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Environmental Inequalities in Ecosystem Services Benefits of Green Infrastructure: A Case Study from China

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Abstract: Rapid urbanization is widespread globally, particularly impacting developing countries. In the face of climate challenges and shrinking public spaces resulting from urbanization, the significance of green infrastructure (GI) for human well-being and sustainability has increasingly taken center stage. This study employs an array of social-environmental benefits to evaluate GI's contributions to human well-being, including mitigation of the urban heat island (UHI) effect, recreational functions, enhanced landscape connectivity, and efficient stormwater management. By mapping GI's advantages, we scrutinized tradeoffs and 'hot spots' linked to these benefits within a metropolitan region. Moreover, we correlated GI's advantages with the well-being of different socio-economic status (SES) groups by global and local regression. The study reveals environmental inequality, with higher SES areas—such as affluent and well-educated neighborhoods—providing superior and multifaceted GI benefits. The income coefficient is significantly positively correlated with the recreation function at the 1% significance level, while the coefficient for education is significant at the 10% level. Moreover, the income coefficient (0.349) surpasses the education coefficient (0.012). Our research also highlights that accessibility to GI's recreational services may be an essential and overlooked indicator of environmental justice, especially for communities with a high proportion of elderly and low-income individuals.

Keywords: environmental justice; socio-economic status; cultural service; multifunctionality; accessibility

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Citation: Xiong, G.; He, R.; Wang, G.; Hong, J.; Jin, Y. Environmental Inequalities in Ecosystem Services Benefits of Green Infrastructure: A Case Study from China. *Forests* **2024**, *15*, 73. https://doi.org/10.3390/f15010073

Academic Editor: Tommaso Sitzia

Received: 13 November 2023
Revised: 21 December 2023
Accepted: 27 December 2023
Published: 29 December 2023

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1. Introduction

Rapid urbanization, driven by population consolidation and urban expansion, transforms cities and their peripheries. These shifts present significant challenges when it comes to preserving urban green spaces and can impact public health and well-being [1,2]. Compelling evidence indicates that swift urbanization is a primary catalyst for biodiversity loss and alterations in landscapes and ecosystems [3,4]. Consequently, the inherent contradiction between socio-economic development and the natural ecosystem leads to disparities in the supply and demand of ecosystem services (ES) [5]. In response to interrelated challenges, urban planners have increasingly embraced the 'green infrastructure' (GI) concept, integrating ecosystems into spatial planning [6,7].

GI encompasses strategically planned networks of natural and semi-natural areas that deliver a multitude of benefits for humans and ecosystems [8]. We define GI as vegetated spaces within urban settings, manifesting as lawns, parks, urban forests, cultivated lands, nature reserves, and wetlands [9]. In our examination, GI benefits are multifunctional and offer a broad spectrum of ES through thoughtful configuration and effective management. A wealth of existing literature underscores GI's proactive role in urban environments and how it can address air pollution reduction, noise abatement, water management, mitigation

of the UHI effect, and public health concerns [10,11]. Furthermore, GI at the neighborhood level, such as pocket parks, playgrounds, leisure areas, and green trails, significantly contributes to urban communities' physical well-being [12].

Previous research has documented that GI furnishes various social and ecological advantages [13]. The ES framework encompasses these benefits within four categories: provisioning, regulating, supporting, and cultural services [14]. However, pertinent studies tend to analyze GI benefits from singular perspectives [15,16]. Some GI research targets the specific needs of different construction projects, as evidenced by the development of GI and its components to address particular issues and ES provision objectives, such as stormwater management or UHI effect mitigation [17]. Such assessments may, however, overlook GI's multifunctionality, leading to potential drawbacks [18]. In general, GI impacts are localized; therefore, it is important to know how to distribute GI in cities under different objectives, and sometimes there are conflicts between different objectives. Synergies and trade-offs necessitate meticulous consideration when evaluating and designing GI. In a recent related study, within the Artificial Intelligence for Ecosystem Services (ARIES) framework, researchers explore the distribution and impact of GI benefits, providing valuable insights for sustainable resource management and urban development [19]. Using modeling techniques, the research explores the complex relationships between ecosystems and the services they provide to humanity [20].

In recent years, research into GI benefits has centered on human health and ecological restoration, delving deeper into their impact on human well-being. For instance, recreational and other cultural ES are closely tied to human activities and require active access to reap their benefits [21]. Nevertheless, experiencing recreational services hinges on the ability to access GI with specific functions (e.g., parks and scenic spots). Ala-Holko [22] has emphasized the importance of incorporating accessibility analysis into mapping cultural ecosystem services. Most relevant studies on green space accessibility often employ Geographic Information Systems (GIS) to measure urban green spaces and combine indicators such as distance and travel time to urban green spaces, the presence or absence of park facilities, and green space supply capacity from an accessibility equity perspective. An accessibility equity perspective involves ensuring that potential gaps or inequalities exist in the use of GI, accessibility, or opportunities among different groups within the population [23].

The unequal accessibility and quality of urban green spaces have become recognized issues of environmental justice among scholars [24,25]. Most studies suggest that in urban areas, green spaces are not always distributed equitably, and people's access is often highly stratified based on factors such as income, ethnic and racial characteristics, age, gender, and (dis)ability [26]. This unequal accessibility may lead to certain communities or groups having relatively greater difficulty in accessing urban green spaces and enjoying the associated health and social welfare benefits compared to other groups. Regarding environmental justice in urban greening studies, a considerable body of research has explored the relationship between green space accessibility and various societal strata. For example, such works have generally revealed the spatial inequities associated with residential segregation as a consequence of factors such as age groups [27–29], race/ethnicity [29,30], educational levels [27,31], and income [32,33] (Table 1). Evidence from these studies implies that lower socio-economic status (SES) and non-white communities perform worse with regard to many aspects of GI benefits, such as stormwater management and air quality, signaling potential inequality. However, related research in developing countries remains scarce. Given that developing countries are still undergoing relatively rapid urbanization processes—and these may affect green resource distribution—comprehending inequalities in GI benefits within developing countries is of the utmost importance.

Table 1. Study of socio-economic status in green accessibility.

Study Characteristics	Geographies	References
Income bracket	Japan; United States; United Kingdom; South Africa; China	[27,28,30–33]
Ethnicity/Race	United States; United Kingdom; South Africa;	[29,30]
Age group	Japan; United States; Guangzhou, China	[27–29]
Housing conditions	United States;	[32]
Gender vulnerability	Japan;	[28]
Education	United States; China	[27,31]

In a metropolis like Chongqing, GI planning must reflect multi-functionality, integrated benefits, and comprehensive responsiveness to significant regional issues while coordinating regional space. Nonetheless, existing research indicates a dearth of practical approaches and applications to achieve multiple sustainable development goals and co-protect cities through innovative and synergistic utilization of the ES provided by GI [34,35]. For example, many urban areas face challenges related to climate change, biodiversity loss, and social inequality; however, they may struggle to implement cohesive strategies that leverage GI to simultaneously mitigate flood risks, enhance biodiversity, and promote social well-being. The study focuses on evaluating GI's multiple benefits through various social-environmental benefits, including the mitigation of the urban heat island (UHI) effect, recreational functions, enhanced landscape connectivity, and efficient stormwater management. Our hypothesis posits that significant disparities exist in GI benefits among different socio-economic status (SES) groups in Chongqing, China.

