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Assessing Spatiotemporal Changes of SDG Indicators at the Neighborhood Level in Guilin, China: A Geospatial Big Data Approach

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Abstract: Due to the challenges in data acquisition, especially for developing countries and at local levels, spatiotemporal evaluation for SDG11 indicators was still lacking. The availability of big data and earth observation technology can play an important role to facilitate the monitoring of urban sustainable development. Taking Guilin, a sustainable development agenda innovation demonstration area in China as a case study, we developed an assessment framework for SDG indicators 11.2.1, 11.3.1, and 11.7.1 at the neighborhood level using high-resolution (HR) satellite images, gridded population data, and other geospatial big data (e.g., road network and point of interest data). The findings showed that the proportion of the population with convenient access to public transport in the functional urban area gradually improved from 42% in 2013 to 52% in 2020. The increase in built-up land was much faster than the increase in population. The areal proportion of public open space decreased from 56% in 2013 to 24% in 2020, and the proportion of the population within the 400 m service areas of open public space decreased from 73% to 59%. The township-level results indicated that low-density land sprawling should be strictly managed, and open space and transportation facilities should be improved in the three fast-growing towns, Lingui, Lingchuan, and Dingjiang. The evaluation results of this study confirmed the applicability of SDG11 indicators to neighborhood-level assessment and local urban governance and planning practices. The evaluation framework of the SDG11 indicators based on HR satellite images and geospatial big data showed great promise to apply to other cities for targeted planning and assessment.

Keywords: SDG11; geospatial big data; sustainable development goals; earth observation; Guilin

1. Introduction

1.1. The SDG11 Indicators

The 2030 Agenda for Sustainable Development and 17 Sustainable Development Goals (SDGs) proposed by the United Nations in 2015 enable the international community to make a scientific understanding and accurate assessment on the sustainable development of global cities, thereby guiding their practical actions [1]. The SDGs seek to provide a comprehensive set of goals and indicators to measure progress towards sustainable development from 2015 to 2030 [2]. However, the holistic and complex nature of the SDGs has severely hampered progress towards these goals. With the date of achieving the goals of the 2030 Agenda approaching, a robust and unified assessment framework and reliable data are crucial for their accurate measurement and the fulfillment of the pledge—to ensure that “no one will be left behind” [1].

The sustainability in cities and urban settlements influences all aspects of sustainable development. The targets and indicators of the 11th Sustainable Development Goal (SDG11) provide a standardized indicator-based assessment framework to track the progress of sustainable urban development and inform policy implementation and practice. According to the Inter-agency and Expert Group on SDG Indicators (IAEG-SDGs), SDG11.2.1, 11.3.1 and 11.7.1 are Tier II indicators. These indicators are conceptually clear and have an internationally recognized methodology and standard, but data are not regularly reported. SDG11.2.1 refers to the proportion of the population that has convenient access to public transport disaggregated by age group, sex, and persons with disabilities. This indicator aims to monitor the use of and access to the public transportation system, alleviate the reliance on private means of transportation, and improve the traffic conditions in areas with a high proportion of transport disadvantaged people. SDG11.3.1 measures how efficiently cities utilize land and is measured as a ratio of the rate at which cities spatially consume land against the rate at which their populations grow. SDG11.7.1 refers to the average share of the built-up area of cities that is open space for public use for all, by sex, age, and persons with disabilities. It enables cities to collect accurate, timely, disaggregated data and information on open space by adopting a systemic approach.

1.2. The Role of Geospatial Big Data for SDG11 Indicators Monitoring

Geospatial big data played an important role in the monitoring of SDG11 indicators. The use of big data such as mobile phone data, transaction data, health records, and social media can complement traditional official statistical data and help fill data gaps in monitoring SDG indicators [3,4]. Earth observation data (EO) obtained from satellites and geospatial data collected by on-site sensors or citizens are recognized as an effective, timely, and continuous information source to support evidence-based decision-making for sustainable urban development [5,6]. Remotely-sensed EO data have the advantage of collecting extensive information on the Earth’s surface at large spatial scales with repeat acquisition cycles, which can supplement or enhance the traditional data sources in urban areas [7–9]. The availability of open remote sensing data and high-performance cloud computing platforms makes it possible to map built-up urban areas or impervious surfaces over large areas with medium and high spatial resolution in recent decades [10,11]. Based on open satellite data, several global built-up area layers have been developed, including the Global Human Settlements Layer (GHSL) from the Joint Research Centre of the European Commission [12], the Global Urban Footprint (GUF) [13], and the World Settlements Footprint (WSF) jointly developed by ESA, the German Aerospace Center (DLR), and the Google Earth Engine team [14]. These products provide information on the global human settlement with spatial resolutions from 10 m to 30 m via processing millions of images from Landsat and Sentinel satellites [15,16]. The accessibility of open geospatial data such as WorldPop population grids and OpenStreetMap road networks facilitates accessibility measurements in cities around the world.

