land

MDPI

Article

Evaluating the Spatial Heterogeneity and Driving Factors of Sustainable Development Level in Chengdu with Point of Interest Data and Geographic Detector Model

Yantao Ling [1], Yilang Zhao [2], Qingzhong Ren [1,*], Yue Qiu [3], Yuerong Zhang [4] and Keyu Zhai [5]

[1] School of Economics and Finance, Chongqing University of Technology, Chongqing 400054, China; lingyantao@cqut.edu.cn
[2] School of Economics and Business Administration, Chongqing University, Chongqing 400045, China; 202302131195@stu.cqu.edu.cn
[3] School of English, Beijing International Studies University, Beijing 100024, China; qiuyue@bisu.edu.cn
[4] Energy Institute, University College London, London WC1E 6BT, UK; yr.zhang@ucl.ac.uk
[5] School of Graduate Studies, Lingnan University, Hong Kong, China; colinzhai@ln.edu.hk
* Correspondence: renqingzhong@cqut.edu.cn

Abstract: Over the past few decades, China has undergone the largest and fastest urbanization process in world history. By 2023, Chengdu's urbanization rate had reached 80.5%, significantly higher than the national average of 66.16%. Studying the urbanization experience of Chengdu is of great significance for optimizing urban planning policies in Chengdu and other cities in China. Although much literature has explored the urbanization process from macro and micro perspectives, studies using a top-down approach to examine urban fringe expansion are relatively scarce. This study first applies the entropy weight method to analyze the spatial-temporal evolution trends of urban development, identifying areas of imbalanced development and prominent issues. Secondly, the K-means machine learning algorithm and nightlight data are used to reconstruct and classify urban regions, and a comparative analysis is conducted with administrative divisions to further identify unreasonable areas in urban spatial distribution and structure. Finally, POI data and the geographical detector method are used to analyze the micro-driving forces in areas of imbalanced development, identifying major limiting factors and solutions. The study found that the gap between urban and rural development in Chengdu is narrowing during the urbanization process, but there is severe differentiation in the second circle of Chengdu, where economic development is accelerating but residents' happiness is declining. Moreover, analysis based on urban nightlight data and land-use data reveals that the expansion areas on the urban-rural fringe are mainly concentrated in the second circle of Chengdu. Micro-level driving factor analysis found that the western region of the second circle has many but small urban settlements, with a dense road network but scattered functional areas. The eastern region has inefficient and extensive use of construction land. Additionally, the mismatch between student status and household registration has resulted in relatively lagging educational resource development, and high entry barriers have hindered the progress of urbanization, leading to low per capita welfare expenditure. These reasons are the main factors causing the decline in residents' happiness, and this impact shows significant differences at different temporal and spatial scales. Encouraging innovation in research and development or education can serve as a long-term and effective driving force for promoting sustainable urbanization. This study provides valuable insights for scientifically planning sustainable urban development and promoting the urbanization process.

Keywords: urban sustainable development; land use efficiency; POI; geographical detector; urban innovation space

check for updates

Citation: Ling, Y.; Zhao, Y.; Ren, Q.; Qiu, Y.; Zhang, Y.; Zhai, K. Evaluating the Spatial Heterogeneity and Driving Factors of Sustainable Development Level in Chengdu with Point of Interest Data and Geographic Detector Model. *Land* **2024**, *13*, 1018. https://doi.org/10.3390/land13071018

Academic Editor: Wenze Yue

Received: 15 May 2024
Revised: 30 June 2024
Accepted: 5 July 2024
Published: 8 July 2024

Copyright: © 2024 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (https://creativecommons.org/licenses/by/4.0/).

1. Introduction

Urbanization has become a key driver of economic growth. According to data from Statista, as of 2022, the global urbanization rate reached 56.9%. Regions with rapid urbanization and strong growth momentum often become important engines leading global economic development [1]. However, the rapid urban expansion also brings a series of challenges and issues, known as "urban diseases". Initially, scholars focused their discussions on urban diseases on the binary relationship between urban and rural areas. Entering the 20th century, European scholars were the first to shift their attention to urban fringe areas, gradually transitioning from qualitative descriptions to quantitative identification and analysis [2]. With the deepening of urbanization research, the urban-rural fringe has become a hot topic of study. In this area, key indicators such as GDP, population, and housing prices show significant fluctuations compared to rural and urban districts, highlighting the complexity and challenges faced by the urban-rural fringe in the urbanization process [3]. According to the "2022 World Cities Report" released by UN-Habitat, the global urbanization rate is expected to reach 68% by 2050, which also means that urbanization will remain a topic of keen interest for countries worldwide for a long time to come.

China is one of the fastest-urbanizing countries in the world. In 1980, China's urbanization rate was 19.36%, rising to 61.43% in 2020, with an average annual increase of 1.05 percentage points, significantly higher than the global average annual increase of 0.42 percentage points over the same period. Against the backdrop of rapid economic growth and skyrocketing population density, peri-urban areas have undoubtedly become focal points. Modern cities are supposed to accommodate diversified functions. However, in the actual process of urban development, due to constraints from multiple factors such as geographical environment, social culture, political system, etc., they often fail to effectively balance the comprehensive strategies for multi-dimensional development, including economic, social, and natural aspects. This rapid urbanization process may not only weaken the resilience of cities in responding to human-made or natural disasters but also lead to the unreasonable fragmentation of urban landscapes in urban-rural fringe areas, which undoubtedly further exacerbates the vulnerability of cities [4,5]. This is not only because they accommodate people from different social backgrounds but also because many of the conflicts encountered during urban planning and development tend to concentrate here [6]. The primary issues currently facing China's peri-urban areas can be summarized as follows: (1) Imbalanced urban development. A few major cities have rapidly expanded due to their excessive functional responsibilities and highly concentrated industries, leading to prominent "urban diseases" like high housing prices, traffic congestion, and environmental pollution. Meanwhile, some small and medium-sized cities and towns lag in infrastructure and public service development, suffer from insufficient industrial support, and lack sufficient employment opportunities, hampering their socioeconomic development potential. (2) The process of urban integration is slow, making it difficult for a large agricultural migrant population to integrate into urban society [7,8]. (3) Construction land is utilized inefficiently, and "land urbanization" is outpacing "population urbanization". There is an excessive pursuit of wide roads and large squares, while new towns, new districts, development zones, and industrial parks occupy too much land. The population density in built-up areas is low, wasting arable land resources [9]. (4) The spatial distribution and scale structure of urban areas are irrational, preventing the release of economic potential and increasing the economic, social, and ecological costs [10]. (5) The protection of natural, historical, and cultural heritage is inadequate, and urban-rural development lacks distinctive features, resulting in the loss of local characteristics and folk culture. The speed of urbanization correlates with the level of urbanization. According to the development experience of developed countries, the change in the urbanization rate presents an S-shape with changes in the level of urbanization. When urbanization is at a moderate level (an urbanization rate of around 30% to 40%), the speed of increase in the urbanization rate will accelerate; once urbanization reaches a high level (an urbanization rate of around 70%), the speed will decline. Facing the current bottlenecks and challenges of urbanization

growth [11], it is urgently necessary to explore and practice a new model of urbanization to achieve sustainable, high-quality, and refined development in modern cities.

Chengdu is a typical case of a large city with vast rural areas, where rural regions account for 91% of the area and urban regions for only 9%. By the end of 2023, Chengdu's urbanization rate among the permanent population had reached 80.5%, which is notably above the national average of 66.16%, whereas the rural permanent population accounted for just 19.5%. How can Chengdu accelerate the high-quality integrated development of urban and rural areas and find a new path that meets the transformation needs of a megacity? How can Chengdu, as a "large city with vast rural areas", achieve mutual progress between the modern metropolis and the beautiful countryside? Addressing these issues will help provide successful experiences for cities in the early stages of urbanization, as well as solutions for those facing urbanization bottlenecks. With this motivation in mind, this paper focuses on Chengdu and explores the following issues:

(1) At the macro level, how has the temporal and spatial evolution of Chengdu's urbanization process unfolded, and what prominent issues have emerged during urbanization?
(2) Where are the prominent regions of uneven development in the urbanization process, and how can they be identified?
(3) At the micro-level, what are the main driving factors behind the irrational urban spatial distribution and structure in areas of imbalanced development?

To address the issues, this paper combines the United Nations Sustainable Development Goals (SDGs), the two-hemisphere theory, and decoupling theory to construct an evaluation index system for sustainable urban development. The entropy weight method is used to assign weights to each indicator, thereby exploring the spatial and temporal evolution trends and prominent issues of urbanization in different regions of Chengdu. Secondly, the paper collects nightlight data of Chengdu and applies machine learning algorithms to spatially classify Chengdu, identifying urban, rural, and peri-urban areas. This classification is validated using land use data. This method identifies regions of prominent imbalanced development in Chengdu's urbanization process. Instead of following Chengdu's original administrative land zoning as the regional division criterion, the paper redefines the regional boundaries using actual nightlight and land use data through big data methods. A comparative analysis is conducted between these newly defined boundaries and the administrative boundaries, helping to accurately identify irrational urban spatial distribution and structure and providing a research basis for identifying prominent issues in urbanization in different regions. Finally, the paper quantifies the land functions in regions of imbalanced development using POI (Points of Interest) data and applies the Geographic Detector to identify the main driving factors behind the imbalance. Given the diversity and complexity of urban planning, different urban development strategies and plans show significant variations. Simply identifying the urban-peri-urban-rural areas is not enough to clarify the driving factors causing imbalanced development in peri-urban areas. Therefore, a scientific method is needed to precisely delineate the constructed peripheral regions of the peri-urban areas. In recent years, POI data, as an emerging and increasingly popular analytical method [12], has surpassed traditional statistical directories like annual reports due to its unique rawness and high customizability [13]. This analytical method aligns precisely with the urban evaluation index system constructed under the United Nations framework in this paper, providing strong data support and new analytical perspectives for urban research [14]. Landscape diversity forms a fundamental basis for urban landscape resilience, reflecting the adaptability of urban ecosystems to external shocks. During the process of urbanization, the uneven distribution of POI points and their high-density agglomeration in local areas both contribute to the intensification of landscape fragmentation, which subsequently exerts a negative impact on urban landscape resilience. By analyzing the categorical information of POI data, this paper also calculates the quantity and distribution density of various types of POI in target areas (such as public facilities, green spaces, parks, wetlands, commercial districts, etc.), thereby assessing the level of urban landscape diversity and urban landscape resilience. As a

crucial support for urban sustainable development, urban resilience enhances the ability of cities to cope with external shocks and changes. For more research on resilience, please see Tampekis et al. (2018) [15], Argyroudis et al. (2020) [16], and Sakellariou et al. (2022) [17]. Then, the paper uses the Geographic Detector to quantify the driving factors of urban expansion, uncovering the internal logic of urban expansion and exploring the reasons hindering urbanization development and their impact on urban landscape resilience [16,18]. Based on this, relevant solutions to urban diseases during urban expansion are proposed to enhance the resilience of urban landscapes and promote sustainable urban development.

The main contributions of this paper are as follows: (1) From a macro perspective, the paper constructs an evaluation index system for urbanization development based on the two-hemisphere theory and decoupling theory, providing a quantitative reference for depicting the spatial and temporal evolution trends of urbanization and identifying prominent issues in the urbanization process. Current related research focuses on exploring the balance between urbanization and the natural environment [19], urbanization and residents' welfare [20], and urbanization and economic development [21]. By referencing the sustainable indicator system constructed by the United Nations, this paper reconstructs an evaluation system for sustainable urban development [22], expanding related research methods. (2) At the meso level, the paper adopts the K-means machine learning algorithm combined with land use data to reconstruct and divide urban areas, identifying regions with irrational urban spatial distribution and structure while facilitating cross-regional integration of land functional spaces. Administrative divisions predate urbanization, so to avoid local biases and heterogeneity caused by administrative boundary divisions, this paper combines and analyzes the actual administrative divisions (i.e., policy-making influence range) with the identification of real peri-urban areas [23]. Currently, methods for identifying and reconstructing urban areas mainly include using land use data, population density, nightlight remote sensing data, and economic indicators like GDP [24], and even distinguishing urban and rural areas by urban landscape gradient changes [25]. However, as big data methods mature, using big data analysis of remote sensing nightlight data to identify urban blocks will be more reliable [26]. (3) From a micro perspective, the paper utilizes the Geographic Detector and POI data to analyze the micro-driving forces of imbalanced development regions from spatial and temporal trends. It identifies the main driving factors leading to imbalanced regional urbanization development and provides solutions, offering a new analytical perspective for urbanization research. Additionally, the research on micro-driving forces delves into the road network topology, attempting to depict the functions of urban plots, providing a highly feasible operational method for refining urban land functions. This evaluation method helps improve urban land use efficiency and provides relevant references for high-level urbanization development.

2. Literature Review

2.1. Spatial and Temporal Evolution of Urban Land Function

Urban land functions represent a spatial process that constantly changes over time [27]. Urban development drives changes and updates in urban land use, and the spatial and temporal evolution patterns of urban land functions and their driving mechanisms have received widespread attention [28]. The spatial and temporal evolution of urban land functions exhibits regular patterns of concentric layer attenuation, center-periphery diffusion, spatial clustering, and path dependence.

First, from a static perspective, urban land functions usually follow a pattern of concentric layer attenuation. Spatially, the land functions in the central urban area tend to be more diverse and denser, while functions become increasingly singular and sparse as the distance from the city center increases. This creates a spatial differentiation of urban functions across different concentric layers [29]. In urban spaces, the central area contains mixed-use zones with commercial, residential, cultural, and other functions, while peripheral areas gradually exhibit singular functions such as industrial and agricultural zones. In urban spaces, the central area contains mixed-use zones with commercial, residential, cultural, and other

functions, while peripheral areas gradually exhibit singular functions such as industrial and agricultural zones. This makes it suitable for high-profit-driven and capital-intensive commercial and residential functions, while land prices gradually decrease towards the periphery, making it more suitable for developing low-economic-density industrial and agricultural functions [30]. Second, the central urban area has a dense transportation network, providing convenience that supports a high concentration of commercial and residential functions. In contrast, poorer transportation conditions in the peripheral areas limit the diversity and density of functions. Additionally, urban history also affects the distribution of land functions. Early urban development often centered around the core area, forming a spatial structure that radiates outward with decreasing intensity [31]. This makes it suitable for high-profit-driven and capital-intensive commercial and residential functions, while land prices gradually decrease towards the periphery, making it more suitable for developing low-economic-density industrial and agricultural functions. Second, the central urban area has a dense transportation network, providing convenience that supports a high concentration of commercial and residential functions. In contrast, poorer transportation conditions in the peripheral areas limit the diversity and density of functions. Additionally, urban history also affects the distribution of land functions. Early urban development often centered around the core area, forming a spatial structure that radiates outward with decreasing intensity [32].

