overall error, followed by RN. RN, IN, EN, and MN extended beyond the Quantity Overall line (Figure 7), which indicated that these types had more intensive quantity disagreements relative to the quantity disagreement overall. The intensity of exchange overall is the difference between the Quantity Overall line and the Quantity + Exchange Overall line. PN and IN had more intensive exchange relative to exchange overall, while EN had exchange equal in intensity to exchange overall. The Quantity + Exchange Overall of 89% implied that the intensity of Shift Overall was 11%, meaning 100% minus 89% (Figure 7). The shift intensity for CN, PN, and NN is entirely to the left of the Quantity + Exchange Overall line;



therefore, CN, PN, and NN had a more intensive shift relative to shift overall. NN had a shift equal in intensity to shift overall.

**Figure 5.** Spatial distribution of mixed functional zones in Kuancheng District predicted by (**a**) Size KDE, (**b**) UDL, and (**c**) TF-IDF.

The overall error for TF-IDF of urban functional zones was 71%, divided between quantity disagreement (57%), exchange (6%), and shift (8%) (Figure 6). EN and NN had the highest overall error, and RN, CN, EN, and MN had more intensive quantity disagreements relative to the quantity disagreement overall. Only MN had a quantity component less intensive than the intensity of the overall quantity component. PN, IN, and MN had more intensive exchange relative to exchange overall, and PN, IN, and MN had a more intensive shift relative to shift overall.

The overall error for UDL of urban functional zones was 43%, divided between quantity disagreement (21%), exchange (11%), and shift (10%) (Figure 6). EN had the highest overall error, followed by RN and MN. CN, PN, EN, and NN had more intensive quantity disagreements relative to quantity disagreement overall. RN and MN had more intensive exchange relative to exchange overall, while IN had exchange equal in intensity

to exchange overall. RN, IN, and MN had a more intensive shift relative to shift overall. Besides, CN and NN had no exchange and shift disagreements.

The Largest Functional Area											
		RN	CN	PN	IN	EN	MUN	NN	Total		
					a. KDE						
	RN	30	19	10	10	1			70		
	CN	12	16	54	43				125		
	PN	12	72	28	24				136		
	IN	9	41	32	190	3			275		
	EN		1	3	2	26			32		
	MUN						40		40		
ä	NN							29	29		
are	Total	63	149	127	269	30	40	29	707		
nal		b. TF-IDF									
l functio	RN	11	5	3					19		
	CN		295	16	4				315		
	PN	1	22	77	2				102		
JUC	IN		8	4	83				95		
ecc	EN		2			16			18		
es	MUN										
Ϋ́L	NN							158	158		
	Total	12	332	100	89	16		158	707		
		c. UDL									
	RN	300			7	9			316		
	CN										
	PN			2	1	3			6		
	IN	10			67	16			93		
	EN	11			15	264			290		
	MUN										
	NN							2	2		
	Total	321		2	90	292		2	707		

**Table 2.** Confusion matrix of functional zones where diagonal number is the number of single functional zones, and the other number is the mixed functional zones.

Note: RN, residential zone; CN, commercial and commercial services facilities zone; PN, public government and public service zone; IN, industrial and mining storage zone; EN, ecological zone; MUN, mixed uniform functional zone; NN, no data zone; KDE, kernel density estimation; TF-IDF, term frequency-inverse document frequency; UDL, U-Net deep learning.



Figure 6. Overall errors of three methods.

Field Survey Data											
		RN	CN	PN	IN	EN	MN	NN	ON	Total	
					a. k	KDE					
	RN	17			3	9	1			30	
	CN	7		2		5	1	1		16	
	PN	3	2	1	1	15	3	3		28	
	IN	22	21	6	39	68	24	10		190	
	EN	1	2	2	1	19			1	26	
	MN	236	43	34	9	31	29	6		388	
	NN				1	10		18		29	
	Total	286	68	45	54	157	58	38	1	707	
_		b. TF-IDF									
ata		9				2				11	
Prediction d	CN	199	35	11	8	16	25		1	295	
	PN	26	8	17	3	15	8			77	
	IN	3	13	3	31	25	8			83	
	EN		2	2		12				16	
	MN	33	3	5	3	12	11			67	
	NN	16	7	7	9	75	6	38		158	
	Total	286	68	45	54	157	58	38	1	707	
		c. UDL									
	RN	233	27	14	4	8	13	1		300	
	PN			1	1					2	
	IN	13	19	13	12	2	8			67	
	EN	27	12	11	12	143	23	35	1	264	
	MN	13	10	6	25	4	14			72	
	NN							2		2	
	Total	286	68	45	54	157	58	38	1	707	

Table 3. Verification confusion matrix of functional zones.



