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Assessing the Association Between Urban Amenities and Urban Green Space Transformation in Guangzhou

Shawei Zhang [1], Jiawen Chen [2], Yuxuan Cai [3], Yuhan Wen [4], Jiaqi Niu [5] and Mingze Chen [6,*]

[1] School of Architecture & Applied Arts, Guangzhou Academy of Fine Arts, Guangzhou 510006, China; zhang_shawei@gzarts.edu.cn
[2] College of Engineering + College of Environmental Design, University of California Berkeley, Berkeley, CA 94720, USA; jiawen_chen@berkeley.edu
[3] Division of the Social Sciences, University of Chicago, Chicago, IL 60637, USA; yuxuanc@uchicago.edu
[4] School of Planning, Design & Construction, Michigan State University, 552 W Circle Dr., East Lansing, MI 48824, USA; wenyuhan@msu.edu
[5] The Bartlett School of Architecture, University College London, Gower Street, London WC1E 6BT, UK; ucbqniu@ucl.ac.uk
[6] Department of Forest Resources Management, University of British Columbia, Vancouver, BC V6T 1Z4, Canada
* Correspondence: mingze.chen@ubc.ca; Tel.: +1-235-965-2346

Abstract: This study explores the intricate relationship between urban amenities and the transformation of urban green spaces (UGS) in Guangzhou, China, over the decade from 2013 to 2022. Amid rapid urbanization, maintaining and expanding green spaces has become increasingly challenging, especially in densely populated urban centers. This research utilizes remote sensing data and Point of Interest (POI) data to assess how different types of urban amenities influence UGS dynamics based on geospatial analytics. The study focuses on the central districts of Guangzhou, a city facing significant urban development pressures, to provide a nuanced understanding of these interactions. Employing both Ordinary Least Squares (OLS) regression and Random Forest (RF) models, the analysis examines the impact of 23 categories of POIs on the spatial and temporal changes in UGS. Key findings reveal that amenities such as auto repair shops, shopping services, and transit facilities are negatively correlated with UGS, indicating that their presence may contribute to the reduction in green space. Conversely, amenities like scenic spots and life services show a positive correlation, suggesting they might support the preservation or expansion of green spaces. The results underscore the dual role of urban amenities in both supporting and constraining green space development, highlighting the need for carefully balanced urban planning strategies. This study provides valuable insights for policymakers and urban planners aiming to promote sustainable urban growth while preserving essential green spaces, ensuring that urban environments remain livable and ecologically resilient.

Keywords: urban green spaces; urban amenities; remote sensing; spatial analysis

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1. Introduction

In recent years, the acceleration of urbanization has led to a series of environmental issues, making the maintenance and construction of urban green spaces (UGS) a crucial means for urban managers to govern and improve residents' living environments. UGS, such as parks, gardens, and nature reserves, are integral parts of the urban ecosystem and play a vital role in enhancing urban livability and sustainability [1]. They provide numerous ecological, environmental, and economic benefits, including improving air quality, regulating temperature, creating wildlife habitats, and increasing property values [2–6]. Additionally, green spaces contribute to the physical and mental health of urban residents and enhance their well-being by offering recreational opportunities, aesthetic enjoyment, and social interaction spaces [7–11].

However, many densely populated cities face significant challenges in maintaining and expanding green spaces, which are often threatened by ever-expanding urbanization [12,13]. To address these challenges, effective strategies for the protection and preservation of UGS are essential. Implementing sustainable urban planning policies that prioritize green space conservation can mitigate the negative impacts of urbanization. For instance, integrating UGS into urban development plans and adopting nature-based solutions can enhance urban resilience [10]. Urban amenities, including schools, hospitals, shopping centers, public transportation facilities, and entertainment venues, play a critical role in urban development [14]. The distribution and accessibility of these amenities can influence land use patterns, thereby affecting green space transformation. On one hand, the presence of urban amenities can enhance the accessibility and utilization of green spaces [15,16]. Amenities around green spaces can make it easier for residents to visit and use these areas for leisure and social activities. The strategic layout of amenities can increase the value and functionality of green spaces, promoting their preservation and integration into the urban structure, driving economic development and regional prosperity [17–19]. Li et al. (2022) emphasize the importance of multifunctional green infrastructure in promoting ecological sustainability and social well-being [14]. On the other hand, due to the limited land resources in cities, there may be competition between amenities and green spaces, especially in high-density urban centers [20]. The construction of amenities might exert pressure on green spaces, reducing the area available for greening and recreation, and impacting the scale and function of green spaces [21]. Some amenities (such as transportation hubs and commercial areas) might cause environmental pollution and ecological damage, like soil compaction, water source pollution, and loss of wildlife habitats, affecting the environmental quality and ecological function of green spaces [22–24]. Therefore, to achieve sustainable and equitable urban development, it is essential to comprehensively consider the impact of urban amenities on green space transformation, monitor and understand their spatiotemporal dynamics, and formulate reasonable urban planning and policies to ensure the coordinated development of green spaces and amenities.

Remote sensing technology has become a powerful tool for monitoring land use and land cover changes, including green space transformation. Over time, remote sensing, through satellite and aerial imagery, can capture large-scale, high-resolution spatial data, providing valuable insights into the extent, distribution, and changes in urban green spaces [25–28]. Guo (2019) used remote sensing, LBS, and GIS data to find that spatial structure, building density, road density, and green space coverage significantly affect PM2.5 pollution exposure [29]. Techniques like Normalized Difference Vegetation Index (NDVI), land use/land cover (LULC) classification, and temporal analysis are widely used to quantify and assess the health and dynamics of UGS. For example, NDVI uses data from infrared and visible light bands to effectively assess vegetation health and coverage [24]. The LULC classification method categorizes remote sensing images into different land use types, such as green spaces, built-up areas, and water bodies, through classification algorithms [30]. This method visually displays the spatial distribution and changes of urban green spaces. Temporal analysis, by examining remote sensing data over a period of time, can reveal the dynamic process of green space changes, identifying trends of green space expansion or reduction [31,32].

According to the above, the distribution of urban amenities is considered a key component of urban development patterns, encompassing the locations of various urban infrastructures that support residents' activities. Notably, the establishment of urban amenities has a dual effect on the development of UGS. Studying the relationship between urban amenities and LULC is crucial for understanding the spatial patterns and environmental changes during urbanization, as the distribution and density of amenities affect land use efficiency and the urban ecological environment. There are multiple ways to obtain urban amenities data. Through comprehensive evaluation, the most appropriate data sources and methods can be chosen based on the research questions, enhancing the accuracy and credibility of the research results. Table 1 lists the currently widely used literature for exploring urban amenities and land use transformation.

Table 1. Studies exploring urban amenities and land use transformation.

Study Topic	Types of Data	Source Data	Method	Publication
Residential living service amenities	Catering and shops, entertainment and leisure, education and healthcare, public service and personal care	POI data from social media	GIS, spatial analysis model	[33]
Land use transformation	Commercial area	POI data from open data map	GIS	[34]
Residential living service amenities	Living service amenities in a certain residential area	POI data from open data map	GIS	[35]
Distribution of urban amenities	Service and consumer goods, public service, transportation service, and tourist attraction	POI data from open data map	NDVI, NDBI, multivariate analytical models	[14]
Distribution of urban amenities	Commercial, services, offices, open spaces, public facilities	POI data from open data map	GIS	[36]
Public transport	Urban street	POI data from map data	GIS, spatial analysis	[37]
Public transport	Sustenance, education, transportation, healthcare, entertainment, finance, commerce and others	POI data from OSM open data map	Three multivariate analytical models	[38]
The spatial distribution of an urban amenity	Street trees, public street and water polygons	Remote sensing, cadastral data	Remote sensing technique	[39]
Urban livability	Urban transit stations, urban transit lines, commercial facilities, medical facilities, schools, parks and squares, markets, road intersections, chemical facilities or gas stations	Remote sensing Advanced Land Observation Satellite (ALOS) images	Remote sensing technique, GIS	[40]
Urban Residential Land Suitability	Shopping centers, parks, and medical services	Remotely-Sensed Images, Social Sensing data (Tencent user density (TUD) and Point of Interest (POI) data), OpenStreetMap Road Network	Image processing and spatial analysis	[41]
Club-based green space	Golf courses	Website database, Baidu map, questionnaires	GIS, survey	[42]
Transportation physical activity among older persons	Stores, streets, places for walking and cycling, neighborhood surroundings, transit stop, commercial, industrial, recreation and park	Questionnaires, GIS	GIS, survey	[43]
Urban life satisfaction	Light, science, education, culture, medical care, government institutions, living services, and transportation infrastructure	Nighttime light data, POI data, and Sina Weibo data	GIS	[44]
Land use transformation	Reservoirs, roads, railways, airports,	Government data, Landsat images, Google Earth	GIS, NDVI	[45]

POI data offer significant advantages over other data sources, including real-time availability, comprehensive coverage, high spatial resolution, ease of access, and rich supplementary information. Derived from regularly updated online map services and navigation applications, POI data provide precise geographic coordinates of various urban facilities—such as restaurants, schools, hospitals, shops, and parks—enabling detailed spatial analyses at a micro level. Many POI data sources (e.g., Google Maps, OpenStreetMap) offer API interfaces or open data, making it more convenient for researchers to access and process this information compared to some government datasets or remote sensing data.