Therefore, from a dynamic perspective, the spatial and temporal evolution of urban land functions also follows the pattern of center-periphery diffusion. Over time, the land functions in the central urban area gradually diffuse and shift toward the periphery, and the peripheral urban area often accommodates these functions. In the early stages of urbanization and industrialization, the urban center was mainly characterized by traditional industrial functions. However, with urban functional replacement and urban renewal [33], traditional industrial zones in the urban center have gradually shifted and diffused to suburban areas, being replaced by denser and more modern functions such as commerce, finance, culture, and technology. As these industries scale up, these functions will gradually diffuse to the urban periphery, forming a wave-like pattern of land function replacement and diffusion from the urban center to the urban periphery [34]. This diffusion pattern is often caused by factors such as urban development, land spatial resources, and infrastructure construction. Specifically, as urban populations grow and economies develop, cities need more land to meet the demand for various functions. However, land resources in the central areas are limited and cannot satisfy the need for urban functional expansion. In contrast, suburban and peripheral urban areas often have more open land resources, leading to the diffusion of urban functions to the outskirts. Meanwhile, as transportation and infrastructure construction continue to improve, the transportation accessibility of peripheral areas increases, attracting more people and businesses to the outskirts. Additionally, newly built transportation hubs and networks also facilitate the diffusion of functions to peripheral areas. In summary, the center-periphery diffusion of urban land functions reflects the dynamism and adaptability of urban spatial structures and land use. It is an inevitable outcome of urbanization and an important manifestation of urban expansion and renewal [35]. However, in the post-urbanization phase, where peripheral urban areas are highly developed, the land functions of the urban center and periphery may gradually balance. Furthermore, phenomena such as suburbanization and counter-urbanization may occur [36], breaking the regularity of center-periphery diffusion and leading to a reverse effect from periphery to center. At the same time, the pattern of center-periphery diffusion will not be limited to within the city but will break through the administrative boundaries of the city. On the one hand, an evolution pattern of center-periphery-external may form; on the other hand, some urban land functions may present a diffusion pattern from central cities to peripheral cities on a broader scale of urban agglomerations and regions [37].

At the same time, spatial clustering is also one of the patterns reflected in the evolution of urban land functions. Similar types of land functions often cluster together spatially, forming functional clusters [38]. For instance, commercial, residential, and industrial zones

with similar functions aggregate in urban spaces, creating relatively independent functional areas. The formation of this spatial clustering pattern is mainly due to the following factors. On one hand, the clustering of similar land functions can improve resource utilization efficiency and economic benefits, creating economies of scale. The clustering of commercial zones generates an agglomeration effect, enhancing shopping convenience and the visibility of functional areas, attracting more consumers. The clustering of residential zones allows for shared use of public service facilities and other public goods, improving resource allocation efficiency. On the other hand, functional clustering reduces transportation and logistics costs, improving production and trading efficiency. For example, the clustering of industrial zones facilitates logistics and transportation between industries, promoting the formation and development of industrial chains. Therefore, the spatial clustering of urban land functions is the result of enterprises pursuing maximum economic utility. However, spatial clustering of land functions may lead to excessive concentration of resources and unbalanced urban spatial development, increasing environmental pressure and social issues [39,40] and exacerbating social inequality. This requires reasonable government guidance to cluster or disperse urban functions to optimize the urban spatial structure and achieve sustainable development.

Additionally, from an evolutionary pattern perspective, the evolution of urban land functions also demonstrates path dependence. The evolution of urban land functions is constrained and influenced by historical development paths [41]. The development and layout of urban land functions are, to some extent, influenced by early planning, land use decisions, and urban historical and cultural preservation, forming historical inertia that is difficult to change easily. Moreover, early infrastructure construction also has a significant impact on the development of urban land functions, such as the layout of transportation networks and the construction of water facilities, which affect the development speed and functional composition of different regions [42]. Additionally, cities contain many heritage areas with historical significance and cultural value, such as ancient city walls, historic buildings, and traditional neighborhoods. To preserve and promote the city's image, urban planning and land use often prioritize the protection of these historical and cultural heritage areas [43], thus limiting land function updates in these areas to some extent, making their land functions relatively fixed and stable. However, this path dependence in the evolution of urban land functions can also be broken and reshaped.

The land system is a composite of natural, economic, and social factors [44]. Numerous studies have shown that the spatial and temporal evolution of urban land functions is the result of a combination of natural geographical conditions, socioeconomic factors, and urban spatial morphology [45]. The topography, climate, vegetation, and other natural geographical conditions of urban plots have an inherent influence on land functions. Topography is a fundamental geographical factor determining the distribution of landscapes and human activity spaces [46]. Rugged terrain can limit land usability and may lead to the concentration or restriction of land use functions. Mountainous areas, with high altitudes and steep slopes, are not suitable for large-scale development and may form forest parks and nature reserves dominated by ecological and tourism functions. The distribution of mountains and rivers also creates natural geographical barriers, limiting the range of functional area diffusion. Temperature, precipitation, and river density affect the climate and soil configuration of urban land [47], shaping different urban landscape patterns [48]. Different vegetation types provide various ecological services, such as air purification and soil and water conservation, directly influencing the ecological function of the land. Vegetation types and distribution also affect urban landscape patterns and living environments, thus impacting the landscape and residential functions of the land. Different vegetation types provide various ecological services, such as air purification and soil and water conservation, directly influencing the ecological function of the land. Vegetation types and distribution also affect urban landscape patterns and living environments, thus impacting the landscape and residential functions of the land [49]. During the evolution of urban land functions, technological progress and economic development gradually break

down natural geographical boundaries with the opening of tunnels and the construction of bridges, leading to new functional evolution. The expansion of urban construction land may result in vegetation clearance, while the expansion of urban green space can improve vegetation coverage. The concentration of population and industry driven by central urban functions increases economic production activities, raises greenhouse gas emissions, and creates the urban heat island effect, thereby affecting local temperature changes. In summary, a city's natural geographical conditions form the inherent basis for the evolution of land functions, yet the evolution of land functions can break through the limitations of natural geographical conditions and alter the original ecosystem [50,51]. Therefore, the evolution of urban land functions results from the combined effects of various factors. It requires consideration not only of the endogeneity between natural geographical conditions and land function evolution but also of other influencing mechanisms, such as socioeconomic factors.

Socioeconomic activities, such as economic growth, population concentration, industrial relocation, urban expansion, and technological progress, are another significant factor in the dynamic evolution of urban land functions [52]. Economic growth drives urban development, shifting land functions from low-efficiency to high-efficiency uses, such as converting agricultural land to commercial, residential, or industrial land. Additionally, economic growth creates new functional demands, promoting the spatial concentration and diffusion of industries and populations, and is considered a key factor in changing urban land use patterns. Furthermore, compared to less developed cities, urban land use transformation is more active in economically advanced cities [38]. Population concentration fosters urbanization, generating more residential and commercial demand and promoting the development of urban services and infrastructure [53]. As population density increases, cities require more housing and public service facilities, potentially leading to the expansion of residential and commercial areas. Industrial relocation implies the renewal of old industrial zones and the construction of new industrial parks, upgrading the functions of the original land. Meanwhile, industrial relocation also creates new growth poles, driving employment growth and population concentration, thereby shaping the functional development of surrounding plots. With industrialization and urbanization, urban expansion leads to the diffusion and replacement of urban land use, with agricultural land in peripheral areas gradually replaced by urban construction land [54]. Moreover, technological progress not only reduces the difficulty of land development and transportation construction but also forms new high-tech industrial clusters. Additionally, the concentration of high-tech enterprises attracts the flow of talents in related industries, which further drives the evolution of urban land functions [55]. In summary, the evolution and transformation of urban land functions are influenced by socioeconomic activities and are also the result of industrialization and urbanization. The evolution of urban land functions aligns with the needs of socioeconomic development, forming a more efficient urban development model, which in turn influences socioeconomic factors such as economic growth and population concentration to some extent. Therefore, there is an interplay between socioeconomic activities and land function changes, and the issue of endogeneity needs to be considered.

Urban spatial morphology and its changes continuously shape the land functions of urban plots [56], including factors like transportation networks, urban compactness, land density, and physical distance. The construction of transportation networks influences the spatial structure and layout of land functions [35]. Different levels of roads divide the city into distinct blocks [57], providing a structural basis for the differentiation of urban land use and the formation of functional areas [58]. Additionally, the formation of transportation hubs and road networks usually improves the accessibility of adjacent plots, thus driving up land value and industrial agglomeration, leading to changes in land function layouts [59]. Moreover, urban compactness and land density also impact the spatial structure of the city, thereby shaping the spatial and temporal characteristics of land use functions. Cities with high compactness and land density tend to develop vertically and utilize land in a three-dimensional manner. This compact urban structure promotes the

concentration and exchange of resources within the city, leading to more multifunctional and comprehensive urban land use [60], potentially resulting in high-rise buildings and mixed-use land layouts. Urban land functions are also closely related to physical distances both within and between cities. At the same time, the importance of green vegetation in urban life in modern cities is gradually increasing [61]. According to the First Law of Geography, everything is related to everything else, but near things are more related than distant things [62]. Therefore, urban land functions are also influenced by the relationships and impacts of surrounding cities [63]. Within cities, the physical distance from the urban center and core functional areas affects the extent of land function diffusion and transfer. Peripheral urban areas, being further from the city center, may become marginalized in economic development, leading to differentiation of land functions. However, physical distance does not fully reflect spatial associations. With increasing economic exchanges and policy cooperation, the planning and construction of integrated urban agglomerations may make the interaction of land functions between cities more apparent beyond the limitations of spatial distance. Additionally, the planning policies of urban development zones can intensify the development and utilization of land in peripheral areas, breaking the original spatial pattern and accelerating the evolution process to form new functional areas [64].

2.2. Functional Division of Land Based on Administrative Space and Its Defects

Currently, research on land use functions often divides urban plots using administrative divisions as basic units [65]. Many studies use administrative spaces for land function division primarily because this method is simple, practical, and highly applicable. Firstly, official statistical data based on administrative spaces are readily accessible. Administrative divisions are the basic units of national territorial division and government management [66]. Relevant land use and socioeconomic data are often collected and organized based on administrative units, making data sources relatively standard. Notably, many studies use socioeconomic data collected based on administrative boundaries to establish relevant indicator systems, enabling the use of Multi-Factor Comprehensive Assessment (MFCA) methods to evaluate land functions within administrative spatial units [67,68]. This research method, based on administrative spaces, is relatively mature and has been widely used. Secondly, dividing land based on administrative spaces facilitates macro-level management and planning by the government. Administrative spatial division is the foundation of government management and planning. It is crucial for government departments to understand the land use status of each administrative region to formulate relevant policies and plans. Moreover, land function research based on administrative spaces enables statistical comparison across regions at multiple scales. The hierarchical structure of administrative divisions is suitable for comparative analysis and regional research at national [69], provincial [70], municipal [71], and county levels [72]. Therefore, numerous studies have used administrative spaces to divide urban plots, forming a relatively mature research paradigm for land functions.

However, as urban land use undergoes complex changes, the limitations of functional divisions based on administrative boundaries have become increasingly apparent, and accurately identifying the latest land functions is crucial for urban studies [39]. Firstly, the natural geographical features of different urban plots are often overlooked in functional divisions based on administrative boundaries. Land use patterns and functions may vary in different geographical environments, yet administrative divisions do not fully reflect these characteristics. Secondly, socioeconomic factors can transcend administrative boundaries and generate jurisdictional spillover effects [73], thereby influencing the land functions of surrounding administrative spaces. Although functional divisions based on administrative spaces can consider spatial relationships through spatial econometric methods, they still cannot accurately capture the range and extent of cross-boundary land function diffusion [74]. Moreover, the interrelationship between urban spatial structure and land functions is also challenging to capture accurately. Urban development and changes

make the urban spatial structure increasingly complex, reflecting and shaping urban land functions and thus creating new spatial divisions.

In addition, zoning based on administrative districts has a coarse granularity and cannot meet the needs of refined urban management. Complex changes in urban land place higher demands on the accuracy of land function identification, while zoning based on administrative space lacks a basis for division and data sources at finer scales [75]. At best, administrative zoning can divide cities down to the street scale, while land use data and socio-economic data at the county level and below are often incomplete. This limits the precision of urban function studies and is not conducive to analyzing the deeper factors of land function evolution [76,77]. In this regard, while administrative unit-scale studies can provide macro policies for decision makers, they ignore differences within administrative units and are not conducive to the development of differentiated land resource management policies [44].

Meanwhile, land use is a dynamic process of change, but administrative space is often static, which cannot accurately reflect the dynamic change and evolutionary process of land use [78]. Especially in the process of urbanization, urban expansion and adjustment of land use structure may lead to inaccurate and inadequate administrative spatial division. Urban land functions can spread and shift across different parcels. The administrative space-based delineation often divides the spatial structure into fixed basic units, which can only reflect the functional changes on the inherently zoned parcels, while the changes in the boundaries of different functional zones are difficult to clearly present.

Therefore, to more accurately grasp the urban land use pattern and functional distribution and to improve the precision of land function division, it is necessary to break the original administrative land space zoning and explore a new way of land function division. This will reflect the diversity and complexity of urban land use more deeply and provide a more scientific basis for urban planning and land resource management.

3. Methodology

3.1. Case Study

Chengdu is facing the "big city disease" and the problem of declining growth rate after the high growth rate of urbanization and is in an important period of urbanization transition and is also a very representative city. From 2014 to 2022, Chengdu advanced from being in 9th place in the national GDP ranking in 2014 to being in 7th place in 2022, and the only high-growth mega-city to be in the top 10 in growth rate during this period is Chengdu. Chengdu is the only high-growth mega-city that is also in the top 10 in terms of growth rate during the period. In addition, Chengdu's urbanization has been one of the most impressive in China in the last decade, leading the way in the central and western regions, with the urbanization rate of the household population reaching 80.5% by the end of 2023, significantly higher than the national average. Chengdu is facing the "big city disease" caused by rapid urbanization in terms of population expansion, traffic congestion, environmental pollution, and resource constraints, as well as the problem of declining urbanization rate after high growth. How to further accelerate the high-quality development of urban-rural integration in Chengdu and take a new road of urban-rural integration that meets the needs of the transformation and development of megacities is of great practical significance to achieve the sustainable, high-quality, and refined development of modern cities. Therefore, Chengdu is chosen as an example.

The object of this paper is the Chengdu metropolitan area, which, according to the definition of the Chengdu municipal government, consists of 12 districts, namely Jinjiang, Qingyang, Jinniu, Wuhou, Chenghua, Longquanyi, Qingbaijiang, Xindu, Wenjiang, Shuangliu, Pixi, Xinjin, five county-level cities, namely Jinyang, Dujiangyan, Pengzhou, Qionglai, Chongzhou, and three counties, namely Jintang, Dayi, and Pujiang; as well as the Eastern New Area of Chengdu, and Chengdu New and High-tech Industrial Development Zone (CNDTZ), Chengdu New District, Chengdu High-tech Industrial Development Zone, and Sichuan Tianfu New District (hereinafter referred to as 'Eastern New District', 'High-tech

Zone' and 'Tianfu New District'). Among them, the '5 + 1' area in the central city' includes the area within 500 m of the outer edge of the Beltway (Fourth Ring Road) and the areas outside the Beltway (Fourth Ring Road) of Jinniu District, Chenghua District, Qingyang District, Jinjiang District, Wuhou District, and Hi-Tech District; the "main city "12 + 2" area" includes 12 municipal districts, high-tech zones, and Tianfu New Area. However, the high-tech zone, Tianfu New Area, the eastern new area belongs to the special economic zone, and there is no separate administrative area division, so according to its original geographic location, it is classified as Wuhou District, Shuangliu District, and Jianyang District.

From an administrative perspective, Chengdu is composed of three concentric circles; please see Figure 1. From the innermost to the outermost, the first is the central five districts: Jinjiang, Wuhou, Qingyang, Jinniu, and Chenghua. They constitute the heart of Chengdu, boasting extremely high urban density and abundant development resources. Next comes the second circle, located between the first and second ring expressways, which serves as the primary area for urban expansion, boasting relatively complete infrastructure and industrial layout. These districts include Xindu, Pidu, Wenjiang, Shuangliu, Longquanyi, and Qingbaijiang. The outermost layer is the third circle, encompassing several counties and cities surrounding Chengdu. While they are further away from the city center, they still possess unique natural resources and development potential. The areas within the third circle include Jianyang City, Jintang County, Pengzhou City, Dujiangyan City, Chongzhou City, Dayi County, Qionglai City, Pujiang County, and Xinjin County.