In detail, this study enriches the existing literature with regard to three aspects. First, it considers the recreational needs of urban residents for GI and employs the Gaussian-based 2SFCA model instead of buffer analysis for a more accurate assessment. Second, and in contrast to previous studies, our research focuses on mapping the distribution of different GI benefits. It explicitly relates them to the well-being of SES groups to enable the identification of the disparities that exist in terms of the benefits gained or lost by various groups. Third, we consider the spatial autocorrelation of GI benefits and examine the spatial nuances of environmental justice using geographically weighted regression (GWR).

The remainder of the paper is organized as follows: Section 2 delineates the study area, data collection, processing, and methodologies employed in our research, including calculations of ecosystem services, the global regression model, and a local regression model. Section 3 describes the results of the spatial distribution of ecosystem service (ES) benefits and their synergies and trade-offs, along with the regression model of the socioeconomic inequality of ES benefits. Section 4 discusses these results, while Section 5 presents conclusions and final thoughts.

2. Materials and Methods

2.1. Study Area

This study examines the Chongqing metropolitan region (defined by district or county boundaries, akin to the "Metropolitan Statistical Area" utilized in the US and EU). It is an area that encompasses 3175 km^2 and envelops nine core urban districts within the major urban area. This area, henceforth referred to as Chongqing, is situated within the entirety of Chongqing Municipality (which refers to the legal boundaries of a city as an administrative entity in China) and consists of 155 districts (Figure 1a). Chongqing presents an ideal setting for quantifying the ES benefits of GI due to the heightened demands that are generated by its large urban population.

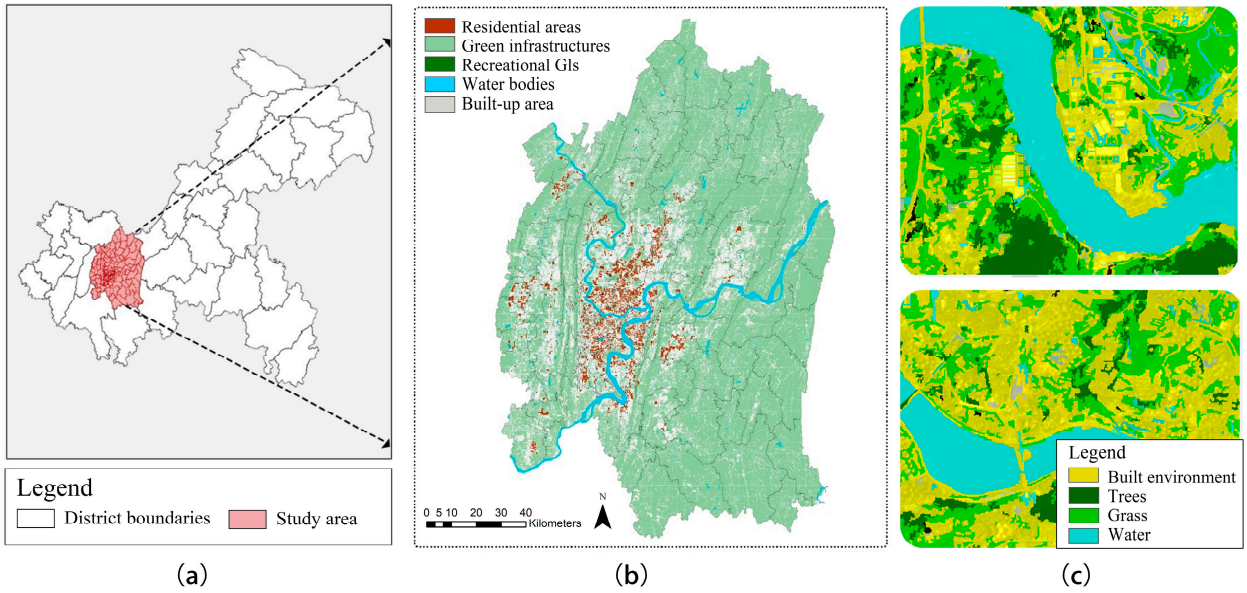

Figure 1. (**a**) Location of study area; (**b**) Distribution of GI, recreational GI, water bodies, and residential areas; (**c**) Semi-automatic Classification results.

Data for the GI analysis were obtained from multiple wavelength bands at different resolutions [36], acquired from the European Space Agency's (ESA) Sentinel-2 satellite. For image identification, we specifically selected images captured during the summer period (mid-June to mid-September) of the year 2020. These images are processed using supervised classification in eCognition [37] and were identified as trees, grass, cropland, built environments, water, etc. (Figure 1c). The GI referred to in the text is wide-ranging, encompassing lawns, parks, urban forests, arable land, nature reserves and wetlands in cities, constituted by the trees, grasslands, and farmland identified in Figure 1c. In addition, we have specifically identified recreational GIs from this range, focusing on those with a substantial scale (>3000 square meters) and service functions, with the main emphasis on the dimension of its recreational function and being more concerned with the close relationship between the GIs and the daily life of the residents (Figure 1b).

2.2. Variables and Data Source

Based on Table 1, we use income, education, aging, and housing condition to quantify individual's or groups' socio-economic status (SES). To avoid multiple collinearity problems in the selected variables, which may affect the final regression results, we used the variance expansion factor (VIF) to identify collinearity (Table 2). When the VIF value is less than 5, there is no collinearity between the data. This analysis ensures that the regression results are robust and reliable for subsequent interpretation. Furthermore, we evaluated the ES benefits of GI by examining the mitigated Urban Heat Island (UHI) effect, recreational functions, enhanced landscape connectivity, and managed stormwater with the well-being of different SES groups. We employed accessibility to recreational GI (e.g., parks and scenic spots) as indicators of GI's recreational function.

Table 2. Descriptive statistics of the independent variables.

Independent Variable	Obs	Mean	SD	Min	Median	Max	VIF
Aging	155	11.56	4.42	0.46	10.93	24.42	2.23
Income	155	7.42	3.73	0.000	9.25	10.24	1.71
Education	155	9.24	13.12	0.31	2.62	60.28	1.48
House condition	155	3.27	2.54	0.00	2.72	16.44	1.05

Data for this study were acquired from a range of sources (Table 3). Firstly, we extract the distribution of GI from the 10 m resolution remote sensing data and land use survey data of Chongqing. To ensure the uniformity and accuracy of our analysis, we validated the derived GI information by using land use survey data (1:10,000) provided by the government. Secondly, street-level statistical data were taken from the 6th National Population Census of the People's Republic of China. Thirdly, street network information was sourced from the "Baidu Sitemap Generator." Lastly, residential data for the Chongqing metropolitan area were procured from the LIANJIA website (https://bj.lianjia.com/),accessed on 1 July 2021. As a housing service platform with a 70% market share of Chongqing's housing market, this website provided data for 5946 residential locations, including basic information such as building names, number of households, longitude, latitude, reference average price, and other attributes.

Table 3. Indicators and data sources.