- - Quantity Overall ...... Quantity + Exchange Overall







Figure 7. Cont.



**Figure 7.** (**left**) Size and (**right**) intensity of differences for Table 3. A positive sign in the quantity disagreement denotes the number of the functional zones in a prediction is greater than in the field survey; a negative sign denotes the number of the functional zones in a prediction is less than in the field survey.

Figure 8 shows the spatial distribution of the prediction results of KDE, TF-IDF, and UDL with field surveys. The KDE results had more IN zones, especially in Lanjia Town, Beihu Street, and Xingye Street. The reason could be that there are many industrial or storage POIs but few other POI types. Therefore, the distribution of POIs in suburban and rural areas may have reduced the accuracy of identification.

The TF-IDF results identified more CNs than in the field survey, and the distribution of different functions was not very accurate. This is because in TF-IDF, the smaller the text frequency (i.e., the number of texts containing a certain word) of a word, the greater its ability to distinguish between different categories of text. If one functional type is in every zone, its IDF is zero; so, TF-IDF thinks it is a noise word, leading to an incorrect result. Thus, TF-IDF is minimally effective for special functional zones.

The UDL results were the most accurate, showing almost the same distribution as the field survey, except for CN. There were no CNs in the UDL results, although commercial and financial land existed in the field survey. This is because there were few CNs in the sampling area, which could be used as samples, making it difficult to identify them through remote sensing.



Figure 8. Cont.

0

2.5

5 km



Figure 8. Spatial distribution of the prediction results of (a) KDE, (b) TF-IDF, and (c) UDL, with (d) field surveys.

Figure 9 shows the comparison of the UDL and the field survey results. The different functional zone (237) results of UDL and the field survey are mainly distributed in Zhanqian Street, Xinfa Street, and Dongguang Street, which are urban central areas. There are also some in Beihu Street, which is part of Changchun's new district. The functional zones, where there are overlaps of functional types (74), are distributed in all the streets within Kuancheng Street, except Balibao Street, Nanguang Street, and Xingye Street. Identical functional types (396) are mainly distributed in Lanjia Town, Fenjin Town, Xinghongshan Town, Xingye Street, north of Tuanshan Street, and west of Beihu Street, which are urban and rural zones.

5 km

25

0



Figure 9. Comparison of (a) UDL and (b) field survey results.

## 3.3. Spatial Pattern of Urban Functional Zones

Kuancheng District is north of Changchun (Figure 10). EN is the largest functional classification area; it is found mostly in peri-urban regions, with many forests and cultivated lands. RN is concentrated in the southern part of Kuancheng, close to Changchun's city center. There are also a few RNs in the northern region since there is some rural residential land there. RNs are mainly distributed in Lanjia Town and Beihu Street, with a small amount distributed on Zhanqian Street and the intersection of Liuying Street, Kaixuan Street, and Qingnian. Most PNs and CNs are located in the southern region, especially in the city center, while RNs are scattered throughout the study area.



Figure 10. Spatial distribution of the urban functional classifications of Kuancheng District.

In general, Kuancheng District forms three development zones. The southern development area is a comprehensive area of the district's main functions. The eastern development area, composed of urban industrial areas and ecological wetland, is the main expansion area for future land development. The western development area is a compound area of industrial and agricultural township development, where the function of Lanjia Town is mainly industrial, supplemented by residential functions.

# 4. Discussion

#### 4.1. Development Current Situation

Kuancheng District, Fenjin Town, and Beihu Street, which belong to the Northeast China Development Open Pilot Area of Changchun, are rapidly expanding urban–rural transition zones. A reasonable layout of functional zones is conducive to the coordinated development of urban and rural areas. This region will be a major expansion space for the future development of the Kuancheng District. It is therefore of great significance for Changchun's sustainable development and will provide an effective reference for establishing land-use planning to scientifically design urban functional layouts. Overall, Kuancheng District is progressing toward achieving the goals of the Land-Use Plan of the Central City of Changchun (2011–2020) (Figure 11), indicating that the plan has had practical instructive significance.



Figure 11. Comparison of (a) field survey and (b) land-use plan.