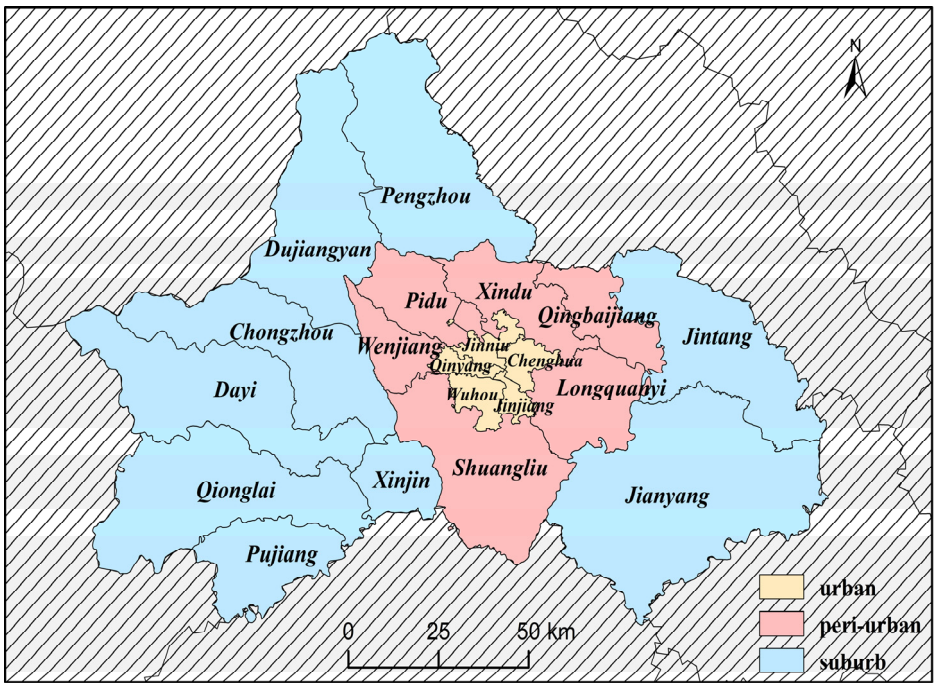


Figure 1. The administrative map and urban circle division of Chengdu City.

3.2. Methods

3.2.1. Evaluation Index System of Urban Sustainable Development

With reference to the two-hemisphere theory and the decoupling theory proposed by the United Nations [14], this paper incorporates the two major indicators of urban ecology and urban development into the same assessment framework and constructs an indicator system to evaluate the level of sustainable development of the city, taking into full consideration the validity, measurability, and data usability of the assessment indicators. As shown in Figure 2, the upper hemisphere is called the "development hemisphere", which includes the city's economic and social systems, including GDP, public services, education level, etc. The lower hemisphere is called the "ecological hemisphere", which includes the city's ecosystem. The degree of match between the two hemispheres reflects the results

of sustainable urban development. The goal of achieving sustainable urban development is to match economic and welfare development in the development hemisphere with environmental and resource consumption in the ecological hemisphere.

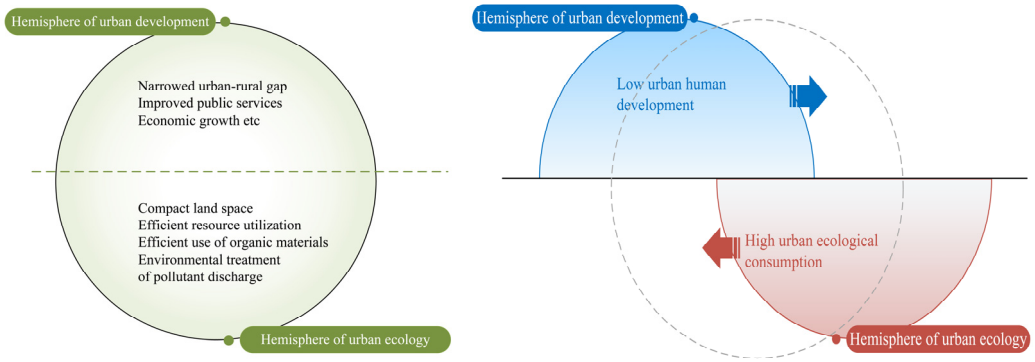


Figure 2. Two hemispheres of urban development and their alignments. (Source: China Sustainable Cities Report 2016) [11].

According to the "decoupling" theory, the relationship between the urban development hemisphere and the ecological hemisphere is of three types: coupling (matching), relative decoupling, and absolute decoupling. When the expansion of the development hemisphere keeps pace with, or even exceeds, the growth of the ecological hemisphere, economic growth relies on the overconsumption of natural resources, leading to serious environmental damage. In this case, the two hemispheres are tightly coupled and ecologically inefficient, which is an unsustainable form of development. When the ecological hemisphere expands at a slower rate than the human development hemisphere, "relative decoupling" is achieved, and greater economic and human development is realized with fewer resources and environmental inputs. "Absolute decoupling" refers to a high level of sustainable development in which economic and welfare growth is sustained without an increase, or perhaps even a decrease, in resource consumption and environmental pollution.

On the basis of the United Nations' SDGs for sustainability, a first-level indicator comprising resource utilization, social welfare, and economic development potential was constructed to evaluate the sustainability level of the target city in terms of resources, population, economy, and social systems [79]. The detailed construction of the indicators is shown in Table 1.

Table 1. Indicator construction for evaluating the urban sustainable development (USD).

Primary Index	Secondary Index	Quantification Method	Unit	Abbreviation
Resources utilization	Air quality index	Composite air quality index	-	AQI
	Proportion of cultivated land	Cultivated land area/land area	%	PCL
	Water resource	Total water resources per capita	10^9 m^3/10^7 person	WR
	Per capita output of grain	Total food production/total population	kg/person	OG
	Annual output value per unit area	Gross value of agricultural, forestry and fisheries production/land area	yuan/km^2	AOV
Happiness index	Public budget	Public budget expenditure per capita	million yuan/person	PB
	Student	Number of students/million	person/million person	STU
	Number of beds per 1000 person	Number of beds/thousand persons	number/thousand person	BED
	Scenic Spots	Number of A-listed attractions per district/area of district	number/hectares unit/hectare	SS

Table 1. *Cont.*

Primary Index	Secondary Index	Quantification Method	Unit	Abbreviation
Economic potential	GDP per unit area	Gross district product/land area	10 thousand yuan/km^2	GDPA
	Urbanization rate	Urbanisation rate of resident population	%	UR
	Number of industrial enterprises above designated size	Number of industrial enterprises above designated size	unit	NIE
	Average property price	Average annual housing price	yuan	APP
	Scientific research strength	Percentage of soft science scores for district colleges and universities	%	SRE
	Incremental effective invention	12-month cumulative valid inventions	Number	IE
	Number of listed companies	Number of listed companies	numer	NLC

In accordance with the UN Sustainability Indicators SDGs, the UN Sustainability Indicators SDG1 (No Poverty), SDG2 (Zero Hunger), and SDG6 (Clean Water and Sanitation) are measured using the unit output of arable land, food, agriculture, forestry, fisheries, and animal husbandry and the unit area of water resources in the first-level indicator Resources utilization [80]. Considering that the air quality problem in the Sichuan Basin is more prominent, large-scale infrastructure investment and the rapid development of the real estate sector have boosted Sichuan's economic development but exacerbated regional air pollution. Therefore, the comprehensive air quality index was used to measure the environmental impacts of its resource use.

The resident well-being indicator is used to measure the ability to rationally plan land use and spatial layout to meet the needs of residents [81], and it includes factors such as consumption, healthcare, and education, corresponding to SDG3 (good health and well-being), SDG4 (quality education), SDG9 (industry, innovation, and infrastructure), and SDG11 (sustainable cities and neighborhoods) [73]. Therefore, the number of secondary school students per 10,000 people, the number of beds per 1000 people, and public expenditure per capita are included in the indicator system, and an additional indicator of the number of A-grade attractions per unit area is introduced, which is more representative of the city's support for culture and tourism than the number of books per unit per capita.

The essence of the economic potential indicator is to measure the efficiency of the use of land [82], which can be corresponded to the SDGs indicators, SDG1 (No Poverty), SDG8 (Decent Work and Economic Growth), SDG9 (Industry, Innovation, and Infrastructure), and SDG11 (Sustainable Cities and Communities). SDG1 and SDG8 are quantified by the GDP per unit, the urbanization indicator, and the number of listed companies. Industry in SDG9 is measured by selecting the number of large-scale industries; innovation corresponds to the incremental number of effective inventions and the research score of regional universities; and SDG11 (Sustainable Urban Communities) and SDG9 (Infrastructure) are measured by using an indicator of house prices in the past year [83].

3.2.2. Entropy Weight Method

As an objective evaluation method, the entropy weight method avoids the bias brought by human subjective factors to the evaluation, and relative to the subjective assignment method, the application of the entropy weight method to the constructed indexes can judge the development of the administrative district from an objective point of view, look for the conflict points of the current urban development, and at the same time, can have a rough understanding of the city's urban and rural area division [22]. Assuming that there are n districts and m indicators, the data is represented by D_{ij}, which is in $i = 1, \cdots, n,\ j = 1, \cdots, m$. x_{ij} denotes the value of the jth indicator in the ith.

Step 1: Data normalization.

Firstly, each indicator of different magnitude was normalized using the min-max method. Different normalization methods were used for positive and negative indicators:

$$\text{Positive indicators}: \ Z_{ij} = \frac{x_{ij} - min\left(x_{1j}, x_{2j} \cdots, x_{nj}\right)}{max\left(x_{1j}, x_{2j} \cdots, x_{nj}\right) - min\left(x_{1j}, x_{2j} \cdots, x_{nj}\right)}, \ j = 1, \cdots, m$$

$$\text{Negative indicators}: \ Z_{ij} = \frac{max\left(x_{1j}, x_{2j} \cdots, x_{nj}\right) - x_{ij}}{max\left(x_{1j}, x_{2j} \cdots, x_{nj}\right) - min\left(x_{1j}, x_{2j} \cdots, x_{nj}\right)}, \ j = 1, \cdots, m$$

Step 2: The share of each sample in the current indicator is as follows.

$$P_{ij} = \frac{Z_{ij}}{\sum_{i=1}^{m} Z_{ij}}$$

Step 3. Calculate the entropy value for each indicator.
For the *j*th indicator, its information entropy is calculated as:

$$E_j = -\frac{1}{lnn} \sum_{i=1}^{n} P_{ij} ln P_{ij}, \ j = 1, \cdots, m$$

The larger E_j is, the larger the information entropy of the *j*th indicator is, and the smaller its corresponding information quantity is.

Step 4. Calculation of the weights of the indicators.
Define the information utility value D_j with the following formula:

$$D_j = 1 - E_j$$

The information utility values were normalized to obtain entropy weights for each indicator:

$$w_j = \frac{D_j}{\sum_{j=1}^{m} D_j}$$

Finally, a composite score for the indicator is calculated:

$$T_i = \sum_{j=1}^{m} x_{ij}$$

3.2.3. K-Means Algorithm and Urban Edge Identification

The K-means algorithm for analyzing urban night light data can reconstruct and divide the urban area and compare the results with the administrative divisions to further identify the unreasonable areas of urban spatial distribution and structure. The K-means clustering algorithm is a very popular unsupervised learning method, with a small amount of computation, a fast output speed, and interpretability. Usually the K-value of the k-means algorithm in a set of data is more difficult to predetermine. However, in this study, the night light data will be used to divide the urban area into regions because the light intensity of the city gradually decreases from the city center to the remote areas, and according to the characteristics of this change in light intensity, to identify the "city centre—urban-rural areas—rural areas" [84], so that the K-value can be easily determined, which is the reason why the k-means algorithm is chosen in this paper. This is also another important reason for choosing the k-means algorithm for cluster analysis of urban and rural areas in this paper.

Classification of urban areas based on k-means clustering requires three steps. First, the extracted DMSP/OLS luminous images are rasterized, and the light intensity data of each pixel point is extracted as (LS), and the range of LS is 0–60. Second, the acquired latitude and longitude of Tianfu Square in the center of Chengdu are transferred to the

raster's same axis (x_0, y_0), and at the same time, the Euclidean distances D_i of each raster point from the center are calculated.

$$D_i = \sqrt[2]{(x_i - x_0)^2 + (y_i - y_0)^2}$$

Finally, the Euclidean distance from the center and the raster light intensity data were clustered and analyzed by k-means to obtain the final extent of the urban-rural boundary.

3.2.4. POI and Urban Functional Area Division

POI (Point of Interest) is widely used in remote sensing analysis due to its detailed latitude and longitude characteristics [85], and compared with traditional remote sensing statistics, POI has the advantages of fast updating, high degree of customization, large quantity, and wide range, which can be used to carry out finer spatial analysis and has a natural advantage in identifying the dynamic and functional changes in urban areas [86,87].

After reading the road network data in Chengdu and processing the roads with topological errors, the road network data is used to subdivide the urban-rural area into i study areas. After importing the k classes of POIs, the POIs distributed in each study area are statistically summarized, followed by classification and discussion of the landing points in each area, and finally the functional characteristics F_i that each study area has are identified.

$$F_i = \frac{POI_i}{\sum_{i=1}^{k} POI_i}$$

POI analysis can not only divide the identified urban conflict areas into functional zones but also provide micro-verification of the results of entropy weight analysis on the level of sustainable development of cities.

3.2.5. Geodetector Model and Driving Forces Analysis

Referring to Qiao et al. (2023), this paper uses the Geodetector method to analyze the driving factors behind urbanization expansion [22]. By combining the obtained driving factors of urbanization expansion with the changing trends of functional zones of urban development identified in POI, it helps to identify the conflicts and solution ideas existing in urbanization and at the same time provides a reference direction for the future development of the city.

The formula for the explanation coefficient q of the detection factor is as follows:

$$q = 1 - \frac{1}{N\sigma^2} \sum_{n=1}^{L} N_h \sigma_h^2$$

q represents the explanatory strength of the detection factor, taking a value between 0 and 1, with a larger value of q representing a stronger explanation. L is the administrative district, N and σ^2 are the number of administrative districts and the variance of the indicator system, and N_h and σ_h^2 are the number of administrative districts and their corresponding variance of the indicator system in each subcategory, respectively.

3.3. Data

The data for the entropy weight method is sourced from the Chengdu Statistical Yearbook from 2014 to 2022, the Chengdu Water Authority, the Chengdu Radio, Film, and Television Bureau, the Chengdu Market Regulation Bureau, and other relevant government agencies. The urban nightlight data comes from the SNPP-VIIRS satellite's nighttime light imagery. SNPP-VIIRS is a new generation of Earth observation satellite launched in 2011, and its on-board Visible Infrared Imaging Radiometer Suit (VIIRS) can capture nighttime light remote sensing imagery (Day/Night Band, DNB band) with a spatial resolution improved to 750 m. The spatial resolution of its nighttime light remote sensing products typically reaches 500 m. The land use data of Chengdu is sourced from the 30-m land use data (1980–2020) nationwide published by the Geographic Information Monitoring

Cloud Platform of the Institute of Geographic Sciences and Natural Resources Research, Chinese Academy of Sciences. POI data is obtained from Gaode Map and Baidu Map, and the coordinate axes of all the above data are unified as WGS_1984. The data of Chengdu's highway network over the years is sourced from OpenStreetMap.