Indicators	Data Sources
Mitigated UHI effect	Dataset of daily values of terrestrial climate data in China (http://data.cma.cn/site/showSubject/id/101.html), accessed on 1 July 2021
Recreation function	Lianjia website (https://cq.lianjia.com/) accessed in 1 July 2021 Open Street Map (www.openstreetmap.org) accessed in 1 July 2021
Increased landscape connectivity	Finer Resolution Observation and Monitoring of Global Land Cover (FROM-GLC) (http://data.ess.tsinghua.edu.cn/fromglc10_2017v01.htmls) accessed in 1 July 2021
Managed stormwater	Precipitation: China Meteorological Background Dataset (https://www.resdc.cn/data.aspx?DATAID=253), accessed in 1 August 2021 Evapotranspiration: A dataset on surface evapotranspiration in the Belt and Road and adjacent regions (2015) (http://www.geodoi.ac.cn/WebCn/doi.aspx?Id=773), accessed in 1 August 2021 Ecosystem Classification Data: Ecological Assessment and Ecological Security Database (http://www.ecosystem.csdb.cn/), accessed in 1 August 2021

2.3. Methods

2.3.1. Accessibility to Recreational GI

Accessibility serves as a crucial indicator in studies of spatial equity and is widely recognized as an effective tool for assessing the quantity and fairness of urban land use. According to previous research [38], we employed the Two-Step Floating Catchment Area (2SFCA) model to evaluate accessibility. This model, based on topological and operational network analysis methods, considers actual road network parameters to assess the time and quantity of residents' accessibility to Recreational GI.

The Gaussian-based 2SFCA model was first proposed by Dai (2011) [39] to correct for distance attenuation in GI accessibility evaluation and has since been widely adopted by many researchers [40–42]. The model has two components. First, the aggregate demand for location i at each threshold travel time t_0 of GI to q, and then the population at location k, which is weighted with a Gaussian function (G) and aggregated to calculate the ratio of services to population R_j:

$$\mathrm{R}_j = \frac{S_q^A}{\sum_{k\{t_{kq} \le d_0\}} G\left(t_{kq}, t_0\right) P_k} \tag{1}$$

where P_k for location k is the population whose centroid is in the catchment area (i.e., $t_{kq} \le t_0$) from GI location q; t_{kq} is the travel time from k (population location) to q (GI location), S_q is the is the area of GI at q location; and G is the attenuation coefficient for distance [39]. The calculation of G is listed below:

$$G\left(t_{kq}, t_0\right) = \begin{cases} \frac{e^{-\left(\frac{1}{2}\right)*\left(\frac{t_{kq}}{t_0}\right)^2} - e^{-\left(\frac{1}{2}\right)}}{1-e^{-\left(\frac{1}{2}\right)}}, & \text{if } t_{kq} \leqslant t_0 \\ 0, & \text{if } t_{kq} > t_0 \end{cases} \tag{2}$$

The GI within t_0 were then searched for each demand population I; the supply-demand ratio R_q is summed, and the spatial accessibility A_i of demand location i is calculated:

$$A_i = \sum_{l \in \{t_{iq} \leqslant t_0\}} G(t_{iq}, t_0) R_i \quad (3)$$

where i represents all green spaces in the catchment, and the accessibility index represents the area of green space services per capita.

2.3.2. Analysis of Hot and Cold Spots Based on G_i* Statistics

We use the G_i* statistic in this paper for identifying statistically significant spatial clustering of high-value (hot spots) and low-value (cold spots). This enabled the identification of whether the benefits of GI have high-value clusters (hot-spot areas) and low-value clusters (cold-spot areas), and also enabled the determination of where high- and low-value areas are spatially clustered [43].

$$G_i* = \frac{\sum_{j=1}^{n} w_{i,j} x_j - \overline{X} \sum_{j=1}^{n} w_{i,j}}{\sqrt{\left[n \sum_{j=1}^{n} w_{i,j}^2 - \left(\sum_{j=1}^{n} w_{i,j} \right)^2 \right] / (n-1)}} \quad (4)$$

where G_i* is the z-score of location i, x_j is the attribute value of location j, w_{ij} is the spatial weight between location i and j, and w_{ij} = 1 if neighbor j is within distance of location i, w_{ij} = 0; otherwise, n is the total number of fishnet grids.

$$\overline{X} = \frac{1}{n} \sum_{j=1}^{n} X_j \quad (5)$$

$$S = \sqrt{\frac{1}{n} \sum_{j=1}^{n} X_j^2 - \left(\overline{X}^2 \right)} \quad (6)$$

For each feature in the dataset, the G_i* statistic returns a z-score as its output. A z-score that is significantly positive shows a pronounced concentration of high values, commonly referred to as a 'hot spot'. Conversely, a z-score that is slightly negative signifies a notable concentration of low values, often referred to as a 'cold spot'. This method offers a more comprehensive illustration of the spatial clustering attributes pertaining to the GIs as opposed to solely examining the extreme values of high or low value in isolation. The results calculated by Equations (4)–(6) are then utilized in the ArcGIS 10.5 toolbox for visualization, placing each raster pixel in the context of the surrounding features for assessment.

2.3.3. Global Regression

In global regression, ordinary least squares (OLS) models, spatial lag models (SLMs) and spatial error models (SEM) [44,45] reveal the relationship that exists between the benefits of GI and different SES groups. OLS models typically ignore spatial correlations, which can lead to biased estimates. When significant spatial autocorrelation existed in the study area, spatial regression was conducted using the Moran's I statistic. Spatial regression models address spatial dependence issues that linear regression analysis cannot handle [46]. We selected the SEM and SLM models for further analysis. SEM is a spatial autocorrelation model that considers the presence of spatial correlation in the error term of the model. It can be used to account for the impact of unknown spatial factors on the distribution of ecosystem services, thereby enhancing the predictive accuracy of the model. SLM is employed to investigate the spatial diffusion effects of the dependent variable,

indicating that the level of ecosystem services in one area may be influenced by the level in adjacent areas and suggesting the potential for spillover effects of ecosystem services among neighboring regions [47,48]. In this case, the SLM considers the addition of a lagged dependent variable to account for autocorrelation in the model, while the SEM attempts to calculate an error term to assess the spatial dependence of independent variables that may have been missed.

The OLS model can be expressed as follows:

$$y = \beta_0 + \sum_{i=1}^{p} \beta_i x_i + \varepsilon \quad (7)$$

where y is the dependent variable, β_0 is the intercept, β_i is the parameter estimation coefficient of the independent variable x_i, p is the number of independent variables, and ε is the error term.

SLM adds a lag term associated with the dependent variable to the OLS model [12], which reflects the spatial autocorrelation of the dependent variable. The formula for the SLM model is as follows:

$$y = \beta_0 + \delta \sum_{i=1}^{p} W_i y + \sum_{i=1}^{p} \beta_i x_i + \varepsilon \quad (8)$$

where δ is the coefficient of the spatial lag term of the dependent variable; the higher the value of δ, the greater the spatial autocorrelation of the dependent variable; and W_i is the spatial lag term weight. The SEM model can be illustrated in detail as follows:

Compared to SLM, SEM considers the error term to be spatially autocorrelated. The model can be elaborated as follows:

$$y = \beta_0 + \sum_{i=1}^{p} \beta_i x_i + \xi \sum_{i=1}^{p} W_i \prime \varepsilon \quad (9)$$

where ε is the coefficient of the spatial error term, which expresses the spatial autocorrelation of the spatial error terms, and W_i' is the spatial weight indicator of ε. Two statistics—R^2 (coefficient of determination) and AIC (Akaike Information Criterion)—were used to compare the effects of these three global regression model estimates used in this study. These two indicators gave a relative measurement of the statistical model's goodness of fit; with a high R^2 value, and lower AIC value, the model is better [33].

