sustainability

MDPI

Article

Exploring the Spatial Pattern of Retail Businesses in Chengdu Based on the Coupling of Nighttime Light Image and POI Data

Ling Jiang *, Binyu Wang, Chuanhui Wen, Tao Zhang and Ji Zhou

School of Resources and Environment, University of Electronic Science and Technology of China, Chengdu 611731, China; binyu_w@126.com (B.W.); tyutwch3914@163.com (C.W.); zhangtao_sre@uestc.edu.cn (T.Z.); jzhou233@uestc.edu.cn (J.Z.)
* Correspondence: jiangl_sre@uestc.edu.cn

Abstract: The rational spatial layout of retail businesses is the foundation for promoting urban economic sustainable development and meeting the growing material living needs of residents. Meanwhile, the spatial correlation between commercial establishments and the population is one of the key factors in achieving a rational spatial layout. This study explores the spatial distribution of retail businesses and its coupling relationship with group activity levels in the central urban area of Chengdu, using a coupling model based on NPP–VIIRS nighttime light images and points of interest (POI) data from various retail outlets in 2023. Results indicate that the spatial distribution of retail commerce in Chengdu exhibits the characteristics of multi-center agglomeration, which is generally consistent with the population distribution. However, the distribution patterns vary among retail areas with different degrees of coupling. In terms of coupling coordination degree distribution, all retail categories show a similar trend to that of Chengdu. The analysis reveals that the retail category significantly influences the coupling degree distribution, while geographical location greatly affects the coupling coordination degree. This research will offer a reference for optimizing a city's commercial spatial structure and scientifically planning enterprise outlet layouts.

Keywords: nighttime light image; POI; spatial coupling; spatial pattern; urban economy

Academic Editor: Antonio Miguel Martínez-Graña

Received: 3 October 2024
Revised: 6 January 2025
Accepted: 16 January 2025
Published: 20 January 2025

Citation: Jiang, L.; Wang, B.; Wen, C.; Zhang, T.; Zhou, J. Exploring the Spatial Pattern of Retail Businesses in Chengdu Based on the Coupling of Nighttime Light Image and POI Data. *Sustainability* **2025**, *17*, 780. https://doi.org/10.3390/su17020780

1. Introduction

As the cornerstone of urban development, business development is increasingly crucial in the process of urbanization. The retail industry has gradually evolved into an indispensable component of business development and a significant indicator of urban prosperity and overall competitiveness. Since the initiation of economic reforms and the opening up of policies, the retail sector has consistently emerged as one of the most fiercely competitive industries in the market, due to transformations in the consumption patterns and capacities of residents, robust promotion by foreign retail enterprises, as well as continuous enhancements in circulation infrastructure and the developmental environment [1].

Recently, the retail industry has emerged as a pivotal driver of domestic demand-led consumption and optimization of the urban industrial structure. In China, the rapid development of urban retail commercial outlets has significantly contributed to urban economic growth. However, various challenges, such as inadequate planning for commercial outlet construction, suboptimal layout of retail outlets, and an imbalanced structure of commercial establishments, have resulted in substantial resource wastage and diminished economic efficiency.

It is crucial to analyze the spatial coupling relationship between different types of retail business and the spatial distribution of the population for developing spatially reasonable retail businesses. This can enhance residents' convenience, optimize urban planning for a seamless transition between old and new governance, and revamp business outlet layouts for enterprises. The corresponding results can provide a reference for the government to optimize urban planning, provide a basis for the layout of modern retail outlets for enterprises, and thus improve the quality of life of residents.

Nighttime light images are a type of remote sensing data that can detect light, fire, and other information on the Earth's surface at night through the sensors on satellites. This type of data serves as a good indicator of human activity. It has been widely used in urban planning, environmental monitoring, economic development, and other fields. As artificial nighttime lights are mainly generated in urban areas, the luminosity values derived from nighttime light images can indirectly reflect the intensity of human activities occurring on the Earth's surface [2]. Presently, this technology finds widespread application in monitoring socio-economic parameters associated with human activities, such as population dynamics, economic growth, and power consumption patterns. Nighttime light images serve as a key source for analyzing urban agglomeration, studying the evolution process of urban systems [3–6], investigating urban economic and industrial development [7], and exploring hierarchical patterns within urban systems [8].

POI (points of interest) data refers to geospatial entities that are closely related to human activities, such as shopping malls, communities, and companies. It is typically represented as a point and encompasses comprehensive attribute information, including type, longitude and latitude coordinates, region, name, and address. The POI data represents a novel generation of geospatial big data that surpasses traditional datasets in terms of broader coverage, enhanced accuracy, faster update speed, and more convenient accessibility [9]. Its extensive applications span various research domains encompassing urban industrial spatial patterns [10,11], delineation of urban functional areas [12], identification of urban centers (boundaries) [13], and analysis of business agglomerations [11,14].

Nighttime light images and the POI data are closely associated with human activities, serving as a common data source for investigating urban spatial structures. Nighttime light images exhibit characteristics, such as abundant data volume, continuous spatiotemporal coverage, wide scope, independence, and objectivity [15]. On the other hand, the POI data possesses attributes like rich information content, rapid update speed, and low acquisition cost. These two types of data can complement each other and present a closely coupled relationship in the spatial dimension, jointly outlining the complex and orderly activity landscape of the city. Consequently, some researchers have explored the integrated application of nighttime light images and the POI data to extract urban built-up areas [13] or study urban economic development [16–18]. However, there is still a lack of overall integration in terms of the spatial coupling relationship between these two types of data.

Nighttime light images can effectively capture the light intensity generated by group activities and reflect the degree of population aggregation; however, they may blur specific regional characteristics [2]. On the other hand, the POI data provides accurate geographic location information but lacks important indicators, such as economic and commercial development scale [19]. Therefore, this study aims to combine the advantages of nighttime light images and the POI data, use nighttime light images to represent group activity information, and incorporate the POI data for behavior analysis to more accurately analyze the coupling relationship between retail commercial spatial distribution and group activity level.

Most existing studies combine nighttime light images with the POI data and explore urban coupling relationships with the help of topological relationships between the data.

Pan et al. (2017) proposed a method for spatializing GDP estimation based on nighttime light images [20]. Wang et al. (2019) used NPP–VIIRS data, POI data, and Weibo check-in data from Beijing, and applied kernel density analysis and overlay analysis to achieve spatial coupling visualization of the data [21]. These methods have significant advantages, as they can deeply understand the coupling relationship between cities, comprehensively present the distribution pattern of elements, and clearly show the location and scope of different functional areas in the city. However, these methods can only conduct qualitative analysis. Liu et al. (2021) used kernel density estimation and normalization coupling model construction methods to obtain the spatial distribution characteristics of retail enterprises in the main urban area of Chongqing, as well as the coupling analysis results between the spatial layout of sub-retail enterprises and regional population [22]. Zhang et al. (2022) integrated and visualized various types of POI data and nighttime light images through methods such as kernel density analysis, data gridding, and bivariate mapping, and finally obtained the coupling correlation analysis results between nighttime light data and POI data in Shaoxing City [23]. The coupling degree and coupling coordination degree models can comprehensively consider the interactions and correlations between multiple factors and can comprehensively reflect the coordination status between systems. At the same time, this model can be used for quantitative analysis, presenting complex relationships with specific numerical values for easy comparison and in-depth research.

As the economic center of western China, Chengdu has demonstrated strong economic strength and a profound industrial heritage. It gathers numerous enterprises and nurtures unlimited innovation and entrepreneurial vitality [24]. Therefore, this study established a model to measure the coupling degree and coupling coordination degree through calculation, quantitatively examined the spatial coupling relationship between various retail business outlets and group activities in the central urban area of Chengdu, and conducted in-depth research on the coupling relationship between different types of retail enterprise group activity levels, classifying and studying their coupling degree and coupling coordination degree in detail. This study will provide valuable insights for optimizing urban commercial spatial structure and scientifically planning enterprise network layouts.

2. Study Area and Data

2.1. Study Area

Chengdu, the capital of Sichuan Province, is located within a geographical range spanning from 102°54′ to 104°53′ E and 30°05′ to 31°26′ N (Figure 1). The commercial space in Chengdu is predominantly concentrated within the central urban area, including 12 administrative districts, named Jinjiang, Qingyang, Jinniu, Wuhou, Chenghua, Xindu, Pidu, Wenjiang, Shuangliu, Longquanyi, Qingbaijiang, and Xinjin. The central urban area of Chengdu had reached a total land area of 4006 square kilometers by the end of 2021 [25]. Meanwhile, the permanent population of Chengdu's central main urban area was recorded as 15,419,400, according to the seventh census data in 2021. In the 2023 national ranking of city business attractiveness, Chengdu leads among emerging first-tier cities in five dimensions: concentration of commercial resources, urban connectivity, citizen engagement, lifestyle diversity, and future adaptability.

Chengdu is an important economic center city in western China and has a significant radiating and driving effect on the economic development of the surrounding areas. The city center of Chengdu serves as a hub for various retail industries. The empirical research conducted on Chengdu city center has strong representativeness and persuasiveness in analyzing the commercial spatial layout of domestic cities.

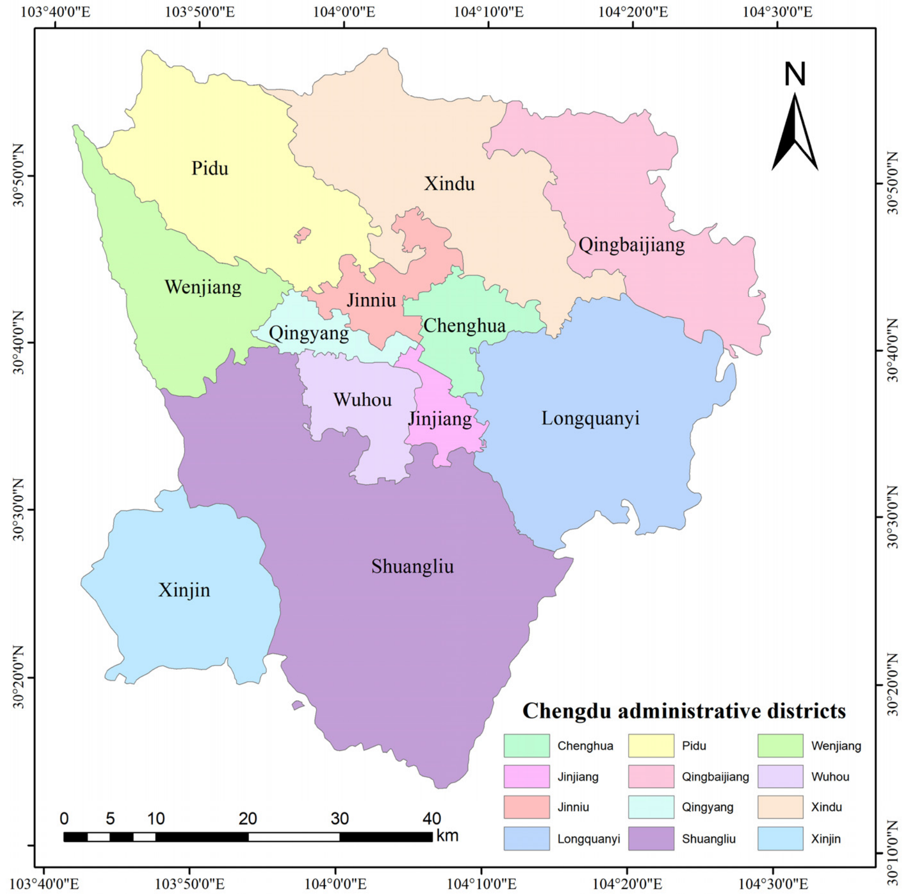

Figure 1. Administrative districts of the central urban area of Chengdu.