However, despite the widespread use of remote sensing data and POI data in urban land use mapping and distribution studies, there is a significant research gap in effectively integrating these two data sources to explore internal urban changes and the spatial correlation between the distribution of urban amenities and urban green spaces. Most existing studies focus on either remote sensing data or POI data independently, which limits the understanding of the complex interactions between urban development and environmental factors. Furthermore, the lack of integrated methodologies hinders the ability to comprehensively analyze urban dynamics and reveal nuanced patterns that could inform sustainable urban planning and management.

To address this gap, this study aims to integrate remote sensing technology with POI data to analyze internal urban changes and investigate the spatial relationships between urban amenities distribution and urban green spaces in Guangzhou. This study will focus on the following three questions:

(1) How can remote sensing technology be used to monitor changes in green space areas in Guangzhou, and how did the UGS change in the past decade?
(2) How can the spatial correlation between urban amenities distribution and green space transformation in Guangzhou be analyzed using POI data?
(3) How do the different types of urban amenities in Guangzhou affect the spatiotemporal characteristics of green space transformation in specific areas?

2. Methods

2.1. Study Area

The study focuses on Guangzhou, China, a significant port city for foreign trade. As of the end of 2023, Guangzhou had a resident population of 18.827 million (2023 Guangzhou National Economic and Social Development Statistical Bulletin, sourced from the Guangzhou Statistics Bureau website. (http://tjj.gz.gov.cn/stats_newtjyw/tjsj/tjgb/qstjgb/content/mpost_9567759.html/, accessed on 15 September 2024). Located near the estuary of the Pearl River Basin, the southern part of the city features an extensive coastal alluvial plain (Overview of Guangzhou's Physical Geography, Guangzhou Municipal Government official website. (https://www.gz.gov.cn/zlgz/gzgk/zrdl/, accessed on 20 September 2024), providing ample prerequisites for the development of urban green spaces. This research primarily targets the central urban area of Guangzhou, including Yuexiu District, Tianhe District, and Haizhu District (Figure 1). This area also forms a core part of the Guangdong−Hong Kong−Macao Greater Bay Area and has faced challenges of imbalanced development and rapid urbanization over the past two decades, leading to an uneven distribution of green spaces and urban infrastructure. In recent years, the Guangzhou government, through the Guangzhou Forestry and Landscape Bureau, has formulated green space system plans and specialized forestry and landscape plans (Public announcement of the "Guangzhou Green Space System Plan (2020–2035)". (http://lyylj.gz.gov.cn/, accessed on 22 September 2024). These efforts aim to improve the environment, enhance public health, and upgrade urban infrastructure. According to 2022 data from the Guangzhou Forestry and Landscape Bureau, the greenery coverage rate in built-up areas reached 44.2%, and the service radius coverage rate of park green spaces achieved 81.2%. Guangzhou continues to advance the construction of a park city, including the restoration of 107,600 square meters of green space and the greening renovation of 170,000 square meters (Official website of the Guangzhou Forestry and Landscape Bureau, Government Affairs

Disclosure. (http://lyylj.gz.gov.cn/, accessed on 20 September 2024). These characteristics provide an opportunity to assess the association between urban amenities and urban green space transformation.

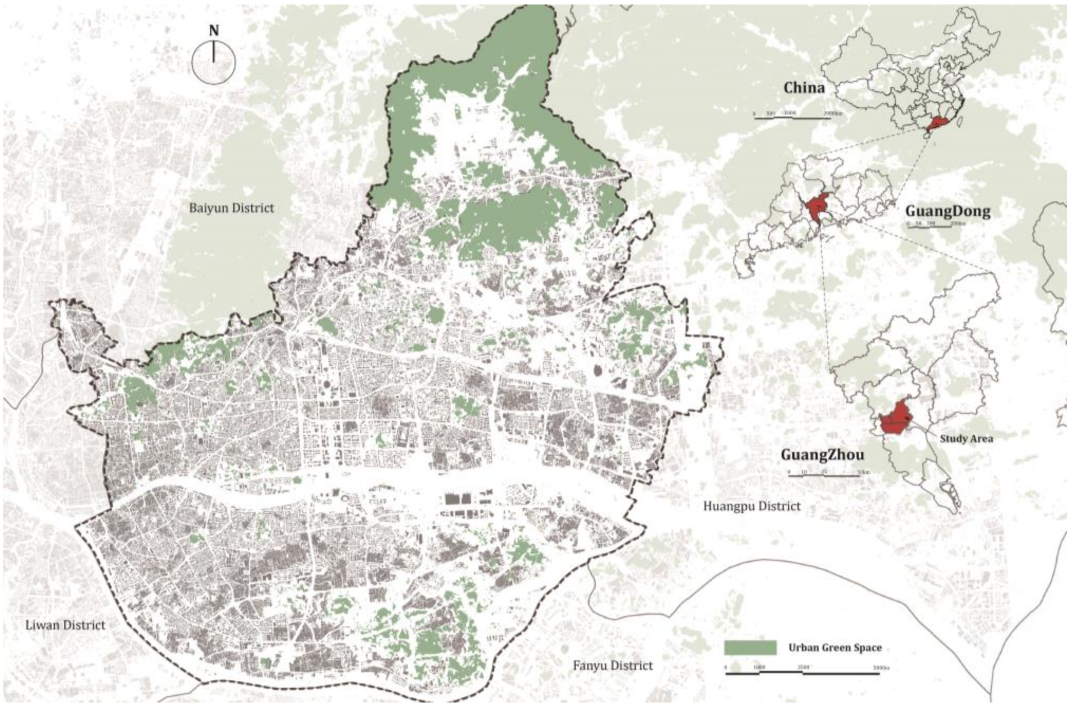

Figure 1. Study area.

As shown in Figure 2, the workflow is divided into several steps. First, we obtained remote sensing data on land use in Guangdong Province from 2013 to 2022. Based on the ArcGIS Pro platform, we identified different land use types and extracted the green space boundaries relevant to this study. Second, we generated a hexagonal grid covering the specified area, with each hexagonal cell having an area of 210,000 square meters. By calculating the green space area and proportion within each hexagonal grid, we were able to analyze annual changes for each grid cell. Third, we downloaded 2024 Point of Interest (POI) data for Guangzhou from the Gaode Map Open Platform. Using the same hexagonal grid as the boundary, we calculated the number and types of POIs within each grid cell for each year from 2013 to 2022. Fourth, we conducted an Ordinary Least Squares (OLS) correlation analysis between the annual UGS area in each grid and 23 types of POI data from 2013 to 2022. Furthermore, we employed the Random Forest method to compare the results, providing a more accurate understanding of the relationship between urban amenities and urban green space transformation in Guangzhou. This analysis includes using R^2 to compare the explanatory power of models across different years, as well as changes in model feature importance, which helps to more accurately identify and track the key factors influencing model performance and their dynamic changes. R^2 serves as a unified standard for evaluating model performance at various time points. As a widely used metric in regression analysis, it facilitates the tracking and analysis of trends in model explanatory power, thus providing richer information on the evolving characteristics of the research subject over time.

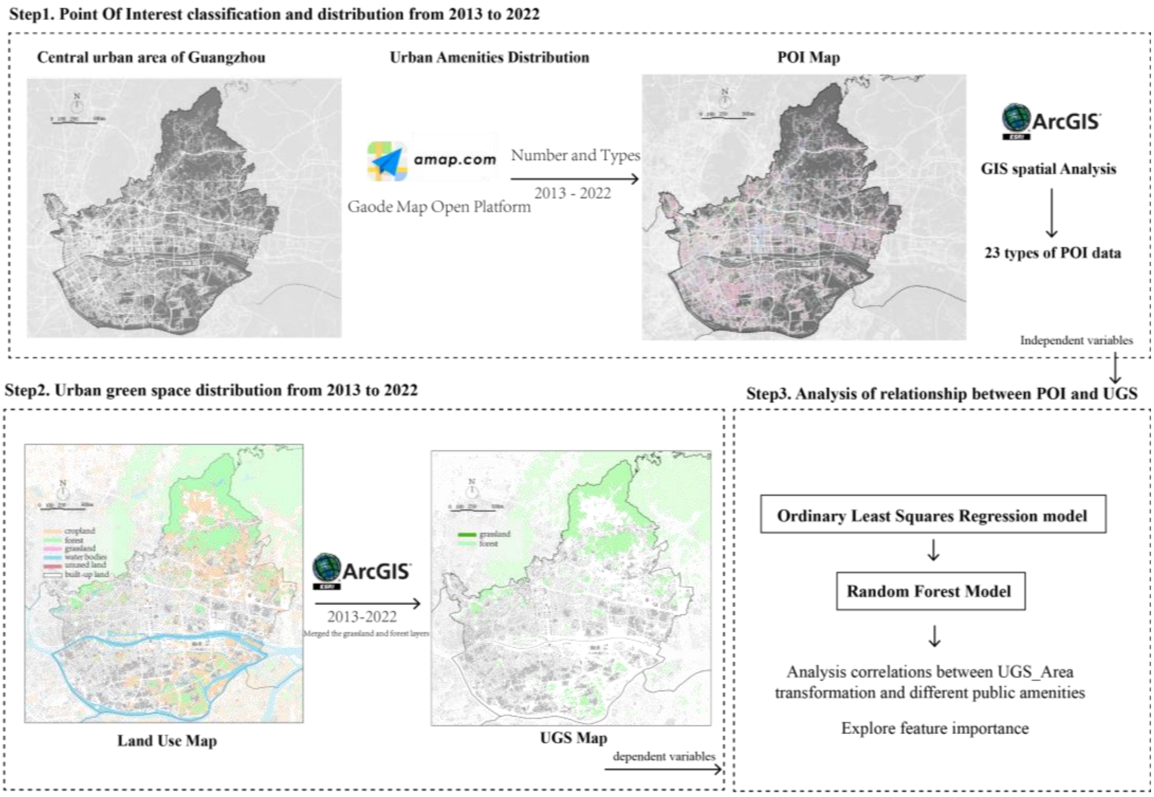

Figure 2. Research workflow.

