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# Mapping the Functional Structure of Urban Agglomerations at the Block Level: A New Spatial Classification That Goes beyond Land Use

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**Abstract:** The functional structure of territorial space is an important factor for analyzing the interaction between humans and nature. However, the classification of remote sensing images struggles to distinguish between multiple functions provided by the same land use type. Therefore, we propose a framework to combine multi-source data for the recognition of dominant functions at the block level. Taking the Guangdong–Hong Kong–Macau Greater Bay Area (GBA) as a case study, its block-level 'production–living–ecology' functions were interpreted. The whole GBA was first divided into different blocks and its total, average, and proportional functional intensities were then calculated. Each block was labeled as a functional type considering the attributes of human activity and social information. The results show that the combination of land use/cover data, point of interest identification, and open street maps can efficiently separate the multiple and mixed functions of the same land use types. There is a great difference in the dominant functions of the cities in the GBA, and the spatial heterogeneity of their mixed functions is closely related to the development of their land resources and socio-economy. This provides a new perspective for recognizing the spatial structure of territorial space and can give important data for regulating and optimizing landscape patterns during sustainable development.

**Keywords:** production–living–ecological (PLE) function; land use/cover change (LUCC); points of interest (POI); open street map (OSM)



**Citation:** Ai, B.; Lai, Z.; Ma, S. Mapping the Functional Structure of Urban Agglomerations at the Block Level: A New Spatial Classification That Goes beyond Land Use. *Land* **2024**, *13*, 1148. https://doi.org/10.3390/land13081148

Academic Editor: Alexandru-Ionuţ Petrişor

Received: 27 June 2024
Revised: 16 July 2024
Accepted: 17 July 2024
Published: 26 July 2024



## 1. Introduction

Since its reform and opening policy was promulgated in 1978, China has been experiencing rapid urbanization [1]. However, its long-term spatial planning concept has caused the steady deterioration of the ecological environment, which directly affects the sustainable development of cities [2,3]. To promote the transformation of their urbanization development mode, the Chinese government has promoted the construction of an ecological civilization to a national strategy [4,5]. In 2012, the 18th National Congress of the Communist Party of China (CPC) listed "Beautiful China" as the goal of the construction of an ecological civilization and formally proposed the national space governance goals of "intensive and efficient production space, livable and moderate living space and beautiful ecological space". The status of ecological functions, at a national level, has been gradually enhanced, and the value of spatial planning for high-quality development has been gradually formulated [6]. This indicates that the optimal arrangement of production, living, and ecology (PLE) functions is a crucial task for China in the construction of an ecological civilization [7]. Therefore, the spatial pattern of PLE functions can reasonably reflect the actual conditions of territorial space; it can also provide key data for evaluating the coordination degree between different PLE functions and exploring optimal combinations of functional units.

The concept of PLE functions originated from research on multiple agricultural functions [8,9]. An area in which people engage in production activities provides a specific production function; a regional unit for people's daily activities mainly provides a living function; and a spatial unit has a dominant ecological function when it is mainly used to provide ecological products and services. Therefore, a land use area can be interpreted as being of a specific type according to its dominant function (a production, living, or ecological function) [10,11], and then a city can be accordingly separated into a combination of different PLE function units. This is generally performed at two typical scales: the microscale and macroscale.

At the microscale, such interpretations generally follow the principle of emphasizing functional attributes based on land use/cover data [12]. The type of land use/cover classified from remote sensing images is usually recognized as one of the PLE functions and only considers this single function. For instance, Fu et al. reclassified different land use types into specific divided PLE spaces to divide Wuhan into different functional spaces [13]. Zhang et al. divided land into three types (P-L-E) of spaces and two types of composite spaces corresponding to different land use/cover types and further evaluated the PLE spaces of Feixi County [14]. In actuality, although sophisticated land use data can be obtained, multiple and mixed functions cannot yet be distinguished for the same land use type [9]. In rural areas, agriculture and forestry farms provide important production and ecological functions [15]; thus, they cannot be simply defined as a production unit or ecological unit according to their land use/cover type [16]. Moreover, commercial premises and residential neighborhoods frequently coexist in the same area of a city and have different functions, and it is incorrect to describe these areas as single objects [17]. To address this, researchers have commonly used expert scoring methods to measure the functional intensity of each land use type [18–20]. A function classification system is first set, and each type of land use is categorized into a function class with the same parameters. Then, a score is given for each function according to expert experience. A score for the PLE function is then obtained for each land use unit. For example, Gao et al. constructed the multi-functional assignment system of production–living–ecological spaces for land use types and assigned different land categories to the LUCC data based on the strength of the function of their PLE space [21]. Although this method can distinguish multiple functions within the same land use type and overcomes the limitation of reclassifying land use/cover data, it cannot yet reflect the functional heterogeneity of each land use type. The same type of land use in different regions may result in unequal function scores, which means that although a function score for each land use area can be obtained, its dominant function cannot be recognized. Obviously, although land use classification can identify ground objects on a finer scale based on the division of physical space [17], its result only explores the underlying semantic information of the region. The components of urban functional spaces are extremely similar visually, and relying only on the visual features of remote sensing imagery pixels is insufficient for accurately dividing the functional areas within a city [22]. To overcome this limitation, it is essential to incorporate other data on social and economic attributes to better reflect functional differences between the same land use types and interpret their dominant functions [23–25].

At the macroscale, PLE functions are typically interpreted at administrative levels such as county, city, or country [10]. Social and economic indices are commonly coupled with land use data to measure comprehensive functional intensity. The areas, values, and proportions of these indices determine the functional intensity of each statistical unit, which is then classified as a PLE function type according to the estimated function intensity. For example, Wubuli et al. integrated socio-economic indicators, DEM data, meteorological data, and land use change data to assess the land use suitability of various functional rural land types using capacity grade patches as evaluation units and further classified the PLE space of rural villages in central and western China through superposition matrix analysis [26]. However, while straightforward to implement, this method lacks sensitivity to local heterogeneity for the functions of the sub-units within administrative areas. It ignores the multifunctional characteristics of the same land use type at finer scales. In particular, the final spatial structure of PLE functions generated by this method greatly relies on available statistical data.

Related research suggests that the fine structure of PLE functions in cities can be interpreted with the advent of big data and social sensing data [27–29]. Accordingly, point of interest (POI) data have been widely adopted owing to their advantages of large sample size, ease of access, and detailed information coverage [11,30,31]. POI data contain extensive information about production, living, and ecological functions within a city, making it possible to accurately identify specific locations such as residential areas, productive areas, and consumer services, parks, and green spaces. Based on this, POI data have been successfully applied to identify urban functional land (e.g., residential land, industrial land, commercial land) in central urban areas by analyzing the relationship between the attributes of POIs and land use functions [32–34]. However, this can be carried out only when a sufficient number of POIs are available. If POIs are lacking in rural areas, the type of functions particularly ecological function at a refined scale cannot be distinguished in large cities.

As China's urbanization enters a new stage, urban areas have become the main spatial carrier [35]. The accurate identification of functional areas and their spatial structure is particularly crucial for urban spatial planning and constructing an ecological society [36]. Spatial scales and geographical characteristics among sub-units of urban agglomeration are more complex than those of a single city [37]. Consequently, it is challenging to interpret the refined structure of PLE functions for an entire urban agglomeration using only land cover/use or POIs. In high-density urban agglomerations with complex structures, urban blocks divided by road networks are basic units directly impacting residents' lifestyles and the overall urban environmental quality through their size, shape, and functional characteristics [38]. From the perspective of planning, a block is also generally regarded as the most suitable and meaningful unit, usually being planned with a dominant PLE function [39]. Accurately recognizing the structure of PLE functions at the block level in whole urban agglomerations is of great importance for territorial spatial planning [40]. However, a unified and efficient method for the specific identification of block-level PLE functions in urban agglomerations is currently lacking. Previous research has indicated that refined road networks and administrative boundaries can provide suitable data for block divisions. For example, Ni et al. used irregular blocks segmented by road network data as spatial analysis units to identify PLE space in urban built-up areas on the Jiaodong Peninsula [41]. Chen et al. utilized road network and POI data to identify the urban functional zones in Shenyang City [42]. The PLE functions of each block can be accurately distinguished according to the attributes of POIs. The dominant function of a block, that is, the type of function with an absolute higher proportion, can be determined based on the complex mapping relation between the attributes of POIs and land cover/use types.