2.2. Nighttime Light Image

The nighttime light image utilized in this study was acquired by the NPP–VIIRS (National Polar-orbiting Partnership–Visible Infrared Imaging Radiometer) sensor, which provides a comprehensive and cost-free data resource. The spatial resolution of the data is approximately 740 m. As an innovative source, the NPP–VIIRS nighttime light image data have gained widespread adoption in urban studies [26]. The transit time of the NPP/VIIRS satellite occurs around midnight, which may result in data gaps in certain areas and periods due to cloud occlusion. In this study, we utilized the monthly NPP–VIIRS data from 2023 as our primary research data source. After excluding the abnormal data (February, March, October, and November), the effective data were used to synthesize the annual average image, and the same data from 2022 were used as the reference data for correction.

The original monthly NPP–VIIRS nighttime light images downloaded from the official website of NOAA/NGDA exhibit issues such as projection distortion, negative values, high values, and unstable light sources. Therefore, it is necessary to preprocess the original image to achieve comparability of long-term sequence light data.

In this study, we initially acquired the monthly NPP–VIIRS data for 2022 and 2023 in the central urban area of Chengdu through image clipping, reprojection, resampling, and removal of erroneous images. Subsequently, a series of processes were employed, including elimination of negative values and synthesis of annual mean images, to address unstable light sources and background noise, as well as eliminate extremely high values. Finally, we synthesized the annual average nighttime light images from 2023, by utilizing the monthly nighttime light images from 2022 as correction data. The four fundamental steps undertaken are listed as follows.

Step 1: Image clipping, reprojection, resampling, and removal of erroneous images.

In this study, ArcMap 10.7 software was first used to crop the monthly NPP–VIIRS image data based on boundary data of the central urban area of Chengdu. Then, nighttime light images were reprojected from the WGS_84 projection coordinate system to the Lambert equal area projection coordinate system in the Chinese region to eliminate deformation effects (specific parameters: first standard latitude: 25°0′0′′; second standard latitude: 47°0′0′′; central meridian longitude: 105°0′0′′; projection origin latitude: 0°). To ensure the applicability and comparability of the data in subsequent processing, this experiment performed resampling on the data after geometric reprojection (specific parameters: the sampling resolution is 500 m × 500 m, and the sampling method is cubic spline interpolation). After that, we removed the images with large areas of errors (February, March, October, and November) to reduce the uncertainties of data missing caused by cloud occlusion.

Step 2: Negative value elimination and annual average image synthesis.

After loading all qualified nighttime light images, it was observed that certain monthly data in the central urban area of Chengdu exhibited negative values. However, theoretically, the brightness value of the nighttime light should be non-negative. Therefore, it is imperative to rectify pixels with a negative value. This compensation process involves utilizing the annual average image from the previous year, which can be obtained through Formula (1).

$$DN_i = \begin{cases} DN_i & DN \geq 0 \\ DN_{LYM} & DN < 0 \end{cases} \quad (1)$$

$$DN_{\mathrm{LYM}} = \frac{\sum_{i=n} DN_i}{n} \quad (2)$$

where DN_i represents the monthly nighttime light value of NPP–VIIRS data, DN_{LYM} denotes the nighttime light value derived from the average annual image of the previous year, and n represents the number of qualified monthly images of that year.

A high-quality monthly nighttime light image has been successfully obtained after implementing a series of data preprocessing operations, such as cropping, reprojection to Lambert projection, resampling, and negative value elimination. Compared with the unprocessed image, the preprocessed monthly image appears clearer, with significantly enhanced contrast, making the differences between bright and dark areas more prominent and noticeable (Figure 2).

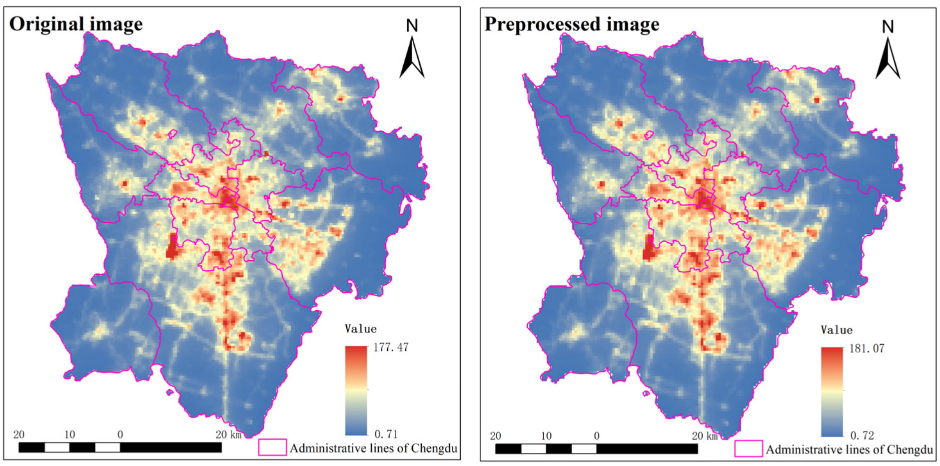

Figure 2. Nighttime light image in January 2023 before and after data preprocessing.

Then, the processed effective nighttime light images are combined into an annual average image to prepare for the next step of processing and analysis.

Step 3: Elimination of unstable light sources and background noise.

Unstable light sources, such as fire, gas, combustion, and volcanoes, are essentially transient light sources. When the light of a particular location does not exist in the previous year, it is considered an unstable light source. Firstly, all annual average images are converted to integers to eliminate weak background lighting values. Then, a binary image is generated based on the results. The 2022 image data is utilized as the benchmark for calculation in this study, and the raster calculator is employed to generate results based on Formula (3). Finally, the obtained outcomes are multiplied by the initial image to mitigate the influence of unstable light sources.

$$DN = \begin{cases} 1 & DN_{J-1} = 1 \;\; and \;\; DN_J = 1 \\ 0 & DN_{J-1} = 0 \;\; or \;\; DN_J = 0 \end{cases} \tag{3}$$

where the DN represents the stable light source in the mean image of the year to be corrected (the year after the reference image), while DN_{J-1} refers to the stable light source in the reference image, and DN_J encompasses all light sources in the mean image of the year to be corrected.

Step 4: Elimination of extremely high value.

The maximum nighttime light value is assumed to represent the peak illumination in the central area of a major urban center, as referenced in the literature [18]. Taking into account economic development principles, it is expected that the maximum nighttime light value for 2023 will not be lower than that of 2022. This study used a focus analysis tool to perform a 3 × 3 mean filtering correction on outlier points in the annual mean image from 2023 to remove the influence of extremely high values.

A stable annual average image was obtained after performing a series of operations, such as eliminating unstable light sources and background noise and eliminating extreme values on the average nocturnal nighttime light images for 2023. Compared with the unprocessed images, the preprocessed annual images highlight the real light source information, and are more accurate and stable, thus providing strong support for more accurate analysis and research (Figure 3).

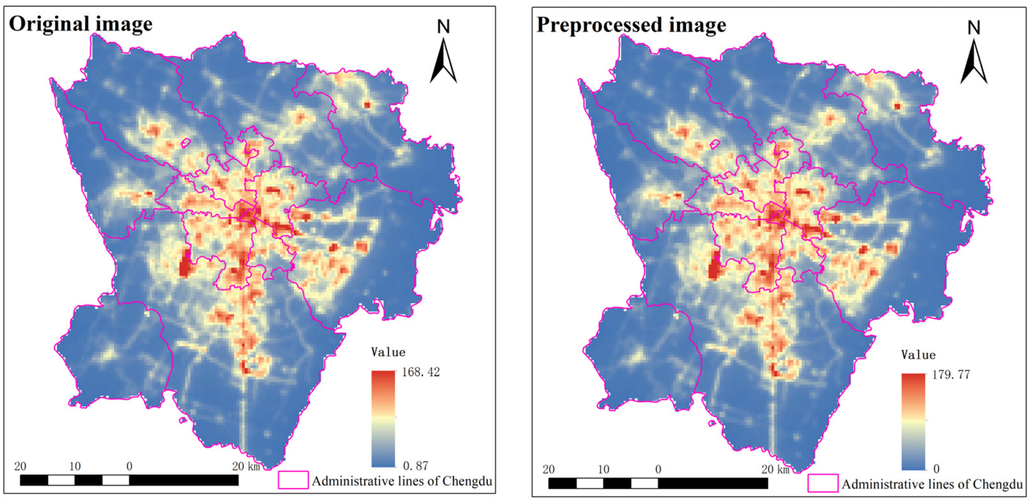

Figure 3. Annual average nighttime light image for 2023 before and after data preprocessing.

2.3. POI Data

The POI data utilized in this study was obtained from the Gaode map open platform (https://lbs.amap.com/, updated in December of 2023) using web crawling based on the amap-poi tool (https://github.com/Civitasv/AMapPoi (accessed on 2 October 2024)).

Finally, a total of 176,711 records from 15 subcategories were selected as the POI data for the retail industry based on the Gaode map's shopping service category under its POI classification, adhering to China's retail format classification standard (GB/T18106-2004) [27] and considering regional data comprehensiveness and integrity.

To ensure research accuracy and data quality, it is imperative to process and screen the POI data. The specific steps involved are as follows:

Step 1: Data cleaning.

In the extracted POI data, some attribute values of the POI data may be missing or duplicated due to errors in the crawling operation, necessitating data cleansing. Subsequent spatial geocoding and inverse coding matching were performed, resulting in the removal of duplicate entries and elimination of low recognition points through telephone queries, ultimately yielding 176,711 valid data.

Step 2: Data classification.

The retail POI data in the shopping service category have been selected based on classification standards provided by Gaode Map Open Platform, encompassing a total of 15 subcategories, namely Convenience Store, Supermarket, Auto Sales, Clothing Store, Plants & Pet Market, Home Electronics Hypermarket, Home Building Materials Market, Cosmetics Store, Auto Parts Sales, Shopping Plaza, Commercial Street, Farmer's market, Stationery & Sports Store, Pharmacy and Franchise Store.