2.3.4. Local Regression

Building upon the global regression, we employed local regression models for further analysis. In contrast to global regression, local regression allows for spatial variability in the relationship between the dependent and independent variables [49]. Considering the spatial heterogeneity of SES groups, where relevant factors may adapt to the supply of SES benefits in different ways and degrees across space, the analysis was conducted using the Geographically Weighted Regression (GWR) model. The GWR model is an extension of traditional multiple linear regression (i.e., Ordinary Least Squares, OLS), embedding the spatial location of attributes into the regression parameters to obtain local estimates of regression and coefficients [44]. The details of such a model can be expressed as follows:

$$y_j = \beta_0(\mu_j, v_j) + \sum_{i=1}^{p} \beta_i(\mu_j, v_j) x_{ij} + \varepsilon_j \quad (10)$$

where μ_j and v_j are the coordinates for each location j, β_0 is the intercept for location j, and β_i is the local parameter estimate for independent variable xi at location j.

In this study, we used the optimal bandwidth determined by minimizing the modified Akaike Information Criterion (AICc). The GWR model produced a set of local regression

results, including local parameter estimates, *t*-test values on the local parameter estimates, local R^2 values and local residuals [45]. Subsequently, we carried out a spatial autocorrelation analysis on the residuals of the model.

2.4. Data Processing

2.4.1. Managing Stormwater

The managing stormwater model was used to simulate the hydrological processes of output water cycle elements, including precipitation, evapotranspiration, surface runoff, subsurface runoff, and groundwater, and was combined with the water balance method to calculate water conservation (*WC*) [50]. The evaluation method used was the water conservation quantity calculation model. The equation is as follows:

$$WC = \sum_{i}^{j} (P_i - ET_i - SF_i) \times A_i \times 10^3 \quad (11)$$

where *WC* is the water conservation (mm), and P_i, ET_i, and SF_i are precipitation, actual evapotranspiration, and surface runoff, respectively (mm). A_i is the area of the *i* location ecosystem type (km^2), and *j* represents the number of ecosystem types in the study area. The P and ET data are sourced from the dataset (Table 3), while SF is calculated using the formula:

$$SF = P_{\mathrm{i}} \times \alpha \quad (12)$$

Here, α represents the average surface runoff coefficient, calculated based on the calculation guidelines provided by the Chinese government. The average surface runoff coefficients for different ecosystem types are provided in the table below (Table 4).

Table 4. Average Surface Runoff coefficients.

Ecosystem Type 1	Ecosystem Type 2	Average Surface Runoff Coefficient (%)
Forest	Evergreen Broadleaf Forest	2.67
	Evergreen Needleleaf Forest	3.02
	Mixed Broadleaf and Needleleaf Forest	2.29
	Deciduous Broadleaf Forest	1.33
	Deciduous Needleleaf Forest	0.88
	Sparse Forest	19.20
Shrubland	Evergreen Broadleaf Shrubland	4.26
	Deciduous Broadleaf Shrubland	4.17
	Needleleaf Shrubland	4.17
	Sparse Shrubland	19.2
Grassland	Meadow	8.2
	Prairie	4.78
	Thicket	9.37
	Sparse Grassland	18.27
Wetland	Wetland	0.00

2.4.2. Reducing the UHI Effect

Vegetation can cool local environments and through so doing help mitigate the UHI. According to previous research [51–53], we utilize the Land Surface Temperature (LST) indicator to assess the UHI Effect. The LST datasets, derived from the Landsat 8 Thermal Infrared Sensor using the Radiative Transfer Equation-Based Method, serve as indicators of UHI in a city. Landsat scenes were identified based on two criteria: (1) less than 10% land cloud cover, and (2) as close to the summer months of the region as possible.

2.4.3. Landscape Connectivity

Landscape connectivity can highly condense landscape pattern information, including the composition and spatial configuration of ecosystems. Using Fragstats software (Version 4.2.1), we calculated three categories for vegetated land cover for each street unit in each city, according to Li [54]. Categories included:

- Describing the area and density of patches; the selected indicators included patch density (PD) and the maximum patch index (LPI);
- Describing the shape of patches, including landscape shape index (LSI), patch area-weighted size (AREA_ AM), and average shape index (SHAPE MN);
- Describing the spatial configuration of the landscape, including DIVISION, MESH, SPLIT, and AI.

The results of the PCA of the standardized values of the selected nine metrics showed that the first component explained a total of 83.65% of the variance of information distribution, demonstrating the efficiency of PCAs in modeling the landscape connectivity index. PCA1 can be interpreted as an overall measure of landscape health or quality. High PCA1 scores suggest landscapes with high vegetation cover, good connectivity, and low fragmentation, indicating a healthier or more ecologically sustainable landscape. As these indicators are dispersed, different components of landscape connectivity, we integrated them using principal component analysis, and a composite landscape pattern index score was derived. We calculated the composite landscape pattern index score for each of the 155 blocks in Chongqing for characterizing landscape connectivity, one of the dependent variables.

3. Results

3.1. Spatial Patterns of GI Benefits

As depicted in Figure 2, discernible spatial differences in the benefits provided by GI exist along the metropolitan center to the suburbs. We calculated a comprehensive multifunctionality index (Figure 2e) by assigning weights to the scores of four ES benefits. In comparison to individual assessments, slight differences emerge in the multiple benefits. However, overall, the results reveal no significant disparities from the center to the suburbs, as the northern and western regions, along with the city center, exhibit higher multiple benefits. In detail, areas excelling in stormwater management, landscape connectivity, and temperature regulation are primarily located in suburban areas, encompassing over 80% of the total urban forest. The northern and south-eastern suburbs demonstrate the greatest capacity for temperature regulation and mitigating UHI effects. Likewise, sites near suburban forests offer high-capacity stormwater abatement. Contrarily, the suburbs exhibit substantially lower GI supply capacities than the urban center. In suburban areas, urban forests and farmland are the dominant land types, while only a small portion is allocated for planned green spaces like scenic areas and suburban parks. Notably, a cluster of high landscape connectivity and stormwater management GI is situated at the confluence of the Yangtze and Jialing Rivers; this area also serves as Chongqing's central business district (CBD).

The G_i* identifies heterogeneous units of ecosystem service values. Figure 3 displays three heterogeneous units: hot spots, cold spots, and random areas. A distinct spatial mismatch exists with regards to the aggregation pattern of the four ecosystem services within the core area. As shown in Figure 3, urban core areas represent hot spots clustered with high recreational functions, while most hot spots offering other benefits are located in peri-urban areas. Excluding leisure functions, significant ES shortages are observed in southwestern Chongqing, whereas most neighborhoods in the north and southeast exhibit ES surpluses.