Therefore, this study attempts to integrate open-source data, including POI, land cover/use data from GlobalLand30, and OpenStreetMap (OSM) data, to identify block-level PLE functions in urban agglomerations. Taking the Guangdong–Hong Kong–Macao Greater Bay Area (GBA) as a case study, we not only investigate whether the introduction of open-source data improves the identification resolution of PLE functions, but also focus on the inner structure of dominant functions in the GBA. The goals of this work are to provide significant data analyzing spatial differentiation of PLE functions and a new perspective for recognizing territorial space structure, which can provide key evidence for land use to form optimal structures in territorial spatial planning.

## 2. Material and Methods

In this study, we identified and analyzed the block-level PLE functions in the GBA using open-source data. The methodology comprises five main steps: (1) the division of spatial units in the GBA and labeling of PLE primary types; (2) preprocessing the POI data; (3) a functional contribution calculation of each POI; (4) PLE function identification of each block; and (5) a PLE structure analysis of the GBA. A technical flowchart is shown in Figure 1.

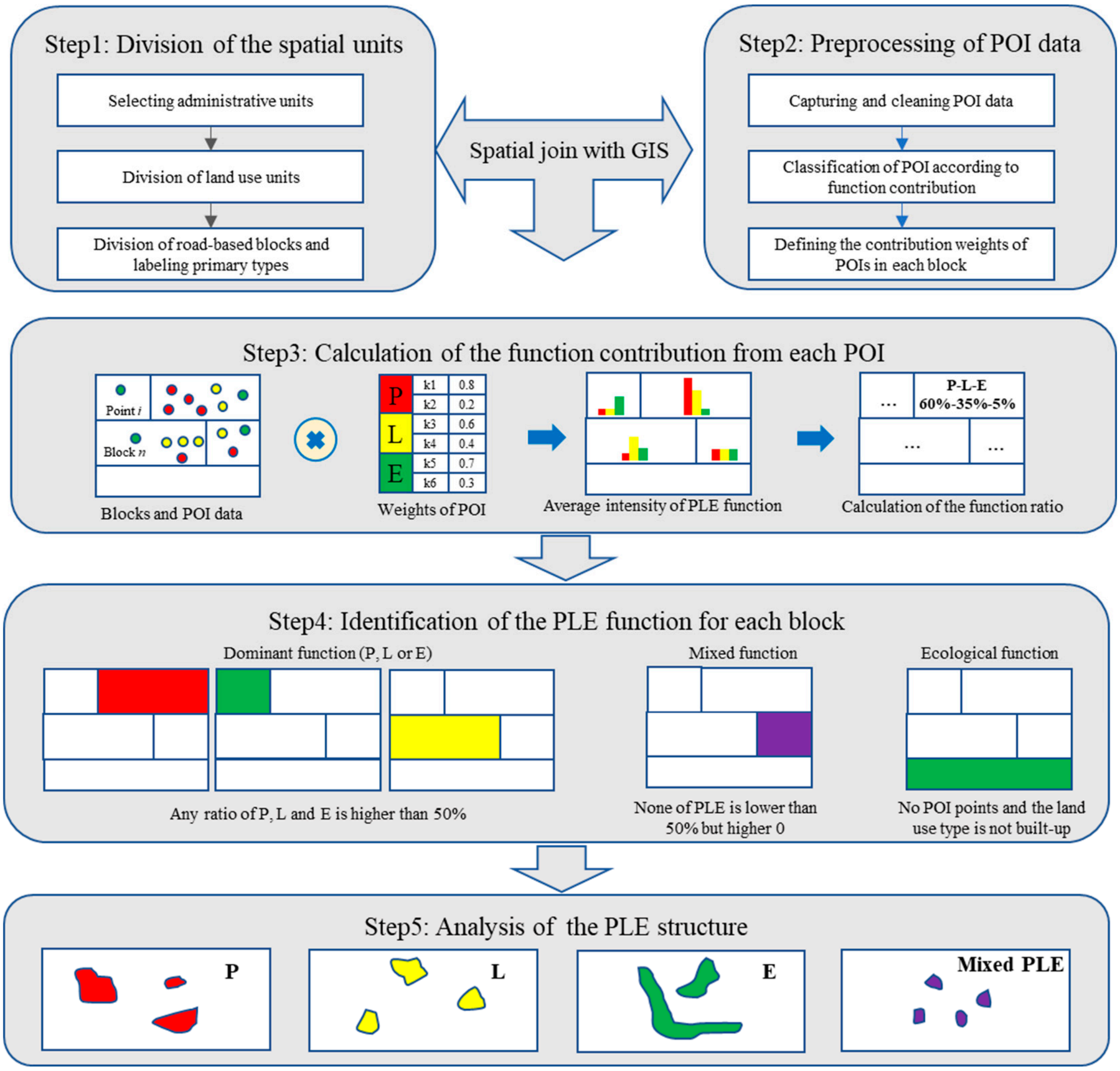


**Figure 1.** Technical flowchart for identifying and analyzing PLE functions at the block level.

*2.1. Study Area and Block Division*

The GBA, located in the southern China, is an urban agglomeration covering an area of approximately 5.6 $\times$ $10^4$ km$^2$. It includes nine cities in Guangdong Province (Guangzhou, Shenzhen, Zhuhai, Foshan, Dongguan, Zhongshan, Huizhou, Jiangmen, and Zhaoqing) and two special districts, Hong Kong and Macao. By 2020, the GBA had over 80 million permanent residents and a gross domestic product (GDP) exceeding 10 trillion CNY. A recent study showed that the GBA is the largest morphologically contiguous urban agglomeration in the world [43]. Rapid urbanization has greatly influenced the spatial structure of PLE functions, resulting in a lopsided spatial pattern. Therefore, identifying high-resolution PLE functions is of great significance for the regulation of land use in territorial spatial planning.

The GBA was first divided into different blocks using a combination of land cover data, road networks, and administrative boundaries. The GlobalLand30 V2020 product, provided by the Ministry of Natural Resources of China (http://www.globallandcover.com/) (accessed on 10 August 2023), was used to extract information on land cover/use. Cultivated land, forest land, grasslands, water bodies, and artificial surfaces were classified for the GBA (Figure 2), with an overall accuracy of approximately 85.72% [44]. The road network for 2020 was derived from OpenStreetMap data (https://www.openstreetmap.org/) (accessed on 1 December 2021), which is an important open source for collecting traffic data. We first converted GlobalLand30 into vector format to obtain land cover/use patches, and then the land cover/use patches were overlaid with the road network and administrative boundaries to divide the blocks. During this process, rivers were not separated by the traffic network to maintain their integrity (Figure 2a). Other natural elements, such as forests, farms, and grasslands, were kept as large patches and only separated into different parts when traffic roads passed through them (Figure 2b). As the superposition will produce many fine raw polygons, we eliminated polygons with an area less than $9 \times 10^4$ m$^2$, as the Code of Urban Residential Areas Planning & Design (GB 50180-2018) [45] provides a criterion that small residential areas are generally between $2 \times 10^4$ m$^2$ and $9 \times 10^4$ m$^2$. Finally, the entire GBA was divided into 49,618 blocks. Then, according to the PLE space classification system proposed by Fu et al. [46], we reclassified different land use types and labeled the primary type of PLE function for each block.