1.3. Research Questions, Motivation and Objectives

The process of sustainable development goals was mostly reported at the national level. Assessing the sustainable development goals locally can track the progress in local sustainable development and provide relevant strategies to guide sustainability practices [17]. The availability of big data (e.g., high-frequency satellite Earth observation data) can power the sustainability practitioners to better monitor and evaluate the progress of sustainable development. As an internationally agreed and reported assessment framework, knowledge and practice gaps still exist on how to link and integrate the indicator measurements into urban governance and planning in the local context [18]. In addition, the complexity of SDG indicator monitoring lies in the trade-offs and synergies between indicators [19–21]. To address the above research gaps and challenges, the following key research questions were raised: (1) whether an assessment framework to evaluate multiple SDG indicators conjunctively can be developed using geospatial big data, and (2) whether the evaluation results of SDG indicators at the neighborhood level can be linked with local urban governance and planning practices.

With a unique karst landform, Guilin city in China was added to the United Nations Educational, Scientific and Cultural Organization (UNESCO)'s world heritage list in 2014. In February 2018, with the theme of "sustainable utilization of landscape resources," Guilin was selected as the innovation demonstration zone of the National Sustainable Development Agenda in China. Taking Guilin city as a case study, this study aims to (1) develop a framework to monitor three SDG11 indicators (indicators 11.2.1, 11.3.1, and 11.7.1) at the neighborhood level using high-resolution satellite data, gridded population data, and other geospatial big data (e.g., road network and point of interest data), (2) to provide a holistic perspective of the progress of sustainable urban development in the study area, and to (3) evaluate the feasibility of integrating SDG11 indicators into urban governance practices in the local context.

2. Literature Review

2.1. Geospatial Datasets for SDG11 Indicators Monitoring

With the advantages of varying spatial and temporal resolution, large spatial coverage, and long temporal coverage, Earth observation data provide an optimal data source for the monitoring of SDG indicators both directly and indirectly [5]. Numerous studies used satellite images from different sensors to assist in monitoring the progress of SDG11. In these studies, the freely accessible global Landsat archive containing millions images was the main source of remote sensing data. Landsat 2/5/7/8 datasets have been used to analyze land use and landscape changes from local to global scales [22–24]. For the evaluation of SDG11.3.1 indicators, the combination of Landsat and satellite images with higher spatial resolution such as Sentinel and SPOT provided more accurate classification results [25]. The SPOT 2 panchromatic imagery has a spatial resolution of 10 m and multispectral imagery has a spatial resolution of 20 m. The SPOT 5 satellite imagery has a spatial resolution of 2.5 m in the panchromatic band and 10 m in multispectral bands. The fusion of remote sensing images and products was also used to obtain urban land cover classification results with higher accuracy [22].

UN-Habitat proposed to use free EO satellite data from Landsat and Sentinel-2 satellites to delineate potential public urban open spaces. Urban green areas comprise of many small-size green spaces, such as gardens, community parks, roadside trees, etc. Although open and free earth observations (10–30 m) with low and medium resolution can provide valuable insights for policymakers and urban managers [26], their relatively coarse spatial resolution tends to cause underestimation of small-sized open spaces [27,28] and leads to low accuracy of open space detection in complex urban areas [29,30]. Streets less than 10 m wide can hardly be detected from Sentinel-2 satellite imagery at 10 m resolution [31]. High resolution remote sensing images (spatial resolution higher than 10 m) are more suitable data sources for open space extraction in urban areas [28]. Most studies use remote sensing images with very high spatial resolution for SDG11.7.1 monitoring, such as PlanetScope [27], RapidEye [28], QuickBird-2 [28,32], WorldView-2 [32] images, etc. Although satellite images from these satellites can capture the details of land surface, they are very costly and their application over large areas is infeasible, especially in areas with cloudy landscapes [33].