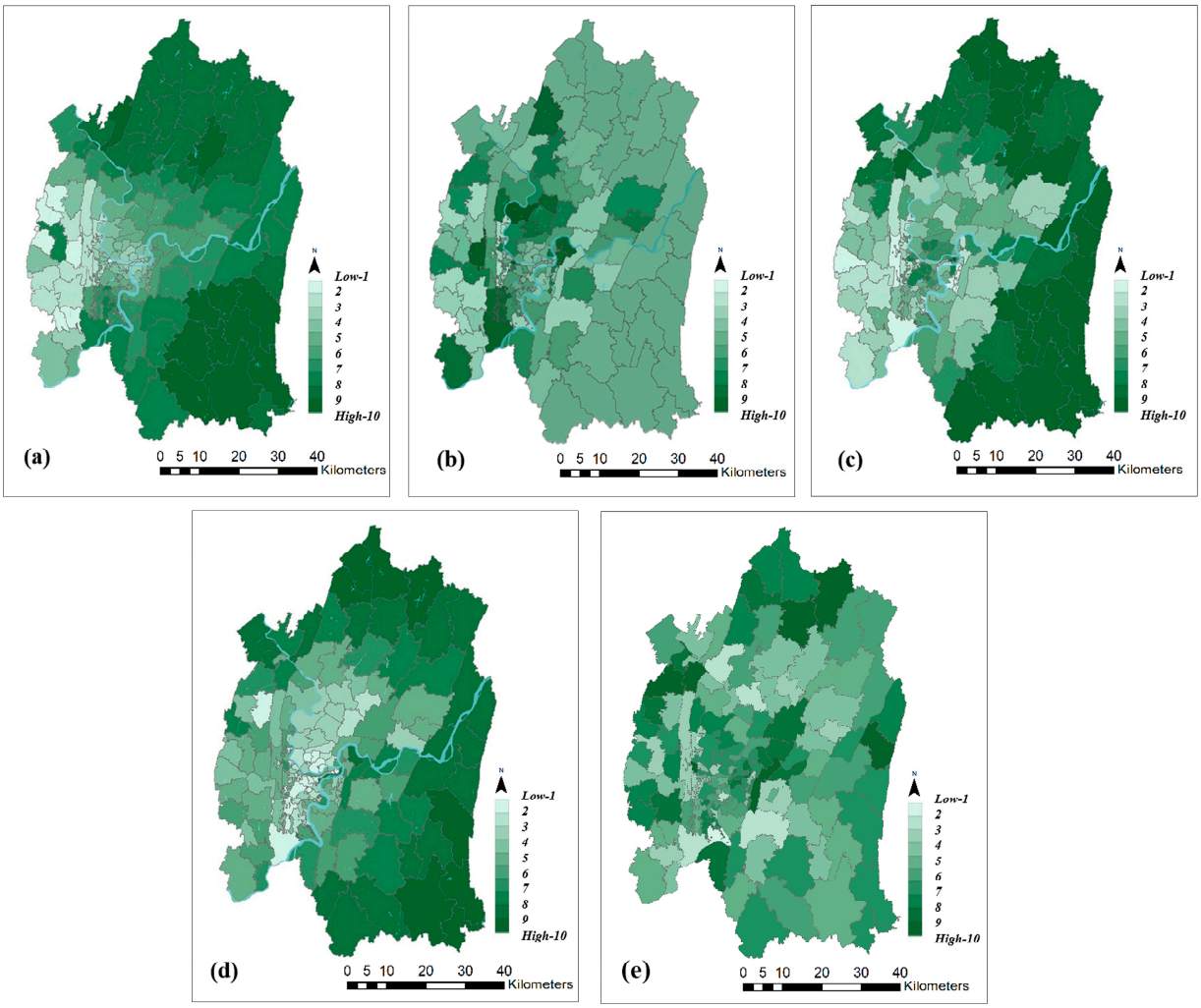

Figure 2. ES benefits provided by GI for 155 blocks (Natural Breaks). (**a**) ES benefit of Mitigated UHI effect. (**b**) ES benefit of Recreation function. (**c**) ES benefit of Landscape connectivity. (**d**) ES benefit of Managed stormwater. (**e**) The weighted sum of 4 ES benefits.

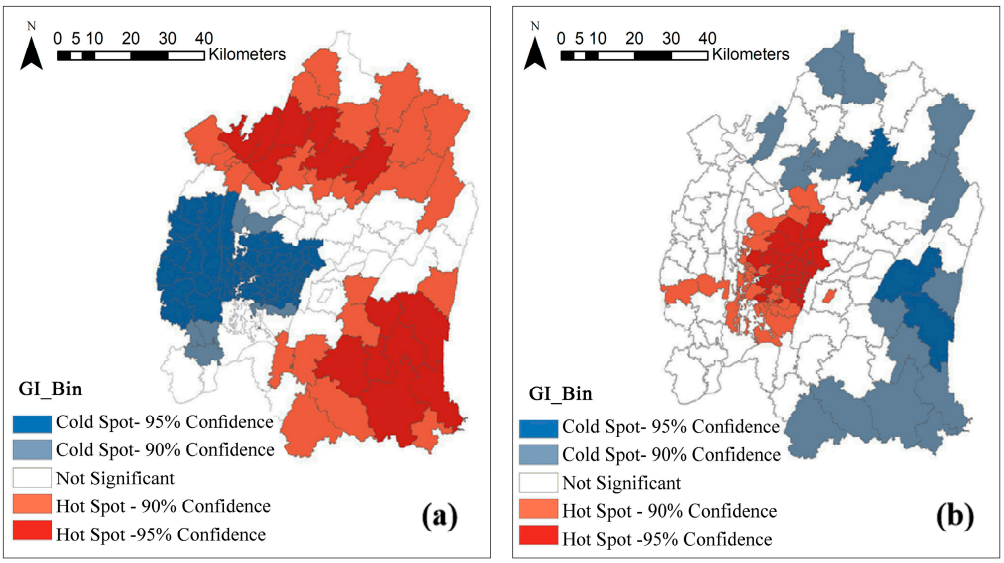

Figure 3. *Cont.*

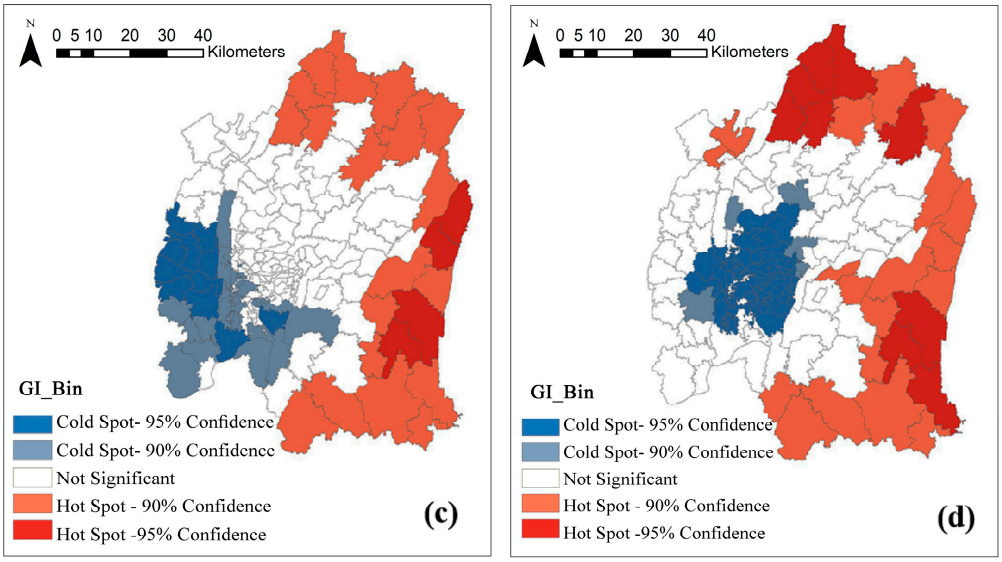

Figure 3. Spatial distribution of hot spots and cold spots. (**a**) ES benefit of Mitigated UHI effect. (**b**) ES benefit of Recreation function. (**c**) ES benefit of Landscape connectivity. (**d**) ES benefit of Managed stormwater.