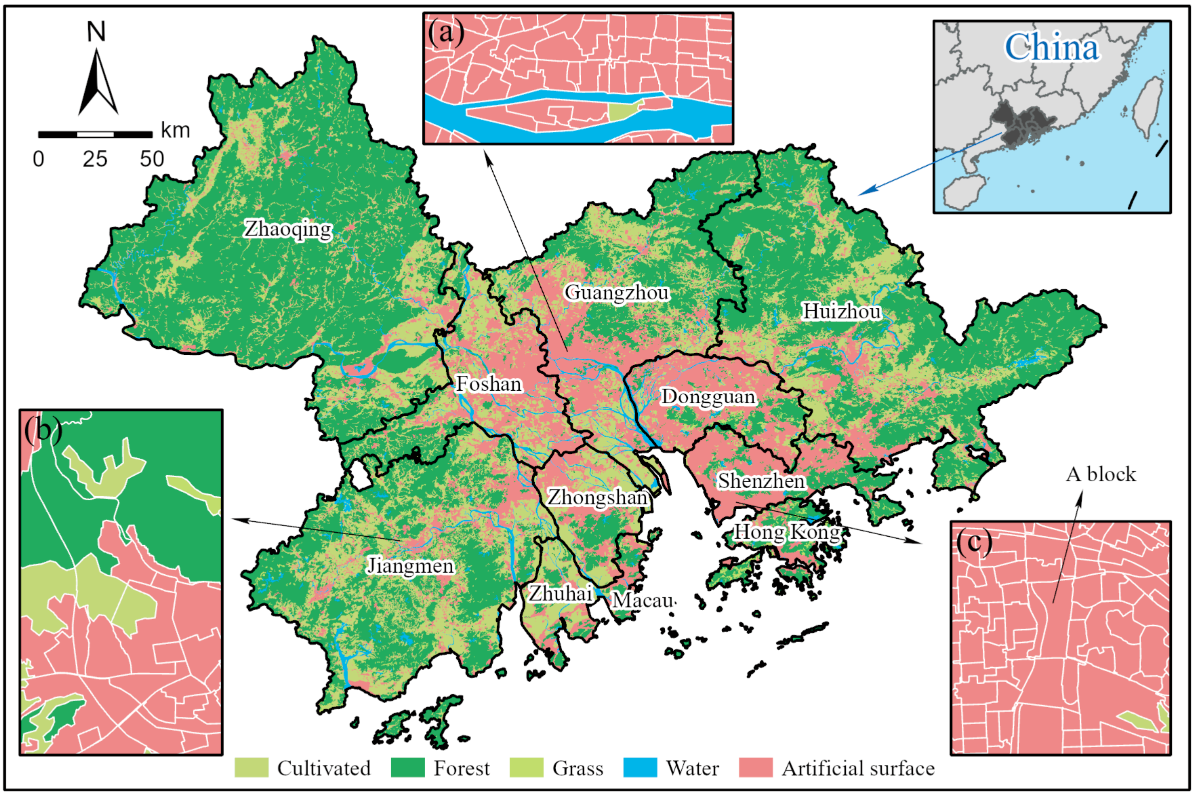


**Figure 2.** Scope of the study area, land use in 2020, and divided blocks: (**a**) the river is not separated to maintain its integrity; (**b**) blocks containing natural elements; and (**c**) blocks within urban areas.

### 2.2. Capturing and Preprocessing POI Big Data

In this study, the POI data of the GBA in 2020 were captured from the AutoNavi electronic navigation map (https://www.amap.com/) (accessed on 1 December 2021), a well-known electronic map in China. These data include information about the location and type of labeled POIs. The original data were complex, comprising more than 1.16 million points, and thus required reclassification before being used to identify PLE functions. POIs in the AutoNavi map are labeled at three levels, namely, major, middle, and sub-categories, with 23 first-level types, 267 second-level types, and 869 third-level types (details available at https://lbs.amap.com/api/webservice/download) (accessed on 1 December 2021). In this study, to efficiently recognize PLE functions, POI big data were primarily processed as follows: (1) POIs with nonfunctional attributes, including "Place name & Address", "Indoor facilities", and "Incidents and Events", were removed. (2) Some categories of POIs were reorganized. For example, accommodations, office buildings, industrial parks, and other built types were originally marked as commercial spaces. These buildings have essentially different functions and must be separated and labeled as new types for each POI. POIs with residential buildings are marked as residential areas, while other POIs with business buildings are marked as business areas. Moreover, enterprises engaged in agriculture, forestry, animal husbandry, and fishery production are often marked as companies in POIs. Although the enterprise attributes are correct, these POIs contribute more to ecological functions. For example, many of these POIs in the GBA are located within gardens and flower companies. Therefore, it is necessary to mark these areas as ecological function units. After reclassification, all POIs were divided into 18 types (Table 1), with a total of 879,565 POIs being used to identify PLE function units.

In general, locations providing functions related to human activities, such as production and living activities, must be labeled with POIs. Conversely, blocks without POI points can be directly identified as primary ecological function units, reclassified according to land cover/use type. Our overlay analysis revealed that a few blocks contain no efficient POIs, and these areas are mostly natural elements, such as great mountains or rivers. Accordingly, these blocks were identified as ecological function units. Based on the primary type of PLE functions reclassified from land cover/use, the functional contribution of each POI to its corresponding block was calculated to further identify the function type of most blocks with POIs. Referring to previous research, the weight for the functional contribution of each POI was set based on its relevance and influence [47]. Therefore, the relevance of the POI is mainly based on the correlation between the functions of different POIs and the various types of PLE functions. For example, residential POIs generally have a higher relevance to living functions than those of shopping services. The relevance index ($\alpha$ in Table 1) was determined using expert sorting and the analytic hierarchy process (AHP). AHP is a decision analysis method that facilitates the systematic analysis of complex problems within hierarchical structures. This method assigns a weight value to each element according to the relative importance of each level by constructing a judgment matrix; it has been widely used in weighting analyses of indices in PLE function recognition studies [21]. We consulted a total of 10 experts to set the scores of POIs belonging to each specific type and then calculated the relevance values of POIs for various PLE function types using AHP. In addition to the number of POIs in a block, the physical area of the POI type also plays an important role in recognizing PLE functions. For example, the number of industrial POIs, such as catering or finance, in a residential community is much larger than that of residential POIs. However, the total area of residential POIs is much larger than that of industrial POIs, and consequently, this residential community is recognized as a living function unit. Therefore, the average area of various POIs in a block is used as a reference index to determine their influence on the identification of the PLE function. The larger the average area, the higher the influence value. This reference index was determined by sampling and analyzing the study area. First, 100 POIs of each type were randomly selected, and the land use areas occupied by each POI were calculated from a 0.5 m resolution remote sensing image. These areas were then accurately corrected through field surveys and web crawler data. The average area of each POI type was estimated and then normalized, with values ranging from 0 to 1. This value was used as the influence value ($\beta$ in Table 1) to determine the function type of each POI.

**Table 1.** POI classification and weight determination for PLE identification.

| PLE Type | | POI Type | Relevance ($\alpha$) | Influence ($\beta$) | Weight ($\omega = \alpha \times \beta$) |
|---|---|---|---|---|---|
| P | P1 | Auto services | 0.083 | 70 | 5.81 |
| | P2 | Enterprises | 0.314 | 90 | 28.26 |
| | P3 | Business buildings | 0.195 | 60 | 11.7 |
| | P4 | Finance & insurance services | 0.069 | 40 | 2.76 |
| | P5 | Logistics & warehousing | 0.056 | 60 | 3.36 |
| | P6 | Major transportation facilities | 0.145 | 70 | 10.15 |
| | P7 | General transport facilities | 0.043 | 20 | 0.86 |
| | P8 | Government organizations & social groups | 0.095 | 40 | 3.8 |
| L | L1 | Residential districts | 0.502 | 90 | 45.18 |
| | L2 | Shopping services | 0.055 | 60 | 3.3 |
| | L3 | Daily life services | 0.106 | 60 | 6.36 |
| | L4 | Food & beverage services | 0.078 | 20 | 1.56 |
| | L5 | Medical services | 0.053 | 60 | 3.18 |
| | L6 | Science/cultural & education services | 0.106 | 60 | 6.36 |
| | L7 | Sports & recreation services | 0.026 | 20 | 0.52 |
| | L8 | Accommodation services | 0.074 | 20 | 1.48 |
| E | E1 | Tourist attractions | 0.75 | 90 | 67.5 |
| | E2 | Agriculture, forestry, grazing and fishing | 0.25 | 80 | 20 |