4. Results and Discussion

4.1. Spatial-Temporal Patterns of Urban Sustainable Development

4.1.1. Temporal Perspective Analysis

Figure 3 shows the overall trend in urban development levels in Chengdu from 2014 to 2022, as well as the trends over time for three primary indicators. Overall, Chengdu's level of urban development saw a noticeable increase after 2016, with subsequent growth weakening and approaching stability. Analysis of the three primary indicators reveals that the level of resource utilization fluctuated around 0.1083, peaking in 2018. The happiness index for residents maintained steady growth at a low level from 2014 to 2022, rising from 0.0473 to 0.0584. The economic indicator showed a significant change, increasing from 0.0798 in 2014 to 0.1415 in 2022, an increase of 43%. Therefore, economic development was the primary driving force behind the urbanization progress in Chengdu between 2014 and 2022.

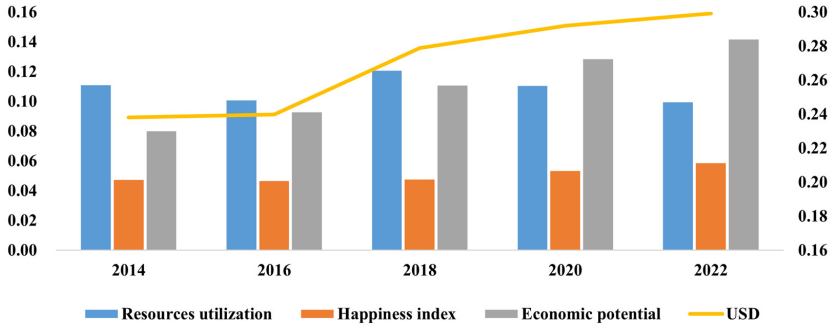


Figure 3. Temporal patterns of urban sustainable development.

4.1.2. Spatial Perspective Analysis

Examining the development trends in various regions, Chengdu's development from 2014 to 2022 indeed showed a priority in the southern region, but this disparity did not widen over time (see Figure 4). In 2014, the urbanization levels in the eastern, western, and northern regions were generally low compared to the south, presenting a significant gap. Over time, the three regions that started slower in development continued their urbanization efforts, and by 2022, the east, west, and north had achieved significant improvements, with the south continuing to lead. Although there have always been differences in development across various directions in Chengdu, these differences did not continue to expand.

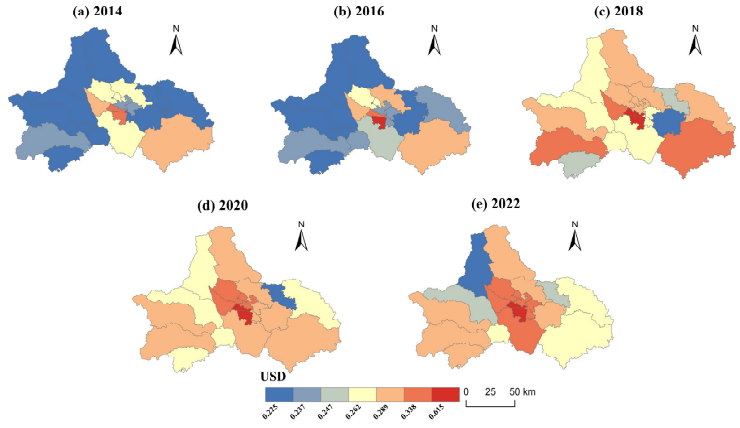


Figure 4. Spatial patterns of urban sustainable development.

4.1.3. Spatiotemporal Perspective Analysis

Finally, this paper analyzes the distribution of urban development in various regions of Chengdu from both temporal and spatial perspectives, identifying underdeveloped areas and their existing issues. The overall urban development score is broken down into three primary indicators: Resource Utilization, Happiness Index, and Economic Potential, in chronological order. The results are shown in Figure 5.

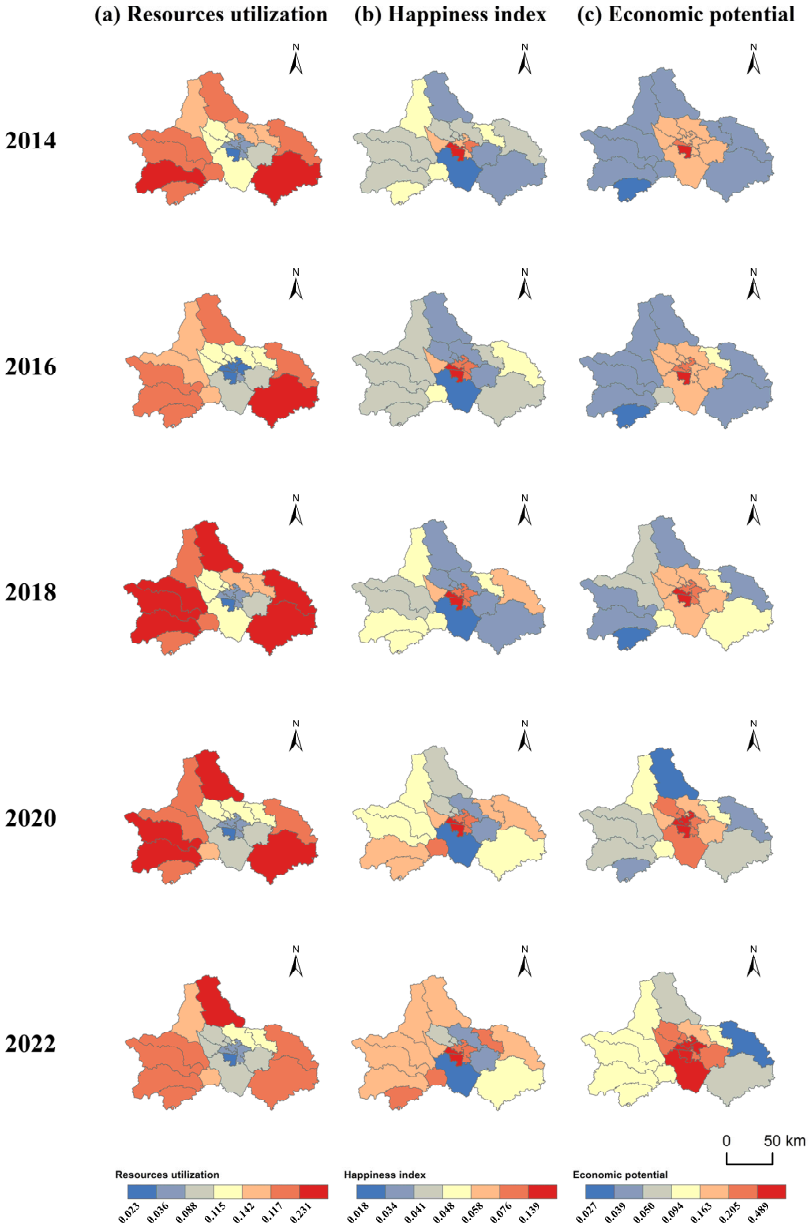


Figure 5. Spatial-temporal patterns of USD. *Note*: From an administrative division perspective, Chengdu is composed of three layers: the first layer consists of the core five urban districts (Jinjiang, Wuhou, Qingyang, Jinniu, and Chenghua), followed by the second layer on the first and second ring roads (Xindu, Pidu, Wenjiang, Shuangliu, Longquanyi, and Qingbaijiang), and finally the third layer is composed of the outer regions (Jianyang, Jintang, Pengzhou, Dujiangyan, Chongzhou, Dayi, Qionglai, Pujiang, and Xinjin).

The results show that between 2014 and 2022, the main issues in Chengdu's urbanization development focused on lower levels of resident happiness and economic potential, with increasing regional imbalances. Resource utilization showed significant fluctuations

from 2014 to 2022. It trended upwards from 2014 to 2018, and then began to decline from 2018 to 2022. However, resource utilization overall displayed a clear three-layer structure, which aligns with the administrative divisions of the core five urban districts, second and third layers, with no significant north-south or east-west disparities within each layer. This indicates that from 2018 to 2022, Chengdu's urbanization process did not sufficiently coordinate the ratio of arable land, development of the primary sector, and natural ecological protection.

In terms of resident happiness, Chengdu's regions did not exhibit an unbalanced east-west concave distribution in 2014 but rather spread from the center outward. After 2018, while the city center continued to maintain high scores, the third layer's scores rose quickly, but the second layer's scores remained largely unchanged, finally forming a noticeable concave distribution in 2022.

Regarding economic potential, the southward trend was not obvious in 2014 (only the high-tech zone in Wuhou district was ahead), and the economic indicators and resource productivity indices were more aligned in 2014 and 2016, showing a clear three-layer distribution. After 2018, the southward trend accelerated, and by 2022, a strong south-weak north trend emerged in the second layer, consistent with the development history of the Tianfu New Area.

Additionally, an analysis of the overall urban development score is presented in Figure 6. From 2014 to 2022, the curvature of the urban development level curve gradually decreased in the time dimension, and there was no significant widening trend in the spatial dimension, indicating that the gap between urban and rural development in Chengdu did not widen from a spatiotemporal perspective but instead showed a narrowing trend.

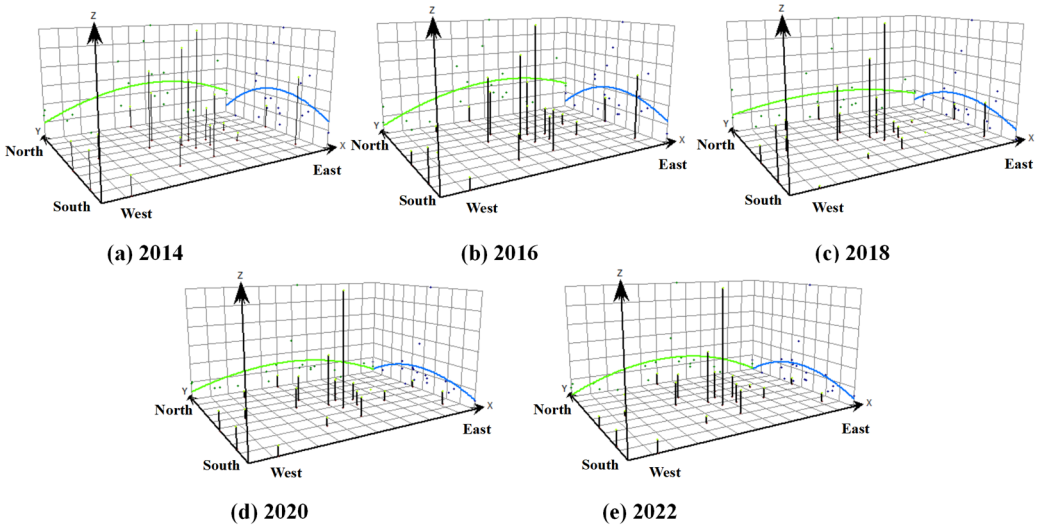


Figure 6. Regional discrepancy of USD. The lines of different colors respectively represent the trend lines fitted by the scatter points projected from 3D data on different planes.

However, between 2014 and 2022, the fastest urban expansion in Chengdu was mainly concentrated in the second layer, where there was a significant increase in economic indicators. However, the happiness index in the second layer has consistently remained at lower scores, indicating a clear imbalance in development in this area during Chengdu's urbanization process, with low resident happiness being a major issue. Therefore, the Section 4.2 will further identify areas of developmental imbalance in the second layer and explore the main reasons for the low happiness of residents from a micro perspective.

4.2. Urban Edge Identification and Urban Expansion Trend

4.2.1. Threshold Determination for Urban Night Light Data Based on the K-Means Algorithm

In this section, the k-means clustering analysis method is used to identify urban, urban-rural, and rural areas in Chengdu through the analysis of urban night light data, and land use data is applied for validation. The primary purpose of distinguishing between urban, urban-rural, and rural areas is to perform a comparative analysis with the administrative divisions of Chengdu to pinpoint the actual locations of the second layer where development imbalances were identified in the previous Section 4.1 and thereby explore the main reasons for the developmental imbalances in the second layer. Initially, an analysis of the urban night light data is conducted to identify the threshold values of light intensity for urban, urban-rural, and rural areas. Subsequent regional restructuring of Chengdu is shown in Figure 7. After analyzing Chengdu's night light data using k-means clustering, the light intensity range identified for urban areas is 35–60, for urban-rural areas 5–35, and for rural areas 0–5. Based on this, Chengdu's regions can be reclassified into three major areas: urban, urban-rural, and rural.

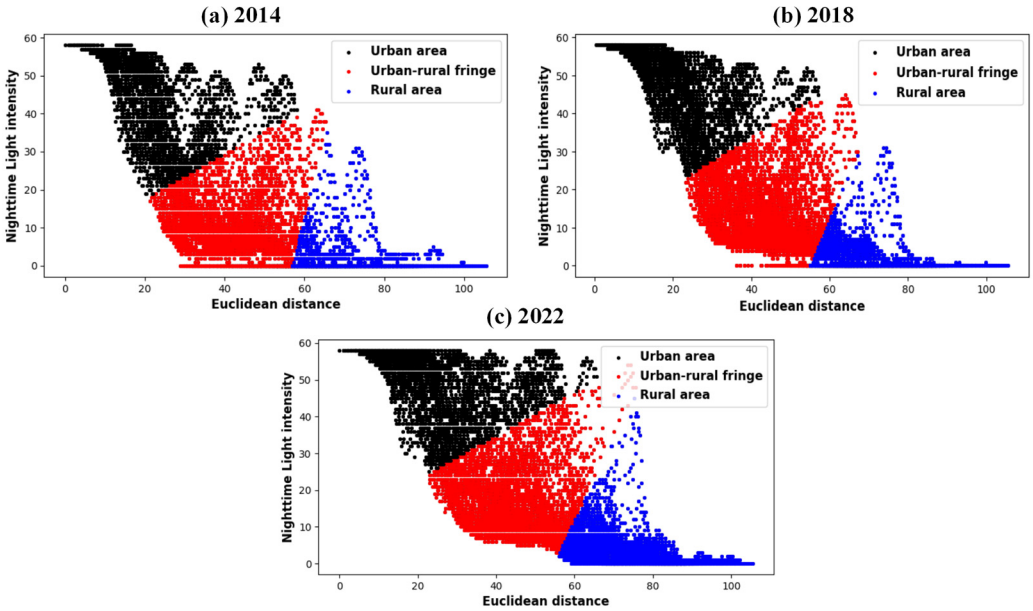


Figure 7. Threshold identification of nighttime light data based on k-means algorithm.

4.2.2. Identification of Urban Boundaries Based on Night Light Data

Building on the three major area classifications identified through the K-means clustering analysis of night light data in the previous Section 4.2.1, this section will analyze the nightlight data of Chengdu's various areas, identifying the scope and regional edges of these three major areas, as shown in Figure 8. The nightlight intensity map clearly shows distinct regional differences within Chengdu. The outermost blue area represents the rural areas with the lowest nightlight intensity. The middle yellow area is the urban-rural interface, and the central red area has the highest night light intensity, representing urban areas. In terms of temporal dimensions, there is a noticeable spreading trend in the urban-rural interface towards the southeast, indicating an expansion trend from the central city and its nearby surrounding areas. At the same time, early independent district centers show a trend of gradual integration. Comparing the night light data map with the urban development conditions of each area from Section 4.1, it is further found that the main expansion areas at the edges of urban and urban-rural interfaces occur primarily within the city's second ring. This once again confirms that Chengdu's urban expansion from 2014 to 2022 mainly took place in the second ring.