2.2. Urban Green Space Transformation 2013–2022 Using Remote Sensing Data

Based on previous research referenced, the method for obtaining remote sensing data on land use in Guangdong Province was based on the 30 m annual land cover dataset of China, produced using 335,709 Landsat scenes available on the Google Earth Engine. This dataset primarily uses a Random Forest classifier for land classification, with an accuracy of approximately 80% (30 m annual land cover and its dynamics in China from 1990 to 2019). The dataset includes annual data from 2013 to 2022 and distinguishes six land types: cropland, forest, grassland, water bodies, built-up land, and unused land. Using the raster-to-polygon tool, we merged the grassland and forest layers to form the green space component. Subsequently, we organized the annual remote sensing data from 2013 to 2022. These steps facilitate a deeper investigation of the characteristics of urban green space transformation within stable spatial relationships. Figure 3 presents the annual distribution of increases and decreases in urban green space from 2014 to 2021. The box plots clearly depict the variation in green space changes within grid cells each year. Green box plots represent grid cells where green space increased, while red box plots show those where green space decreased. The figure illustrates significant fluctuations in green space changes during the period from 2014 to 2021, with varying levels of increase and decrease across different years. These trends reflect the dynamic nature of urban green space, influenced by factors such as urban expansion and infrastructure development. Although 2022 was included in the analysis, the data show no significant change between 2021 and 2022. This lack of variation is likely attributable to the impact of the COVID-19 pandemic, which may have caused a slowdown or halt in urban planning and construction activities, resulting in stable green space for that year.

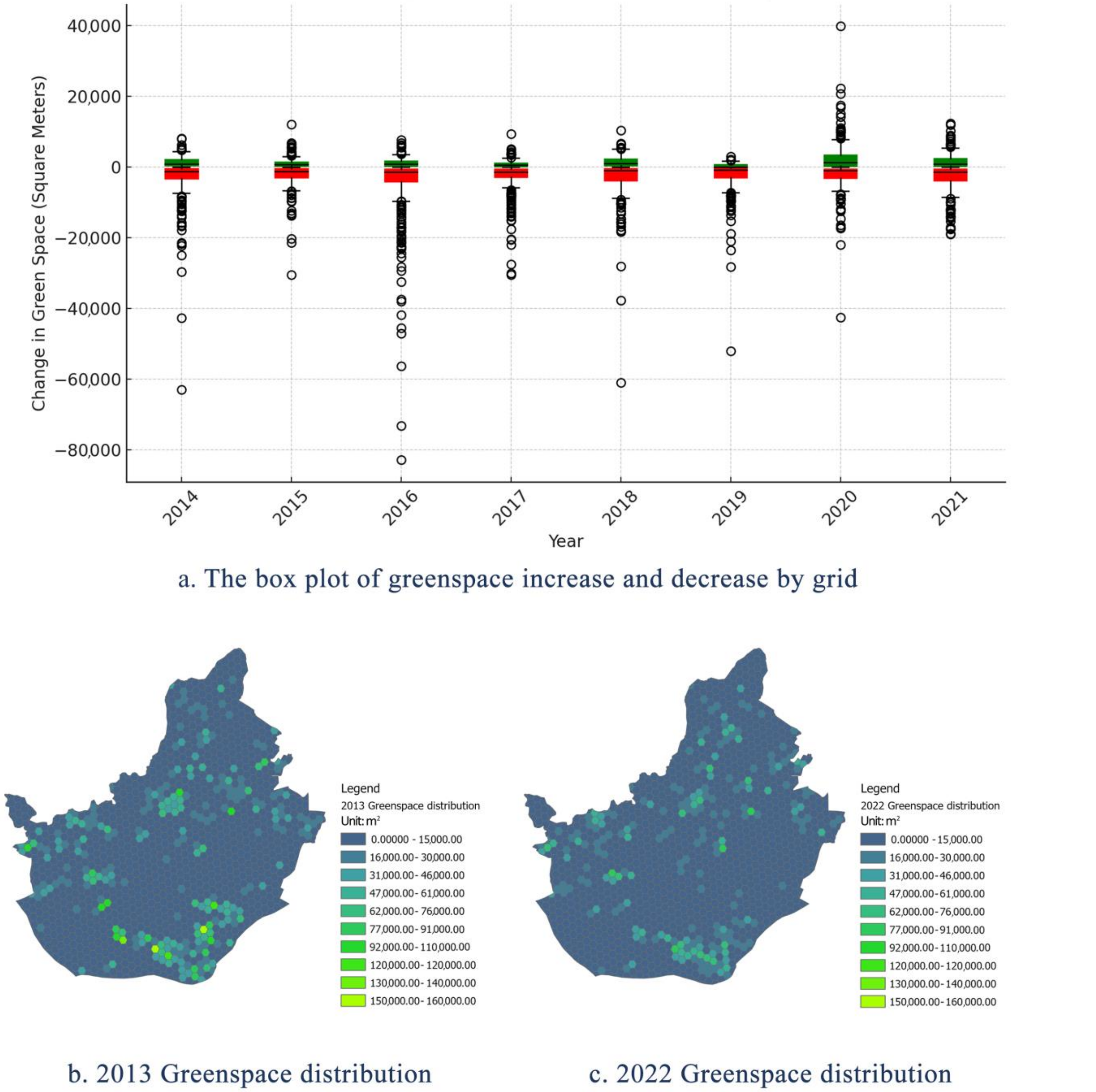

Figure 3. The annual changes in green space from 2013 to 2022 (Appendix A: Maps by year).

2.3. POIs

According to existing research, there is a certain relationship between urban green spaces and the density, diversity, and accessibility of urban Points of Interest (POIs). In previous studies, the density of specific POIs per unit area is often used to measure relevant special indicators, such as exploring the number of parks as an indicator of urban livability. Therefore, we used function-based data (i.e., POIs) to calculate variables for urban green space transformation, including functional density, functional diversity, and accessibility. We downloaded 2024 POI data (a total of 1,015,533 records) from the Gaode Map Open Platform. Each POI included four types of information: name, category, coordinates, and classification. After data preprocessing, including deduplication and re-aggregating statistics based on the study area boundaries, we retained 274,308 valid records within the defined study range. All data were grouped into 23 clusters, including shopping services, living services, dining services, corporate enterprises, traffic facilities, indoor facilities, and transportation services. The Gaode Maps POI classification system consists of three hierarchical levels: primary categories, secondary categories, and tertiary categories. Among these, there are 23 primary categories, 267 secondary categories, and 869 tertiary categories. All data are grouped into 23 clusters, including shopping services, living services, dining services, corporate enterprises, traffic facilities, indoor facilities, and transportation services. In this study, we used the types, total count, and density of POIs within each hexagonal grid as indicators. A density index was employed to evaluate the 23 categories of urban POIs within hexagonal grids of radius r = 300. First, we measured the spatial distribution and spatial quantity of all POIs based on the tessellated hexagonal grids, allowing us to infer the relationship between green space area and POI data from the variations in the data. Subsequently, kernel density analysis was conducted to further assess the relationship between urban amenities and urban green space.

2.4. Regression (OLS, RF)

2.4.1. OLS

Ordinary Least Squares (OLS) is a fundamental method used in statistics to estimate the parameters of a linear regression model. It is a powerful and widely used technique for fitting linear models to data by minimizing the sum of squared errors between observed and predicted values. Previous studies have employed OLS to evaluate and visualize the correlation between one dependent variable and one or more variables with a prediction [32,46]. The OLS common algorithm is based on Equation (1).

$$\Upsilon = X\beta + \varepsilon \tag{1}$$

where Y is the vector of observed dependent variable values. X is the matrix of independent variables (including a column of ones if there's an intercept). β is the vector of unknown regression coefficients to be evaluated. ϵ is the vector of errors or residuals.

The OLS estimates for β can be computed using Formula (2).

$$\hat{\beta} = \left(X^T X\right)^{-1} X^T y \tag{2}$$

2.4.2. Random Forest

Admittedly, OLS tends to ignore spatial characteristics of data, while previous studies have indicated that a Random Forest (RF) regression model serves as a productive method to test geospatial data with a high prediction performance, and it is easier to estimate feature importance [47,48]. RF is a supervised machine learning method that combines multiple decision trees to improve predictive performance. RF can handle quantities of independent decision trees during the training [49], and each decision is made by collecting a subset of training samples from the original large dataset [50]. It is less prone to overfitting compared to individual decision trees. Overall, compared to traditional models, it provides a robust classification process and validates the suitability of the data for exploring feature importance [51,52].