### 2.3. Calculating the Total, Average, and Ratio of Function Intensity

With the support of GIS tools, the weights for each type of POI were associated with each POI, and then the functional intensities of the productive services ($P$), living services ($L$), and ecological services ($E$) in the blocks were obtained by multiplying the POIs in each unit and their corresponding weights. Function intensity is calculated using Formula (1):

$$F^n_{(P,L,E)} = \sum_i^m P^n_{i(P,L,E)} \times \omega_i \tag{1}$$

where $F$ is the function intensity of $P$, $L$, and $E$ in spatial block $n$; $P^n_i$ is the POI point $i$ $(i = 1,\ 2,\ \cdots,\ m)$ that located in block $n$; and $\omega$ is the weight of each POI type. As the area of each block is inconsistent, using the total function intensity may hinder comparisons between different blocks. Thus, the value of the total function intensity in a block is further transformed into the average ground intensity, and the function proportions of $P$, $L$, and $E$ in each block are calculated accordingly to determine the type of $PLE$ function, which can be expressed as Formula (2).

$$R^n_{(P,L,E)} = \frac{F^n_{(P,L,E)}/A^n}{F^n_{(PLE)}/A^n},\ F^n_{(PLE)} = F^n_{(P)} + F^n_{(L)} + F^n_{(E)} \tag{2}$$

where $R^n_{(P,L,E)}$ is the ratio of $P$, $L$, and $E$ in spatial block $n$; $A^n$ is the area (ha) of block $n$; and $F^n_{(PLE)}$ represents the total function intensity of $P$, $L$, and $E$ in block $n$.

## 3. Results

According to the above methods, the total, average, and ratio of the function intensity for the PLE in each block were calculated; the results are shown in Figure 3. The total function intensity only considers the number of POIs and their contribution to PLE function, with a higher number of POIs corresponding to a higher functional intensity of the block. However, when considering the difference in block area, the pattern of the function intensity in the PLE unit presents obvious spatial differences. The proportion of function intensity for a PLE unit can effectively be used to analyze the dominant types of P, L, and E in each block, which plays an important role in identifying PLE units.

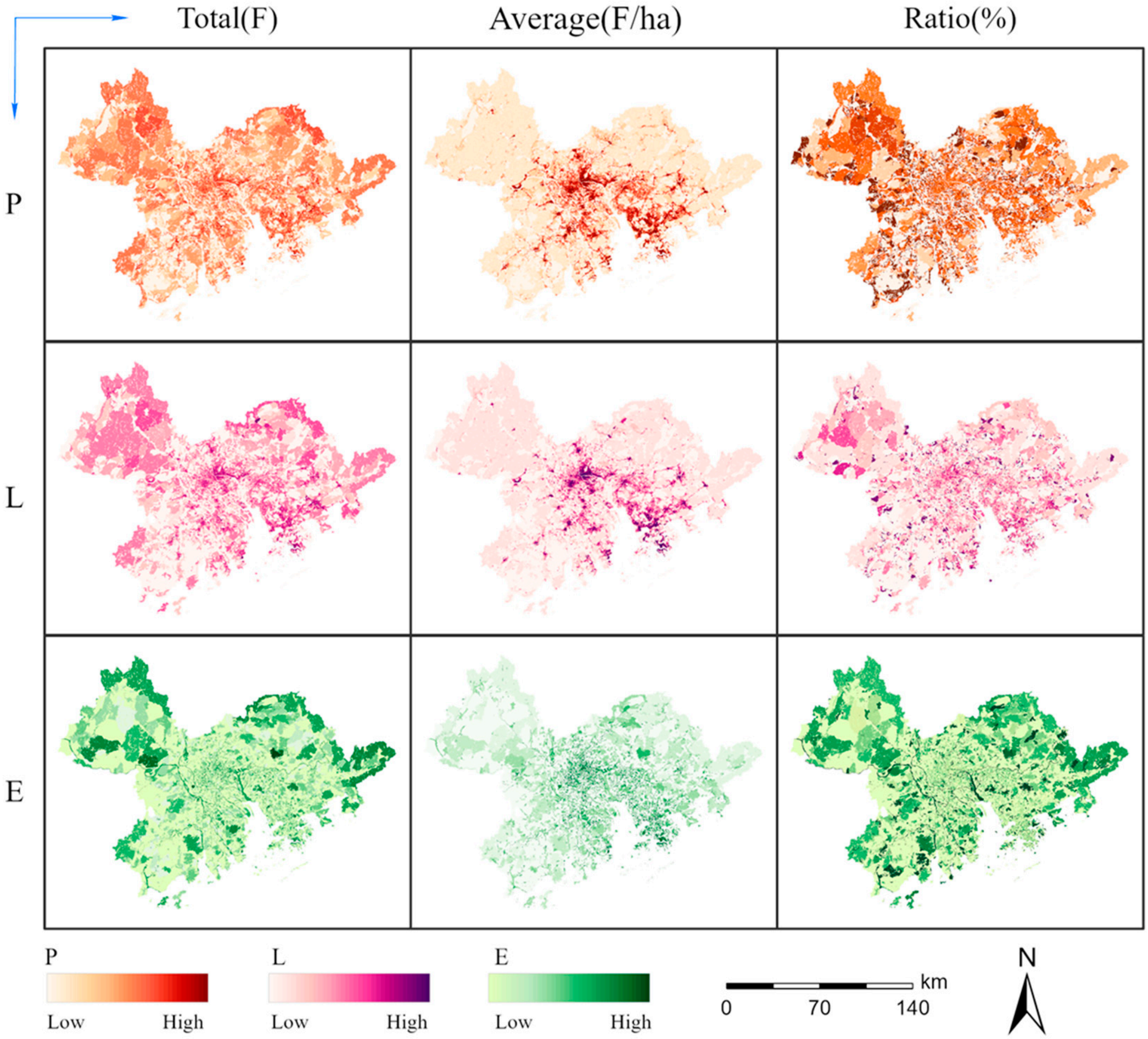


**Figure 3.** Total, average, and proportional function intensity of different PLE function units.

### *3.1. Definition and Spatial Pattern of PLE Functions in the GBA*

Based on the function intensity proportion for the PLE functions in each block, the attributes of production, living, and ecological function units were determined according to the following decision-tree rules. First, if the proportion of any function type is higher than that of the other two types, the block is directly classified as having that dominant function. Second, if the proportions of the three functions are very close, the block is likely to be marked as a mixed unit labeled PLE. Third, if the proportions of any two function types are close, the block is labeled as another mixed space composed of these two function types. There are many mixed spaces within the city, such as commercial and residential complexes, which provide both residential and commercial services. To quantitatively express the above decision-tree rules, we set the tri-sectional and intermediate proportions as breaking points, as shown in Figure 4. For example, if the proportion of production, living, and ecological functions is 67%, 25%, and 8%, respectively, the block unit can be directly classified as a production unit. If the proportion of production, living, and ecological functions is 45%, 40%, and 15%, respectively, the block unit can be directly classified as a PL unit.