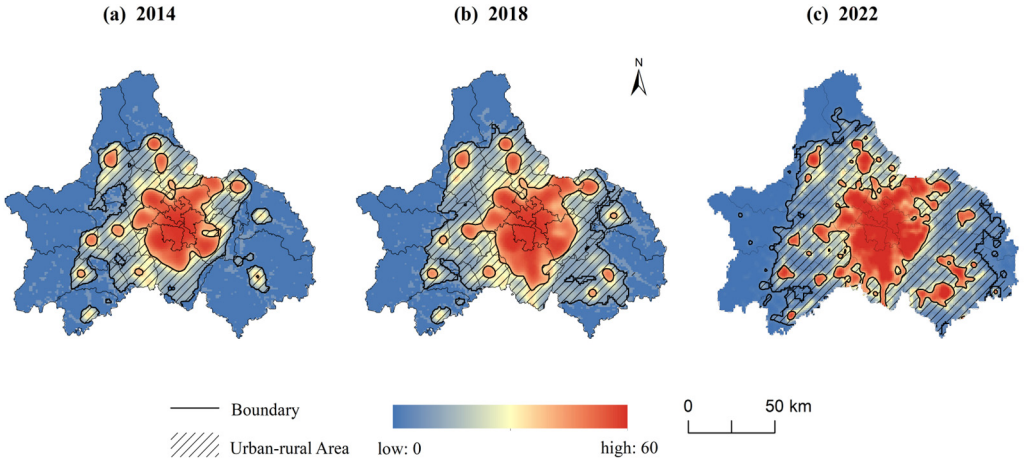


Figure 8. Evolution map of nighttime light intensity distribution and regional edges.

4.2.3. Urban Expansion Trend Analysis Based on Land Data

To further verify the reliability of the results, this paper uses land use data from Chengdu and combines it with a mask overlay of the urban-rural interface identified from the night light data. The results find that the city's expansion is primarily towards the southeast direction. The masked graphic results show that urban areas with concentrated pink and rural areas with very little land development are well identified. The diverse colors in the masked areas align with the characteristics of the urban-rural interface as land currently under development. If the urban and rural areas from 2014, 2018, and 2022 are overlaid, as shown in Figure 9d, it can be observed that the expansion in the western regions is relatively slow, while the south and east are the complete opposite, with the eastern area exhibiting a very strong expansion trend.

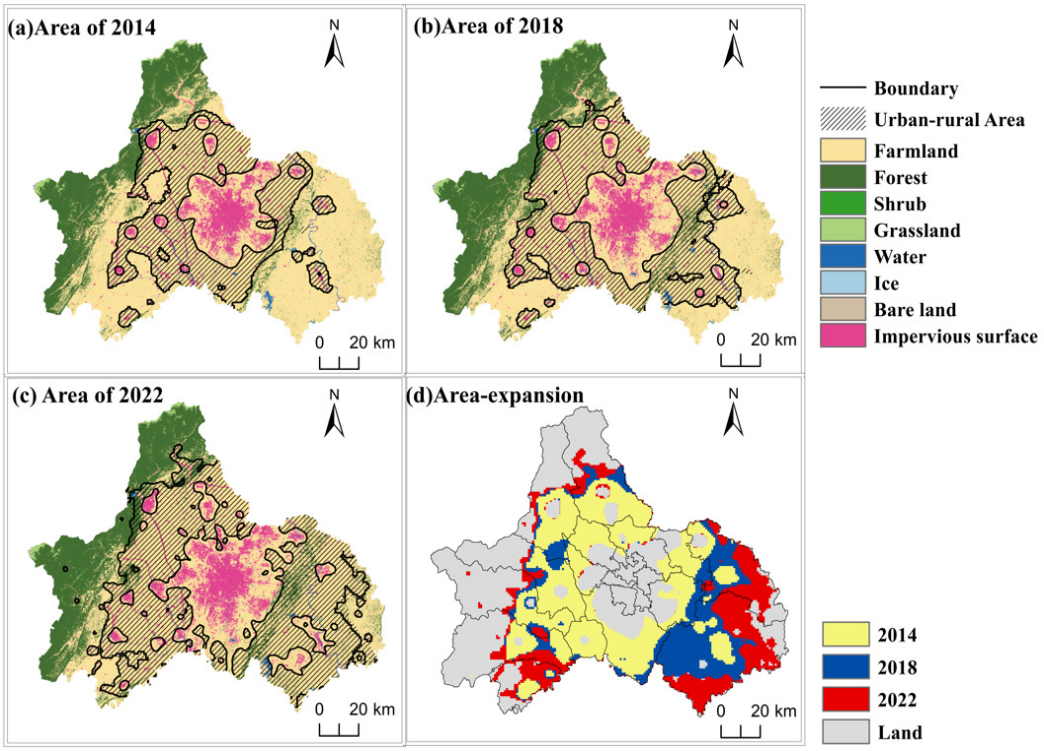


Figure 9. Land use distribution and urban expansion trend.

4.3. POI and Identification of Urban Functional Zones

This section will explore the issue of developmental imbalances in the urban-rural interface areas of Chengdu from the perspectives of urban planning and land use. Firstly, historical road network data for Chengdu will be accessed. Then, POI data retrieved from Gaode Maps and Baidu Maps will be merged with the road network data of the urban-rural interface to analyze the distribution of Chengdu's road networks in these areas, as well as the main functions of buildings surrounding different roads, followed by a functional zoning of each urban street. Through the analysis of road network distribution and functional zoning of urban areas, this study will investigate the shortcomings in urban planning and land use in the urban-rural interface areas. To maintain consistency with the previous research focus, this paper takes the primary indicators of urban sustainability evaluation as the classification basis and categorizes each point of interest (POI) into one of the three primary indicator categories. The classification of POIs is presented in Table 2.

Table 2. Classification of POI and Functional Area Division.

Functional Categorization	Medium Categories	POI
Happiness index	Public facilities	Public telephone, newspaper and magazine stand service area, public toilet, and shelter et al.
	Science, Education, and Culture	School, training center, research institution, library and cultural palace et al.
	Medical and Healthcare	Clinic, general hospital, emergency center, and specialist hospital et al.
	Tourist Attractions	Park, scenic spot, temple, square, zoo, and botanical garden et al.
Economic potential	Companies and Enterprises	Company, factory and agriculture, forestry, animal husbandry, and fishery base et al.
	Shopping and Services	Home furnishing, specialty store, shop, comprehensive market, sporting goods store et al.
	Financial Institutions	Bank, insurance agency, security company et al.
	Business and Residential Areas	Residential area, building and industrial park et al.
Resources utilization	Blank area of POI	-
Mixed functional area	All	All

Note: The total points of interest in the mixed functional area encompass many different functional zones, but the overall number of points of interest is relatively small.

The distribution of POI data, as shown in Figure 10, indicates an overall upward trend in the number of interest points in urban-rural fringe areas, rising from 72,150 in 2014 to 131,037 in 2022, with an average annual growth rate of 7.74%. This suggests improvements in various aspects such as the scale, economy, and urban planning of these areas. This observation also implies that the diversity of urban landscapes is undergoing a persistent augmentation, which has subsequently contributed to an enhancement of the resilience of urban landscapes to a certain extent and, concomitantly, has furnished potential avenues for fostering sustainable urban development.

From the perspective of the scale and growth rate of POI functional areas (see Figure 11), the number of shopping and services has grown from 6026 in 2014 to 28,815 in 2022, with an average annual growth rate of 21.6%. Moreover, in 2022, shopping and services accounted for 42% of the total POI, indicating that the resident population in urban-rural fringe areas is demanding increasingly diverse goods and services, and consumption is rapidly upgrading. The number of companies and enterprises has also increased from 3174 in 2014 to 11,536 in 2022, achieving an average annual growth rate of 217.5%. In 2022, companies and enterprises accounted for 17% of the total POI, suggesting that the economic vitality of urban-rural fringe areas is improving and reflecting the improvement of the entrepreneurial environment.

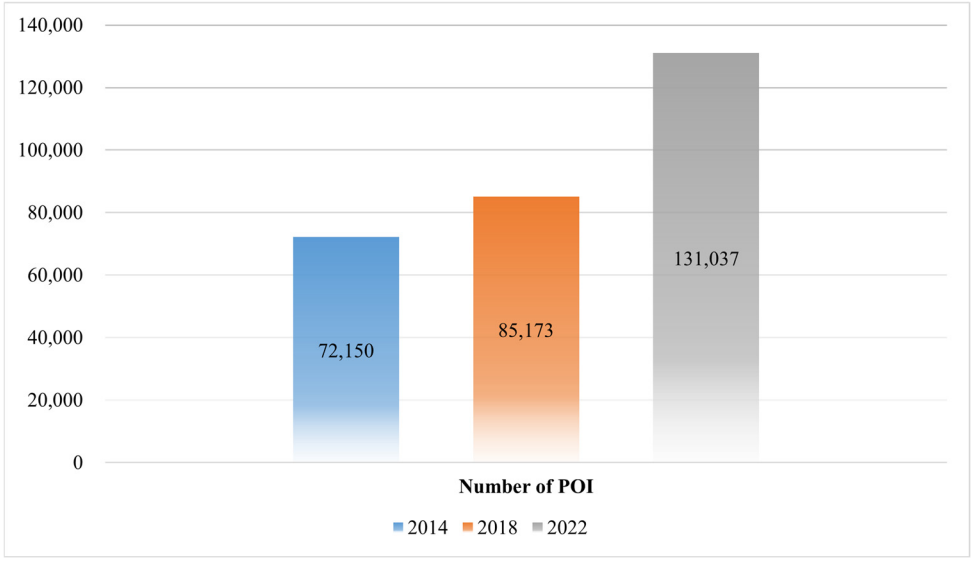


Figure 10. Changes in number of POI during 2014 to 2022.

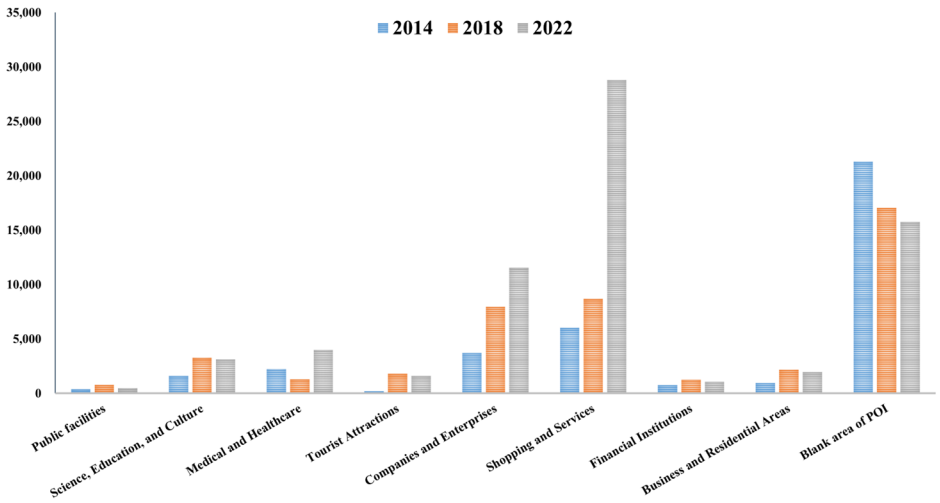


Figure 11. Changes in interest points during 2014 to 2022.

Surprisingly, the POI in the urban-rural fringe area of Chengdu that grew the fastest is tourist attractions, from 207 in 2014 to 1584 in 2022, achieving an average annual growth rate of 28.9%, which is also the fastest-growing POI. This indicates that Chengdu is fully utilizing its natural and cultural resources, injecting new momentum and vitality into economic development while also enhancing its international reputation and influence. The proportion of blank area of POI exceeds 20%, but it is showing a downward trend. This suggests that with urban development and planning adjustments, some existing mixed-use functional areas may face re-planning or functional transformation.

In order to further analyze the changes in functional areas in urban-rural fringe areas, we first investigate the road network data, which can provide insights into the general development status of each block. By combining this with POI data for functional area identification and classification of each block, it is possible to discern the actual functions each block serves in the process of urban development. Comparing these results with the developmental directions of administrative planning allows for an evaluation of whether the spatial distribution and scale of urban planning are reasonable. To more visually display the results, this paper selects three areas with the largest proportions of urban-rural area in the northwest, southwest, and southeast directions as examples. Each area covers a 25 km $\times$ 25 km region for enhanced observation, with results shown in Figures 12 and 13.

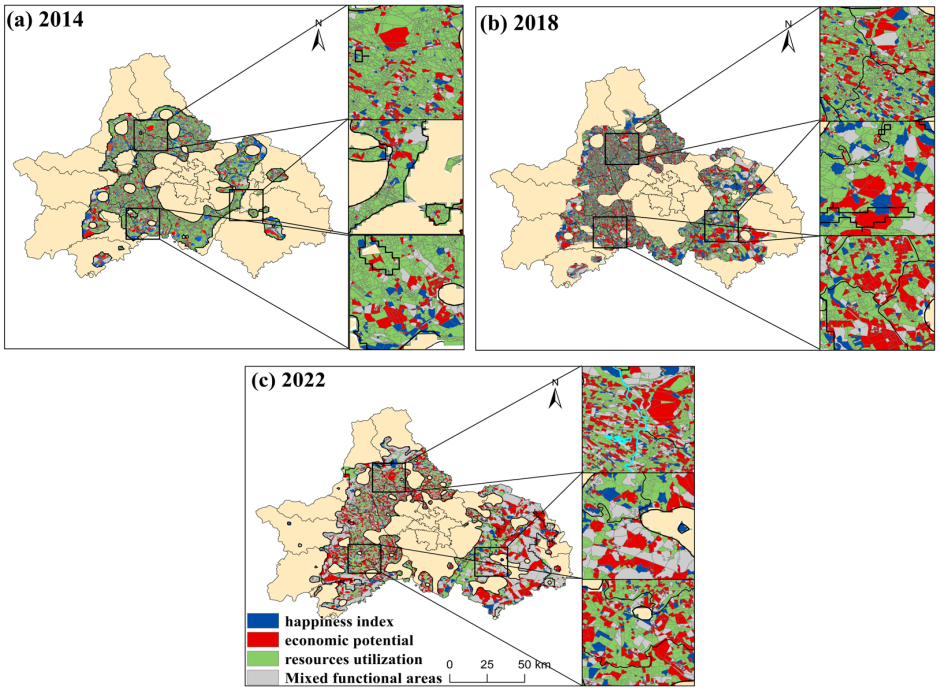


Figure 12. The evolution trend of functional areas in urban-rural fringe areas.