3.2. Socioeconomic Inequality of ES Benefits

The regression results between the four GI benefits and the SES variables (Aging, Income, Education, and Housing) were estimated and are presented in Table 5. Spatial regression coefficients were employed to demonstrate the relative role of each variable. Moran's I values were significant at $p < 0.01$, indicating the existence of spatial dependence in all regressions. In all three models, excluding the recreation function, LM (lag) and LM (error) were significant at $p < 0.01$. Consequently, SEM or SLM regression was more appropriate than OLS for subsequent analyses in this study. Moreover, the spatial regression results confirmed that SEM or SLM outperformed OLS for regressions, as R^2 and Log likelihood values increased and AIC values decreased, thereby corroborating the model's suitability. We selected the best-fit regression models (with the lowest AIC values) for each ecosystem service benefit and presented them for comparison in Table 5. Additionally, Supplementary Materials (Tables S1–S4) displays the detailed estimation results of OLS, SLM, and SEM with regards to the four GI benefits.

SLM (1) in Table 5 presents the regression results of the mitigated UHI effect. Income is significant and positively correlated with the mitigated UHI effect, with the coefficient being significant at the 1% level. The results reveal that neighborhoods with a relatively high proportion of higher-income groups have a corresponding increase in the mitigated UHI effect capacity. The capacity for mitigating UHI also exhibits a significant negative correlation with areas containing a greater proportion of aging populations at the 1% significance level, suggesting that neighborhoods where a larger percentage of elderly individuals reside are exposed to elevated environmental temperatures, which could pose health risks for a greater number of senior citizens. Housing conditions also play a crucial role, as they are statistically positively correlated with mitigated UHI effects at the 5% significance level, indicating that areas with a high proportion of older housing (such as the old town) may suffer fewer effects of UHI effects.

Additionally, regression OLS (2) presents the results of the recreation function. The income coefficient is statistically positively correlated with the recreation function at the 1% significance level, suggesting that affluent communities perform better with regard to walking accessibility and that such residents require less time to access recreational GIs. Furthermore, aging is statistically negatively correlated with the recreation function, with the coefficient being significant at the 1% level. This indicates that areas with a greater proportion of aging populations may have a poorer supply capacity for recreational GI.

Moreover, the table reveals that the proportion of older housing is statistically negatively correlated with the recreation function, with the coefficient being significant at the 10% level, strongly suggesting that areas with a high proportion of older housing, i.e., (the old town) may have a shortage of recreational GI supply.

Table 5. Regression analysis of UGS supply capacity.

Variables	Mitigated UHI Effect	Recreation Function	Landscape Connectivity	Managed Stormwater
	SLM (1)	OLS (2)	SLM (3)	SLM (4)
Aging	−0.213 ***[1] (−2.851)	−0.199 *** (−2.722)	0.013 *** (3.274)	0.389 (1.261)
Income	0.363 *** (4.646)	0.349 *** (4.549)	−0.016 *** (−3.681)	−1.018 *** (-2.960)
Education	0.015 * (0.305)	0.012 * (0.247)	0.008 *** (3.064)	−0.729 *** (−3.253)
Housing	0.173 ** (−1.962)	−0.167 * (−1.870)	0.010 ** (2.120)	0.616 * (1.655)
Constant	5.242 *** (2.817)	4.812 *** (3.388)	0.248 *** (2.817)	34.879 *** (4.253)
Lagged Coeff (Rho)	0.978 *** (69.241)	—	0.427 *** (4.916)	0.548 *** (7.447)
Lagged Coeff (Lambda)	—	—	—	—
R square	0.571	0.4401	0.525	0.711
Adjusted square	—	0.421	—	—
Akaike information criterion (AIC)	−515.1512	752.7109	−147.1991	1213.475
Robust LMLAG	0.000 *** (34.193)	—	0.000 *** (33.176)	0.004 ** (8.071)
Robust LMERR		—	—	—

[1] *, ** and *** indicate significant differences at 10%, 5%, and 1% test levels, respectively.

SLM (3) in Table 5 displays the regression results of landscape connectivity. The income coefficient is statistically negatively correlated with landscape connectivity and significant at the 1% level, suggesting that landscape connectivity is inadequate in neighborhoods with a high concentration of higher-income groups. Landscape connectivity also exhibits a significant positive correlation with aging populations and the percentage of older housing, with coefficients reaching the 5% significance level. Remarkably, the education coefficient is statistically positively correlated with landscape connectivity and significant at the 1% level, indicating that areas with high landscape connectivity are inhabited by more highly educated groups. Furthermore, the significance of the lag coefficient (Rho) demonstrates that landscape connectivity distribution exhibits positive spatial dependence.

SLM (4) in Table 5 presents the regression results of managed stormwater. The income coefficient is statistically negatively correlated with managed stormwater and significant at the 1% level, suggesting that managed stormwater capacity is inadequate in neighborhoods with a high concentration of higher-income groups. Managed stormwater also exhibits a significant positive correlation with aging populations and with regard to the percentage of older housing; coefficients reached the 5% significance level. Notably, unlike the other three benefits, the education coefficient is statistically negatively correlated with stormwater management and is significant at the 1% level. In addition, the significance of the lag coefficient (Rho) indicates that managed stormwater distribution also exhibits positive spatial dependence.

Beyond employing OLS, SLM, and SEM from a global perspective, we also considered local regression. Consequently, the GWR model was used to provide local coefficients and test values for the relationship between SES and the four GI benefits. Table 6 displays the

parameters in the GWR models, with the model goodness-of-fit of GI benefits under four criteria reaching 0.860, 0.508, 0.601, and 0.673, respectively, higher than those of the OLS models. The results indicate that the GWR model better explains local variations in impact and reduces the spatial autocorrelation of model residuals.

Table 6. Statistical test comparison of OLS and GWR.

	Mitigated UHI Effect		Recreation Function		Landscape Connectivity		Managed Stormwater	
Variable	**OLS**	**GWR**	**OLS**	**GWR**	**OLS**	**GWR**	**OLS**	**GWR**
R^2	0.478	0.903	0.440	0.553	0.440	0.628	0.5951	0.727
Adj. R^2	0.459	0.860	0.421	0.508	0.425	0.601	0.5843	0.673
AICc	−139.856	−360.718	721.934	713.762	−131.356	−163.680	217.120	209.165

Figure 4 reveals the high spatial heterogeneity of the GWR coefficients of SES to GI. As a supplement to global regression results, we found that, in the urban center, the income coefficient is positively correlated with UGS capacity for all four benefits (Figure 4b,f,j,n). The results imply that high-income groups enjoy higher recreation functions and ES benefits of GI in the urban center, exposing an implicit and region-specific inequality with regard to human well-being. Despite the limited co-benefit areas that exist in urban centers, it is more evident that scarce resources are unevenly distributed across affluent neighborhoods. Moreover, there is a robust positive correlation between education and ES benefits in the suburbs (Figure 4c,g,k,o), suggesting that a highly educated area in a suburban area is positively associated with a wide range of high ecosystem services, especially in the northeast and southwest. A notable finding is the negative association between a significant proportion of older housing and recreation (Figure 4h), particularly prominent in the northern and western parts of the city. The coefficients in these areas exhibit substantial variation and display considerable heterogeneity.