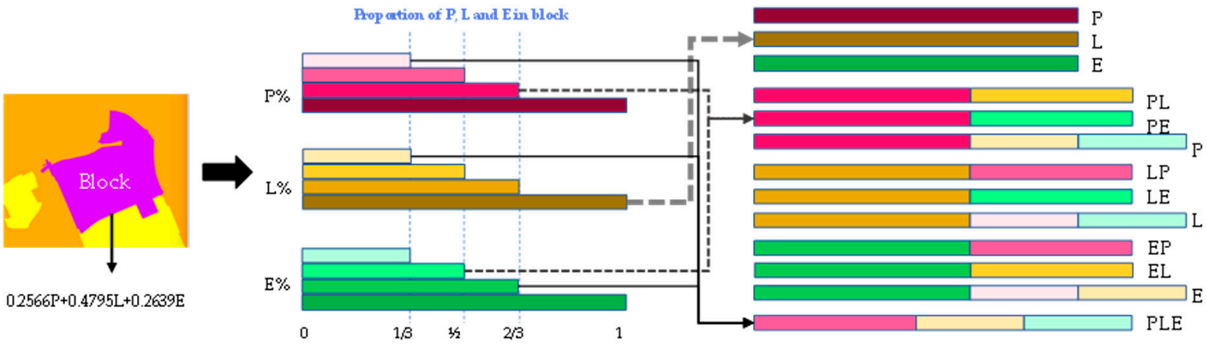


**Figure 4.** Identification principle for determining the function type of blocks in the GBA.

Based on the above principle, the identified pattern of PLE blocks in the GBA is shown in Figure 5. In general, ecological spaces occupy the largest proportion of the total area in the GBA, while living–ecological (LE) spaces account for the smallest. The spatial distribution of ecological spaces covers almost the entire GBA region. However, the size of ecological spaces in the central area of the GBA is significantly smaller than that in the peripheral zones. This reflects a weaker ecological function in the central part of the GBA, possibly due to landscape fragmentation resulting from intensive human activities [48]. Living spaces are mainly concentrated in the central and eastern parts of the GBA, with particularly dense distribution in the coastal zones, but generally scattered and small in size. In contrast, production spaces are more prominent in the northern and western regions of the GBA, characterized by strong connectivity and extensive coverage. In terms of the composite spaces, production–living (PL) and production–ecological (PE) areas encompass a larger area than that of LE. The production–living–ecological spaces are commonly observed in economically developed coastal cities such as Guangzhou, Shenzhen, and Hong Kong (Figure 5b,c,e,g,h).

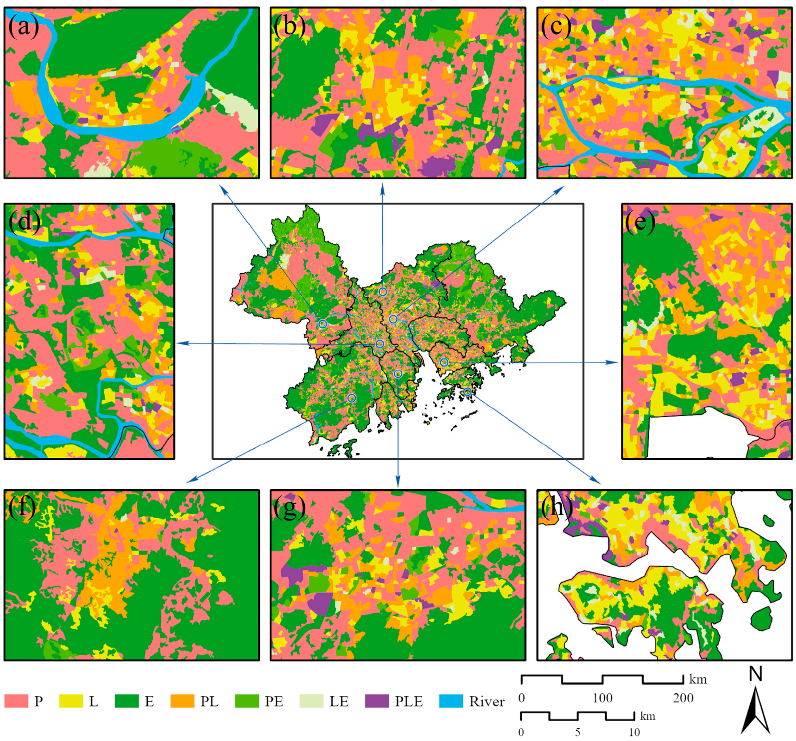


**Figure 5.** Distribution pattern of different dominant function types in the GBA, where (**a**–**h**) are the local spatial distribution in Zhaoqing, western Guangdong, southern Guangzhou, Foshan, Shenzhen, Jiangmen, Zhongshan, Hong Kong.

### 3.2. Accuracy Validation of PLE Recognition

To validate the accuracy of PLE recognition using multiple-source data, 10% of the blocks in each category were randomly selected to evaluate the identification result. A visual interpretation of 0.5 m resolution images from Google Earth, supplemented by field interviews and street view data, was used as ground truth data. A point-to-point comparison was conducted to calculate recognition accuracy. If the proportion of PLE functions in a block was similar to that interpreted from the 0.5 m images, then the recognition result was considered accurate. Several typical examples were selected to further examine the recognition efficiency. A comparison is shown in Figure 6.

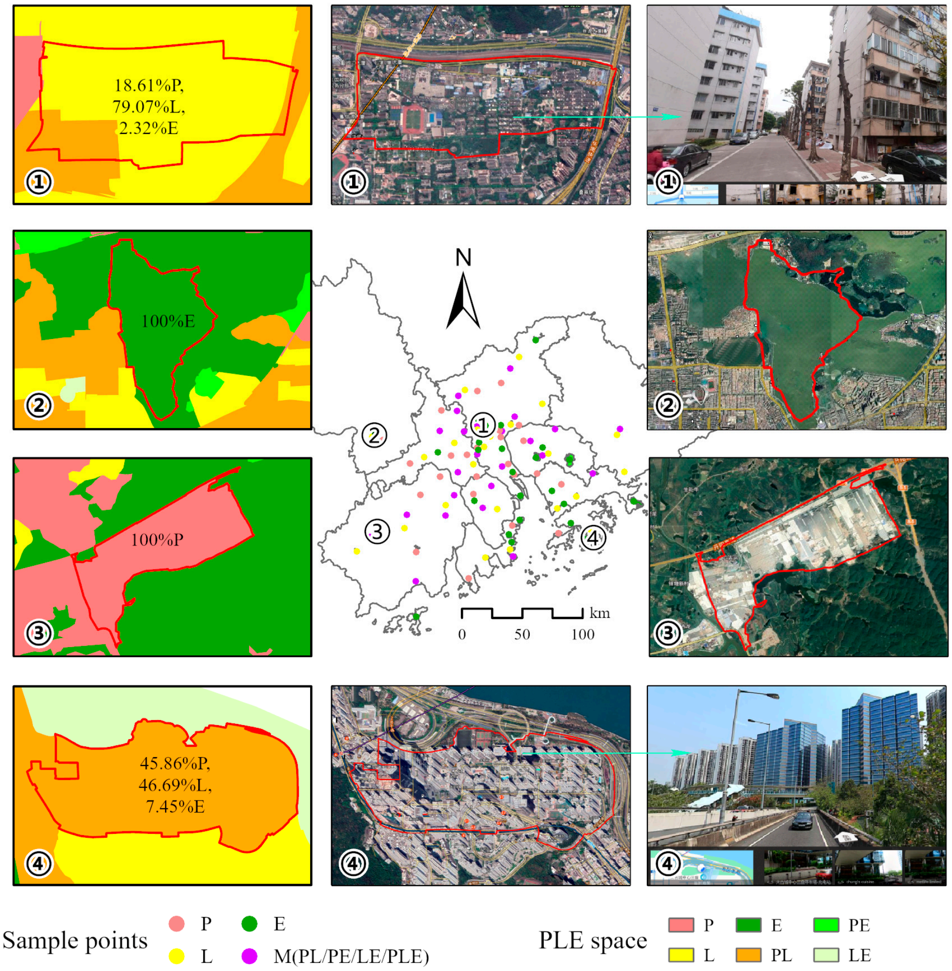


**Figure 6.** Accuracy validation of PLE identification by comparison of high-resolution images and street view map, where ①–④ are examples of PLE identification results in this study.