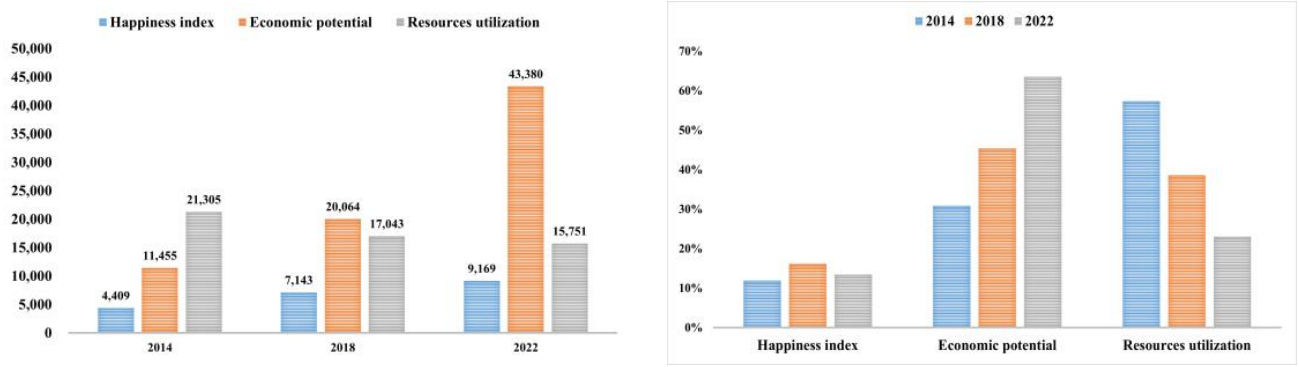


Figure 13. Changes in POI and structural alterations within the functional areas.

This process is typically based on urban planning and spatial analysis methods, examining various factors such as land use, building types, population distribution, and economic activities within a region to determine its primary functions, such as residential, commercial, industrial, and cultural zones. Identifying urban functional zones aids urban planners, policymakers, and researchers in better understanding and grasping the spatial structure and developmental dynamics of cities, providing a scientific basis for urban planning and policy formulation. From the perspective of functional zones, there is a clear trend of outward expansion at the urban-rural interface, primarily towards the east. However, from 2014 to 2022, the green areas that mainly served resource functions have gradually decreased, indicating a decline in land use efficiency at the urban-rural interface. This result is consistent with the overall downward trend in resource utilization rates calculated using the entropy weighting method, suggesting a reduced balance between natural resource exploitation and protection in Chengdu.

The changes in the blue zones, representing resident happiness, have been minimal, indicating that Chengdu has shortcomings in improving resident welfare in its urbanization process. In the entropy weighting method assessment, there was a slight increase in happiness scores in the second layer, but this may be due to the happiness brought by rural populations moving into the city for work rather than a true increase in total investment

in resident welfare and improvements in urban planning. In the core five urban districts, due to explicit and implicit conditions such as high housing prices and the hukou system, population mobility is reduced, creating high barriers for new entrants to the urbanization process, with most people congregating in the urban-rural interface. The increase in population size leading to a decrease in per capita public budget in the urban-rural interface could be one reason. Therefore, facing the dilemma of significantly lower tax revenues than in the core urban areas, the urban-rural interface bears the dual pressures of growing demands for population welfare and higher levels of economic development, making it challenging to allocate resources and provide public services effectively.

Over the past decade, the functional areas that have increased the most in the urban-rural interface are the red economic potential zones and mixed-use zones. This indicates that the main driving force for the improvement in Chengdu's urbanization scores from 2014 to 2022 has been driven primarily by real estate development and new factory constructions. In 2014, the economic zones were mainly surrounded by resource zones, which made circulation of economic elements costly and difficult to leverage economies of scale. However, by 2022, economic zones and mixed-use zones have gradually intersected, forming a larger area, while the proportion of mixed-use functional areas is continuously decreasing. The results indicate that this merging trend is expected to continue.

Under the strong eastward expansion trend in southeast Chengdu, the eastward expanding blocks cover larger areas, and the functional zones in newly developed expansions are more concentrated and cover more land. However, the expansion speed in the western regions is lower, with dense road networks and low concentrations of functional zones, making urban planning less reasonable. Combining land use data, the main reasons for the developmental disparities between the east and west areas are: (1) while restricted by the arable land red line, the western area has larger hills and forests, increasing development costs. Developing these hills and forests also contradicts the concept of sustainable development; (2) the presence of many small towns in the west results in a dense road network, where unplanned and extensively grown old towns face high development and demolition costs, making redevelopment on the existing old town foundations a more rational choice. The eastern region, with its vast rural farmland resources, flat terrain, and low land development costs, offers significant economic advantages in resource allocation, infrastructure construction, and future development potential, making it the most rational choice for expansion.

4.4. Driving Factor Analysis

This section further identifies the micro-level driving factors and their impact on regional development imbalances based on the analysis of POI data in the functional areas of the urban-rural interface. Using the Geodetector geographic detector, the evaluation involves quantitative analysis where secondary indicators of urbanization development levels are used as independent variables, and the overall scores of each administrative district serve as the dependent variables. This approach assesses the driving factors in the urbanization process of the urban-rural interface from a micro perspective. The results are presented in Table 3:

Table 3. Microscopic driving force analysis.

Resources Utilization		**Economic Potential**		**Happiness Index**	
Indicators	**q-Statistic**	**Indicators**	**q-Statistic**	**Indicators**	**q-Statistic**
AQI	0.17	GDPA	0.60	PB	0.10
PCL *	0.28	UR *	0.24	STU	0.008
WR *	0.26	NIE	0.12	BED *	0.48

Table 3. *Cont.*

Resources Utilization		Economic Potential		Happiness Index	
Indicators	**q-Statistic**	**Indicators**	**q-Statistic**	**Indicators**	**q-Statistic**
OG *	0.24	APP *	0.50	SS *	0.61
AOV *	0.32	SRE *	0.55	-	-
-	-	IE	0.74	-	-
-	-	NLC *	0.66	-	-
Mean	0.253		0.489		0.317
Variance	0.002		0.044		0.054
Coefficient of variation	0.193		0.43		0.733

Note: * denotes significance at 5%.

In this section, using POI data analysis on functional areas of the urban-rural interface, further investigation is conducted into the micro-level driving factors contributing to regional development imbalances and their impact. Through the use of the Geodetector tool, secondary indicators assessing urbanization development levels are employed as independent variables, with the overall scores of each administrative district serving as dependent variables, to quantitatively analyze the drivers in the urbanization process of the urban-rural interface from a micro perspective. The results are presented in Table 3.

The values of secondary indicators within Resource Utilization primarily range from 0.2 to 0.3 and are statistically significant, albeit contributing minimally overall, with little variation among values. Combined with the slight fluctuation in resource ratings from 2014 to 2022 using the entropy weighting method and the decrease in green functional areas from POI data, it can be inferred that the urbanization of lands such as arable fields and forests in the urban-rural interface has not had a strong negative externality on the primary sector and natural resources. This indicates that the Chengdu government has not sufficiently balanced issues of agriculture, arable land protection, and urban development.

In the Economic Potential category, aside from the urbanization rate (UR) at 0.24 and the number of large enterprises (NIE) at 0.12, other indicators are around 0.5–0.7 and possess strong explanatory power. Interestingly, the number of listed companies (NLC) is significant, whereas the number of large enterprises is not. This may be due to listed companies being recorded by their place of registration. Although numerous listed companies are based in the urban-rural interface, policy constraints on urban planning and environmental regulation prevent the development of large industrial enterprises, especially heavily polluting ones. In rural areas, due to fewer constraints, large-scale industrial enterprises tend to relocate there, which explains why NIE values are small and insignificant in the urban-rural interface. However, this also results in pollution being transferred nearby, with rural areas potentially becoming pollution havens.

Furthermore, UR's explanatory power for the overall city score is not as high as expected. Combining entropy weighting and POI data analysis, possible reasons include: (1) While urbanization has led to the aggregation of population and resources, the newly urbanized population lacks the necessary skills and knowledge to fully engage in high-value industries or contribute significantly to regional economic development. A low and insignificant number of effective inventions (IE) also indicates that the human resources in the urban-rural interface have not yet been fully converted into economic development drivers. (2) Although urbanization rates in urban-rural areas have increased, integration between urban and rural areas is lacking, leading to a long-term lack of significant improvement in the happiness index of residents and widening the gap with economic development. Insufficient urban-rural integration, resulting in uneven resource distribution and imbalances in public services, impacts the overall level of urban development. (3) An increased urbanization rate also raises the demand for infrastructure and public services. A low per capita welfare (PB) index indicates that infrastructure and public services in the area lag behind the pace of urbanization, with issues like traffic congestion and strained educational

resources potentially affecting the quality and outcomes of urbanization, thus limiting its role in promoting economic development and urbanization levels.

The housing price index (APP) has a significant driving force, indicating that land development in the urban-rural interface is one of the main drivers of urbanization. However, considering the gradual tightening of land finances, the sustainability of land finance is in question. The significance of the higher education and research (SRE) index, second only to the number of listed companies (NLC), is due to universities in the area effectively utilizing urban-rural resources to foster urban-rural integrated development. Furthermore, universities, as bases for scientific research and technological innovation, not only provide a continuous supply of high-quality talent for urbanization but also, through research and development, facilitate the generation and widespread application of new technologies in the urban-rural interface, promoting innovative regional economic development. Continuing to advance scientific and technological innovation is a key focus for further promoting sustainable urban development.

In terms of resident happiness, the explanatory power of resource utilization and economic potential is slightly lower, with a significant imbalance evident in resident happiness. Indicators such as per capita welfare (PB) and student ratio (STU) are not only low but also insignificant. The explanatory power of beds per thousand people (BED) and scenic spots per unit area (SS) is greater. To further analyze the reasons, this paper collected the trend in the permanent population changes across various districts and counties in Chengdu from 2014 to 2022, as shown in Figure 14. The data reveals that the population growth in Chengdu's urban-rural fringe areas, particularly in the Shuangliu District of the second circle, is the most pronounced. Meanwhile, the urban population has not experienced significant growth, suggesting that the urban-rural fringe areas have become the main gathering places for migrant and rural populations. Combining the analysis results from the geographical detector, it is further confirming that residents in urban-rural fringe areas face greater life pressures and have relatively limited resources per capita. Additionally, policies related to school districts and household registration have caused the development of educational resources to lag behind the urbanization process. Parents who have just moved to the city for work, unable to afford high housing prices, are unable to register locally, meaning their children cannot receive education alongside them. These factors have negatively impacted urban residents' sense of happiness.

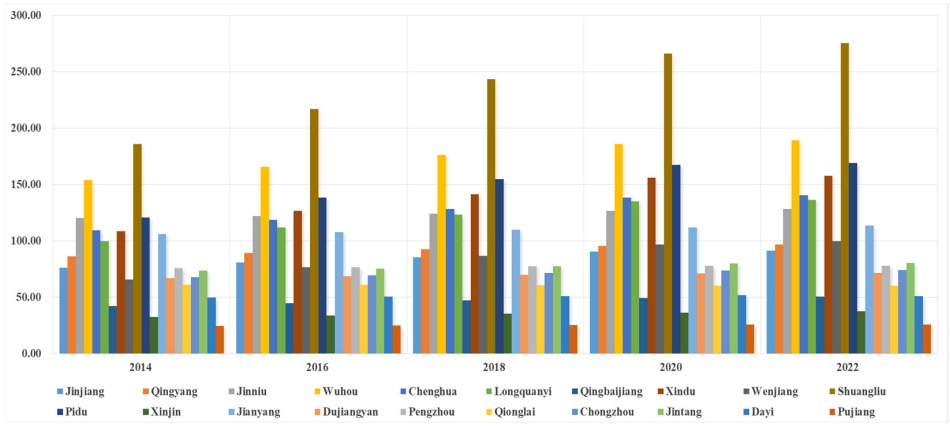


Figure 14. Changes in permanent population across regions of Chengdu city from 2014 to 2022 (unit: 10,000 people).

However, unexpectedly, the scenic spots per unit area have the highest explanatory power and produce the greatest positive impact among the happiness evaluation indicators in this study. This is because Chengdu, as a leading tourist city nationally, has a high level of development in cultural and tourism sectors. The data in Figure 10 also confirms this result, showing that the fastest-growing POI in the urban-rural fringe areas of Chengdu is

Tourist Attractions, increasing from 207 in 2014 to 1584 in 2022, with an average annual growth rate of 28.9%, which is also the fastest-growing POI among all. This indicates that Chengdu is fully utilizing its natural and cultural resources.

The survey campaign of "The Most Happy City in China" is sponsored by Oriental Outlook and has been held for 17 consecutive years so far. The "2023 China Urban Happiness Report" shows that Chengdu has been named "China's Most Happy City" for 15 consecutive years [88]. At the same time, the Longquanyi District, Shuangliu District, and Wenjiang District in the second tier have been named "2023 China's Most Happy Districts". This survey was conducted using the "Urban Happiness Index System Based on Big Data" developed by the China Happy City Laboratory, which covers comprehensive happiness indicators such as education, healthcare, ecological environment, transportation, employment, urban attractiveness, etc. The research results of the report suggest that the high happiness level of Chengdu residents is primarily due to: the improvement of people's livelihood through urban renewal and the increase in employment opportunities; the city's rapid development providing more job opportunities; the gradual increase in the proportion of cultural tourism, which has boldly innovated in inheriting historical cultural traditions, handling the relationship between tradition and modernity, inheritance and development, and better satisfying the spiritual and cultural needs of urban residents, thereby enhancing the city's soft power and sense of happiness. The results of the urban sustainability level (shown in Figure 3) and the analysis based on POI data and geographic detectors in this paper also support this conclusion. Although the enhancement of natural landscapes and cultural tourism indicators provides some soft support for residents' subjective sense of happiness, due to the lack of direct and crucial hard support factors such as education, healthcare, and housing, the resilience and recovery capabilities of urban-rural fringe areas may be weaker compared to urban and rural areas when facing unpredictable external shock.

5. Discussion

Overall, Chengdu's urban spatial development strategy, which focuses on "advancing east, expanding south, controlling west, reforming north, and optimizing the center", aligns well with actual practices. This strategy has transformed Chengdu from being "a city squeezed between two mountains" to "a city connected to two wings", playing a significant role in addressing "big city diseases" and promoting sustainable urban development. However, there are still factors in Chengdu's urbanization process that restrict the high-quality development of urbanization.

Analysis using the k-means machine learning algorithm on urban nightlight data combined with entropy weighting method analysis reveals that during Chengdu's rapid urbanization process, the happiness of residents in the urban-rural interface has stagnated, and the gap between this and economic indicators has been gradually widening. Further analysis with the Geodetector and POI data highlights several issues:

The urbanization process in the urban-rural interface is lagging. During urbanization, the urban-rural interface has concentrated a large number of migrant workers, whose strong mobility in the area leads to unstable employment. Improvements might be made by enhancing social security for temporary workers and labor dispatch systems and by strengthening adult re-education, with financial support or increased promotion of skills such as carpentry, to accelerate the integration of rural migrants into urban areas. Gradually reducing discriminatory policies between urban and rural areas could allow urbanization benefits to be fairly distributed among all residents. In 2024, Chengdu opened the channel for compulsory education for migrant children, but there are still policy restrictions for middle and high school admissions. "Citywide high school admissions are managed by district, and without approval, general high schools may not enroll students across districts. In 2024, the city set up 17 enrollment districts. Sichuan Tianfu New Area, Chengdu High-tech Zone, Jinjiang, Qingyang, Jinniu, Wuhou, and Chenghua districts together form one enrollment district ('5 + 2' area), with the other 16 districts (cities) each forming their own". The separation of

school and household registration means that even if children move into the city with their parents, they must return to their original registration location for further education, leading to a mismatch between educational environment and advancement opportunities.