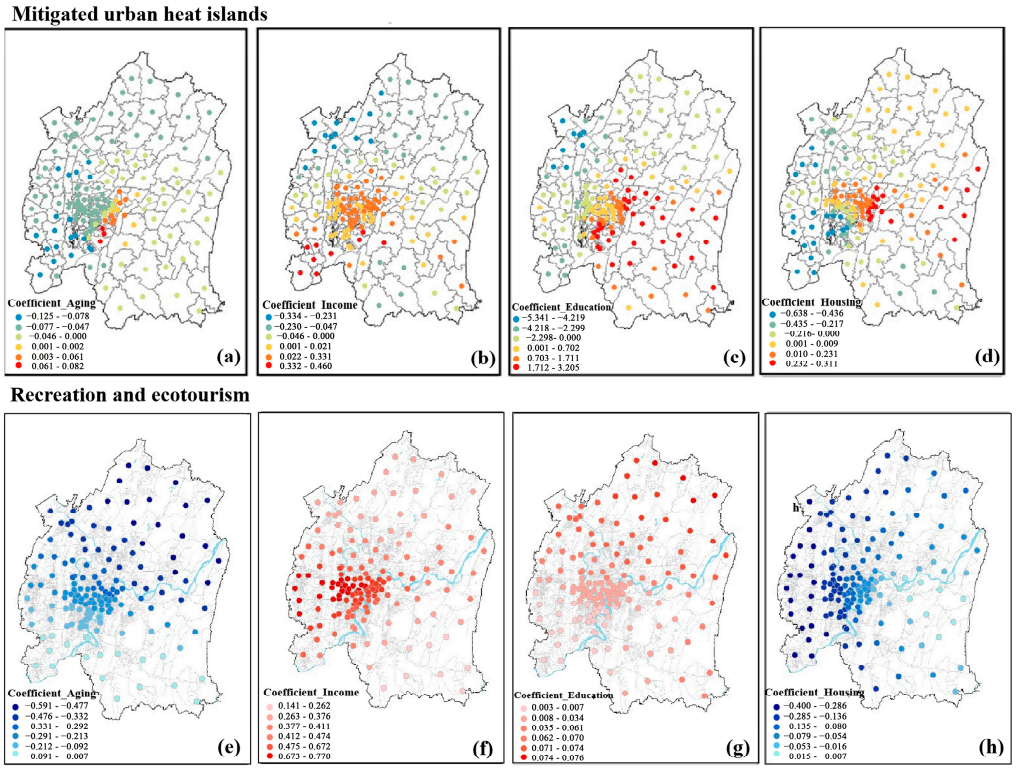

Figure 4. *Cont.*

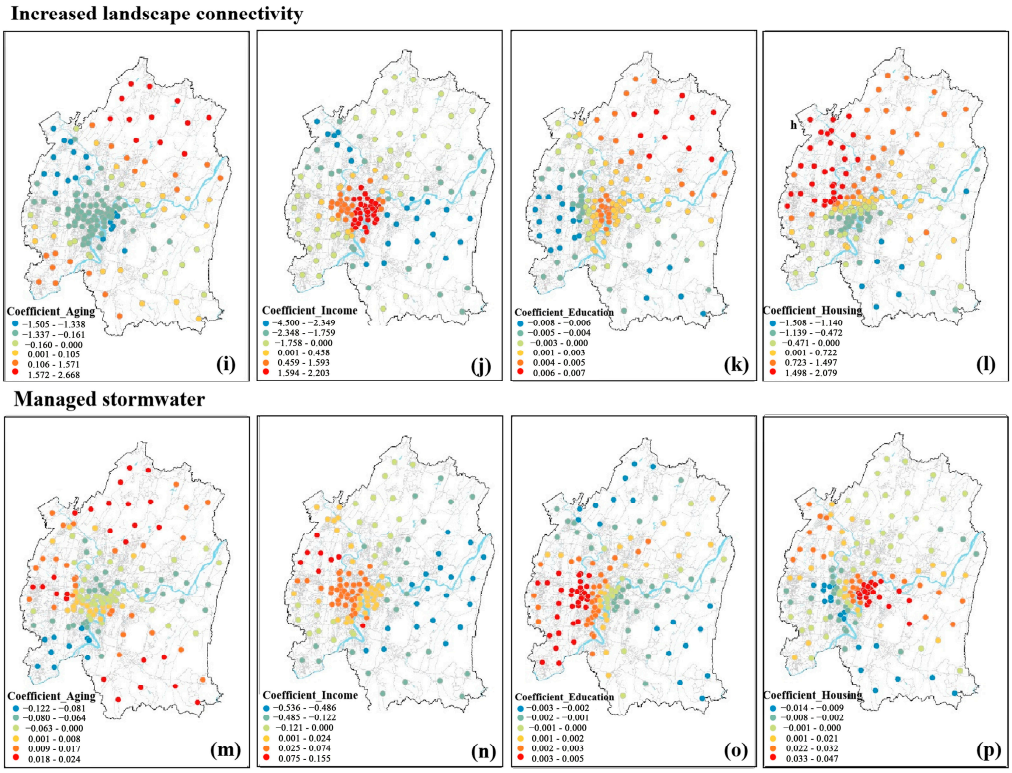

Figure 4. The GWR regression coefficients of UGS supply capacity at 155 blocks. 'Redder' areas have more positive coefficients, while 'bluer' areas have more negative coefficients. (**a**–**d**) The regression coefficients of mitigated UHI effect for 155 blocks. (**e**–**h**) The regression coefficients of recreation function for 155 blocks. (**i**–**l**) The regression coefficients of landscape connectivity for 155 blocks. (**m**–**p**) The regression coefficients of managed stormwater for 155 blocks.

4. Discussion

Serving as a vital nexus between the natural environment and human societies, GI profoundly influences the quality of life for urban inhabitants. This study meticulously delineates multifaceted GI benefits at the census tract level within a city, providing substantial evidence of GI supply inequality from various perspectives. Our regression analysis not only aligns with our initial hypothesis but also reveals disparities in GI benefits concerning individual income, education, age, and housing conditions, with income emerging as the most significant determinant. Notably, certain previously under-examined cultural ecosystem services significantly contribute to the existing inequalities in GI supply. The developed city center, for instance, boasts superior recreational and leisure functions compared to less developed suburban neighborhoods. Local regression further emphasizes that high socio-economic status (SES) groups tend to occupy areas with relatively elevated ecosystem service benefits, despite urban centers exhibiting lower ES benefits. This existing pattern may potentially exacerbate gentrification and increase green inequalities between low- and high-income cohorts.