As shown in Figure 6, block ① is in Guangzhou City and the proportions of production, living, and ecological functions calculated from multiple open-source data are approximately 18.61%, 79.07%, and 2.32%, respectively. The proportions of PLE space calculated from the visual interpretation for this block are approximately 25.79%, 68.24%, and 5.98%, respectively. Although the proportions of PLE functions from these two methods are different, both indicated that this block is dominated by living function. Further, we checked the street view map of this block and found that it mainly includes a university campus while the surrounding area mainly includes catering and other services. Only a very small area of companies and enterprises faces the street in the north. Therefore, identifying this block as a living function unit is reasonable.

Another set of typical examples is shown in blocks ② and ③, and their recognition accuracy is easy to validate. They were labeled as ecological and production units with the assistance of POI big data. In fact, they can also be easily recognized from high-resolution remote sensing images. Block ② is Qixinghu Park of Zhaoqing City; it is a water body in the image and was correctly detected with multiple open-source data. Block ③ is an industrial development zone in Jiangmen. The image shows that it is far from the town and is represented as an impervious surface. Classifying this block as a production unit is accurate. Block ④ is identified as a mixed function unit for both production and living functions in Hong Kong; the proportions of production, living, and ecological functions are 45.86%, 46.69%, and 7.45%, respectively. The proportions of production and living functions are very close and both lower than 50%. This indicates that the distribution of land use in this block presents a very tight and mixed assignment dominated by production and living functions, with a mixed distribution of a few ecological function areas. Street-view images further show that many high-rise residential areas and commercial areas are included in this block. Therefore, this block can reasonably be considered as a unit mixed with different functions.

All selected samples were validated by individual comparisons based on the above methods, with most recognition accuracies exceeding 95%. Recognition errors mainly occurred in blocks within large communities where residential and commercial land use showed a mixed distribution, and the number of collected POIs for each type of function was unbalanced. A small deviation in the quantitative calculation of function intensity with the assistance of POI big data can directly result in significant variations in the detection results. In general, it is difficult to exactly identify function types, even when using high-resolution satellite images and street view maps. Overall, the accuracy validation verified that using POI big data as important auxiliary data to identify PLE function units can meet the application requirements of territorial spatial planning and decision-making in the GBA.

### *3.3. Structure of PLE Functions in the GBA at the City Scale*

The proportion of each dominant function type in each city was calculated and the results are shown in Figure 7. According to the national garden city standards proposed by China's government, all types of green areas and waters within a built-up area should account for at least 43% of the total built-up area [17]. Therefore, achieving a balance between the development of living and production spaces and ecological conservation is crucial. A disordered spatial pattern of PLEs within the same region can exert pressure on limited land resources, resulting in the inefficient use of spatial resources and undermining the coordinated and sustainable development of urban structures [49]. An excessively high proportion of a production-related function types can encroach upon living spaces in urban agglomerations. Conversely, a more balanced structure of PLE functions can satisfy residents' daily needs more easily [17]. Great differences are observed in the dominant function types among cities, and most of the cities in the GBA are dominated by ecological function based on the area proportion of function intensity in PLE blocks. Over 40% of the total area in Macao and Shenzhen is dominated by production and living functions; more than 50% of the total area in Jiangmen, Huizhou, and Hong Kong is dominated by ecological functions; while approximately 50% of the total area of Zhongshan, Zhuhai, and Guangzhou is dominated by ecological functions. Regarding the type of mixed functions, Zhaoqing and Huizhou have a relatively higher ratio of dominant functions that include production and ecological services; Shenzhen, Macau, and Dongguan have a relatively high ratio of dominant functions that include production and living services; and Guangzhou, Dongguan, and Hong Kong have a higher relative ratio of dominant functions than other cities that include production, living, and ecological services. The ratio of mixed functions is closely related to the development of land resources and the level of social and economic development. Shenzhen, Dongguan, Foshan, and Zhaoqing, which are important production bases in the GBA and have many manufacturing businesses, high-tech enterprises, and forest plantations, have the highest proportion of production functions among the 11 cities. Among the core cities in the GBA (excluding edge cities such as Zhaoqing, Jiangmen, and Huizhou), Hong Kong has the best coordinated development of PLE functions, which can be explained by the following two aspects. First, Hong Kong has controlled the proportion of human activity space to within 50% of the total area; and second, the proportions of mixed, production, and living functions are relatively similar. Taking Jiangmen as an example, the proportion of production spaces significantly exceeds that of living spaces, while mixed spaces are insufficient, indicating a need to optimize the land spatial pattern. This illustrates how the composition of different PLE function types within a city can help understand and resolve conflicts between human activities and territorial spatial layout, and mixed spaces can ensure a sustainable and healthy living environment for residents. Moreover, our research reveals that mixed spaces are relatively rare in the GBA cities, and peripheral areas are predominantly composed of single or dual function types (Figure 5), highlighting the necessity for optimization in these regions. Generally, as population and GDP grow, the overall ecological function of urban agglomerations tends to decline [21]. For sustainable development in the GBA, it is crucial to enrich the land use multifunctionality, promote urban layouts based on PLE functional distribution heterogeneity, and further facilitate the high-quality development of territorial spatial patterns.

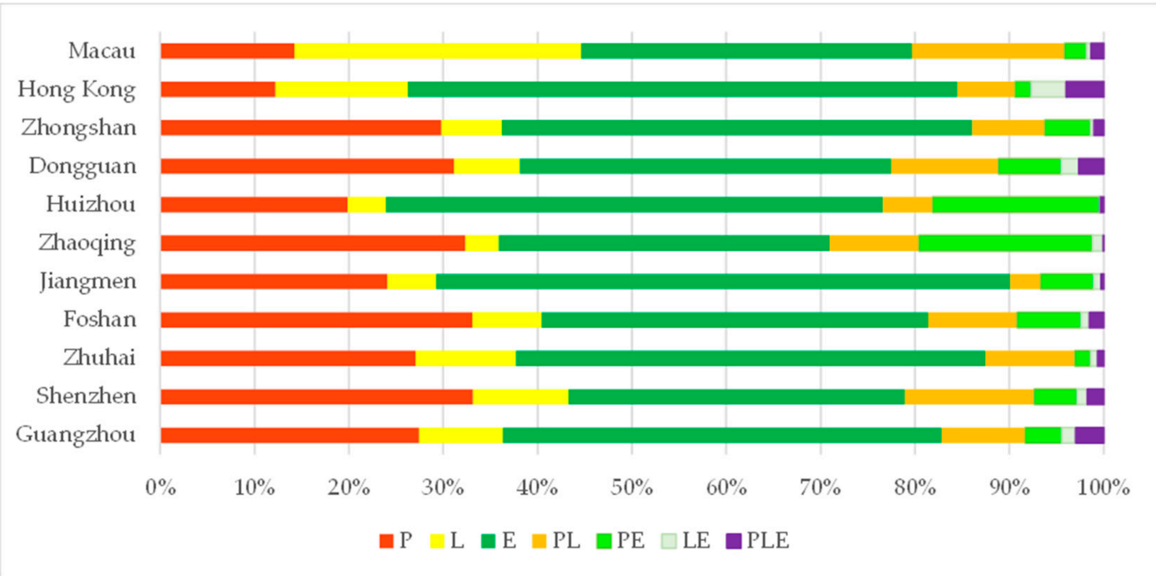


**Figure 7.** Quantity structure of dominant function types in different cities of the GBA.

## 4. Discussion

The spatial distribution characteristics of PLE function types in the GBA observed in our study align closely with findings from other relevant research [21,50]. For example, our analysis of GBA PLE function types in 2020 revealed that ecological spaces constitute the largest proportion, with living spaces being predominantly distributed in the central and eastern parts, while production spaces are more prominent in the northern and western areas. These findings are consistent with the conclusions drawn by Gao et al. and Wang et al. [21,50]. However, it is noteworthy that Gao et al. discovered that the order of PLEs in the GBA were ecological space > production space > living space, whereas Wang et al. concluded the following: ecological space > living space > production space. This discrepancy may be attributed to the fact that neither study mentioned the spatial distribution of mixed function types or the inherent difficulty in distinguishing between living and production spaces [17]. To our knowledge, no previous studies have investigated the spatial distribution patterns of both single and composite PLE functional types in the GBA region at the block-level. Therefore, our study results may serve as a pioneering example in this regard.