Construction land in the urban-rural interface is extensive and inefficient. Analysis based on POI and road network data shows that functional area blocks in the eastern region are very large, indicating immature road construction and low population density. Urban development pursues "pancake-style" expansion, excessively favoring wide roads and new districts. Furthermore, the eastern region's block classification is primarily red economic indicators, suggesting that new towns prioritize economic construction and development zones and industrial parks occupy too much land. Past reliance on land finance has led local governments to approve land development without considering the objective laws of industrial development. For instance, Tianfu New Area already exhibits infrastructure far exceeding the needs of its population density, with expansion in the Chengdu-Chongqing economic belt primarily planned in large blocks. Beyond development zones and industrial parks, large commercial shopping cities and ultra-high-rise residential complexes are also built in areas with low traffic networks and population density, burdening finances and reducing resource efficiency. Establishing new performance evaluation methods, incorporating sustainability and social assessment indicators into officials' performance evaluations, and referencing the construction industry's lifelong accountability system could mitigate policy shortsightedness and ensure policy consistency, significantly aiding the business environment for enterprises.

Since May 2017, the Chengdu Municipal Planning and Management Bureau has been implementing the "Eastward Advance" strategic master plan. The "Eastward Advance" region is designated as a priority development area, comprehensively advancing the construction of public services, ecological environments, and infrastructure. Establishing the Eastern New District of Chengdu helps break the single-center pancake urban structure, optimizing urban space and enhancing the city's energy level and core competitiveness. However, attention must be paid to matching fiscal revenue and expenditure with talent and industrial development. Research finds that the current population of the Eastern New District far falls short of its infrastructure-carrying standards. As of late 2022, Chengdu's local government debt balance stood at 464.05 billion yuan, ranking high among prefecture-level cities, with debt distribution in each district associated with the layer division, with the second layer (urban-rural interface) contributing half of the debt. Under fiscal risk control constraints, allocating limited financial resources to encourage corporate R&D, scientific research, or education could be a long-term effective way to promote sustainable urban development. It is commendable that Chengdu leverages its historical resources to develop tourism and performs well in developing and protecting natural and historical cultural heritage. Not only does this promote green industry and tourism, but it also enhances Chengdu's image in China and internationally, offering a valuable model for urban construction.

6. Conclusions

This paper first constructs an indicator system for assessing urban sustainable development based on the United Nations Sustainable Development Goals (SDGs), the two hemispheres theory, and decoupling theory and applies the entropy weighting method to evaluate the spatiotemporal trends of urbanization in Chengdu's districts, identifying imbalanced areas and key existing issues in urbanization development. Secondly, the K-means machine learning algorithm is used to analyze urban night light data combined with land use data to spatially segment Chengdu, further identifying whether problem areas are primarily urban, urban-rural interfaces, or rural. Finally, using POI data, the land functions in areas with uneven development during the urbanization process are quantified, and the Geodetector tool is applied to identify the micro-level driving factors behind the uneven development. The main findings of the study include:

At the macro level, economic development is currently the primary driver of urbanization in Chengdu, but a development model heavily focused on the economy has led to the neglect of resident welfare, which is a prominent issue in Chengdu's urbanization process. From 2014 to 2022, the southern region of Chengdu has consistently led, with the eastern, western, and northern regions also achieving significant improvements. Although there have always been differences in development across various directions in Chengdu, these differences have not continued to expand. Looking at the three major indicators of sustainable urban development, the overall trend of resource utilization efficiency is declining, indicating that Chengdu's urbanization process has not adequately balanced the proportion of arable land, the development of the primary sector, and the protection of natural ecosystems. The happiness of residents has not shown a state of spreading from the city center outward. Due to the second layer's scores remaining essentially unchanged, there is a clear concave distribution feature where the happiness of residents in the inner and outer city continues to rise but stagnates in the middle. In terms of economic potential, there is a clear state of spreading from the city center outward. Overall, there is a clear disparity between economic development and the improvement of resident welfare in Chengdu.

The areas of uneven development during the urbanization process are mainly concentrated in the urban-rural interface, which includes the second urban ring areas composed of Xindu, Pidu, Wenjiang, Shuangliu, Longquanyi, and Qingbaijiang districts. Analysis of urban nightlight data using the K-means machine learning algorithm reveals a clear three-layer structure in Chengdu's regional distribution, namely urban-urban-rural interface-rural areas. Over time, there is a clear spreading trend in the urban-rural interface towards the southeast, showing a trend of expansion from the central city and its nearby surrounding areas. Earlier, more independent district centers have shown a trend of gradual integration. Further analysis found that the expansion areas at the edge of the city and urban-rural interface mainly occur in the second urban ring. Application of land use data combined with nightlight data identified in the urban-rural interface through mask combination analysis confirms this conclusion.

The main reasons for the irrational development of the urban-rural interface can be attributed to the slow process of urbanization, inefficient use of construction land, and unreasonable urban and industrial spatial distribution. (1) The urban-rural interface has become the main gathering place for rural migrants, who have high mobility, making it difficult for residents of the urban-rural interface to find stable employment. Due to a lack of stable cash flow, loan applications are not smooth, effectively raising the threshold for home purchases in the area. Moreover, apart from buying homes, there are no other effective channels for most migrant workers to settle in the city, meaning many of them cannot obtain urban household registration and enjoy urban resident benefits. The floating population in the urban-rural interface causes per capita public spending and welfare to be lower. The mismatch between school and household registration causes the development of educational resources to lag behind the process of urbanization. High barriers to citizenship slow down the urbanization process, leading to a decline in resident happiness. Current enrollment measures ensure fairness in college entrance examinations; students who enter city schools with their parents must have a complete three-year study phase or else return to their original registration location for the college entrance exam, which constrains the urbanization process. The focus of urbanization can gradually shift from economic development to focusing on people, improving the level of resident welfare. Gradually promoting equal enjoyment of basic urban public services for non-registered permanent residents could help. Also, reasonable government debt management, allocating funds for corporate R&D, university research, and education, can form a sustained driving force for high-quality economic development, thereby increasing fiscal revenue, enhancing per capita fiscal spending for permanent residents, and comprehensively improving the welfare level of the permanent population.

(2) The eastern region is characterized by extensive and inefficient construction, while the western region has an unreasonable distribution of urban and industrial spaces. The eastward expansion area has experienced "pancake-style" urban structure, with infrastructure capacity far exceeding the current population size. The current population density in the Eastern New District of Chengdu is approximately 440 people per square kilometer, far below the city average of 1493 people per square kilometer. Large CBD commercial shopping cities, ultra-high-rise residential complexes, development zones, and industrial parks are mainly built far from the urban area, which, while bringing financial burdens, also lowers the efficiency of urban land resource use. Care should be taken to prevent the emergence of "ghost towns" similar to those seen in other newly developed areas after the concept of the new district wanes. The western region, mainly consisting of old urban areas, has a dense block road network, many small towns, small scales, high population density, and weak service functions, leading to inefficient clustering and high costs for urban re-planning such as demolition. Local government debt constraints are a major barrier to improving urban planning. It is recommended that the eastern region fully utilize its spacious regional advantages to develop intensive industries and natural ecological tourism, gradually attracting talent to reside and then developing residential housing and commercial circles, making rational use of land resources to prevent "ghost towns". Combining big data monitoring with policymaking can gradually optimize fiscal revenue and expenditure and talent training and introduction, fully leveraging resource advantages to optimize industrial structure. In the western region, under the constraint of controlling fiscal risks, limited financial inputs into encouraging corporate R&D, scientific research, or education can innovatively and sustainably drive urban development. It is commendable that Chengdu can adaptively rely on historical resources to develop the tourism industry, not only promoting the development of the green industry and tourism but also enhancing Chengdu's image in China and internationally, providing a valuable model for urban construction.

Author Contributions: Conceptualization, Y.L. and Q.R.; methodology, Y.L. and Y.Z. (Yilang Zhao); software, Y.Z. (Yilang Zhao); validation, Y.L. and Q.R.; formal analysis, Y.L. and Y.Q.; investigation, Y.L. and Y.Z. (Yuerong Zhang); resources, Y.L. and Y.Z. (Yilang Zhao); data curation, Y.Z. (Yilang Zhao), Q.R. and Y.Q.; writing—original draft preparation, Y.L. and Q.R.; writing—review and editing, Y.Q., Y.Z. (Yuerong Zhang) and K.Z.; visualization, Y.L. and Y.Z. (Yilang Zhao); supervision, Y.L., Q.R. and Y.Q.; project administration, Y.L.; funding acquisition, Y.L. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the Scientific Research Foundation of Chongqing University of Technology, grant number 2022ZDR002; the Chongqing Social Science Planning Project, grant number 2023BS025; the Humanities and Social Science Research Projects of Chongqing Education Commission, grant number 23SKJD109; and the Higher Education Scientific Research Project of Higher Education Institute of Chongqing, grant number cqgj23084C.

Data Availability Statement: The data are available from the corresponding authors upon reasonable request.

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

References

1. Antrop, M. Landscape change and the urbanization process in Europe. *Landsc. Urban Plan.* **2004**, *67*, 9–26. [CrossRef]
2. Feng, Z.; Peng, J.; Wu, J. Using DMSP/OLS nighttime light data and K–means method to identify urban–rural fringe of megacities. *Habitat Int.* **2020**, *103*, 102227. [CrossRef]
3. Liu, Z.; Robinson, G.M. Residential development in the peri-urban fringe: The example of Adelaide, South Australia. *Land Use Policy* **2016**, *57*, 179–192. [CrossRef]
4. Achillopoulou, D.V.; Mitoulis, S.A.; Argyroudis, S.A.; Wang, Y. Monitoring of transport infrastructure exposed to multiple hazards: A roadmap for building resilience. *Sci. Total Environ.* **2020**, *746*, 141001. [CrossRef]
5. Kundu, S.; Rana, N.K.; Mahato, S. Unravelling blue landscape fragmentation effects on ecosystem services in urban agglomerations. *Sustain. Cities Soc.* **2024**, *102*, 105192. [CrossRef]
6. Wang, X.; Hu, P.; Zhu, Y. Location choice of Chinese urban fringe residents on employment, housing, and urban services: A case study of Nanjing. *Front. Archit. Res.* **2016**, *5*, 27–38. [CrossRef]

7. Mikhaeil, E.; Okulicz-Kozaryn, A.; Valente, R.R. Subjective well-being and urbanization in Egypt. *Cities* **2024**, *147*, 104804. [CrossRef]
8. Li, H.; Chen, K.; Yan, L.; Yu, L.; Zhu, Y. Citizenization of rural migrants in China's new urbanization: The roles of hukou system reform and rural land marketization. *Cities* **2023**, *132*, 103968. [CrossRef]
9. Zhang, Y.; Wang, J.; Liu, Y.; Yue, W. Quantifying multiple effects of land finance on urban sprawl: Empirical study on 284 prefectural-level cities in China. *Environ. Impact Assess. Rev.* **2023**, *101*, 107156. [CrossRef]
10. Yang, G.; Xu, R.; Chen, Y.; Wu, Z.; Du, Y.; Liu, S.; Qu, Z.; Guo, K.; Peng, C.; Chang, J.; et al. Identifying the greenhouses by Google Earth Engine to promote the reuse of fragmented land in urban fringe. *Sustain. Cities Soc.* **2021**, *67*, 102743. [CrossRef]
11. China Sustainable Cities Report 2016: Measuring Ecological Input and Human Development. Available online: https://www.cn.undp.org/content/china/en/home/library/democratic_governance/china-sustainable-cities-report-2016--measuring-ecological-input.html (accessed on 30 November 2016).
12. Zhang, X.; Xie, Y.; Jiao, J.; Zhu, W.; Guo, Z.; Cao, X.; Liu, J.; Xi, G.; Wei, W. How to accurately assess the spatial distribution of energy CO_2 emissions? Based on POI and NPP-VIIRS comparison. *J. Clean. Prod.* **2023**, *402*, 136656. [CrossRef]
13. Lu, T.; Lansing, J.; Zhang, W.; Bechle, M.J.; Hankey, S. Land Use Regression models for 60 volatile organic compounds: Comparing Google Point of Interest (POI) and city permit data. *Sci. Total Environ.* **2019**, *677*, 131–141. [CrossRef]
14. Cang, J.; Wu, P.; Lin, S. Redefining the boundaries of Chinese cities—Analysis based on multisource geographical big data. *Cities* **2024**, *149*, 104984. [CrossRef]
15. Tampekis, S.; Samara, F.; Sakellariou, S.; Sfougaris, A.; Christopoulou, O. An eco-efficient and economical optimum evaluation technique for the forest road networks: The case of the mountainous forest of Metsovo, Greece. *Environ. Monit. Assess.* **2018**, *190*, 1–15. [CrossRef]
16. Argyroudis, S.A.; Mitoulis, S.A.; Hofer, L.; Zanini, M.A.; Tubaldi, E.; Frangopol, D.M. Resilience assessment framework for critical infrastructure in a multi-hazard environment: Case study on transport assets. *Sci. Total Environ.* **2020**, *714*, 136854. [CrossRef]
17. Sakellariou, S.; Sfoungaris, G.; Christopoulou, O. Territorial resilience through visibility analysis for immediate detection of wildfires integrating fire susceptibility, geographical features, and optimization methods. *Int. J. Disaster Risk Sci.* **2022**, *13*, 621–635. [CrossRef]
18. He, Q.; Yan, M.; Zheng, L.; Wang, B. Spatial stratified heterogeneity and driving mechanism of urban development level in China under different urban growth patterns with optimal parameter-based geographic detector model mining. *Comput. Environ. Urban Syst.* **2023**, *105*, 102023. [CrossRef]
19. Cui, L.; Wang, J.; Sun, L.; Lv, C. Construction and optimization of green space ecological networks in urban fringe areas: A case study with the urban fringe area of Tongzhou district in Beijing. *J. Clean. Prod.* **2020**, *276*, 124266. [CrossRef]
20. Pacione, M. Private profit, public interest and land use planning—A conflict interpretation of residential development pressure in Glasgow's rural–urban fringe. *Land Use Policy* **2013**, *32*, 61–77. [CrossRef]
21. Yin, G.; Lin, Z.; Jiang, X.; Qiu, M.; Sun, J. How do the industrial land use intensity and dominant industries guide the urban land use? Evidences from 19 industrial land categories in ten cities of China. *Sustain. Cities Soc.* **2020**, *53*, 101978. [CrossRef]
22. Qiao, W.; Hu, B.; Guo, Z.; Huang, X. Evaluating the sustainability of land use integrating SDGs and its driving factors: A case study of the Yangtze River Delta urban agglomeration, China. *Cities* **2023**, *143*, 104569. [CrossRef]
23. Zeng, C.; Yin, Y.; Guo, L.; Liu, C.; Zhang, Y.; Huang, Z. Integrating the administrative spillover effect into the spatial governance system to revisit land development: A study in urban-rural fringe areas of Wuhan and neighboring cities, China. *Land Use Policy* **2024**, *139*, 107060. [CrossRef]
24. Cattivelli, V. The methods used to identify urban, rural, and intermediate territories at European level: A comparison of the methods developed in the framework of TERCET and ESPON. *Cities* **2023**, *143*, 104556. [CrossRef]
25. Vizzari, M.; Sigura, M. Landscape sequences along the urban–rural–natural gradient: A novel geospatial approach for identification and analysis. *Landsc. Urban Plan.* **2015**, *140*, 42–55. [CrossRef]
26. Chen, W.; Xu, Q.; Zhao, K.; Hao, L.; Pu, C.; Yuan, S.; Chui, S.; Zhao, H.; Yang, K. Spatiotemporal expansion modes of urban areas on the Loess Plateau from 1992 to 2021 based on nighttime light images. *Int. J. Appl. Earth Obs. Geoinf.* **2023**, *118*, 103262. [CrossRef]
27. Gao, Y.; Wang, Z.; Xu, F. Geospatial characteristics and the application of land use functions in the Yangtze River Economic Belt, China: Perspectives on provinces and urban agglomerations. *Ecol. Indic.* **2023**, *155*, 110969. [CrossRef]
28. Liu, C.; Xu, Y.; Lu, X.; Han, J. Trade-offs and driving forces of land use functions in ecologically fragile areas of northern Hebei Province: Spatiotemporal analysis. *Land Use Policy* **2021**, *104*, 105387. [CrossRef]
29. Tian, G.; Wu, J.; Yang, Z. Spatial pattern of urban functions in the Beijing metropolitan region. *Habitat Int.* **2010**, *34*, 249–255. [CrossRef]
30. Du, J.; Thill, J.-C.; Peiser, R.B. Land pricing and its impact on land use efficiency in post-land-reform China: A case study of Beijing. *Cities* **2016**, *50*, 68–74. [CrossRef]
31. Liu, X.; Li, Y.; Zhang, S.; Niu, Q. Spatiotemporal patterns, driving mechanism, and multi-scenario simulation of urban expansion in Min Delta Region, China. *Ecol. Indic.* **2024**, *158*, 111312. [CrossRef]
32. Dong, T.; Jiao, L.; Xu, G.; Yang, L.; Liu, J. Towards sustainability? Analyzing changing urban form patterns in the United States, Europe, and China. *Sci. Total Environ.* **2019**, *671*, 632–643. [CrossRef] [PubMed]
33. Shi, H.; Li, Q.; Zhang, S.; Chen, W. How does urban innovation affect construction land use change in China? An analysis based on the network linkage perspective. *Expert Syst. Appl.* **2024**, *249*, 123676. [CrossRef]