Step 3: Data format conversion and reprojection.

The data format of the acquired POI data was changed from CSV format to the shapefile file format. Meanwhile, its projection was changed to the Lambert projection coordinate system (Figure 4).

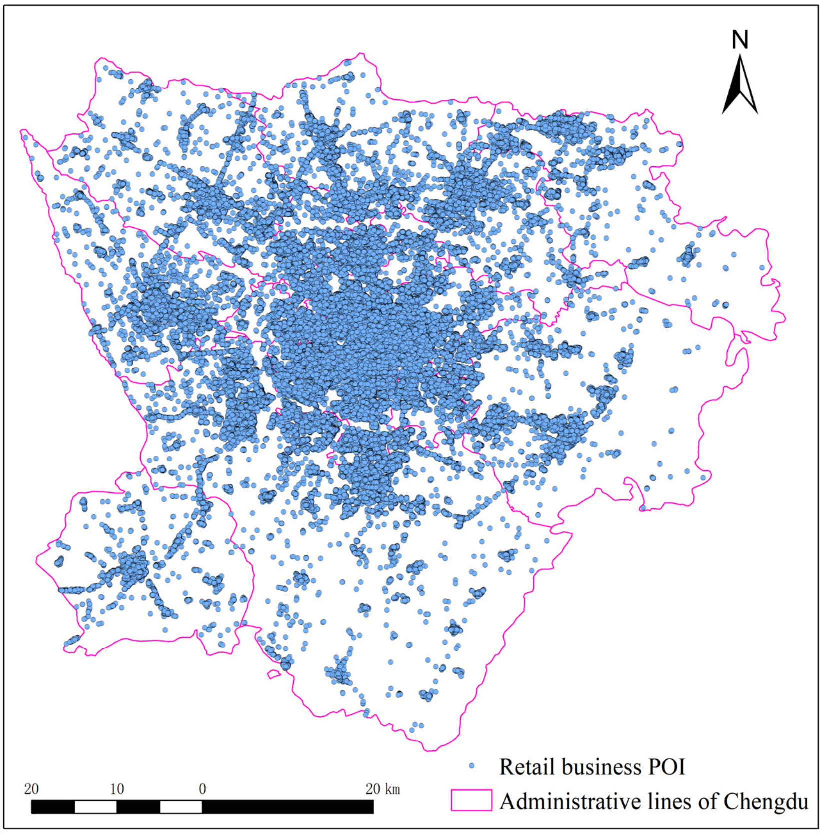

Figure 4. POI distribution of retail businesses in the central urban area of Chengdu.

3. Methodology

The spatial relationship between the POI data of retail commerce in the central urban area of Chengdu and the nighttime light image was visualized using various methods, mainly including kernel density analysis, variable normalization, data gridding, two-factor mapping, and constructing a unified coupling model.

These methods have significant advantages in characterizing the spatial agglomeration characteristics of retail enterprises, unifying data standards, integrating multi-source data, and visualizing multi-factor spatial relationships [21]. They can more accurately present the spatial distribution patterns and coupling characteristics of the retail industry, providing more scientific and effective decision-making for commercial planning.

3.1. Kernel Density Analysis

The kernel density analysis method was employed to calculate the spatial density of a specific type of service industry in its surrounding neighborhood, facilitating the examination of agglomeration patterns within the study area. This method essentially involves computing the value per unit area based on point elements, subsequently fitting each point or line into a smooth conical surface and ultimately generating a continuous density surface (Figure 5). The kernel density estimation can be broadly elucidated as assigning weights to individual events throughout the analysis process, by leveraging a clustering algorithm for data density function. Greater weight is assigned to service industries located closer to the central point, while those situated further away receive comparatively lower weightage.

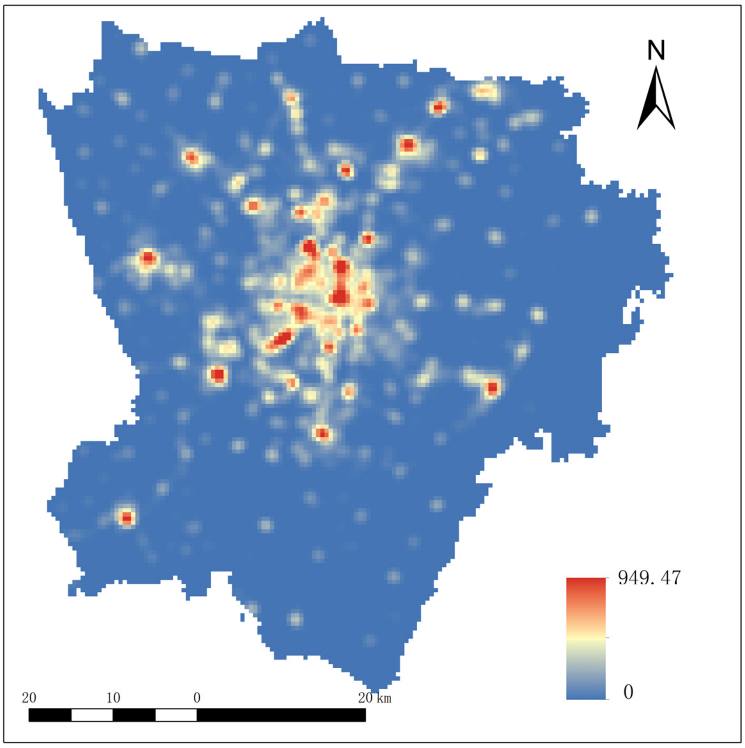

Figure 5. Distribution of POI kernel density of retail businesses in main urban areas of Chengdu.

The calculation formula can be expressed as follows:

$$f(x) = \frac{1}{nh^2\pi}\sum_{i=1}^{n} K\left[\left(1 - \frac{(x-x_i)^2 + (y-y_i)^2}{h^2}\right)\right]^2 \quad (4)$$

where $f(x)$ is the kernel density calculation function of a retail enterprise outlet, K represents the kernel function, while $(x - x_i)^2 + (y - y_i)^2$ indicates the distance between point (x_i, y_i) and (x, y), h refers to the bandwidth parameter, and n signifies the number of POI points within a specific range. To determine an appropriate bandwidth for kernel density estimation, it is essential to consider both spatial dispersion and regional research scale. This study effectively addresses these requirements by adopting Silverman's rule of thumb [28] to calculate an optimal bandwidth value.

$$SearchRadius = 0.9 \times min\left(SD, \sqrt{\frac{1}{ln(2)}} \times D_m\right) \times n^{-0.2} \tag{5}$$

where SD is the weighted standard distance, which is calculated by considering the regional scale and geographical characteristics of Chengdu's main urban area, D_m represents the weighted median distance, and n denotes the total number of POI points. To match the spatial data of subsequent operations, an output cell size of 500 m is selected.

3.2. Variable Normalization

Normalization is the process of transforming data to fit within a specific range required for research purposes. Data normalization helps to improve the comparability of different types of data and avoid the impact of different dimensions. The normalization formula used in this study normalizes the nighttime light image and POI kernel density data to the range [0, 1] (Figure 6).

$$x_{nor} = \frac{x - x_{min}}{x_{max} - x_{min}} \tag{6}$$

where x_{nor} is the normalized result, x is the nighttime light image and POI kernel density data to be normalized, and x_{max} and x_{min} are the maximum and minimum values in the data to be normalized, respectively.

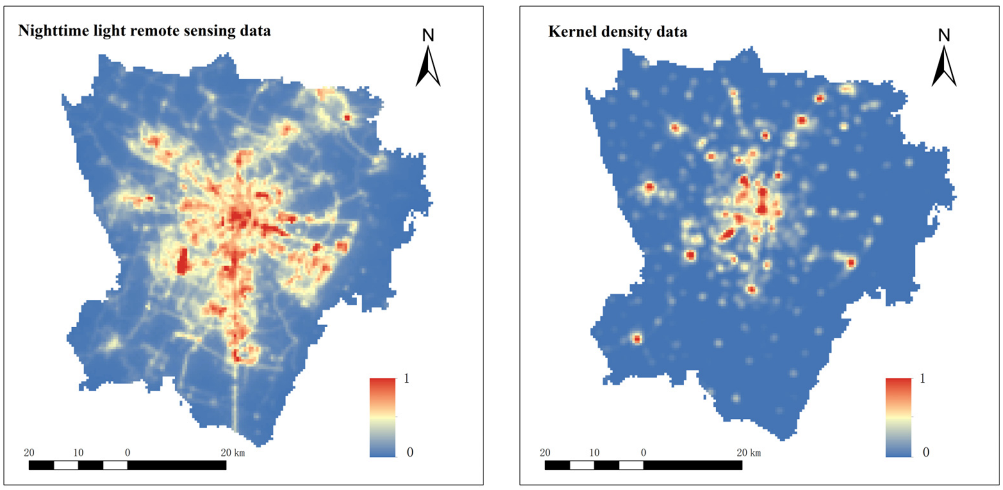

Figure 6. Normalized nighttime light image and normalized POI kernel density data for 2023.

3.3. Data Gridding

Data gridding refers to the process of dividing and storing spatial data and attributing data using grids of different scales, inspired by the concept of grid maps [29]. It transforms point data within a space into two-dimensional planar data based on spatial topological relationships, thereby achieving more efficient data storage and processing. Unlike traditional administrative divisions, the gridded approach enables pixel-level analysis, where each grid can not only contain administrative attributes but also accommodate data, such as light brightness, POI kernel density values, and population density. Data gridding can unify various raster data standards, facilitating a comparison and analysis of different types of data, and can improve the convenience and efficiency of information. This study uses the most commonly used quadrilateral grid for raster data gridding.

In this study, we first used ArcMap software to create a raster grid with a resolution of 500 m × 500 m, then clipped it to the size of the central urban area of Chengdu. Subsequently, the previously processed data is subjected to raster-to-point conversion, followed by interpolation analysis using the inverse distance weighting method. Finally, the interpolation results are extracted into the fishnet surface to form unified gridded data (Figure 7).