*4.1. Recognition Influenced by Proportions of POIs*

Coupling POI big data with land cover/use types can reasonably be used to identify dominant PLE function patterns and structures. In general, POI big data reflect human activity characteristics. With enough equally distributed POIs, PLE function spatial patterns can be reliably identified. However, in practical applications, PLE functions are not in equilibrium, and POI type, quantity, and quality are not completely balanced in geo-space. For instance, in this study, 53.82%, 43.28, and 2.9% of the 879565 POIs were collected for production, living, and ecological functions, respectively. POIs recording P2, P7, L2, P8, L6, L1, P4, P3, L8, and L4 types accounted for 87.89% (Figure 8). This unbalanced collection of POIs may correspondingly reduce the recognition accuracy of the PLE function units. When the collected POIs in each block present an unbalanced distribution among types, different judgments of PLE functions will occur. For example, Zhaoqing's higher proportion of production blocks was largely due to many forests being labeled as POIs providing forest product services, thus identifying these areas as production blocks.


**Figure 8.** Proportions of POIs for different PLE functions (Logo icons demonstrate representative annotation points for different types of POIs).

On the other hand, there may not be enough POIs in rural areas. Actually, the distribution of POIs basically reflects the intensity of human activity, thus directly determining the function intensity of land use. If there are few POIs in some blocks, it means that the land uses in those blocks generally serve ecological functions. The number of POIs cannot influence the function intensity of those blocks. In this study, primary PLE functions were first identified using land cover/use data, with POIs being applied to improve recognition accuracy, providing acceptable PLE recognition results, even in rural areas.

*4.2. Recognition Influenced by Relevance and Influence*

To recognize the dominant PLE function type of a block, the values of relevance and influence for each POI are required. Relevance was determined using expert sorting and AHP, which combines subjective and objective methods for determining the relevance weight. Experts with sufficient experience and knowledge of the relationship between PLE functions and POI attributes can provide relatively objective and reliable judgments. As for the influence, we considered both POI number and area as main factors in block type recognition, with the influence weight being set according to the average area of POI type, determined by random sampling analysis. Accuracy validation reflects that identification errors mainly occur in blocks within large residential areas, where the POIs collected for each type present an unbalanced distribution. Usually, large residential communities are designed as a closed scope and absolutely dominated by residential areas, and it is reasonable to divide large communities into living units from the perspective of practical functions. However, large communities in China are usually surrounded by commercial entities with larger areas than other functional units. Meanwhile, the number of residential POIs is smaller than that of commercial POIs. Based on these factors, when identifying the block type, the contribution of residential areas to functions cannot eliminate the influence of commercial POIs.

Taking Zhongcun Street, Panyu District, Guangzhou City as an example, several typical large communities are observed, as shown in Figure 9. Area A is Clifford Estates, a famous and typical large residential community in the GBA, with a total area of 500 ha and a permanent resident population of exceeding 300,000. This area was correctly identified as a living function unit based on the collected POIs. However, block B, which is subdivided from region A, was misjudged as a small production and living function unit. The main reason was that this block was classified as artificial land based on the 30 m resolution land cover/use data, and all the collected POIs in this block are parking lots (i.e., P7 type), an issue that persists even when using a combination of POIs and land cover/use data for identification. In fact, high-resolution remote sensing images indicate that it is a pond, and it would be more reasonable to label this block as an ecological unit, considering its physical attributes and dominant functions. Refined land cover/use data are needed to improve the identification accuracy. Areas C and E are also large residential communities with thousands of houses. As the surrounding street includes a few small companies, such as decoration design, garages, retail stores, and others, the number of POIs in non-residential areas is significantly higher. Consequently, these two blocks were misinterpreted as production units, which resulted in a miscalculation. Regarding block D, although it is similar to block C and was classified as artificial land in 30 m resolution land cover products derived from remote sensing images, it is mainly composed of building material companies. Because a few POIs only capture such information, it was correctly recognized as a production block.

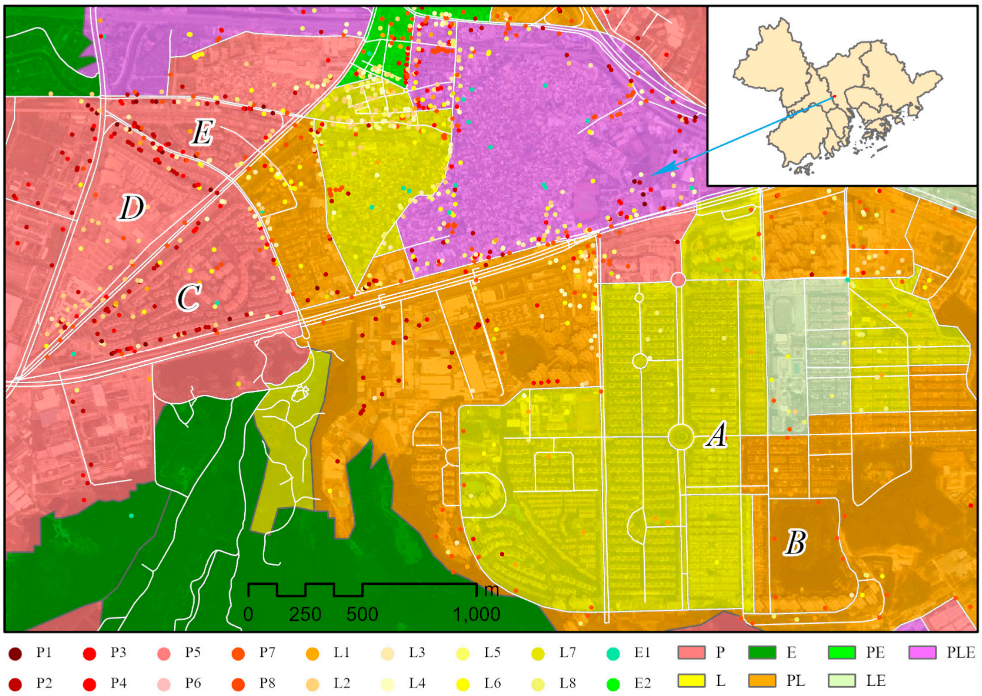


**Figure 9.** Typical cases of identified PLE blocks overlaid with high-resolution imagery, including residential communities (**A**,**C**,**E**) an ecological space (**B**) and a production space (**D**).

The above analysis shows that the identification accuracy of PLE blocks meets the requirements for analyzing territorial spatial structures in the GBA. The weight set for the function contribution of each POI to the corresponding PLE block has proven to be rational, and the method of determining PLE functions at the block level could be applied to other regions. However, deficiencies were observed when more precise influence and relevance values were required, and refined results of PLE blocks are provided at higher resolutions.

### *4.3. Comparing the PLEs with the Land Use Product Derived from High-Resolution Images*

To better illustrate the advantages of our proposed PLE function type identification method over traditional classification results that solely rely on land use/cover data, urban blocks with different proportions of PLE functions were randomly sampled and compared with the ESA global land cover product at 10 m resolution (https://worldcover2020.esa.int/) (accessed on 15 October 2023). The interpretation accuracy of the PLE blocks was further validated using high-resolution imagery from Google Earth (Figure 10).