Generally, OLS is a simple and interpretable model suited for linear relationships, while Random Forest is powerful, flexible, and capable of handling complex, non-linear data with interactions. In this study, we applied OLS and RF to measure the relationship between UGS and urban amenities in a long time series. The process was run in the ArcGIS, after which the final value of R^2 was used to measure the model performance.

3. Results

3.1. Verify the Relationship Between Urban Green Space and Infrastructure

To reveal the relationship between changes in urban green space (UGS) and urban amenities development, and to uncover the underlying spatial distribution logic, we conducted an Ordinary Least Squares (OLS) correlation analysis between annual UGS area and 23 types of POI data from 2013 to 2022 (Table 2). The figure illustrates the correlation data between UGS and POIs over ten consecutive years, showing that from 2013 to 2023, the R^2 value decreases exponentially year by year, indicating a reduction in explanatory power. Significant statistical effects were observed for POI types such as auto repair, living services, shopping services, traffic facilities, and scenic spots, where *p*-values for /t/ were less than 0.05 at a significant level, demonstrating stronger explanatory power.

Table 2. Descriptive summary of variables.

Variable	Description	Mean		Std. Dev.	Max	Source
Urban Green Spaces (UGS)						
	2014_UGS_area	25,958.63718	54,525.45988	0	216,605.312	
	2015_UGS_area	25,712.73968	54,324.91852	0	216,605.312	
	2016_UGS_area	24,720.57214	53,769.22216	0	216,605.312	
	2017_UGS_area	24,101.39029	53,383.80103	0	216,605.312	
Direct Variable	2018_UGS_area	23,629.00769	53,294.3073	0	216,605.312	Scraped from Google Earth Engine
	2019_UGS_area	0.023062173	0.053141277	0	0.216605312	
	2020_UGS_area	23,083.0739	53,196.02921	0	216,605.312	
	2021_UGS_area	22,676.82557	52,820.02104	0	216,605.312	
	2022_UGS_area	22,676.82557	52,820.02104	0	216,605.312	
Points of Interest (POIs)						
	event_activities	0.002277904	0.047691115	0	1	
	transport_facility_services	11.60971906	15.18045945	0	79	
	accommodation_services	3.737281701	7.763462641	0	121	
	sports_leisure_services	3.688686409	5.516648017	0	50	
	public_facilities	1.987091875	4.301584899	0	64	
	companies_enterprises	18.64616553	29.41172348	0	311	
	medical_health_services	4.307517084	6.79947564	0	49	
	business_residential	8.461655277	10.89021317	0	54	
	place_name_address_info	13.12908125	17.9222836	0	207	
	indoor_facilities	10.53986333	63.02276303	0	759	
	motorcycle_services	0.041002278	0.233556286	0	3	
Indirect Variable	government_organizations_ social_groups	7.255884586	12.25813937	0	104	Scraped from the Gaode Map Open Platform
	auto_services	3.203492787	11.89274075	0	337	
	auto_repair	0.596810934	1.319973578	0	12	
	auto_sales	0.45254366	1.850056267	0	32	
	lifestyle_services	30.29005315	46.46455982	0	402	
	science_education_ cultural_services	8.377372817	12.43595892	0	145	
	shopping_services	41.50645406	65.224182	0	554	
	transit_facilities	10.62034928	12.80263362	0	68	
	roadside_facilities	0.050873197	0.343846797	0	4	
	finance_insurance_services	2.496583144	5.474952264	0	68	
	scenic_spots	1.146545178	2.693106812	0	35	
	dining_services	26.13515566	42.27781132	0	377	

Auto repair, traffic facilities, and shopping services exhibited negative correlations, while scenic spots and living services showed positive correlations. From the POI attribute table, the scenic spots category represents parks, plazas, and related attractions, which largely determine UGS changes. Therefore, the more scenic spots within a hexagonal grid, the more significant the changes in UGS. The R^2 value decreased from 0.166 in 2013 to 0.140 in 2022, showing a reduction in explanatory power. The R^2 value declined more rapidly between 2013 and 2018, with the sharpest drop occurring between 2016 and 2017, where the R^2 value decreased by 0.007. In the four years following 2018, the R2 value changed relatively little, reflecting the fluctuation of UGS over the 10-year period (Figure 4)

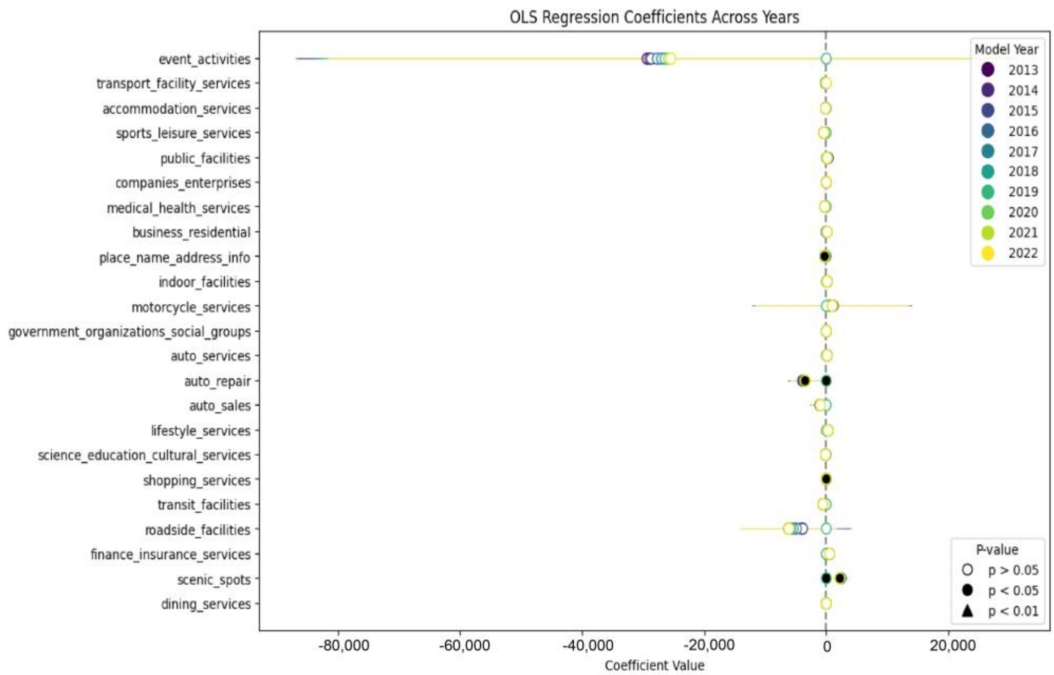

Figure 4. OLS regression coefficients across years.

3.2. The Change in Urban Green Space Is Related to Social Background

The Random Forest algorithm, an ensemble method composed of decision trees, combines multiple weak classifiers to achieve higher accuracy and generalization performance for the overall model. Using Random Forest enables a better output of feature importance, identifying the most explanatory features. From 2013 to 2022, the R^2 value continued to show a year-by-year decreasing trend (Table 3). As a significant part of the urban space, UGS exhibited more noticeable changes in R^2 values in Table 3 compared to the OLS correlation analysis, making the Random Forest analysis more suitable for this study. Specifically, the R^2 value decreased from 0.2929 in 2013 to 0.2475 in 2022, with a difference of 0.0454. During the period from 2013 to 2018, the R^2 value gradually decreased, but from 2018 to 2019, it increased against the trend, rising from 0.2547 to 0.2611. From 2020 to 2021, the change in the R^2 value was minimal, and in 2022, it remained unchanged from 2021.

Table 3. Comparison of R2 values between least square method and random forest.

		2013	2014	2015	2016	2017	2018	2019	2020	2021	2022
OLS	R^2	0.166	0.162	0.160	0.153	0.150	0.146	0.143	0.143	0.140	0.140
RF	R^2	0.2929	0.2826	0.2777	0.2751	0.2658	0.2547	0.2611	0.2468	0.2475	0.2475

The fluctuation in the data reflects the relationship between urban green space and urban amenities in the context of societal developments. Between 2013 and 2018, more active urban development activities led to a negative correlation between green space and infrastructure development, with some erosion of urban green spaces. However, by 2018, the total area of urban green spaces increased relative to the total infrastructure, leading to green space development over this period. Beginning in early 2020, the global COVID-19 pandemic inevitably restricted urban development activities, which is also reflected in the R^2 values. This aligns with our expectations, and from 2021 to 2022, the R^2 value remained unchanged (Figure 5).