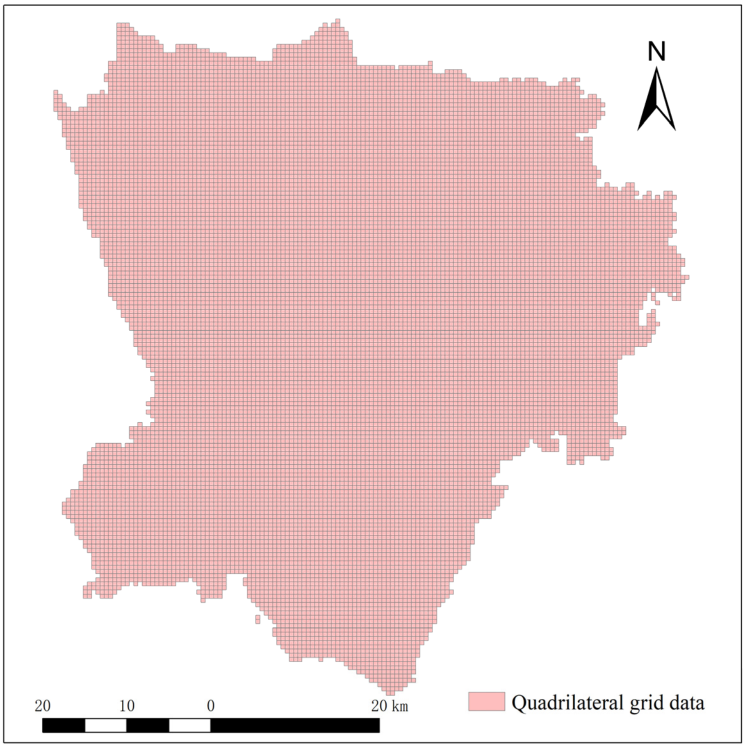

Figure 7. Quadrilateral grid data in main urban areas of Chengdu.

3.4. Construction of Unified Coupling Model

The coupling degree is a measure of the degree of close connection between two things. Analyzing the coupling relationship between business distribution and group activity level distribution to test the degree of interaction and influence between them in space. The nighttime light image brightness value is used to replace the group activity level distribution, the dispersion standardization formula is used to normalize the POI kernel density data and nighttime light image brightness value, and the coupling degree model between commercial space and population size is constructed for analysis. See the coupling degree and coupling coordination degree model in document [26] for the specific model:

When $n = 2$,

$$C = \sqrt{\frac{U_1 U_2}{\left(\frac{U_1+U_2}{2}\right)^2}} = \frac{2\sqrt{U_1 U_2}}{U_1 + U_2} \tag{7}$$

where C is the coupling degree, indicating the strength of the coupling relationship between systems, U_1 and U_2 are normalized nighttime light brightness and POI kernel density data, respectively. The range of the coupling degree C is [0, 1], The higher the value of C, the higher the coupling degree between the two datasets; and, on the contrary, the lower the value, the lower the degree of coupling between them. That is, the coupling degree C quantifies the level of concordance between the brightness of nocturnal illumination and the density value of POI, with lower values indicating a weaker correspondence and higher values indicating a stronger correspondence.

$$T = \sum_{i=1}^{n} a_i \times U_i,\ \sum_{i=1}^{n} a_i = 1 \quad (8)$$

where T is a comprehensive evaluation index, reflecting the complementary relationship between subsystems and a_i is the weight of the i subsystem. Here, it is considered that the nighttime light image brightness is as important as the POI kernel density value, that is, a_i is equal to 0.5.

$$D = \sqrt{C \times T} \quad (9)$$

where D represents the coupling coordination, reflects the benign coupling degree in the coupling interaction relationship, and describes the coordination quality of the relationship.

The coupling coordination degree D is classified as follows: "Lower" indicates a situation characterized by both low levels of nighttime light brightness and POI kernel density, referred to as "low–low"; "Low" corresponds to the combined levels of "low–medium" and "medium–low"; "Medium" corresponds to the combined levels of "low–high", "high–low", and "medium–medium"; "High" corresponds to the combined levels of "medium–high" and "high–medium"; while finally, "Higher" represents the highest level denoted as "high–high".

3.5. Two-Factor Mapping

Two-factor mapping is a visualization analysis method that can be used to show the coupling relationship between two variables. This method divides two variables into three according to their values and adopts a 3 × 3 grading method so that the combinations of high and low values of the two variables form a gradient and certain distinguishability [23]. In this study, two-factor mapping can demonstrate the relationship between the distribution of retail enterprises and group activity levels, which helps to discover spatial distribution patterns and coupling characteristics.

4. Results and Discussion

4.1. Overall Spatial Coupling Relationship

The visualization of the spatial relationship between nighttime light image and the POI data in the central urban area of Chengdu for 2023 is presented, and the resulting visual analysis examines the similarities and differences in coupling between the spatial distribution of retail enterprises and group activity level.

Results illustrate that the coupling degree C ranges from 0 to 1, while the coupling coordination degree D ranges from 0 to 0.810366. This conforms to the definition of the two concepts, and the total strength of the interaction must be greater than the strength of the benign interaction.

To accurately reveal the natural distribution law of data, this study uses the natural breaks classification method to determine the optimal data grouping strategy. The method can maximize the similarity of the same type of data and enhance the differences between different types of data. In this study, the coupling degree C and the coupling coordination degree D are classified into five levels: Lower, Low, Medium, High, and Higher, based on the natural breakpoint classification method (Table 1).

As shown in Figure 8, the coupling degree in the central region of the study area is higher and gradually decreases towards the periphery. Moreover, multiple highly coupled centers exist within the region, with significantly higher coupling degrees observed in the northern and western areas compared to their southern and eastern counterparts.

Table 1. Classification of coupling degree *C* and coupling coordination degree *D*.

	Lower	Low	Medium	High	Higher
C	0.154089	0.384880	0.615653	0.841648	1
D	0.070372	0.163609	0.288939	0.439606	0.810366

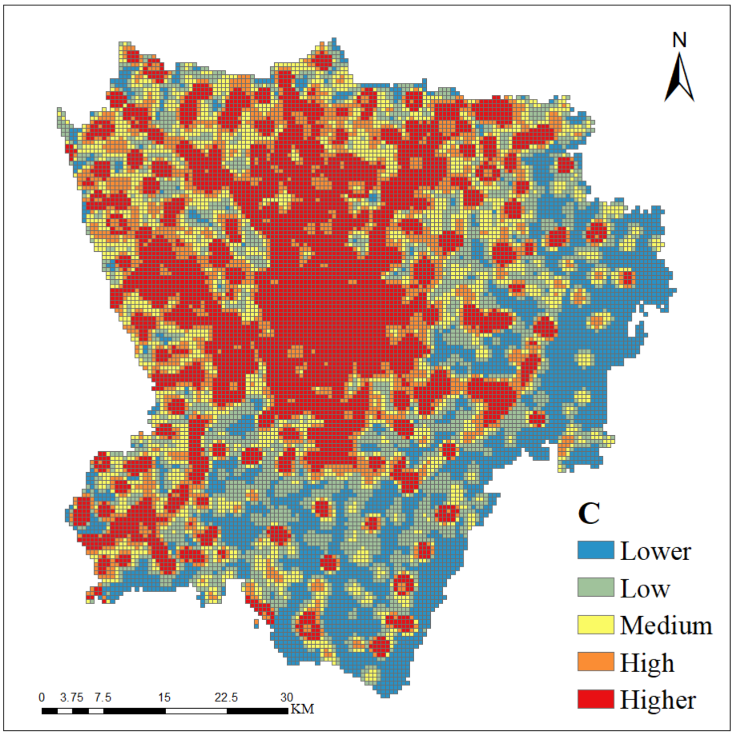

Figure 8. Coupling degree of nighttime light brightness and POI kernel density in Chengdu central urban area for 2023.

Table 2 presents statistical data on coupling degrees. It shows that regions characterized by medium or above levels of nighttime light brightness and retail POI kernel density accounted for 63.50% of the total study area, while areas exhibiting lower coupling degrees constituted 19.40%. These findings suggest that, despite considering the spillover effect of the nighttime light image, a mismatch between retail commercial activity intensity and group activity level distribution persists in Chengdu.

Table 2. Proportion of coupling degree *C* and coupling coordination degree *D*.

	Lower	Low	Medium	High	Higher
C	0.1940	0.1710	0.1613	0.1546	0.3191
D	0.1420	0.0590	0.0895	0.1136	0.5959

As shown in Figure 9, the areas with higher coupling coordination are more concentrated in the central part of the study area, and gradually decrease from the center to the surroundings, compared to the coupling degree diagram. This phenomenon further highlights the key position of the central area in urban commercial activities, as well as the more coordinated relationship between commercial activities and group activities.

According to Table 2, a statistical analysis of coupling coordination degree data reveals that medium and above levels of coupling coordination degrees for nighttime light brightness and retail POI kernel density account for 79.90% of the total study area. This indicates that, in Chengdu, there is a moderate or higher level of coupling coordination between retail commercial activities and group activity levels in most areas. Among them, the proportion of regions with a medium or higher coupling coordination degree is higher than the corresponding proportion of the coupling degree, which indicates that the high interdependence of the two, through effective coordination mechanisms, makes it possible to achieve a better overall performance in maintaining stability and promoting growth. There is still a relatively underdeveloped portion covering 14.2% of the total study area—referred to as the "low–low" level—characterized by low nighttime light brightness and retail POI kernel density. This may be due to the relatively lagging economic development in these areas, incomplete infrastructure, outflow of population, etc. These factors interact with each other, leading to both retail commercial activities and group activities being at a low level, and the coupling coordination degree is poor.

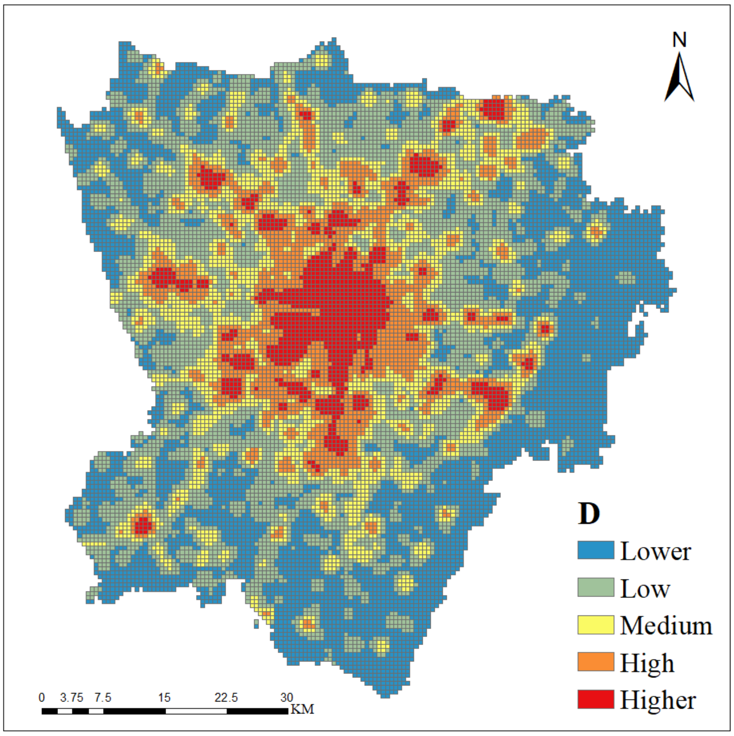

Figure 9. Coupling coordination degree diagram of nighttime light brightness and POI kernel density in Chengdu central urban area for 2023.