## 4.2. Comparison with Exiting Studies

Many studies have attempted to produce urban functional zone maps using remotesensing images and POI data. Here, we compare our study with several previous studies in terms of data sources, study area, and methods (Table 4). First, regarding data sources, the distribution and number of points of interest have some effects. POI data are points of different activities, such as shopping, working, studying, and dining, which reflect people's preferences and social functions [53]. Although POI data provides good semantic information, there is a greater concentration of POIs near areas that have a high population density [26] because POIs are associated with people's activities. There are fewer POIs in suburban or rural areas, which may lead to a lower level of accuracy for identifying urban functional zones. In addition, there may be many small shops, restaurants, barbershops, public baths, and other service functions scattered around residential areas, whose distributions are more intensive than residential distributions. This could have an adverse effect on the identification results for functional zones. Apart from POI data, vector data from OSM also contains geospatial semantics for its geo-objects [54] and can also provide semantics for urban functional zones.

As for remote sensing, in submeter-level high-resolution images, ground object types are more diverse, texture types and regions are significantly increased, and texture features are more variable. They are, however, more expensive. Although medium-resolution images are easy to acquire and can cover large spatial areas, it is difficult to produce fine-grained urban functional zones based on them because of their lower spatial resolution [55]. The cost and spatial resolution of meter-level high-resolution images range between the two. Therefore, many aspects should be considered in remote-sensing image selection. Compared with only using remote-sensing images, adding semantic information to remote-sensing images has higher classification accuracy. Urban functional zones composed of various geographic objects (such as buildings, roads, and vegetation) [55] are regions with unified functions, relatively independent and connected with each other, and constituting an organic whole with a reasonable layout. As buildings in the city are divided by roads, urban functional zones have a close relation to the regions formed by the city road network [21]. Moreover, the fixed-size grid division method destroys the integrity of the land use pattern [55], so the division of units by road network is more consistent with the definition and scope of the urban functional area than the grid. However, if the study area is large (such as a country), the larger size of the grid partition performs better macroscopically [56].

Authors	Data Source	Study Area	Mapping Unit	Methods
Xin et al. [6]	MHRI SHRI	Beijing and Wuhan	Roads	BOVW (bag of visual word) model and SDA (semi-supervised discriminant analysis) dimensionality reduction approach
Du et al. [55]	MHRI	Beijing and Shanghai	Objects	Multi-scale semantic segmentation network
Heiden et al. [12]	MHRI	Munich	Pixels	Automated multi-stage processing system
Myint et al. [13]	SHRI	Phoenix, Arizona	Objects	Object-based classifier
Chen et al. [14]	MPPD	Yuexiu District, Guangzhou	Buildings	Improved k-medoids method
Du et al. [22]	MHRI POI	Three districts in Beijing	Roads	LDA, SVM
Hong and Yao [21]	POI	Guangzhou	Roads	Infomap community detection algorithm
This study	SHRI POI	Kuancheng District, Changchun	Roads	UDL, KDE, TF-IDF

Table 4. Comparison with existing studies.

Note: SHRI: submeter-level high-resolution images; MHRI: meter-level high-resolution images; MPPD: mobile phone positioning data; POI: point of interest.

This study identified urban functional zones with POIs and GF-2 images using three methods: KDE, TF-IDF, and UDL. We first consider the limitations of KDE. Different bandwidths affect the results [18,57,58]. When the bandwidth is small, details can be detected, and a finer mesh density estimate can be obtained, while a larger bandwidth produces a smoother distribution and is suitable for the overall analysis [58]. In this study, 500 was chosen as the bandwidth for KDE, which was determined by the functional areas. It will be necessary to conduct further research to compare the effects of different bandwidths. TF-IDF is a natural language processing method that cannot explain how one spatial point is determined by its surroundings [40]. In this study, TF-IDF performed poorly in identifying urban functional zones because it only considered distribution frequency and ignored potential semantic information behind the POIs. Researchers use this method to mine static functions from POIs [59] or measure the importance of different POI categories [41]. For deep learning in supervised learning, deep neural networks [60], deeper-feature convolutional neural networks [36], KDE [46], and hierarchical semantic cognition [26] have been used to identify urban functional zones. Their accuracy is a little bit higher than that of unsupervised learning, such as the clustering algorithm.

#### 4.3. Limitations and Future Work

This study's results indicate that we can effectively identify urban functional zones, especially mixed functional zones, which is of great practical significance to the optimization and coordination of urban space. Nevertheless, this research has certain limitations. First, the deep learning method had little accuracy when identifying CNs. One reason is that there are few commercial lands to use as samples; the other is that it is difficult to separate commercial land from residential land using remote sensing. Because of the mixed functional zones, the UDL results were not accurate. There are multiple functional types in one zone, especially in economically developed urban central areas. The area ratio of different functional areas results in a lower accuracy of UDL when identical functional types are compared.