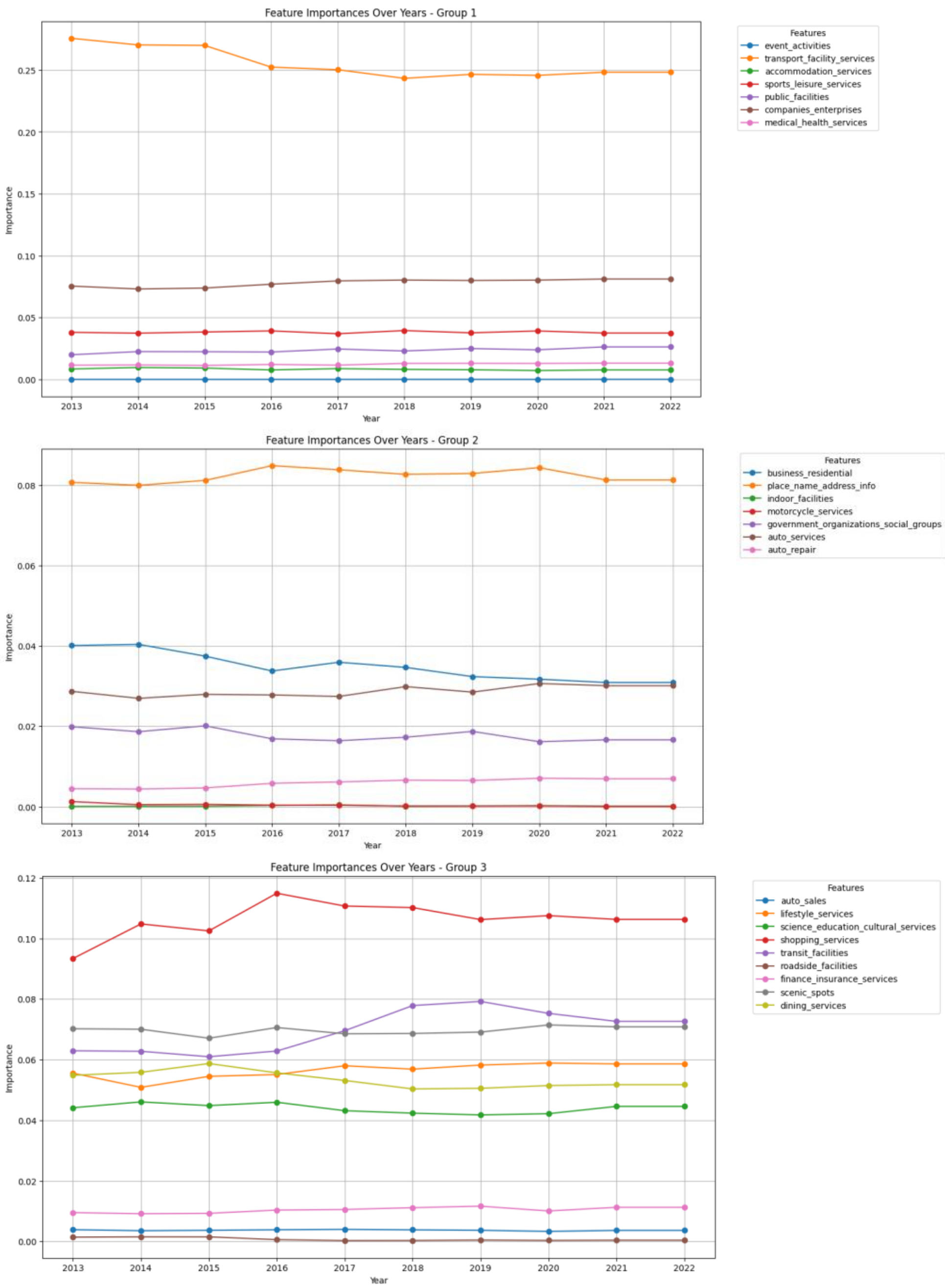

Figure 5. Changes in Random Forest characteristics from 2013 to 2022.

4. Discussion

This study examines the intricate relationship between urban amenities and the transformation of UGS in Guangzhou from 2013 to 2022, with the goal of understanding how different types of amenities impact green space dynamics. Through the use of remote sensing data, Point of Interest (POI) data, and both Ordinary Least Squares (OLS) regression and Random Forest (RF) models, the analysis has identified significant correlations between various urban amenities and changes in UGS. The findings provide several key insights into the complex interactions between urban development and green space preservation, highlighting both challenges and opportunities for sustainable urban planning.

4.1. Impact of Urban Amenities on UGS Transformation

One of the main findings of this study is the dual role of urban amenities in either supporting or limiting UGS. Amenities such as auto repair shops, shopping services, and transit facilities were found to have a negative correlation with UGS, indicating that their presence may contribute to the reduction in green spaces. This result is consistent with previous research suggesting that urban infrastructure development, particularly in densely populated areas, competes with land designated for green spaces [17,53]. The expansion of transportation facilities, in particular, often requires substantial land use, which can lead to the encroachment upon or fragmentation of UGS, further reducing their ecological functionality [54].

Conversely, amenities such as scenic spots and life services showed a positive correlation with UGS. Scenic spots, which often include parks, plazas, and other recreational areas, seem to play a vital role in promoting the preservation or even expansion of green spaces. This aligns with findings from other studies, where the presence of aesthetically and recreationally valuable amenities has been shown to increase public demand for green spaces [55], prompting local governments and developers to prioritize their conservation. This dynamic suggests that strategic urban planning that incorporates recreational and aesthetic amenities could be a pathway toward maintaining and enhancing UGS in urban centers [17].

In contrast, certain amenities analyzed in this study, such as medical health services, dining services, and public facilities, showed no significant correlation with UGS changes. This lack of impact may stem from their development patterns, which are generally less land-intensive and tend to adapt to existing urban infrastructure without directly encroaching on green spaces [56]. For example, medical health services and dining services often occupy pre-established urban plots rather than requiring the conversion of green space into developed land [10]. Similarly, public facilities such as libraries and post offices are typically planned in areas with limited competition for green space. Moreover, these amenities may also have localized impacts, such as the creation of small green spaces like courtyards, that are not captured at the broader scale of this analysis. The neutral relationship observed for these amenities highlights the need for more granular studies to uncover any subtle or context-specific dynamics that might exist between UGS and urban development.

4.2. Temporal Dynamics of UGS Changes

The temporal analysis reveals important trends in UGS transformation over the decade studied. From 2013 to 2018, there was a marked decline in UGS, which can be attributed to the rapid pace of urbanization in Guangzhou during this period. The city's development boom led to increased demand for land for infrastructure and commercial purposes, further exacerbated by population growth and rising housing demands [57]. These factors likely intensified the competition for land, with UGS being sacrificed in favor of more immediate urban development needs.

However, starting in 2018, a notable shift occurred, with the rate of UGS decline slowing down, and in some areas, even reversing. This trend can be linked to the increasing awareness among both the public and policymakers of the importance of green spaces for urban livability and environmental sustainability. Several local government initiatives aimed at enhancing urban greenery, such as the "park city" concept introduced in Guangzhou, have likely contributed to the stabilization and recovery of UGS during this period [58]. These efforts reflect a growing recognition that green spaces are not merely aesthetic features but essential components of urban ecosystems that provide critical services, including air quality improvement, temperature regulation, and recreational opportunities [56,59].

The COVID-19 pandemic also played a role in shaping UGS dynamics, particularly from 2020 onwards. Lockdown measures and restrictions on construction activities may have temporarily slowed down the loss of green spaces, while simultaneously underscoring the value of accessible green areas for urban residents during times of crisis. Numerous studies have documented the increased use of parks and green spaces during the pandemic as people sought outdoor areas for physical activity and mental well-being [60–63]. This shift in public behavior has reinforced the need to protect and expand UGS as an integral element of urban resilience.

4.3. Model Comparisons and Insights

The use of both OLS and RF models in this study provided a robust methodological framework for assessing the relationship between urban amenities and UGS. While OLS regression is a widely used technique for evaluating linear relationships, it has limitations when dealing with spatially complex and non-linear data, which is where the RF model proved advantageous. The RF model's ability to handle non-linear relationships and interactions between variables allowed for a more nuanced understanding of the factors driving UGS transformation [64].

For instance, the RF model revealed that certain amenities, such as traffic facilities, had a more pronounced negative effect on UGS than initially suggested by the OLS model. This finding highlights the importance of using more sophisticated models that can capture the multifaceted nature of urban development processes. Furthermore, the RF model's higher predictive accuracy reinforces its suitability for urban ecological studies, where interactions between built environments and natural systems are often non-linear and context-dependent.

4.4. Implications for Urban Planning and Policy

The results of this study have significant implications for urban planning and policy in Guangzhou and other rapidly urbanizing cities. First, the identification of specific urban amenities that negatively impact UGS suggests the need for targeted interventions to mitigate their effects. For example, policies could be implemented to incentivize the integration of green infrastructure into the design of new transportation and commercial developments [65]. Green roofs, vertical gardens, and other nature-based solutions could help offset the loss of UGS while contributing to the ecological sustainability of urban environments [65–68].

Second, the positive correlation between recreational amenities and UGS underscores the potential for leveraging public spaces, such as parks and plazas, to promote green space preservation. Urban planners should prioritize the creation of multi-functional spaces that not only meet recreational and social needs but also enhance ecological connectivity and biodiversity [69]. Integrating green spaces into the urban fabric in ways that are accessible and beneficial to the public can help ensure their long-term protection and relevance [1].