In summary, the overall spatial coupling relationship between the distribution of retail commercial space in Chengdu and the level of group activities shows certain complexity and significant differences in different areas. Further in-depth research and analysis are needed to provide more targeted references for urban commercial planning and enterprise layout.

4.2. Spatial Coupling Relationship Among Administrative Regions

To deeply analyze the differences between various administrative regions in Chengdu in terms of the coupling of retail commerce and group activities, this study has analyzed the relevant data of each administrative district in the central urban area of Chengdu.

As shown in Table 3, the top five districts in the order of coupling degree between the nighttime light brightness and POI kernel density in Chengdu, from high to low, are Wuhou, Jinniu, Qingyang, Jinjiang, and Chenghua. As shown in Table 4, the top five districts in the order of coupling coordination degree are Wuhou, Qingyang, Jinniu, Jinjiang, and Chenghua.

Table 3. Classification ratio of coupling degree *C* for each district for 2023.

	Lower	Low	Medium	High	Higher	Medium and Above
Wuhou	0	0.0121	0.038	0.1226	0.8273	0.9879
Jinniu	0.0091	0.0492	0.0783	0.1457	0.7177	0.9417
Qingyang	0.003	0.0788	0.097	0.1182	0.703	0.9182
Jinjiang	0	0.0651	0.0945	0.2248	0.6156	0.9349
Chenghua	0.01	0.1116	0.1295	0.2211	0.5279	0.8785
Wenjiang	0.0325	0.0853	0.2181	0.2524	0.4116	0.8821
Pidu	0.0375	0.1431	0.218	0.1962	0.4053	0.8195
Xindu	0.0498	0.1223	0.2118	0.2336	0.3825	0.8279
Xinjin	0.1923	0.1815	0.1884	0.1676	0.2703	0.6263
Shuangliu	0.2816	0.2422	0.1487	0.1081	0.2195	0.4763
Qingbaijiang	0.3216	0.2038	0.1714	0.1231	0.18	0.4745
Longquanyi	0.4214	0.1992	0.1307	0.1087	0.14	0.3794

Table 4. Classification ratio of coupling coordination degree *D* for each district for 2023.

	Lower	Low	Medium	High	Higher	Medium and Above
Wuhou	0	0.0035	0.1019	0.3817	0.513	0.9966
Qingyang	0	0.1515	0.2	0.2455	0.403	0.8485
Jinniu	0	0.071	0.2004	0.3898	0.3388	0.929
Jinjiang	0	0.0912	0.2704	0.3941	0.2443	0.9088
Chenghua	0.01	0.1932	0.1873	0.3725	0.2371	0.7969
Pidu	0.2644	0.36	0.204	0.1314	0.0402	0.3756
Xindu	0.1725	0.4374	0.2227	0.1289	0.0384	0.39
Wenjiang	0.2559	0.3799	0.2243	0.1029	0.0369	0.3641
Longquanyi	0.5057	0.2354	0.1201	0.1029	0.0358	0.2588
Shuangliu	0.3934	0.2987	0.1714	0.105	0.0314	0.3078
Qingbaijiang	0.5083	0.2541	0.1383	0.0774	0.0218	0.2375
Xinjin	0.4556	0.3992	0.1158	0.0193	0.01	0.1451

The districts with the highest proportion of areas at the higher levels of coupling degree and coupling coordination are both Wuhou, with respective percentages of 82.73% and 51.3%. Similarly, Wuhou also has the highest proportion of areas at the medium and above levels for both coupling degree and coupling coordination, with percentages of 98.79% and 99.66%, respectively. A high coupling degree implies that, in Wuhou, there is a strong match between retail commercial development and group activity level, with a minimal likelihood of oversupply or insufficient supply, indicating a more mature and comprehensive overall construction. However, it also suggests that group activity levels are susceptible to fluctuations in retail commercial activities. A high degree of coupling coordination suggests that retail commercial activities are capable of sensitively and effectively responding to novel changes in group activities, and that the entire system possesses high economic stability and strong resilience against risks.

The nighttime light brightness and POI kernel density coupling degree of 12 administrative regions in Chengdu for 2023 was mapped by two-factor combinations, and the visual nighttime light remote sensing and POI kernel density coupling map of 12 administrative districts in Chengdu was obtained (Figure 10).

As shown in Figure 10, the distribution of coupling degrees in each region is similar to that in the central urban area of Chengdu, which is composed of several centers with higher coupling degrees and zones with decreasing coupling degrees from the center to the surrounding areas. This indicates that within the entire Chengdu city area, there is a certain universal pattern in the mutual relationship between commercial development and population agglomeration. However, due to the unique geographical, economic, and cultural factors of different administrative regions, there are differences in the specific values of the coupling degree and the details of the spatial distribution.

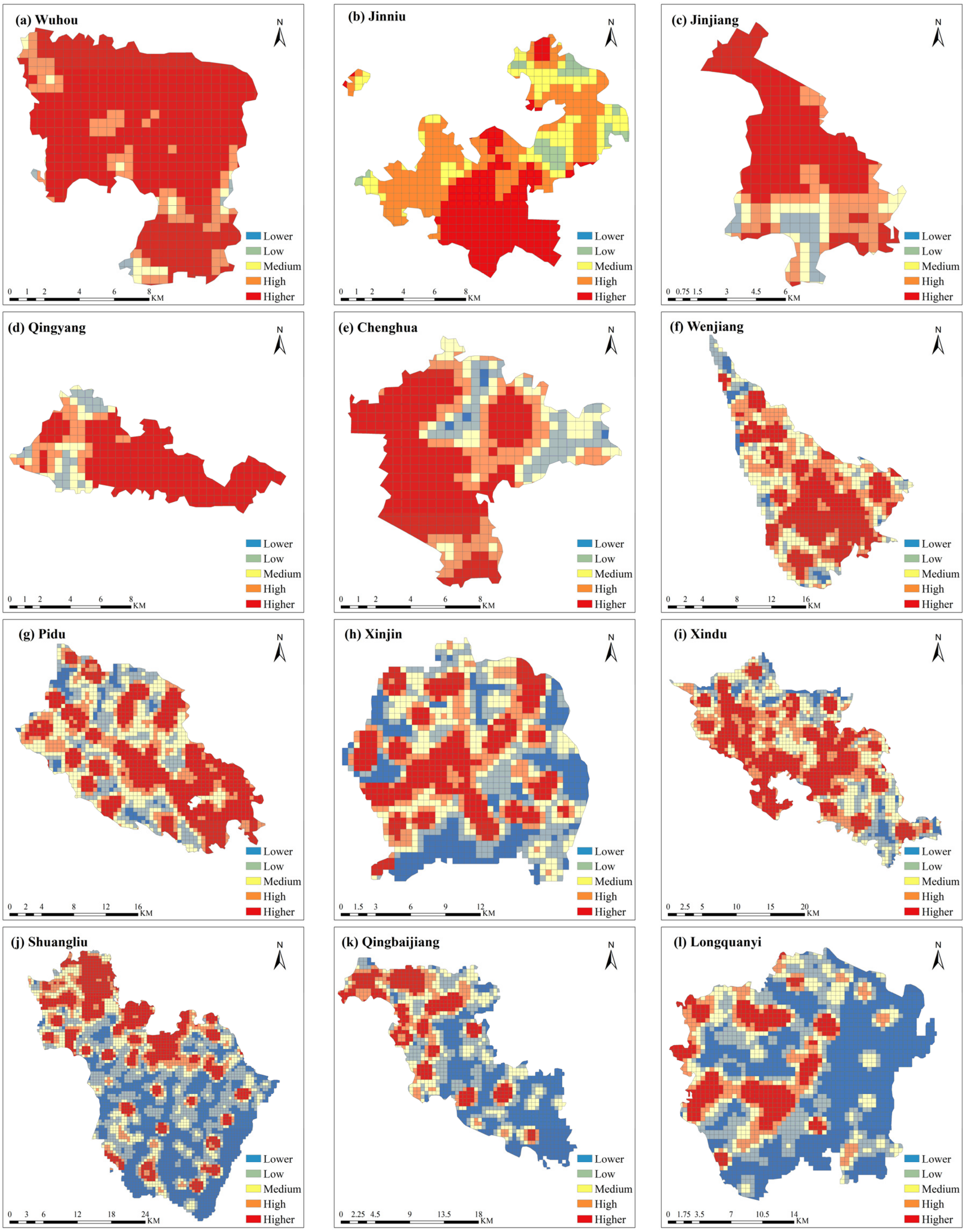

Figure 10. Coupling degree of nighttime light brightness and POI kernel density in Chengdu's Administrative Districts for 2023.

The coupling coordination degree of nighttime light brightness and POI kernel density in 12 administrative districts of Chengdu for 2023 was mapped by two-factor combinations, and the visual relationship between the coupling coordination degree of nighttime light remote sensing and POI kernel density in 12 administrative districts of Chengdu was obtained (Figure 11).