In our analysis of the relationship between individual ecosystem services and socio-economic status (SES) groups, we uncovered insights overlooked in previous research. Regions characterized by a higher proportion of older housing experience a reduced impact from the urban heat island effect. Older neighborhoods, with their more established trees and abundant green spaces, play a vital role in mitigating this effect [55]. The presence of trees contributes to shade and cooling through evapotranspiration, releasing water vapor into the air, effectively countering the warming effects associated with impervious surfaces in urban areas [56,57]. Additionally, our findings reveal that low-income areas are associated with more effective stormwater management benefits. These areas typically feature distinct land use patterns, characterized by a prevalence of vacant or undeveloped

land [58], facilitating superior natural absorption of stormwater compared to densely built and paved high-income areas [59]. This underscores the significance of considering both socio-economic and environmental factors in understanding and optimizing ecosystem service benefits.

The prevailing viewpoint suggests a correlation between income levels and environmental inequality, particularly in terms of access to green spaces. Higher-income areas are generally characterized by more plentiful, accessible, and well-maintained public and private GI compared to their lower-income counterparts [27,30,33]. This trend is notably pronounced in large cities, particularly those in middle-to-low-income countries, where populations exceeding 1 million are disproportionately affected [60]. Our investigation in Chongqing reveals a similar trend, indicating that individuals with lower incomes and educational levels face limited access to GI. Interestingly, areas with older housing, like old city districts, show a positive correlation with three ecosystem service (ES) benefits of GI. This finding contrasts with a study in Guangzhou [31], suggesting nuanced relationships between green space accessibility, housing characteristics, and environmental justice in Chongqing's urban landscape. Understanding these nuances is crucial for addressing environmental inequalities and implementing targeted interventions to improve green space access for all residents.

Consistent with prior research [61–63], we emphasize a strong correlation between the recreational function of GI and higher education and income areas. This association is particularly pronounced among higher-income areas, underscoring their increased engagement in recreational GIs for direct leisure benefits. Additionally, areas with higher education levels exhibit a positive correlation with specific GI benefits, such as mitigating the urban heat island effect (UHI) and enhancing landscape connectivity. However, both higher-income and higher-education areas exclude stormwater management benefits, possibly due to the infrequent occurrence of such events in regular GI functionality [64]. This suggests that evaluating human well-being in terms of stormwater management capacity may not be immediately evident or explicitly stated.

Numerous authors have highlighted how ecosystem changes result in trade-offs among various types of ecosystem services [21,65,66]. Abundant research has mapped the spatial distribution of ecosystems and scrutinized their interactions through interdisciplinary methodologies, including biophysical simulation models like InVEST and scenario analyses that combine remote sensing, GIS, and statistical approaches. Nevertheless, conflicting results and opinions have often arisen from different studies. For example, our study reveals synergistic relationships between stormwater management and landscape connectivity in the Chongqing metropolitan area, whereas results from Detroit [67] present these factors as trade-offs. Such discrepancies underscore the complex nature of trade-offs between multiple ecological benefits in different cities and how these may be correlated with each city's individual structures and development processes.

Our findings also shed light on the overlooked challenges faced by elderly individuals in accessing recreational green spaces in Chongqing due to its unique topography. Drawing insights from Hong Kong's similar topography and urban structure [68], we propose strategically implementing pocket parks in Chongqing's downtown areas. Inspired by the success of this approach in Hong Kong, strategically placed pocket parks can serve as crucial green open spaces within urban centers. These parks have the potential to address accessibility issues faced by marginalized groups, particularly the elderly, even in areas with challenging walking conditions. By strategically siting these green spaces, we can create more opportunities for diverse communities to enjoy accessible public green areas, fostering overall well-being and inclusivity in the urban environment.

As we all know, GI plays a pivotal role in achieving sustainable urban development. Our findings highlight distinct spatial distribution variations in GI benefits between urban and suburban areas. In the urban center, GI spaces are smaller and more dispersed, potentially limiting local ecological benefits. Nevertheless, intricate parks and interspersed green spaces cater to residents' recreational and leisure needs [69]. Consequently, we

propose that policymakers invest in diverse GIs tailored to the specific requirements of each region. For suburban areas, the construction of village pocket parks and the enhancement of urban forest development can provide additional cultural service functions for local communities. In urban centers, a stronger emphasis on the ecological functions of GI is crucial to address the unique challenges and opportunities posed by the urban environment. Initiatives such as constructing and maintaining rooftop gardens, green corridors, and other measures can significantly contribute to the overall well-being of urban residents. By adopting strategies that consider both the cultural and ecological dimensions of GI, policymakers can ensure better alignment between different regions and their environmental service capabilities, fostering a more harmonious and sustainable urban development.

5. Limitations

There is undoubtedly room for improvement in our assessment. Specifically, a more in-depth investigation into informal spaces within these areas is warranted, necessitating a clearer differentiation. Additionally, the distinctive attributes of green spaces, encompassing size, amenities, design, and landscape coverage, demand deeper exploration. Beyond the scope of walking distance, these factors significantly influence the appeal of GI to residents. To establish a more comprehensive understanding and offer practical insights, future research endeavors should focus on refining and expanding upon this study. Furthermore, our method for assessing certain ecosystem services may be relatively simplistic, lacking the complexity and comprehensiveness needed. Subsequent research can make substantial improvements by comparing the results of different assessment methods. This approach not only contributes to a more nuanced understanding of the complexities involved but also informs spatial planning decisions. Delving into the intricacies of green space attributes and their impact on residents allows researchers to guide urban planners in cultivating a metropolitan area that is both more equitable and sustainable.

6. Conclusions

In conclusion, our study provides valuable insights into the intricate relationship between SES groups and the benefits of GI in the Chongqing metropolitan area. We have identified significant disparities in GI benefits associated with income, education, age, and housing conditions, with income and education emerging as the most crucial determinants, despite their many differences. Moreover, the study sheds light on cultural ecosystem services that have been overlooked, contributing to existing inequalities. Our findings highlight challenges faced by marginalized groups, particularly the elderly, in accessing recreational GIs. To address these disparities and promote inclusivity in urban environments, we propose strategic interventions. Notably, the spatial distribution differences in GI benefits between urban and suburban areas underscore the importance of tailored development strategies. Recommendations advocate for investments in diverse GIs that cater to the specific needs of different regions, taking into account both ecological and cultural dimensions to enhance overall well-being and inclusivity.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/f15010073/s1, Table S1: Regression models of mitigated UHI effect for 155 blocks; Table S2: Regression models of recreation function for 155 blocks; Table S3: Regression models of landscape connectivity for 155 blocks; Table S4: Regression models of managed stormwater for 155 block.

Author Contributions: Conceptualization, R.H., G.X. and Y.J.; methodology, Y.J. and G.X.; software, G.X.; validation, R.H., J.H. and G.W.; data curation, G.X.; writing—original draft preparation, G.X.; writing—review and editing, J.H. and G.W.; visualization, G.X. and Y.J.; supervision, R.H.; project administration, R.H. and J.H.; funding acquisition, R.H. All authors have read and agreed to the published version of the manuscript.

Funding: This research was supported by the China Scholarship Council (202207560001) and the Hainan Provincial Natural Science Foundation of China (423MS020).

Data Availability Statement: The source of all the data used in this study is provided in the manuscript.

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

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