Finally, the study's findings highlight the importance of adopting a spatial-temporal approach to urban green space management. Through the spatial-temporal dynamic analysis of urban UGS evolution, landscape pattern and driving force, it is concluded that ecological restoration has slowed down the trend of green space reduction, and it is suggested that decision makers should guide sustainable green space management through this spatial-temporal approach [32]. Insights into how UGS changes in response to urbanization and greening policies are essential for guiding sustainable urban development. By studying the green landscape pattern index of Shanghai over the past 25 years, combined with the relevant planning and policies of urban green space, it is concluded that rapid urbanization and green policy jointly affect the spatial-temporal dynamics of UGS. On this basis, we can put forward the inspiration for Shanghai's new urban planning and policy [26,32]. By understanding how UGS and urban amenities evolve over time and in relation to each other, urban planners can develop more effective strategies for balancing urban growth with environmental sustainability [70]. This approach is particularly important in cities like Guangzhou, where rapid development pressures can quickly erode natural spaces if not carefully managed [71].

4.5. Limitations and Future Research

While this study provides valuable insights into the relationship between urban amenities and UGS, it has several limitations. The reliance on POI data, for example, means that the analysis may not fully capture informal or unregistered amenities that also play a role in shaping UGS dynamics. Future research could incorporate additional data sources, such as crowd-sourced or field survey data, to provide a more comprehensive picture of urban amenities. On the other hand, the R^2 value in this study is relatively low. Although urban green space and infrastructure are important components of urban development, the relationship between the two may not be significant enough. Future studies can explore more explanatory variables to improve the interpretability of the model.

Moreover, while the RF model performed well in predicting UGS changes, there remains a need for further refinement of spatial analysis techniques that can account for the heterogeneity of urban environments. Integrating more detailed land use data, such as building heights or impervious surface cover, could enhance the accuracy of future models and lead to more precise policy recommendations.

5. Conclusions

This study investigates the complex interplay between urban amenities and the transformation of UGS in Guangzhou, China, from 2013 to 2022. Utilizing remote sensing and Point of Interest (POI) data, along with Ordinary Least Squares (OLS) and Random Forest (RF) models, the research identifies significant correlations between various amenities and changes in UGS. Key findings reveal that amenities like auto repair shops and transit facilities negatively impact UGS, while scenic spots and life services tend to support green space preservation. The study highlights a temporal shift in UGS dynamics, with a decline from 2013 to 2018 due to rapid urbanization, followed by a stabilization and recovery post-2018, driven by heightened public awareness and government initiatives. The use of RF modeling offers deeper insights into the non-linear relationships affecting UGS, underscoring its relevance in urban ecological research.

There is a decreasing trend in the explanatory power of both OLS and Random Forest analyses over the 10-year period, with R^2 values declining from 0.166 to 0.140 and 0.2929 to 0.2475, respectively. Notably, the sharpest decrease in R^2 for OLS occurred between 2016 and 2017 (0.007), while Random Forest showed a temporary increase from 0.2547 to 0.2611 between 2018 and 2019, highlighting the dynamic relationship between urban green spaces and urban amenities. However, due to limitations in data coverage and accuracy, incorporating high-precision remote sensing imagery and temporal changes in POI data could significantly enhance future research. This research provides valuable implications for urban planners and policymakers, emphasizing the need for strategic interventions that balance urban growth with green space preservation, ultimately promoting sustainable urban environments.

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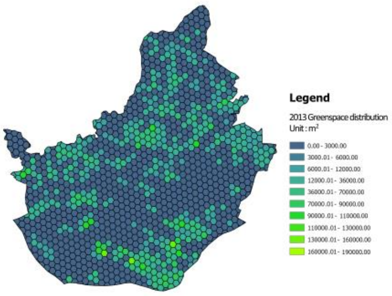
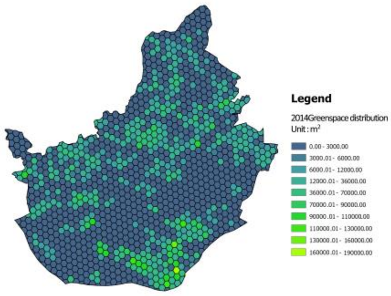
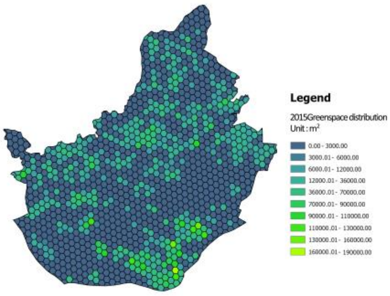
Appendix A The Changes in Green Space by Year from 2013 to 2022