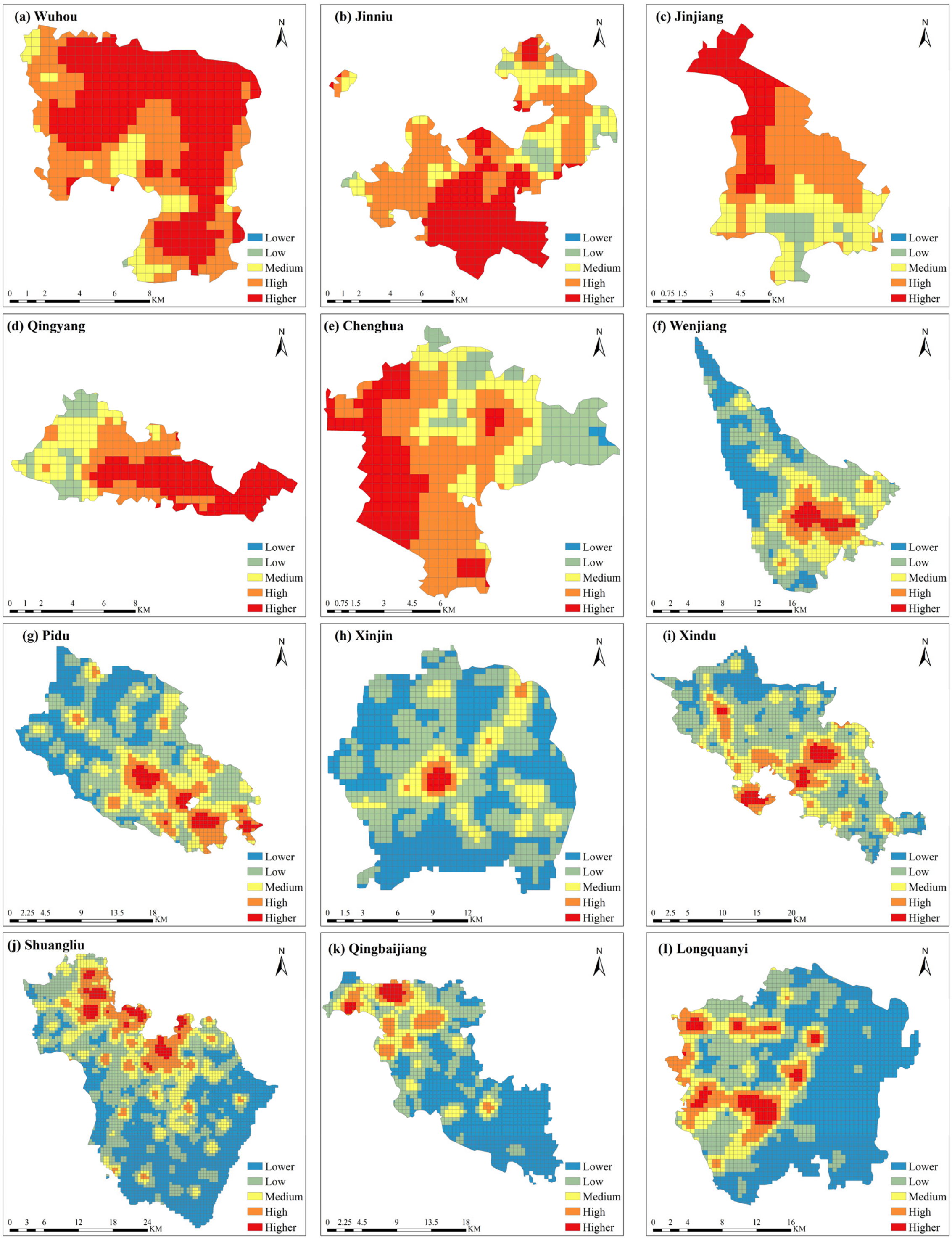

Figure 11. Coupling coordination degree of nighttime light brightness and POI kernel density in Chengdu's Administrative Districts for 2023.

As shown in Figure 11, in most areas, many centers with higher coupling degrees become decremental zones under the coupling coordination degree, with only a few centers maintaining their central status in the coupling coordination degree. Take the more developed Wuhou as an example. Although the coupling degree and coupling coordination level are both high in the same geographical space there are still certain differences. In some emerging commercial streets, although the retail industry is developing rapidly and the coupling degree with group activities is high, there may be improvement in coordinating product supply and adjusting service quality when dealing with emergencies or seasonal consumption fluctuations. This also reflects that, even in areas with high coupling coordination, there is still a need to further optimize the commercial layout and operational strategies.

4.3. Spatial Pattern of Retail Format

It is crucial to fully understand the spatial coupling characteristics of various retail formats for a comprehensive understanding of the retail commercial layout in Chengdu.

As shown in Table 5, the top five retail categories in terms of the proportion of areas with medium and above coupling degrees are home building materials market, convenience store, franchise store, pharmacy, and farmer's market. The coupling degree of the top three categories is relatively close, all exceeding 55%, and there is a significant gap from the other categories. This indicates that these three types of retail businesses are better aligned with the needs of group activities compared to other categories, and fluctuations in the group activity level may also have a greater impact on the operations of these three types of retail businesses.

Table 5. Classification ratio of coupling degree *C* of each retail industry for 2023.

	Lower	Low	Medium	High	Higher	Medium and Above
Home Building Materials Market	0.2301	0.1635	0.1867	0.1998	0.2199	0.6065
Convenience Store	0.1769	0.2269	0.2803	0.2351	0.0809	0.5962
Franchise Store	0.2525	0.1776	0.1805	0.1631	0.2263	0.5699
Pharmacy	0.2972	0.2433	0.2808	0.1582	0.0204	0.4594
Farmer's market	0.3502	0.2514	0.2424	0.1255	0.0305	0.3984
Home Electronics Hypermarket	0.3482	0.2790	0.2474	0.1121	0.0133	0.3728
Supermarket	0.2854	0.3655	0.3046	0.0440	0.0005	0.3491
Clothing Store	0.4971	0.1823	0.1260	0.1045	0.0900	0.3206
Plants & Pet Market	0.4740	0.3521	0.1459	0.0221	0.0059	0.1740
Auto Sales	0.4994	0.3502	0.0986	0.0445	0.0074	0.1504
Auto Parts Sales	0.4547	0.4308	0.0883	0.0202	0.0060	0.1145
Stationery & Sports Store	0.5174	0.3738	0.1038	0.0050	0.0000	0.1088
Cosmetics Store	0.5253	0.3702	0.1023	0.0022	0.0000	0.1045
Shopping Plaza	0.8175	0.1802	0.0023	0.0000	0.0000	0.0023
Commercial Street	0.9476	0.0524	0.0000	0.0000	0.0000	0.0000

As shown in Table 6, the top five retail categories in terms of the proportion of areas with medium and above coupling coordination degrees are home building materials market, franchise store, convenience store, pharmacy, and farmer's market. Although there have been slight changes in the rankings compared to the proportion of coupling, these five retail categories remain in the top five. This indicates that retail business categories that better align with group activity demands will have more development opportunities. Furthermore, after market mechanisms, multiple stores within the same highly coupled and coordinated retail category still need to operate in a 'concentrated' manner geographically, which also demonstrates the close relationship between group activities and these retail businesses.

Commercial streets, shopping plazas, and auto parts sales in the medium and above level coupling degree of the area accounted for less than 10% of the total area.

For commercial streets and shopping malls, although the commercial activity intensity carried by their individual POI data is high, their large spatial scale, comprehensive, and relatively wide service radius led to an unclear data representation of their coupling relationship with surrounding group activities. Commercial streets and shopping malls are often the landmarks and consumption centers of cities, attracting consumers from the entire city including the surrounding areas. The influence of their commercial activities exceeds mere geographical proximity, their low coupling degree may not mean that there is a mismatch, which is also a factor to be considered in future research using the POI data. Commercial streets and shopping plazas in the medium and above level coupling coordination degree of the area accounted for close to 0% of the total area. Due to the business characteristics of these two retail categories, where the majority of group activities and transactions occur on days off, the representativeness of the collected data needs to be improved. Therefore, the low coupling coordination between these two categories cannot be interpreted as a low level of commercial development.

Table 6. Classification ratio of coupling coordination degree *D* of each retail industry for 2023.

	Lower	**Low**	**Medium**	**High**	**Higher**	**Medium and Above**
Home Building Materials Market	0.3446	0.3157	0.2048	0.1214	0.0135	0.3398
Franchise Store	0.3779	0.3015	0.1722	0.1143	0.0341	0.3206
Convenience Store	0.3383	0.3818	0.1967	0.0818	0.0014	0.2799
Pharmacy	0.4296	0.3281	0.1931	0.0493	0.0000	0.2424
Farmer's market	0.4778	0.2953	0.1770	0.0493	0.0006	0.2269
Clothing Store	0.5496	0.2313	0.1401	0.0670	0.0122	0.2192
Home Electronics Hypermarket	0.4668	0.3250	0.1832	0.0233	0.0017	0.2082
Supermarket	0.4527	0.3442	0.1979	0.0052	0.0000	0.2031
Plants & Pet Market	0.5690	0.2937	0.1322	0.0051	0.0000	0.1373
Auto Sales	0.5705	0.3047	0.1169	0.0079	0.0000	0.1248
Stationery & Sports Store	0.6036	0.2743	0.1166	0.0056	0.0000	0.1221
Cosmetics Store	0.5930	0.3024	0.1041	0.0006	0.0000	0.1046
Auto Parts Sales	0.5569	0.3530	0.0820	0.0081	0.0000	0.0901
Shopping Plaza	0.7397	0.2291	0.0310	0.0003	0.0000	0.0312
Commercial Street	0.7991	0.1961	0.0048	0.0000	0.0000	0.0048

As shown in Figure 12, the coupling distribution of the above-mentioned retail categories, whose areas with medium and above horizontal coupling degree account for a large proportion of the total area, is similar to that of Chengdu's downtown area. This indirectly indicates that the coupling degree development of Chengdu's downtown area is related to the coupling degree development of these retail industries. The distribution of retail categories whose regions with medium and above level coupling degrees account for a small proportion of the total region has its characteristics, which may be related to the narrow consumer groups targeted by some retail categories. If the demographic structure of a certain area does not match the target customer group of the brand, it will inevitably lead to a low coupling degree with community activities. This mismatch is more based on the operator's consideration of commercial efficiency and the precise positioning of target customers.

According to Figure 13, the distribution of coupling coordination degree of all retail categories is basically as follows: the center has the highest level of coupling coordination degree, the coupling coordination degree from the center to the outside gradually decreases, and some categories also form sub-centers with relatively high coupling coordination degree around them. In general, it is similar to the coupling degree distribution in Chengdu city center. However, the distribution of retail categories with a small proportion of the area at the medium and above levels of coupling coordination differs from the distribution of those with a small proportion of the area at the medium and above levels of the coupling degree. In the coupling degree distribution, there is a big difference in the distribution trend among these categories. In the coupling coordination degree distribution, the distribution trend of these categories is similar, only the degree of development is different. This shows that the coupling coordination degree and the coupling degree are more affected by the retail category, and the coupling coordination degree is more affected by the geographical location. The closer to the city center, the more policy concerns, social resources, and people flow it has, so that any retail category can pursue more development opportunities.