Second, this study used single datasets to identify urban functional zones, only from the functional perspective of land-use types, without integrating remote-sensing images and POI data; thus, the social and economic functions were ignored. In addition, although the division of units by road networks is feasible in many studies [21,61,62], there may be mixed functions in these units. As buildings are more detailed than road networks when dividing urban units, they have more potential for researching urban functions and structures [14,38]. In future research, we plan to integrate different datasets to exhaustively analyze the various functions of urban functional areas and explore urban functional structures. As a basic unit for identifying urban functions, we plan to use buildings, if possible, to determine functional areas more accurately.

### 5. Conclusions

As the basic unit of urban development and planning, urban functional zones can help urban planners develop better strategies, while also helping researchers to better understand the urban structure and environment. With the development of remote-sensing images and crowdsourced geographic information data, it has become easier to identify urban functional areas. We used Kuancheng District, Changchun, China, as the study area. We obtained 17,665 Gaode POIs, acquired on 30 September 2020, and used GF-2 images and OpenStreetMap road data for this study, which were acquired in September 2019 and 30 September 2020, respectively. Then, we used OSM road data for map segmentation and KDE, TF-IDF, and UDL methods to identify urban functional zones. These zones included residential zones (RN), commercial and commercial services facilities zones (CN), public administration and public service zones (PN), industrial and mining storage zones (IN), and ecological zones (EN). Finally, we compared the results of the three methods with a field survey. The results suggested that deep learning had the lowest overall error (43%) compared with KDE (83%) and TF-IDF (71%).

This study confirmed the feasibility of using remote-sensing images and POI data to detect urban functional zones. This approach can provide a perspective on urban transformation processes and prove useful for city management and planning. Further, we identified the current distribution of urban functional zones in the Kuancheng District. This can help city managers make adjustments, especially with regard to the Territorial Spatial Planning of Changchun (2020–2035). In general, using remote-sensing images with UDL methods to explore urban functional zones can provide new ideas for investigating urban functional areas and the urban spatial structure. Such work can support the intensive and economic use of urban land and achieve the sustainable development of cities. In future work, open social data will be combined with remote-sensing images to better identify urban functions, such as POI, mobile phone positioning, and social software check-in data.

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#### Appendix A

The appendix is a table of types of original and aggregated POIs, which contains five labels at the first level, twenty-two labels at the second level, and the original labels at the third level.