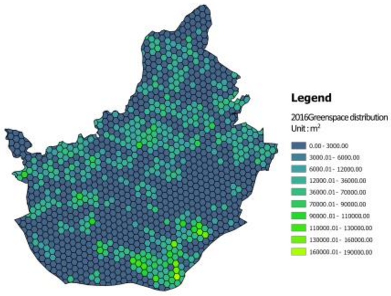
2013 Greenspace distribution



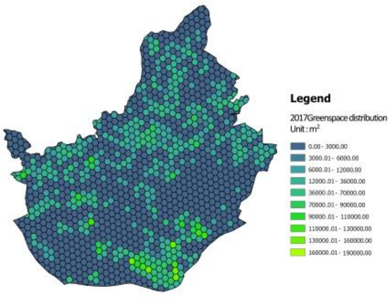
2014 Greenspace distribution



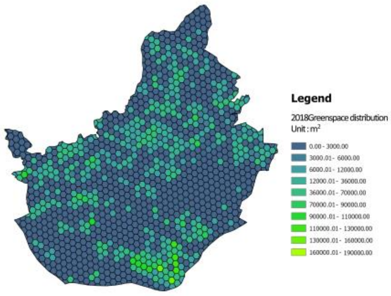
2015 Greenspace distribution



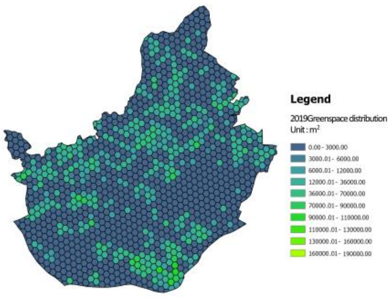
2016 Greenspace distribution



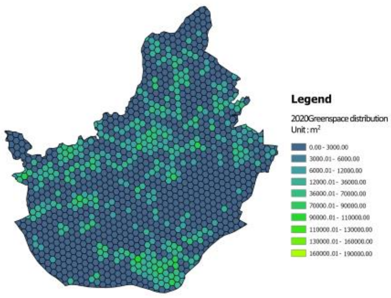
2017 Greenspace distribution



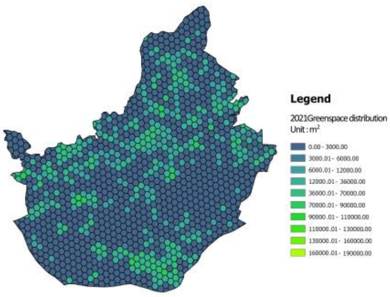
2018 Greenspace distribution



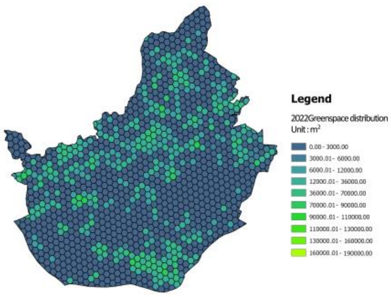
2019 Greenspace distribution



2020 Greenspace distribution



2021 Greenspace distribution



2022 Greenspace distribution

References

1. Li, F.; Zheng, W.; Wang, Y.; Liang, J.; Xie, S.; Guo, S.; Li, X.; Yu, C. Urban Green Space Fragmentation and Urbanization: A Spatiotemporal Perspective. *Forests* **2019**, *10*, 333. [CrossRef]
2. Wolch, J.R.; Byrne, J.; Newell, J.P. Urban Green Space, Public Health, and Environmental Justice: The Challenge of Making Cities 'Just Green Enough'. *Landsc. Urban Plan.* **2014**, *125*, 234–244. [CrossRef]
3. Bowler, D.E.; Buyung-Ali, L.; Knight, T.M.; Pullin, A.S. Urban Greening to Cool Towns and Cities: A Systematic Review of the Empirical Evidence. *Landsc. Urban Plan.* **2010**, *97*, 147–155. [CrossRef]
4. Demuzere, M.; Orru, K.; Heidrich, O.; Olazabal, E.; Geneletti, D.; Orru, H.; Bhave, A.G.; Mittal, N.; Feliú, E.; Faehnle, M. Mitigating and Adapting to Climate Change: Multi-Functional and Multi-Scale Assessment of Green Urban Infrastructure. *J. Environ. Manage.* **2014**, *146*, 107–115. [CrossRef] [PubMed]
5. Meerow, S.; Newell, J.P. Spatial Planning for Multifunctional Green Infrastructure: Growing Resilience in Detroit. *Landsc. Urban Plan.* **2017**, *159*, 62–75. [CrossRef]
6. Shen, X.; Chen, M.; Li, X.; Gao, S.; Yang, Q.; Wen, Y.; Sun, Q. Advancing Climate Resilience through a Geo-Design Framework: Strengthening Urban and Community Forestry for Sustainable Environmental Design. *J. For. Res.* **2024**, *35*, 117. [CrossRef]
7. Tzoulas, K.; Korpela, K.; Venn, S.; Yli-Pelkonen, V.; Kaźmierczak, A.; Niemela, J.; James, P. Promoting Ecosystem and Human Health in Urban Areas Using Green Infrastructure: A Literature Review. *Landsc. Urban Plan.* **2007**, *81*, 167–178. [CrossRef]
8. Markevych, I.; Schoierer, J.; Hartig, T.; Chudnovsky, A.; Hystad, P.; Dzhambov, A.M.; De Vries, S.; Triguero-Mas, M.; Brauer, M.; Nieuwenhuijsen, M.J. Exploring Pathways Linking Greenspace to Health: Theoretical and Methodological Guidance. *Environ. Res.* **2017**, *158*, 301–317. [CrossRef] [PubMed]
9. Bratman, G.N.; Anderson, C.B.; Berman, M.G.; Cochran, B.; De Vries, S.; Flanders, J.; Folke, C.; Frumkin, H.; Gross, J.J.; Hartig, T.; et al. Nature and Mental Health: An Ecosystem Service Perspective. *Sci. Adv.* **2019**, *5*, eaax0903. [CrossRef] [PubMed]
10. Zhang, P.; Cui, Y.; Luo, K.; Zhang, T.; Yang, Y.; Li, J.; Chen, M.; Chen, H.; He, Q.; Yu, Z.; et al. Examining the Audiovisual Therapy Effects on Hospital Groups of Varying Linear Canopy Landscapes and Those with Hydrodynamic Forces. *Front. Public Health* **2024**, *12*, 1324260. [CrossRef] [PubMed]
11. Zhang, B.; Song, Y.; Liu, D.; Zeng, Z.; Guo, S.; Yang, Q.; Wen, Y.; Wang, W.; Shen, X. Descriptive and Network Post-Occupancy Evaluation of the Urban Public Space through Social Media: A Case Study of Bryant Park, NY. *Land* **2023**, *12*, 1403. [CrossRef]
12. Jabbar, M.; Yusoff, M.M.; Shafie, A. Assessing the Role of Urban Green Spaces for Human Well-Being: A Systematic Review. *GeoJournal* **2022**, *87*, 4405–4423. [CrossRef] [PubMed]
13. Fuller, R.A.; Gaston, K.J. The Scaling of Green Space Coverage in European Cities. *Biol. Lett.* **2009**, *5*, 352–355. [CrossRef]
14. Zhang, D.; Wu, Y.; Liu, M. Characterizing Sprawl Development in Urban China: A Perspective from Urban Amenity. *Land* **2023**, *12*, 1180. [CrossRef]
15. Rigolon, A. A Complex Landscape of Inequity in Access to Urban Parks: A Literature Review. *Landsc. Urban Plan.* **2016**, *153*, 160–169. [CrossRef]
16. Hoffimann, E.; Barros, H.; Ribeiro, A.I. Socioeconomic Inequalities in Green Space Quality and Accessibility—Evidence from a Southern European City. *Int. J. Environ. Res. Public. Health* **2017**, *14*, 916. [CrossRef]
17. Jim, C.Y.; Chen, W.Y. Recreation–Amenity Use and Contingent Valuation of Urban Greenspaces in Guangzhou, China. *Landsc. Urban Plan.* **2006**, *75*, 81–96. [CrossRef]
18. Jim, C.Y.; Chen, W.Y. Impacts of Urban Environmental Elements on Residential Housing Prices in Guangzhou (China). *Landsc. Urban Plan.* **2006**, *78*, 422–434. [CrossRef]
19. Larondelle, N.; Lauf, S. Balancing Demand and Supply of Multiple Urban Ecosystem Services on Different Spatial Scales. *Ecosyst. Serv.* **2016**, *22*, 18–31. [CrossRef]
20. McDonald, R.I.; Aronson, M.F.J.; Beatley, T.; Beller, E.; Bazo, M.; Grossinger, R.; Jessup, K.; Mansur, A.V.; Puppim De Oliveira, J.A.; Panlasigui, S.; et al. Denser and Greener Cities: Green Interventions to Achieve Both Urban Density and Nature. *People Nat.* **2023**, *5*, 84–102. [CrossRef]
21. Hunter, R.F.; Cleland, C.; Cleary, A.; Droomers, M.; Wheeler, B.W.; Sinnett, D.; Nieuwenhuijsen, M.J.; Braubach, M. Environmental, Health, Wellbeing, Social and Equity Effects of Urban Green Space Interventions: A Meta-Narrative Evidence Synthesis. *Environ. Int.* **2019**, *130*, 104923. [CrossRef]
22. Nieuwenhuijsen, M.J. Urban and Transport Planning Pathways to Carbon Neutral, Liveable and Healthy Cities; a Review of the Current Evidence. *Environ. Int.* **2020**, *140*, 105661. [CrossRef]
23. Khomenko, S.; Nieuwenhuijsen, M.; Ambros, A.; Wegener, S.; Mueller, N. Is a Liveable City a Healthy City? Health Impacts of Urban and Transport Planning in Vienna, Austria. *Environ. Res.* **2020**, *183*, 109238. [CrossRef] [PubMed]
24. Burant, A.; Selbig, W.; Furlong, E.T.; Higgins, C.P. Trace Organic Contaminants in Urban Runoff: Associations with Urban Land-Use. *Environ. Pollut.* **2018**, *242*, 2068–2077. [CrossRef] [PubMed]
25. Kong, F.; Yin, H.; Nakagoshi, N. Using GIS and Landscape Metrics in the Hedonic Price Modeling of the Amenity Value of Urban Green Space: A Case Study in Jinan City, China. *Landsc. Urban Plan.* **2007**, *79*, 240–252. [CrossRef]
26. Shen, X.; Padua, M.G.; Kirkwood, N.G. Transformative Impact of Technology in Landscape Architecture on Landscape Research: Trends, Concepts and Roles. *Land* **2024**, *13*, 630. [CrossRef]
27. He, W.; Chen, M. Advancing Urban Life: A Systematic Review of Emerging Technologies and Artificial Intelligence in Urban Design and Planning. *Buildings* **2024**, *14*, 835. [CrossRef]