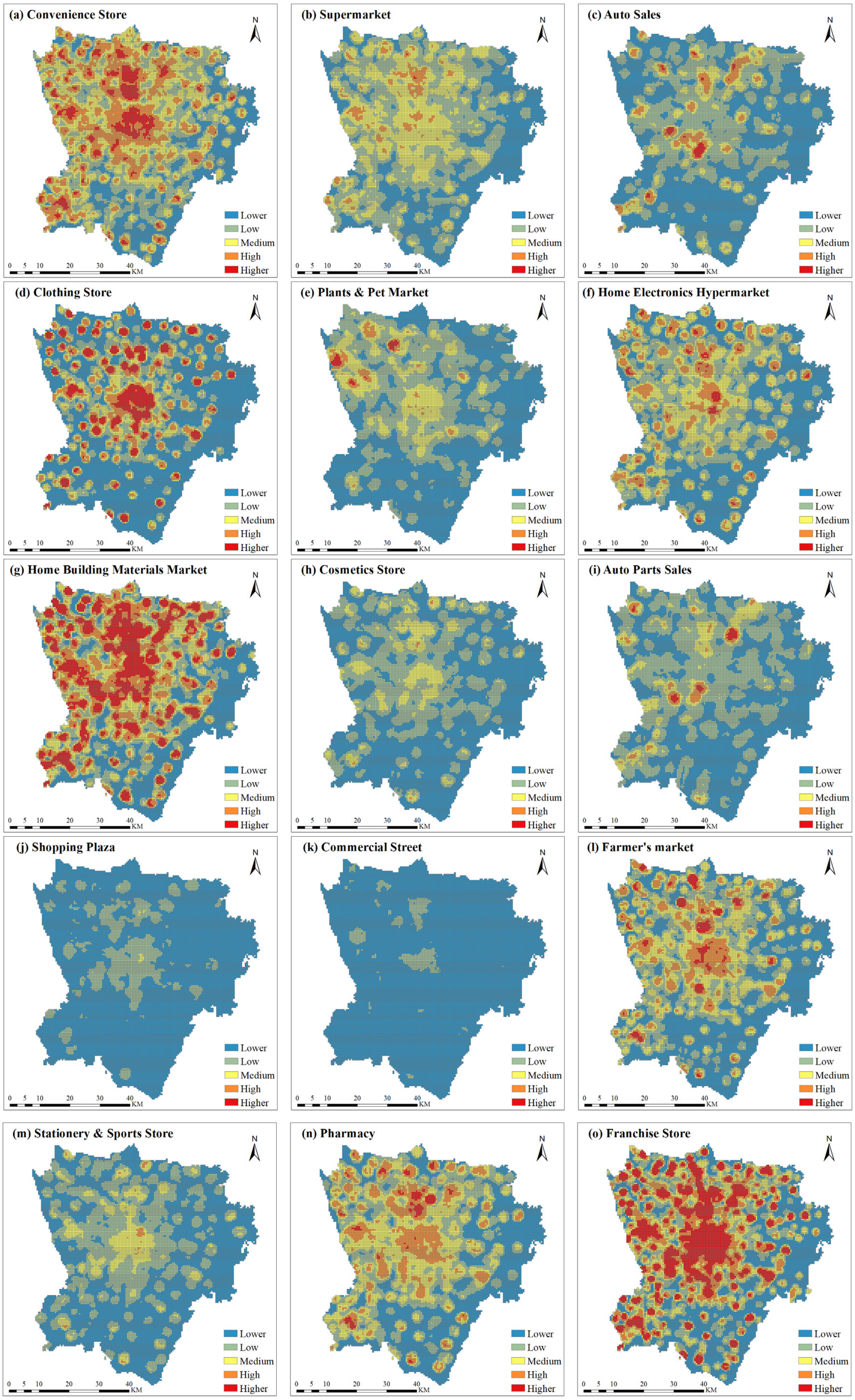

Figure 12. Relationship between nighttime light brightness and kernel density coupling of various types of retail POI for 2023.

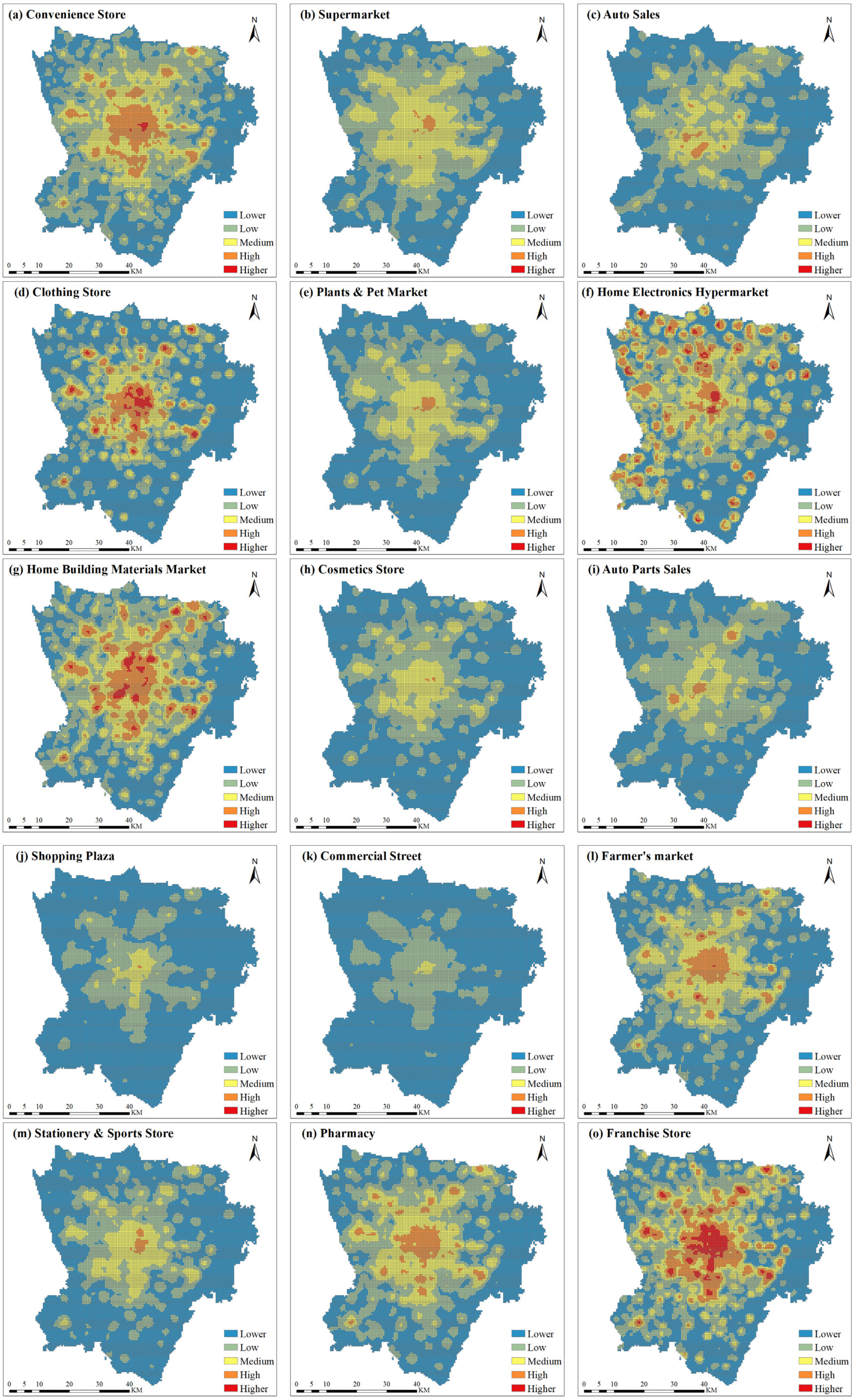

Figure 13. Relationship between nighttime light brightness and kernel density coupling coordination of various types of retail POI for 2023.

In summary, there are significant differences in the spatial patterns of different retail models in Chengdu, which are not only reflected in the degree of group activities but in the distribution characteristics of coupling coordination. In the process of urban commercial planning and retail enterprise layout, these factors should be fully considered, commercial resources should be reasonably allocated, and spatial layout optimized to enhance the overall efficiency and service quality of urban commerce.

4.4. Main Conclusion

The activities of retail enterprises are not evenly distributed in spatial distribution and remain related to the dynamics of group activities. The main findings are listed as follows.

First, in terms of spatial distribution characteristics, the spatial distribution of retail enterprises in the urban area of Chengdu presents the characteristics of multi-center agglomeration of "one area, three belts". That is, the central urban areas of five administrative districts in the central urban area of the first circle are the core to extend to the northwest, northeast, and due south, and it shows the characteristics of polycentric aggregation outside the second circle. In terms of the degree of aggregation, the kernel density values of the five administrative regions in the central urban area are significantly higher than those in other regions.

The "one area, three belts" multi-centered agglomeration pattern may be the result of various factors working together. The five administrative districts in Chengdu's main urban area are the origins or core areas of urban development, featuring complete infrastructure, convenient transportation networks, and rich public service resources. These attract a large population, providing a sufficient customer base for retail enterprises. Historical and cultural factors, commercial traditions, and government planning orientations also play significant roles in the agglomeration of retail enterprises. Additionally, some areas have formed characteristic commercial streets due to their unique historical and cultural backgrounds, such as Kuanzhai Alley and Jinli Ancient Street, which attract specific types of retail enterprises to settle in.

Second, in terms of coupling relationships, the spatial pattern of retail enterprises in the central urban area of Chengdu matches the group activities, but there are also areas with poor coupling of various types of retail formats. This kind of retail enterprise layout is multi-centered in space, similar to the pattern of large cities such as Shanghai and Beijing.

The degree of coupling between different types of retail businesses and community activities varies, which is closely related to the characteristics of the businesses and the needs of consumers. Convenience stores and farmers' markets, for instance, are primarily aimed at meeting the immediate daily needs of residents, and their distribution tends to be close to communities, thus showing a high degree of coupling with the population distribution. On the other hand, large commercial formats, such as shopping malls and commercial streets, are more dependent on the overall consumption capacity of the area, accessibility of transportation, and commercial atmosphere. Their layout may be greatly influenced by urban planning, land use policies, and markets, leading to a more complex relationship with community activities.

Similar to large cities like Shanghai and Beijing, Chengdu's multi-centric retail layout reflects the common patterns found in the urbanization process. As the city size expands and the population grows, a single commercial center becomes insufficient to meet the needs of all residents. A multi-centric commercial layout helps to improve the coverage of commercial services. Chengdu's retail layout focuses on integrating local cultural characteristics and consumer habits, creating distinctive commercial clusters, and thus forming a multi-centric retail layout.

4.5. Relevant Suggestions

Policy implications and suggestions are listed as follows:

First, retail enterprises should fully understand the spatial layout rules of the acceptance industry and adjust measures to local conditions. Retail enterprises can actively participate in the planning of commercial space layout, enhance their initiative in spatial layout, optimize the layout of commercial outlets at the microlevel, fill in the commercial blanks, and strengthen the coupling relationship with group activities. For instance, convenience stores can adjust product types and service hours based on the demographic and consumption needs of the surrounding communities; large supermarkets can consider opening new stores in areas with rapidly growing populations but relatively insufficient commercial facilities to meet residents' one-stop needs.

Second, the decision-making department should reasonably use top-level design means, such as infrastructure construction and relevant preferential policies, to consciously guide the relocation of the business combination of urban business centers, optimize the layout from top to bottom, enrich the business types, and expand the coupling range. For example, increase the investment in infrastructure, such as transportation and utilities, in newly developing urban areas to improve the commercial investment environment; formulate policies, such as tax incentives and rent subsidies, for specific commercial sectors or areas to encourage enterprises to move in or transform and upgrade, thereby promoting the optimization and coordinated development of commercial space.