34. Kuang, W.; Chi, W.; Lu, D.; Dou, Y. A comparative analysis of megacity expansions in China and the U.S.: Patterns, rates and driving forces. *Landsc. Urban Plan.* **2014**, *132*, 121–135. [CrossRef]
35. Li, C.; Zhao, J.; Xu, Y. Examining spatiotemporally varying effects of urban expansion and the underlying driving factors. *Sustain. Cities Soc.* **2017**, *28*, 307–320. [CrossRef]
36. Mitchell, A. Making sense of counterurbanization. *J. Rural. Stud.* **2004**, *20*, 15–34. [CrossRef]
37. Chakraborty, S.; Dadashpoor, H.; Novotný, J.; Maity, I.; Follmann, A.; Patel, P.P.; Roy, U.; Pramanik, S. In pursuit of sustainability–Spatio-temporal pathways of urban growth patterns in the world's largest megacities. *Cities* **2022**, *131*, 103919. [CrossRef]
38. Zhou, G.; Li, C.; Li, M.; Zhang, J.; Liu, Y. Agglomeration and diffusion of urban functions: An approach based on urban land use conversion. *Habitat Int.* **2016**, *56*, 20–30. [CrossRef]
39. Jiao, J.; Jin, Y.; Yang, R. An approach to exploring the spatial distribution and influencing factors of urban problems based on Land use types. *Sustain. Cities Soc.* **2024**, *104*, 105321. [CrossRef]
40. Lin, J.; Zhang, W.; Wen, Y.; Qiu, S. Evaluating the association between morphological characteristics of urban land and pluvial floods using machine learning methods. *Sustain. Cities Soc.* **2023**, *99*, 104891. [CrossRef]
41. Brown, D.G.; Page, S.; Riolo, R.; Zellner, M.; Rand, W. Path dependence and the validation of agent-based spatial models of land use. *Int. J. Geogr. Inf. Sci.* **2005**, *19*, 153–174. [CrossRef]
42. Jedwab, R.; Kerby, E.; Moradi, A. History, Path Dependence and Development: Evidence from Colonial Railways, Settlers and Cities In Kenya. *Econ. J.* **2017**, *127*, 1467–1494. [CrossRef]
43. Alumäe, H.; Printsmann, A.; Palang, H. Cultural and Historical Values in Landscape Planning: Locals' Perception. In *Landscape Interfaces: Cultural Heritage in Changing Landscapes*; Palang, H., Fry, G., Eds.; Springer: Dordrecht, The Netherlands, 2003; pp. 125–145.
44. Ren, J.; Ma, R.; Huang, Y.; Wang, Q.; Guo, J.; Li, C.; Zhou, W. Identifying the trade-offs and synergies of land use functions and their influencing factors of Lanzhou-Xining urban agglomeration in the upper reaches of Yellow River Basin, China. *Ecol. Indic.* **2024**, *158*, 111279. [CrossRef]
45. Chen, M.; Lu, Y.; Ling, L.; Wan, Y.; Luo, Z.; Huang, H. Drivers of changes in ecosystem service values in Ganjiang upstream watershed. *Land Use Policy* **2015**, *47*, 247–252. [CrossRef]
46. Meybeck, M.; Green, P.; Vörösmarty, C. A new typology for mountains and other relief classes: An application to global continental water resources and population distribution. *Mt. Res. Dev.* **2001**, *21*, 34–45. [CrossRef]
47. Boone, R.B.; Conant, R.T.; Sircely, J.; Thornton, P.K.; Herrero, M. Climate change impacts on selected global rangeland ecosystem services. *Glob. Change Biol.* **2018**, *24*, 1382–1393. [CrossRef] [PubMed]
48. Hunsberger, C.; Work, C.; Herre, R. Linking climate change strategies and land conflicts in Cambodia: Evidence from the Greater Aural region. *World Dev.* **2018**, *108*, 309–320. [CrossRef]
49. Ng, C.N.; Xie, Y.J.; Yu, X.J. Measuring the spatio-temporal variation of habitat isolation due to rapid urbanization: A case study of the Shenzhen River cross-boundary catchment, China. *Landsc. Urban Plan.* **2011**, *103*, 44–54. [CrossRef]
50. Nayak, D.; Shukla, A.K.; Devi, N.R. Decadal changes in land use and land cover: Impacts and their influence on urban ecosystem services. *Aqua Water Infrastruct. Ecosyst. Soc.* **2024**, *73*, 57–72. [CrossRef]
51. Xun, B.; Yu, D.; Liu, Y.; Hao, R.; Sun, Y. Quantifying isolation effect of urban growth on key ecological areas. *Ecol. Eng.* **2014**, *69*, 46–54. [CrossRef]
52. Hernik, J.; Gawroński, K.; Dixon-Gough, R. Social and economic conflicts between cultural landscapes and rural communities in the English and Polish systems. *Land Use Policy* **2013**, *30*, 800–813. [CrossRef]
53. Zhu, C.; Zhang, X.; Zhou, M.; He, S.; Gan, M.; Yang, L.; Wang, K. Impacts of urbanization and landscape pattern on habitat quality using OLS and GWR models in Hangzhou, China. *Ecol. Indic.* **2020**, *117*, 106654. [CrossRef]
54. Foley, J.A.; DeFries, R.; Asner, G.P.; Barford, C.; Bonan, G.; Carpenter, S.R.; Chapin, F.S.; Coe, M.T.; Daily, G.C.; Gibbs, H.K.; et al. Global Consequences of Land Use. *Science* **2005**, *309*, 570–574. [CrossRef]
55. Marchesani, F.; Masciarelli, F.; Doan, H.Q. Innovation in cities a driving force for knowledge flows: Exploring the relationship between high-tech firms, student mobility, and the role of youth entrepreneurship. *Cities* **2022**, *130*, 103852. [CrossRef]
56. Antipova, A. City Structure and Spatial Patterns. In *Urban Environment, Travel Behavior, Health, and Resident Satisfaction*; Springer International Publishing: Cham, Switzerland, 2018; pp. 153–204.
57. Luo, T.; Zhang, T.; Wang, Z.; Gan, Y. Driving forces of landscape fragmentation due to urban transportation networks: Lessons from Fujian, China. *J. Urban Plan. Dev.* **2016**, *142*, 04015013. [CrossRef]
58. Hu, T.; Yang, J.; Li, X.; Gong, P. Mapping Urban Land Use by Using Landsat Images and Open Social Data. *Remote Sens.* **2016**, *8*, 151. [CrossRef]
59. Oruonye, E.D. An assessment of the impact of road construction on land use pattern in urban centres in nigeria, a case study of Jalingo LGA, Taraba State Nigeria. *Mediterr. J. Soc. Sci.* **2014**, *5*, 82–88. [CrossRef]
60. Peng, J.; Chen, X.; Liu, Y.; Lü, H.; Hu, X. Spatial identification of multifunctional landscapes and associated influencing factors in the Beijing-Tianjin-Hebei region, China. *Appl. Geogr.* **2016**, *74*, 170–181. [CrossRef]
61. Coisnon, T.; Musson, A.; Pene, S.D.; Rousselière, D. Disentangling public urban green space satisfaction: Exploring individual and contextual factors across European cities. *Cities* **2024**, *152*, 105154. [CrossRef]
62. Tobler, W.R. A Computer Movie Simulating Urban Growth in the Detroit Region. *Econ. Geogr.* **1970**, *46*, 234–240. [CrossRef]

63. Xiao, R.; Liu, Y.; Huang, X.; Shi, R.; Yu, W.; Zhang, T. Exploring the driving forces of farmland loss under rapidurbanization using binary logistic regression and spatial regression: A case study of Shanghai and Hangzhou Bay. *Ecol. Indic.* **2018**, *95*, 455–467. [CrossRef]
64. Kubacka, M.; Piniarski, W. Searching for optimal solutions in a landscape fragmentation assessment: A case study from Poland–Identification of spatial data and methods. *Ecol. Indic.* **2024**, *163*, 112118. [CrossRef]
65. Ou, Y.; Kim, E.; Liu, X.; Nam, K.-M. Delineating functional regions from road networks: The case of South Korea. *Environ. Plan. B Urban Anal. City Sci.* **2023**, *50*, 1677–1694. [CrossRef]
66. Farmer, C.J.Q.; Fotheringham, A.S. Network-Based Functional Regions. *Environ. Plan. A Econ. Space* **2011**, *43*, 2723–2741. [CrossRef]
67. Pérez-Soba, M.; Petit, S.; Jones, L.; Bertrand, N.; Briquel, V.; Omodei-Zorini, L.; Contini, C.; Helming, K.; Farrington, J.H.; Mossello, M.T.; et al. *Land Use Functions—A Multifunctionality Approach to Assess the Impact of Land Use Changes on Land Use Sustainability*; Springer: Berlin/Heidelberg, Germany, 2008; pp. 375–404.
68. Zhang, Y.; Long, H.; Tu, S.; Ge, D.; Ma, L.; Wang, L. Spatial identification of land use functions and their tradeoffs/synergies in China: Implications for sustainable land management. *Ecol. Indic.* **2019**, *107*, 105550. [CrossRef]
69. Song, X.; Huang, Y.; Wu, Z.; Ouyang, Z. Does cultivated land function transition occur in China? *J. Geogr. Sci.* **2015**, *25*, 817–835. [CrossRef]
70. Fan, Y.; Jin, X.; Gan, L.; Jessup, L.H.; Pijanowski, B.C.; Yang, X.; Xiang, X.; Zhou, Y. Spatial identification and dynamic analysis of land use functions reveals distinct zones of multiple functions in eastern China. *Sci. Total Environ.* **2018**, *642*, 33–44. [CrossRef] [PubMed]
71. Liu, C.; Xu, Y.; Huang, A.; Liu, Y.; Wang, H.; Lu, L.; Sun, P.; Zheng, W. Spatial identification of land use multifunctionality at grid scale in farming-pastoral area: A case study of Zhangjiakou City, China. *Habitat Int.* **2018**, *76*, 48–61. [CrossRef]
72. Luo, Y.; Lü, Y.; Liu, L.; Liang, H.; Li, T.; Ren, Y. Spatiotemporal scale and integrative methods matter for quantifying the driving forces of land cover change. *Sci. Total Environ.* **2020**, *739*, 139622. [CrossRef]
73. Zeng, C.; Song, Y.; He, Q.; Liu, Y. Urban–rural income change: Influences of landscape pattern and administrative spatial spillover effect. *Appl. Geogr.* **2018**, *97*, 248–262. [CrossRef]
74. Menezes, T.; Roth, C. Natural Scales in Geographical Patterns. *Sci. Rep.* **2017**, *7*, 45823. [CrossRef]
75. 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]
76. Dijkstra, L.; Florczyk, A.J.; Freire, S.; Kemper, T.; Melchiorri, M.; Pesaresi, M.; Schiavina, M. Applying the Degree of Urbanisation to the globe: A new harmonised definition reveals a different picture of global urbanisation. *J. Urban Econ.* **2021**, *125*, 103312. [CrossRef]
77. Storper, M. Governing the Large Metropolis. *Territ. Politics Gov.* **2014**, *2*, 115–134. [CrossRef]
78. Brenner, N. Standortpolitik, State Rescaling and the New Metropolitan Governance in Western Europe. *Disp—Plan. Rev.* **2003**, *39*, 15–25. [CrossRef]
79. Yi, P.; Li, W.; Zhang, D. Sustainability assessment and key factors identification of first-tier cities in China. *J. Clean. Prod.* **2021**, *281*, 125369. [CrossRef]
80. Avtar, R.; Aggarwal, R.; Kharrazi, A.; Kumar, P.; Kurniawan, T.A. Utilizing geospatial information to implement SDGs and monitor their Progress. *Environ. Monit. Assess.* **2019**, *192*, 35. [CrossRef]
81. Giles-Corti, B.; Moudon, A.V.; Lowe, M.; Cerin, E.; Boeing, G.; Frumkin, H.; Salvo, D.; Foster, S.; Kleeman, A.; Bekessy, S.; et al. What next? Expanding our view of city planning and global health, and implementing and monitoring evidence-informed policy. *Lancet Glob. Health* **2022**, *10*, e919–e926. [CrossRef] [PubMed]
82. Zitti, M.; Ferrara, C.; Perini, L.; Carlucci, M.; Salvati, L. Long-Term Urban Growth and Land Use Efficiency in Southern Europe: Implications for Sustainable Land Management. *Sustainability* **2015**, *7*, 3359–3385. [CrossRef]
83. Fulman, N.; Grinblat, Y.; Benenson, I. A project-based view of urban dynamics: Analyzing 'leapfrogging' and fringe development in Israel. *Cities* **2024**, *148*, 104908. [CrossRef]
84. Fu, B.; Xue, B. Temporal and Spatial Evolution Analysis and Correlation Measurement of Urban–Rural Fringes Based on Nighttime Light Data. *Remote Sens.* **2024**, *16*, 88. [CrossRef]
85. Wu, R.; Wang, J.; Zhang, D.; Wang, S. Identifying different types of urban land use dynamics using Point-of-interest (POI) and Random Forest algorithm: The case of Huizhou, China. *Cities* **2021**, *114*, 103202. [CrossRef]
86. Qian, J.; Liu, Z.; Du, Y.; Liang, F.; Yi, J.; Ma, T.; Pei, T. Quantify city-level dynamic functions across China using social media and POIs data. *Comput. Environ. Urban Syst.* **2021**, *85*, 101552. [CrossRef]
87. Zhang, J.; Zhao, X. Using POI and multisource satellite datasets for mainland China's population spatialization and spatiotemporal changes based on regional heterogeneity. *Sci. Total Environ.* **2024**, *912*, 169499. [CrossRef] [PubMed]
88. Decoding "Happy Chengdu" in the "Happiness Report". Available online: http://www.sc.xinhuanet.com/20231201/0948be5504514d7db98575a783f56cb4/c.html (accessed on 1 December 2023).

Disclaimer/Publisher's Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.