28. Shen, X.; Chen, M.; Ge, M.; Padua, M.G. Examining the Conceptual Model of Potential Urban Development Patch (PUDP), VOCs, and Food Culture in Urban Ecology: A Case in Chengdu, China. *Atmosphere* **2022**, *13*, 1369. [CrossRef]
29. Guo, L.; Luo, J.; Yuan, M.; Huang, Y.; Shen, H.; Li, T. The Influence of Urban Planning Factors on PM2. 5 Pollution Exposure and Implications: A Case Study in China Based on Remote Sensing, LBS, and GIS Data. *Sci. Total Environ.* **2019**, *659*, 1585–1596. [CrossRef]
30. Zhang, X.; Estoque, R.C.; Murayama, Y. An Urban Heat Island Study in Nanchang City, China Based on Land Surface Temperature and Social-Ecological Variables. *Sustain. Cities Soc.* **2017**, *32*, 557–568. [CrossRef]
31. Berger, C.; Rosentreter, J.; Voltersen, M.; Baumgart, C.; Schmullius, C.; Hese, S. Spatio-Temporal Analysis of the Relationship between 2D/3D Urban Site Characteristics and Land Surface Temperature. *Remote Sens. Environ.* **2017**, *193*, 225–243. [CrossRef]
32. Zhang, K.; Chen, M. Multi-Method Analysis of Urban Green Space Accessibility: Influences of Land Use, Greenery Types, and Individual Characteristics Factors. *Urban For. Urban Green.* **2024**, *96*, 128366. [CrossRef]
33. Cai, Z.; Kwak, Y.; Cvetkovic, V.; Deal, B.; Mörtberg, U. Urban Spatial Dynamic Modeling Based on Urban Amenity Data to Inform Smart City Planning. *Anthropocene* **2023**, *42*, 100387. [CrossRef]
34. Yin, J.; Fu, P.; Cheshmehzangi, A.; Li, Z.; Dong, J. Investigating the Changes in Urban Green-Space Patterns with Urban Land-Use Changes: A Case Study in Hangzhou, China. *Remote Sens.* **2022**, *14*, 5410. [CrossRef]
35. Wang, K.; Wang, W.; Li, T.; Wen, S.; Fu, X.; Wang, X. Optimizing Living Service Amenities for Diverse Urban Residents: A Supply and Demand Balancing Analysis. *Sustainability* **2023**, *15*, 12392. [CrossRef]
36. Kaufmann, T.; Radaelli, L.; Bettencourt, L.; Shmueli, E. Scaling of Urban Amenities: Generative Statistics and Implications for Urban Planning. *EPJ Data Sci.* **2022**, *11*, 50. [CrossRef]
37. He, X.; Kozlowski, M.; Ujang, N.B.; Ma, Y. Defining Inner-City Transitional Street Typology Using Point of Interest (PoI) Data in Hillside Cities of China. *Sustainability* **2024**, *16*, 4690. [CrossRef]
38. Hu, N.; Legara, E.F.; Lee, K.K.; Hung, G.G.; Monterola, C. Impacts of Land Use and Amenities on Public Transport Use, Urban Planning and Design. *Land Use Policy* **2016**, *57*, 356–367. [CrossRef]
39. Landry, S.M.; Chakraborty, J. Street Trees and Equity: Evaluating the Spatial Distribution of an Urban Amenity. *Environ. Plan. A* **2009**, *41*, 2651–2670. [CrossRef]
40. Fu, B.; Yu, D.; Zhang, Y. The Livable Urban Landscape: GIS and Remote Sensing Extracted Land Use Assessment for Urban Livability in Changchun Proper, China. *Land Use Policy* **2019**, *87*, 104048. [CrossRef]
41. Huang, H.; Li, Q.; Zhang, Y. Urban Residential Land Suitability Analysis Combining Remote Sensing and Social Sensing Data: A Case Study in Beijing, China. *Sustainability* **2019**, *11*, 2255. [CrossRef]
42. Wenjie, W.; Chen, Y.; Ye, L. Perceived Spillover Effects of Club-Based Green Space: Evidence from Beijing Golf Courses, China. *Urban For. Urban Green.* **2020**, *48*, 126518. [CrossRef]
43. Nyunt, M.S.Z.; Shuvo, F.K.; Eng, J.Y.; Yap, K.B.; Scherer, S.; Hee, L.M.; Chan, S.P.; Ng, T.P. Objective and Subjective Measures of Neighborhood Environment (NE): Relationships with Transportation Physical Activity among Older Persons. *Int. J. Behav. Nutr. Phys. Act.* **2015**, *12*, 108. [CrossRef] [PubMed]
44. He, X.; Zhou, Y.; Yuan, X.; Zhu, M. The Coordination Relationship between Urban Development and Urban Life Satisfaction in Chinese Cities—An Empirical Analysis Based on Multi-Source Data. *Cities* **2024**, *150*, 105016. [CrossRef]
45. Liu, Y.; Shaker ul, din; Jiang, Y. Urban Growth Sustainability of Islamabad, Pakistan, over the Last 3 Decades: A Perspective Based on Object-Based Backdating Change Detection. *GeoJournal* **2021**, *86*, 2035–2055. [CrossRef]
46. Terfa, B.K.; Chen, N.; Zhang, X.; Niyogi, D. Spatial Configuration and Extent Explains the Urban Heat Mitigation Potential Due to Green Spaces: Analysis over Addis Ababa, Ethiopia. *Remote Sens.* **2020**, *12*, 2876. [CrossRef]
47. Hu, S.; Ge, Y.; Liu, M.; Ren, Z.; Zhang, X. Village-Level Poverty Identification Using Machine Learning, High-Resolution Images, and Geospatial Data. *Int. J. Appl. Earth Obs. Geoinformation* **2022**, *107*, 102694. [CrossRef]
48. Huang, R.; Wu, W.; Yu, K. Building Consistent Time Series Night-Time Light Data from Average DMSP/OLS Images for Indicating Human Activities in a Large-Scale Oceanic Area. *Int. J. Appl. Earth Obs. Geoinformation* **2022**, *114*, 103023. [CrossRef]
49. Hong, Z.; Xu, W.; Liu, Y.; Wang, L.; Ou, G.; Lu, N.; Dai, Q. Retrieval of Three-Dimensional Green Volume in Urban Green Space from Multi-Source Remote Sensing Data. *Remote Sens.* **2023**, *15*, 5364. [CrossRef]
50. Chen, Q.; Zhong, C.; Jing, C.; Li, Y.; Cao, B.; Cheng, Q. Rapid Mapping and Annual Dynamic Evaluation of Quality of Urban Green Spaces on Google Earth Engine. *ISPRS Int. J. Geo-Inf.* **2021**, *10*, 670. [CrossRef]
51. Zhang, M.; Wang, J.; Zhang, F. The Influence of Spatial Heterogeneity of Urban Green Space on Surface Temperature. *Forests* **2024**, *15*, 878. [CrossRef]
52. Čeh, M.; Kilibarda, M.; Lisec, A.; Bajat, B. Estimating the Performance of Random Forest versus Multiple Regression for Predicting Prices of the Apartments. *ISPRS Int. J. Geo-Inf.* **2018**, *7*, 168. [CrossRef]
53. Graham, S. Constructing Premium Network Spaces: Reflections on Infrastructure Networks and Contemporary Urban Development. *Int. J. Urban Reg. Res.* **2000**, *24*, 183–200. [CrossRef]
54. Cervero, R.B. Linking Urban Transport and Land Use in Developing Countries. *J. Transp. Land Use* **2013**, *6*, 7–24. [CrossRef]
55. Zhang, H.; Chen, B.; Sun, Z.; Bao, Z. Landscape Perception and Recreation Needs in Urban Green Space in Fuyang, Hangzhou, China. *Urban For. Urban Green.* **2013**, *12*, 44–52. [CrossRef]

56. Chen, M.; Cai, Y.; Guo, S.; Sun, R.; Song, Y.; Shen, X. Evaluating Implied Urban Nature Vitality in San Francisco: An Interdisciplinary Approach Combining Census Data, Street View Images, and Social Media Analysis. *Urban For. Urban Green.* **2024**, *95*, 128289. [CrossRef]
57. Meng, L.; Sun, Y.; Zhao, S. Comparing the Spatial and Temporal Dynamics of Urban Expansion in Guangzhou and Shenzhen from 1975 to 2015: A Case Study of Pioneer Cities in China's Rapid Urbanization. *Land Use Policy* **2020**, *97*, 104753. [CrossRef]
58. Wang, W.Q.; Liu, C.H.; Chen, Y.F.; Zhang, Y.L. Core Meaning and Scientific Path of the Concept of Open Sharing of Urban Park Green Spaces Under the Goal of Park City. *Landsc. Archit.* **2023**, *30*, 28–34.
59. Dhiman, S. *Sustainable Development and Environmental Stewardship: Global Initiatives Towards Engaged Sustainability*; Dhiman, S., Ed.; Springer International Publishing: Cham, Germany, 2023; ISBN 978-3-031-28884-5.
60. Bustamante, G.; Guzman, V.; Kobayashi, L.C.; Finlay, J. Mental Health and Well-Being in Times of COVID-19: A Mixed-Methods Study of the Role of Neighborhood Parks, Outdoor Spaces, and Nature among US Older Adults. *Health Place* **2022**, *76*, 102813. [CrossRef] [PubMed]
61. Jackson, S.B.; Stevenson, K.T.; Larson, L.R.; Peterson, M.N.; Seekamp, E. Outdoor Activity Participation Improves Adolescents' Mental Health and Well-Being during the COVID-19 Pandemic. *Int. J. Environ. Res. Public. Health* **2021**, *18*, 2506. [CrossRef] [PubMed]
62. Pouso, S.; Borja, Á.; Fleming, L.E.; Gómez-Baggethun, E.; White, M.P.; Uyarra, M.C. Contact with Blue-Green Spaces during the COVID-19 Pandemic Lockdown Beneficial for Mental Health. *Sci. Total Environ.* **2021**, *756*, 143984. [CrossRef] [PubMed]
63. Wen, Y.; Shen, X.; Shen, Y. Improving Immersive Experiences in Virtual Natural Setting for Public Health and Environmental Design: A Systematic Review and Meta-Analysis of Randomized Controlled Trials. *PLoS ONE* **2024**, *19*, e0297986. [CrossRef]
64. Speiser, J.L.; Miller, M.E.; Tooze, J.; Ip, E. A Comparison of Random Forest Variable Selection Methods for Classification Prediction Modeling. *Expert Syst. Appl.* **2019**, *134*, 93–101. [CrossRef] [PubMed]
65. Lennon, M. Green Infrastructure and Planning Policy: A Critical Assessment. *Local Environ.* **2015**, *20*, 957–980. [CrossRef]
66. Cristiano, E.; Deidda, R.; Viola, F. The Role of Green Roofs in Urban Water-Energy-Food-Ecosystem Nexus: A Review. *Sci. Total Environ.* **2021**, *756*, 143876. [CrossRef]
67. Dhakal, K.P.; Chevalier, L.R. Managing Urban Stormwater for Urban Sustainability: Barriers and Policy Solutions for Green Infrastructure Application. *J. Environ. Manage.* **2017**, *203*, 171–181. [CrossRef] [PubMed]
68. Sikorska, D.; Ciężkowski, W.; Babańczyk, P.; Chormański, J.; Sikorski, P. Intended Wilderness as a Nature-Based Solution: Status, Identification and Management of Urban Spontaneous Vegetation in Cities. *Urban For. Urban Green.* **2021**, *62*, 127155. [CrossRef]
69. Heymans, A.; Breadsell, J.; Morrison, G.; Byrne, J.; Eon, C. Ecological Urban Planning and Design: A Systematic Literature Review. *Sustainability* **2019**, *11*, 3723. [CrossRef]
70. Zhou, X.; Wang, Y.-C. Spatial–Temporal Dynamics of Urban Green Space in Response to Rapid Urbanization and Greening Policies. *Landsc. Urban Plan.* **2011**, *100*, 268–277. [CrossRef]
71. Li, Y.-Y.; Ren, B.-T.; Chen, Y.-S.; Huang, L.-C.; Sun, C.-G. Multiscale Spatiotemporal Dynamics Analysis of Urban Green Space: Implications for Green Space Planning in the Rapid Urbanizing Hefei City, China. *Front. Ecol. Evol.* **2022**, *10*, 998111. [CrossRef]