Third, urban planners need to integrate commercial space planning more closely with the overall urban development strategy. When designing new urban areas or renovating ones, they should reserve sufficient land for different types of retail businesses based on population density and consumer demand forecasts. For instance, in newly built residential areas, space for small convenience stores and community service centers should be reserved at the planning stage to ensure the convenience of residents' daily lives. At the same time, attention should be paid to the reasonable layout of different types of retail businesses to avoid excessive concentration or dispersion. In commercial areas, a good commercial environment should be created by improving the surroundings and public facilities to enhance the appeal of retail businesses.

4.6. Limitations and Prospects

Although this study has conducted a relatively in-depth analysis of the spatial pattern of retail commerce in Chengdu and its coupling relationship with group activities, there are still some limitations.

In terms of data, during the acquisition of the POI data, although a series of data processing and screening were carried out, there may still be some data that are not updated or inaccurate, which could affect the accuracy of the research results. We can strengthen cooperation with POI data providers to ensure timely updates, establish a dynamic monitoring mechanism, and combine field research to calibrate data.

In terms of research models, the coupling degree and coupling coordination degree models constructed in this study, while capable of quantitatively analyzing the relationship between commercial and group activities, are relatively simplified and may not fully consider other potential influencing factors.

Future work can further expand the study area and time range and provide an in-depth analysis of the impact mechanisms of different factors on the evolution of retail commercial patterns. It can also explore how to build a more scientific and reasonable commercial space layout evaluation indicator system to better guide the sustainable development of urban commerce. Specifically, in the new development stage after the pandemic recovery, developing new strategies to make the commercial layout more adapted to the new market demand and changing trends.

5. Conclusions

Taking the main urban area of Chengdu as the research area, this study uses POI data and nighttime light images to study the spatial pattern of urban retail enterprises and their coupling relationship with group activities.

Retail enterprises in Chengdu are distributed in a multi-center cluster of "one area, three zones", with five administrative zones in the central urban area as the core and extending to the surrounding areas. Overall, the spatial pattern of retail enterprises is compatible with group activities, but the coupling situation of some retail formats is not good. This distribution pattern is similar to that of big cities and is the result of the synergistic effect of various factors, such as urban development process, historical and cultural inheritance, and government planning guidance. The multi-center layout effectively improves the coverage and efficiency of commercial services and deeply integrates local characteristic culture.

The following suggestions are proposed in this study: retail enterprises should understand the layout rules, adjust their business strategies according to the community situation, and participate in planning and optimizing their outlets. The decision-making department should make good use of top-level design to guide the migration of commercial centers, optimize layout, and enrich business formats. Urban planners need to combine urban strategies, reserve land based on population and demand, and reasonably layout and improve the commercial environment.

This study also has certain limitations, as the POI data may not be updated in a timely or accurate manner, and the model is relatively simplified, failing to fully cover all potential influencing factors. Future research can further broaden the research area and time span, deeply analyze the mechanisms of various factors on the evolution of retail business patterns and focus on building a more scientific and comprehensive evaluation index system for commercial space layout, to better meet the new trends and demands of commercial development in the post-pandemic era and effectively promote the sustainable development process of urban commerce.

Author Contributions: Conceptualization, L.J.; methodology, L.J.; project administration, L.J.; writing—original draft preparation, L.J.; writing—review and editing C.W. and T.Z.; funding acquisition, L.J. and J.Z.; resources, B.W.; data curation, B.W.; formal analysis, B.W.; visualization, B.W.; investigation, C.W.; validation, C.W.; supervision, T.Z. and J.Z. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by Joint Funds of the National Natural Science Foundation of China (grant number U23A2018), and the University–Industry Collaborative Education Program of the Chinese Ministry of Education (grant numbers 220603776134950 and 230902313160058).

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The raw data supporting the conclusions of this article will be made available by the authors upon request.

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

References

1. Mitchell, A.; Kirkup, M. Retail development and urban regeneration: A case study of Castle Vale. *Int. J. Retail Distrib. Manag.* **2003**, *31*, 451–458. [CrossRef]
2. Yu, B.; Wang, C.; Gong, W.; Chen, Z.; Shi, K.; Wu, B.; Hong, Y.; Li, Q.; Wu, J. Nighttime light remote sensing and urban studies: Data, methods, applications, and prospects. *Natl. Remote Sens. Bull.* **2021**, *25*, 342–364. [CrossRef]
3. Zhang, H.; Liang, C.; Pan, Y. Spatial Expansion of Built-Up Areas in the Beijing–Tianjin–Hebei Urban Agglomeration Based on Nighttime Light Data: 1992–2020. *Int. J. Environ. Res. Public Health* **2022**, *19*, 3760. [CrossRef] [PubMed]

4. Xie, Y.; Weng, Q. Updating urban extents with nighttime light imagery by using an object-based thresholding method. *Remote Sens. Environ.* **2016**, *187*, 1–13. [CrossRef]
5. Chen, Y.; Liu, X.; Li, X. Analyzing Parcel-Level Relationships between Urban Land Expansion and Activity Changes by Integrating Landsat and Nighttime Light Data. *Remote Sens.* **2017**, *9*, 164. [CrossRef]
6. Chai, C.; He, Y.; Yu, P.; Zheng, Y.; Chen, Z.; Fan, M.; Lin, Y. Spatiotemporal Evolution Characteristics of Urbanization in the Xiamen Special Economic Zone Based on Nighttime-Light Data from 1992 to 2020. *Land* **2022**, *11*, 1264. [CrossRef]
7. Ustaoglu, E.; Bovkır, R.; Aydınoglu, A.C. Spatial distribution of GDP based on integrated NPS-VIIRS nighttime light and MODIS EVI data: A case study of Turkey. *Environ. Dev. Sustain.* **2021**, *23*, 10309–10343. [CrossRef]
8. Wu, B.; Yu, B.; Yao, S.; Wu, Q.; Chen, Z.; Wu, J. A surface network based method for studying urban hierarchies by night time light remote sensing data. *Int. J. Geogr. Inf. Sci.* **2019**, *33*, 1377–1398. [CrossRef]
9. Ye, X.; Tan, H.; Zhang, Y.; Zhang, L.; Zhang, Z. *Research on Convenience Index of Urban Life Based on POI Data*; Journal of Physics: Conference Series; IOP Publishing: Bristol, UK, 2020; p. 012073.
10. Zheng, D.; Li, C. Research on Spatial Pattern and Its Industrial Distribution of Commercial Space in Mianyang Based on POI Data. *J. Data Anal. Inf. Process.* **2020**, *8*, 20. [CrossRef]
11. Lu, C.; Pang, M.; Zhang, Y.; Li, H.; Lu, C.; Tang, X.; Cheng, W. Mapping Urban Spatial Structure Based on POI (Point of Interest) Data: A Case Study of the Central City of Lanzhou, China. *ISPRS Int. J. Geoinf.* **2020**, *9*, 92. [CrossRef]
12. Hu, Y.; Han, Y. Identification of Urban Functional Areas Based on POI Data: A Case Study of the Guangzhou Economic and Technological Development Zone. *Sustainability* **2019**, *11*, 1385. [CrossRef]
13. Zhang, J.; Yuan, X.-D.; Lin, H. The Extraction of Urban Built-Up Areas by Integrating Night-Time Light and POI Data—A Case Study of Kunming, China. *IEEE Access* **2021**, *9*, 22417–22429.
14. Xue, B.; Xiao, X.; Li, J. Identification method and empirical study of urban industrial spatial relationship based on POI big data: A case of Shenyang City, China. *Geogr. Environ. Sustain.* **2020**, *1*, 152–162. [CrossRef]
15. Li, X.; Elvidge, C.; Zhou, Y.; Cao, C.; Warner, T. Remote sensing of night-time light. *Int. J. Remote Sens.* **2017**, *38*, 5855–5859. [CrossRef]
16. Wei, J.; Zhong, Y.; Fan, J. Estimating the Spatial Heterogeneity and Seasonal Differences of the Contribution of Tourism Industry Activities to Night Light Index by POI. *Sustainability* **2022**, *14*, 692. [CrossRef]
17. Zhou, L.; Shi, Y.; Zheng, J. Business Circle Identification and Spatiotemporal Characteristics in the Main Urban Area of Yiwu City Based on POI and Night-Time Light Data. *Remote Sens.* **2021**, *13*, 5153. [CrossRef]
18. Zhou, Y.; He, X.; Zhu, Y. Identification and Evaluation of the Polycentric Urban Structure: An Empirical Analysis Based on Multi-Source Big Data Fusion. *Remote Sens.* **2022**, *14*, 2705. [CrossRef]
19. Tong, D.; Ge, Z.; Zhu, F. Study on the spatial distribution characteristics of rural tourism resources based on POI data: Jizhou District, Tianjin City as an example. *J. Agric. Resour. Environ.* **2024**, *41*, 240.
20. Pan, S. Spatial coupling between housing development and economic growth based on night light remote sensing and residential POI. *J. Geo-Inf. Sci.* **2017**, *19*, 646–652.
21. Wang, Y.; Wang, Z.; Deng, Z.; Cheng, P.; Li, Y. Spatial Coupling Analysis Between POI, Luminous Remote Sensing and Weibo Sign-in Data: A Case Study of Beijing. *Remote Sens. Inf.* **2019**, *34*, 18–26.
22. Liu, J.; Liu, G.; Chen, Z. Research on the coupling relationship between retail enterprise spatial layout and population based on POI data and night light remote sensing: Taking the main urban area of Chongqing as an example. *Mod. Bus.* **2021**, *12*, 100–103.
23. Zhang, K.; Chang, F. Town Research on the Coupling Correlation of Commercial Space in Shaoxing City Based on POI and Luminous Light Data. *Archit. Cult.* **2022**, *11*, 118–120.
24. Min, L.; Wei, J.; Yang, Z. Experience, Current Situation, and Countermeasures of New Economic Development in Chengdu City. *Chin. Mark.* **2020**, *25–26*, 48.
25. Chengdu Municipal Bureau of Statistics; Chengdu Survey Team of National Bureau of Statistics. *Chengdu Statistical Yearbook 2022*; China Statistics Press: Beijing, China, 2023.
26. Zheng, Y.; Shao, G.; Tang, L.; He, Y.; Wang, X.; Wang, Y.; Wang, H. Rapid Assessment of a Typhoon Disaster Based on NPP-VIIRS DNB Daily Data: The Case of an Urban Agglomeration along Western Taiwan Straits, China. *Remote Sens.* **2019**, *11*, 1709. [CrossRef]
27. *GB/T18106-2004*; Classification of Retail Formats. General Administration of Quality Supervision, Inspection and Quarantine of the People's Republic of China, China National Standardization Administration: Beijing, China, 2004.
28. Silverman, B.W. *Density Estimation for Statistics and Data Analysis*; Routledge: London, UK, 2018.
29. Zhou, C.; Ou, Y.; Ma, T. Research Progress in Geographic Grid Models. *Prog. Geogr.* **2009**, *28*, 657–662.