Monitoring the progress of achieving the sustainable development goals through the global indicator framework increased the demand for data that are high in quality, broad in coverage, frequently available, and spatially disaggregated from countries around the world [34]. In addition to remote sensing data, geospatial data collected voluntarily using a wide range of technologies and methods provided supplementary datasets to insufficient official data and improved the monitoring of sustainable development goals [3]. Fried et al. [35] leveraged open data, including OpenStreetMap road network and WorldPop population data to derive the values of SDG 11.2.1 indicator and accessibility metrics and identified transport inequalities of low-income communities.

2.2. Methods for SDG11 Indicators Monitoring

Since the adoption of SDGs in 2015, the SDG11.2.1, SDG11.3.1, and SDG11.7.1 indicators have been used to monitor and assess the progress of sustainable urban development in numerous studies (Table 1). The popularity of SDG11.2.1 is attributed to its simple estimation methods and interpretation of results. However, researchers argued that it was not comprehensive to use a single SDG11.2.1 indicator to evaluate the traffic accessibility of cities or countries. Other indicators should also be measured in decision-making for transportation facility improvement. Tiznado-Aitken et al. [36] evaluated the accessibility of Santiago's pedestrian environment based on Lorenz curves, Gini coefficient, and Foster-Greer-Thorbecke (FGT) poverty measures. Brussel et al. [37] found that the SDG indicator 11.2 could not represent the traffic reality well and proposed accessibility indicators that could provide a more diversified, complete, and realistic picture of the transportation system's performance. Fried et al. [35] supplemented the analysis results of SDG11.2.1 through a more detailed location-based accessibility analysis and revealed traffic inequality in low-income communities.

Early studies used remote sensing images, machine learning classification methods, and GIS technology to analyze urban growth and sprawl processes [38]. More advanced techniques, such as deep learning and scenario modeling, were applied for SDG11.3.1 monitoring and prediction [39–41]. Kussul et al. [39] proposed a method for land cover classification and land productivity assessment using medium and high spatial resolution satellite data and deep learning methods. Wang et al. [40] used the spatio-temporal interaction method and Pearson's method to monitor the spatio-temporal changes of SDG 11.3.1. Lu et al. [41] monitored and predicted changes in urban land use efficiency indicators based on remote sensing and scenario modeling in a coastal megacity from 2000 to 2030. Remote sensing and geospatial big data can help understand the spatiotemporal dynamics of urban green space under the urbanization [42], accessibility [43], and walkability [44]. However, the detailed mapping of urban open public space and the measurement of SDG11.7.1 indicators still needs localized data and strong urban data collection capacity [45].

Table 1. Literature review of three SDG11 indicators using geospatial data.

SDG Indicator	Data Source	Spatial Resolution	Study Area	References
SDG11.2.1	An underlying road network,	100 m	Nairobi, Kenya	Fried et al. [35]
	a general transit feed specification package,			
	WorldPop population,			
	an opportunity dataset.			
SDG11.2.1	Public transport stops,		Santiago, Chile	Tiznado-Aitken et al. [36]
	road network,			
	georeferenced information.			
SDG11.3.1	Built-up areas,	30 m, 250 m, 1 km	10,000 urban centers	Melchiorri et al. [23]
	resident population,	250 m, 1 km		
	settlement typologies.	1 km		