Aggregated Type	Big Category *	Mid Category *
Residential	Residential Area	Residential Area
	Accommodation Service	Hotel, Hostel, Accommodation Service Related
	Auto Dealers	Audi Franchised Sales, BMW Franchised Sales, Porsche Franchised Sales, Beiben Trucks Sales, BAIC MOTOR Sales, Honda Franchised Sales, Peugeot Citroen Franchised Sales, Peugeot Citroen, Chengdu Dayun Automotive Sales, Volkswagen Franchised Sales, MAN Sales, Dongfeng Truck Sales, DFM Franchised Sales, Ferrari Franchised Sales, Fiat Franchised Sales, Toyota Franchised Sales, Ford Franchised Sales, Foton Truck Sales, Qoros Sales, GAC Trumpchi Sales, Haima Sales, Hongqi Sales, CAMC Sales, Truck Sales, Geely Franchised Sales, JAC Truck Sales, JAC Sales, JAGUAR Franchised Sales, Chrysler Franchised Sales, Renault Franchised Sales, Land Rover Franchised Sales, Mercedes-Benz Truck Sales, Mercedes-Benz Franchised Sales, MG Sales, Luxgen Sales, Chery Franchised Sales, KIA Franchised Sales, Automobile Sales, Nissan Franchised Sales, ROEWE Sales, Mitsubishi Franchised Sales, Shaanxi Heavy-duty Truck Sales, Subaru Franchised Sales, SCANIA Sales, General Motors Franchised Sales, Volvo Truck Sales, Hyundai Franchised Sales, FAW Jiefang Sales, Chang'an Sales, Great Wall Sales, SINOTRUK Sales
Commercial And Commercial Services Facilities	Auto Repair	Audi Franchised Repair, BMW Franchised Repair, Porsche Franchised Repair, Beiben Trucks Repair, BAIC MOTOR Repair, Honda Franchised Repair, Peugeot Citroen Franchised Repair, Peugeot Citroen, Chengdu Dayun Automotive Repair, Volkswagen Franchised Repair, MAN Repair, Dongfeng Truck Repair, DFM Franchised Repair, Ferrari Franchised Repair, Fiat Franchised Repair, Toyota Franchised Repair, Ford Franchised Repair, Foton Truck Repair, Qoros Repair, GAC Trumpchi Repair, Haima Repair, Hongqi Repair, CAMC Repair, Truck Repair, Gerly Franchised Repair, JAC Truck Repair, JAC Repair, JAGUAR Franchised Repair, Chrysler Franchised Repair, Renault Franchised Repair, Land Rover Franchised Repair, Mercedes-Benz Truck Repair, Mercedes-Benz Franchised Repair, MG Repair, Luxgen Repair, Chery Franchised Repair, KIA Franchised Repair, Automobile Repair, Automobile Comprehensive Repair, Nissan Franchised Repair, Subaru Franchised Repair, SCANIA Repair, General Motors Franchised Repair, Volvo Truck Repair, Hyundai Franchised Repair, FAW Jiefang Repair, Chang'an Repair, Great Wall Repair, SINOTRUK Repair
	Auto Service	Charging Station, Used Automobile Dealer, Filling Station, Filling Station, Other Energy Station, Automobile Service Related, Automobile Rescue, Automobile Club, Automobile Parts Sales, Automobile Maintenance/Decoration, Automobile Rental, Car Wash
	Commercial House	Industrial Park, Building, Commercial House Related
	Daily Life Service	Move Service, Lottery Store, Electric Supply Service Office, Telecom Office, Travel Agency, Beauty and Hairdressing Store, Job Center, Funeral Facilities, Photo Finishing, Daily Life Service Place, Professional Service Firm, Ticket Office, Repair Store, Logistics Service, Laundry, Bath & Massage Center, Information Centre, Baby Service Place, Post Office, Agency, Water Supply Service Office
	Finance & Insurance Service	Insurance Company, Finance Company, Finance & Insurance Service Institution, Bank, Bank Related, Securities Company, ATM
	Food & Beverages	Food & Beverages Related, Tea House, Bakery, Coffee House, Fast Food Restaurant, Icecream Shop, Dessert House, Foreign Food Restaurant, Leisure Food Restaurant, Chinese Food Restaurant
	Motorcycle Service	Motorcycle Service Related, Motorcycle Repair, Motorcycle Sales
	Shopping	Convenience Store, Supermarket, Clothing Store, Personal Care Items Shop, Shopping Related Places, Plants & Pet Market, Home Electronics Hypermarket, Home Building Materials Market, Shopping Plaza, Commercial Street, Special Trade House, Sports Store, Stationary Store, Franchise Store, Comprehensive Market

 Table 1. Types of original and aggregated POIs.

Aggregated Type	<b>Big Category</b> *	Mid Category *			
	Culture & Education	School			
	Governmental Organization & Social Group	Industrial and Commercial Taxation Institution, Public Security Organization, Traffic Vehicle Management, Democratic Party, Social Group, Foreign Organization, Governmental Organization, Governmental & Social Groups Related			
Dublic Community And	Medical Service	Veterinary Hospital, Emergency Center, Disease Prevention Institution, Medical ar Health Care Service Place, Pharmacy, Clinic, Special Hospital, Hospital			
Public Government And Public Service	Public Facility	Newsstand, Public Toilet, Public Facility, Public Phone, Emergency Shelter			
	Science, Culture & Education Service	Museum, Media Organization, Archives Hall, Convention & Exhibition Center, Driving School, Science & Technology Museum, Science & Education Cultural Place, Research Institution, Art Gallery, Training Institution, Planetarium, Library, Cultural Palace, Arts Organization, School, Exhibition Hall			
	Sports & Recreation	Holiday & Nursing Resort, Golf Related, Sports & Recreation Places, Recreation Place, Theatre & Cinema, Recreation Center, Sports Stadium			
Industrial And Mining Storage	Enterprises	Factory, Company, Enterprises, Farming, Forestry, Animal Husbandry and Fishery Base, Famous Enterprise			
Ecological	Tourist Attraction	Scenery Spot, Tourist Attraction Related, Park & Square, Park & Plaza			
	Pass Facilities	Gate of Buildings, Gate of Street House, Pass Facilities, Virtual Gate			
	Road Furniture	Road Furniture, Service Area, Traffic Light, Warning Sign, Signpost, Toll Gate			
Transportation	Transportation Service	Commuter Bus Station, Taxi, Subway Station, Port & Marina, Bus Station, Border Crossing, Railway Station, Airport Related, Transportation Service Related, Ferry Station, Light Rail Station, Ropeway Station, Parking Lot, Coach Station			

Table 1. Cont.

Note: Big category \* and mid category \* are original types of points of interest downloaded from https://lbs.amap.com/api/webservice/download (accessed on 30 September 2020).

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