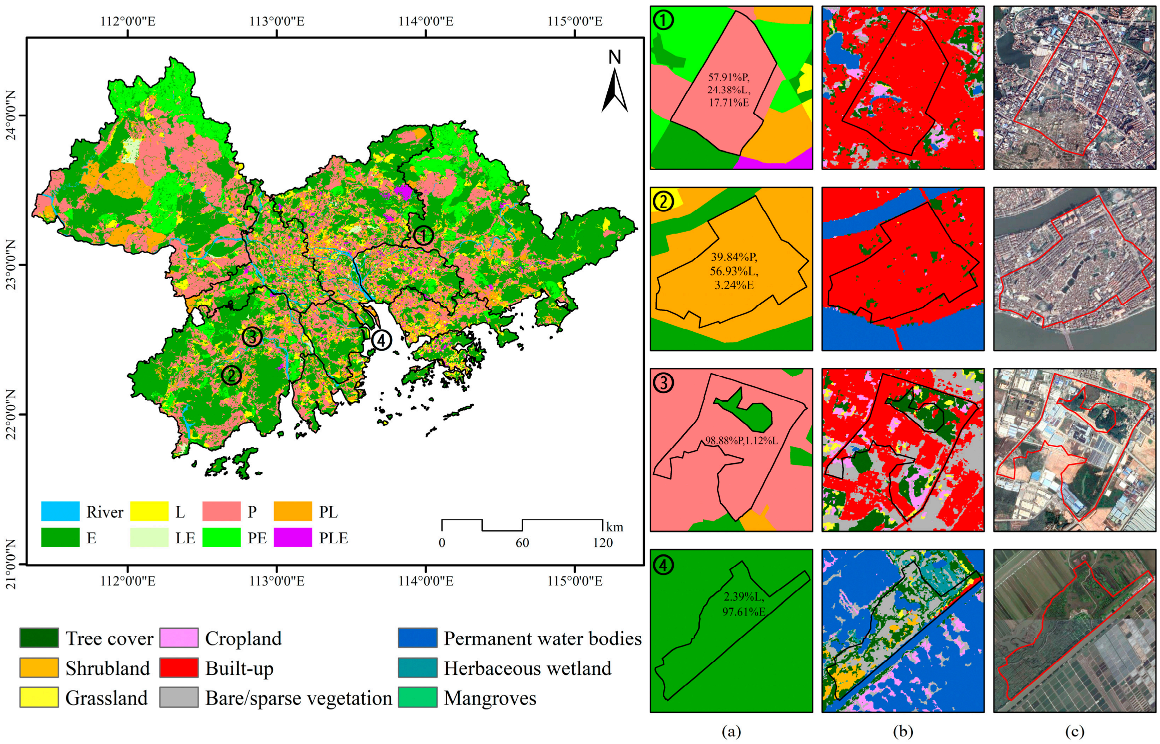


**Figure 10.** Comparison between PLE identification result and classification product. (**a**) Examples of PLE identification results in this study. (**b**) ESA land cover product at 10 m resolution. (**c**) Google Earth images. ①–④ are the examples for the comparison.

Taking blocks ① and ② as examples, despite both being categorized as 'Built-up' in the classification product, the actual dominant functions of these two blocks are inconsistent. According to our recognition results, block ① is dominated by production function, while block ② is interpreted as a unit mixed mainly with production and living functions. This indicates that while ground objects can be classified from high-resolution images at a fine scale, functional units within the same land use type cannot be efficiently separated. Coupling POI big data with classic social attributes can facilitate better interpretations of production and living functions [22,51]. Although the accuracy of PLE recognition has improved somewhat, it still has limitations. For instance, a segment of block ③ should have been defined as an ecological unit according to the high-resolution image from Google Earth, but the proportion of ecological function calculated from multiple open-source data was 0% in this study. Two main factors may have contributed to this recognition error. Firstly, each block was labeled as a primary type of PLE function through reclassifying land cover/use data. Therefore, any inaccuracies in the land cover/use classification within the blocks would subsequently affect the identification result. Secondly, the lack of ecological attributes in POIs in the block may also lead to the under-identification of PLE functions. This may require finer land cover data [52] or further coupling with other big data, such as the spatial relationship between urban functional zones [53], to better address the issue. As for block ④, this demonstrates that with an accurately classified land cover product and sufficient POI data in the block, even a small proportion of functional units can be identified using our method. Overall, although the proposed method may lack precision when land classifications are inaccurate and POIs are insufficient, it still maintains a certain level of accuracy and reliability compared to the identification results obtained solely from high-resolution remote sensing images. In future studies, consideration will be given to combining finer land use/cover data with other spatial relationship data and further utilizing the synergy mechanism between remote sensing images and POIs to map high-precision and wide-range PLE function units.

### *4.4. Uncertainties and Future Work*

It is noteworthy that despite the fact that PLE function identification has received widespread academic attention in recent years, a clear and unified standard for its classification is currently lacking [21]. Building upon previous research, this study utilized land use/cover data and POI data as the core and assigned weights based on different attributes and POIs to identify different types of PLE function from a block-level perspective. Overall, this approach combines human activity characteristics with physical environment characteristics to effectively and extensively identify the PLE function types of urban spaces, yielding relatively accurate results. This approach provides an effective demonstration case and data basis for optimizing the identification of function types in urban agglomerations. However, there remains room for optimization in this methodology. Primarily, the identification of PLE function types in this study heavily depended on the types and attributes of POI data, with the weight assignment process still having potential for improvement. Some scholars have collected a large number of statistical data or indicators to construct correlation evaluation models to optimize weight assignments [54]. Secondly, the resolution of the land use/cover data also influences the recognition of PLE function types. A limitation is that only one type of artificial land use can be classified to describe urban conditions, and internal structures cannot be separated from each other [15]. Therefore, future research can consider the incorporation of more human activity characteristics. In addition to existing human activity data, integrating peak travel patterns and vehicle data [17] could more effectively assist POI data in distinguishing between production and living functions.

Future research could also combine POI data with innovative classification methods of remote sensing images at a finer scale. Moreover, a temporal combination dataset of POI, OSM, and LUCC data should be established to generate dynamic patterns of refined PLE functions at the block level, which could be used to diagnose the coordination degree of PLE functions and promote an optimal combination structure.

## 5. Conclusions

Land use/cover change data, particularly those classified from satellite remote sensing images, have long been regarded as important materials for recognizing the landscape structure of earth surfaces in large areas. The main limitation of this method is that only comprehensive land use/cover types, namely, construction land, water area, and forest land, can be identified and separated. Thus, this method cannot identify the refined structure of PLE functions regarding human–land relationships for spatial planning and regulation.

This study proposed a PLE identification framework based on the combined application of LUCC, OSM, and POI data in urban agglomerations. The main conclusions can be summarized as follows: (1) POI big data can further identify PLE functions in large-scale areas based on remote sensing classification data. (2) This technique can provide more refined information for analyzing the inner pattern of PLE functions and overcome the limitations of coarse identifications in dense urban areas based solely on land cover/use data. These data can effectively separate dominant functions and different combination functions at the block level. (3) Our accuracy validation indicated that the combined use of POIs and land cover/use data can efficiently separate multiple and mixed functions of the same land use type. (4) A great difference was observed in the dominant function types among the cities in the GBA, and the ratio of mixed functions presents spatial heterogeneity and is closely related to the development of land resources and socio-economy. If dynamic open-source data can be acquired, the evolution pattern of PLE functions can be efficiently detected, which is highly significant for providing scientific evidence for the regulation of landscape patterns in territorial spatial planning. In future work, research could be further improved in two aspects: considering more human activity characteristics and building high-precision and multi-scale PLE function type recognition.

**Author Contributions:** Conceptualization, B.A. and S.M.; methodology, S.M. and Z.L.; software, Z.L.; validation, B.A., S.M. and Z.L.; formal analysis, B.A.; investigation, S.M.; resources, B.A.; data curation, Z.L.; writing—original draft preparation, B.A.; writing—review and editing, B.A. and Z.L.; supervision, S.M.; funding acquisition, B.A. All authors have read and agreed to the published version of the manuscript.

**Funding:** This research was supported by the National Natural Science Foundation of China [grant number 42071261], Open Fund Project supported by Key Laboratory of Marine Environmental Survey Technology and Application, Ministry of Natural Resources [grant number MESTA-2021-A005], the Project supported by the Basic and Applied Basic Research Foundation of Guangdong Province [2020A1515011225].

**Data Availability Statement:** Data will be made available on request.

**Acknowledgments:** The authors gratefully acknowledge editors and reviewers for raising suggestions and comments on this paper.

**Conflicts of Interest:** The authors declare no conflicts of interest.

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