Table 1. *Cont.*

SDG Indicator	Data Source	Spatial Resolution	Study Area	References
SDG11.3.1	A GIS raster dataset of built-up areas,	1 km	Global	Estoque et al. [24]
	a statistical dataset of population.	250 m, 1 km		
SDG11.3.1	Landsat-5/8 images,	30 m	Beijing–Tianjin–Hebei region, China	Zhou et al. [22]
	built-up area products,	30 m		
	WorldPop population,	100 m		
	ancillary datasets.	30 m		
SDG11.3.1	LULC,	30 m	Mainland China	Wang et al. [46]
	census data,			
	DMSP/OLS,	1 km		
	administrative boundary map.			
SDG11.3.1	Landsat-5/8 images,	30 m	Tianjin, China	Lu et al. [41]
	topographic data,	30 m		
	road network,			
	demographic data.	100 m		
SDG11.3.1	Built-up areas,	1 km	Global	Schiavina et al. [47]
	resident population,			
	settlement typologies,			
	functional urban area.			
SDG11.3.1	Landsat 5 TM images,	30 m	South Africa	Mudau et al. [25]
	SPOT 2/5 sensors images,	Panchromatic 10/2.5 m; multispectral 20/10 m		
	census data.			
SDG11.3.1	Landsat 2/5/7/8 images,	80/30 m	Southern Brazil	Moro et al. [21]
	Sentinel-3B OLCI-WFR satellite images.	300 m		
SDG11.3.1	Built-up area,	100 m	the Yangtze River Delta, the Middle Reaches of the Yangtze River, and Chengdu–Chongqing, China	Wang et al. [40]
	population data,	100 m		
	boundaries maps.			
SDG11.3.1	Resident population,	1 km	Poland and Lithuania	Calka et al. [48]
	CORINE land cover 2000/2018	12.5 m		
SDG11.7.1	PlanetScope images,	3.7–4.1 m	The Athens Metropolitan Area	Verde et al. [27]
	Sentinel-1 images,			
	ground range-detected products.			
SDG11.7.1	Sentinel-2A images,	10 m	Hangzhou, China	Deng et al. [49]
	SPOT-2/3/5 images,	XS 20 m/PAN 10 m/XS 10&20 m		
	reference and ancillary data.			

2.3. Research Challenges

A review of recent research shows that Earth observation data can effectively support the government in addressing sustainable development goals and monitoring the implementation of SDG indicators. The rapid development of Earth observation technologies and big data platforms will continue to play a role in expanding indicators and targets that can be effectively measured and monitored globally. However, the success of SDG11 implementation depends largely on the availability of high-quality assessment data [2,3]. Although satellite data has been widely used in SDG indicator evaluation, the spatial resolution of remote sensing images used varies from 2.5 m to 1 km (Table 1). High-resolution satellite data has become increasingly available. Its potential for urban built-up areas and open space mapping and monitoring can be further evaluated. Data fusion methods and more advanced data processing techniques, such as deep learning, should be exploited to improve the accuracy and reliability of geospatial products and information derived from remote sensing images. Data sharing and openness should also be promoted to better support the monitoring of SDG11 indicators.

Analytical frameworks, tools, and analyses that enable interlinkages between targets and indicators can provide more insights on how various interacting forces led to specific outcomes, thereby helping establish connections between science and policy [50]. Researchers argued that it is not comprehensive to use a single indicator to evaluate the traffic accessibility of cities. However, the majority of previous studies using geospatial data focused on the measurement of one specific indicators. Multiple indicators can be assessed conjunctively to draw policy and practice implications for sustainable urban development. Comprehensive assessment framework involving multiple indicators should be developed and implemented to provide sound policy guide for city governors in future studies.

Despite the fact that the methodologies and approaches of SDG indicator monitoring with Earth observation data have been developed, the assessment was mainly performed at a city, regional and national level. Few studies conducted neighborhood level analysis and incorporated the assessment results with local urban planning and governance practices. Localized urban practices using open geospatial data and SDG indicators is beneficial for guiding cities and regions, especially in developing countries, to assess sustainable development progress and support policy-making processes.

3. Study Area

Guilin City (Figure 1) is located in the northeastern part of Guangxi Zhuang Autonomous Region, China. It is located between 109°36′ to 111°29′E and from 24°15′ to 26°23′N. The territory is 236 km long from north to south and 189 km wide from east to west. Guilin has a subtropical monsoon climate with an average annual precipitation of 1887.6 mm and an annual mean temperature of 18.9 °C. The core urban area of Guilin city includes six districts, Xiufeng, Qixing, Xiangshan, Diecai, Yanshan, and Lingui, covering an area of 2767 km^2. Guilin has a typical karst landform and is a world-famous scenic city. Considering its extraordinary natural beauty and aesthetic values, the World Heritage Committee added the Guilin Karst to UNESCO's world heritage list in 2014. Guilin is also the political, economic, cultural, and technological center in the northeastern part of Guangxi Province.

With the rapid economic development, anthropogenic activities have become increasingly intensive in Guilin in the last decades. The over-development and exploitation of natural landscapes have led to considerable pressure on the sensitive and fragile ecological environment [51]. The contradiction between the growth of natural resource utilization demand and the actual environmental carrying capacity has become increasingly prominent. The evaluation and monitoring of SDG indicators can provide valuable information for the construction of the innovation demonstration zone of the National Sustainable Development Agenda and for protecting the ecological environment in local areas.

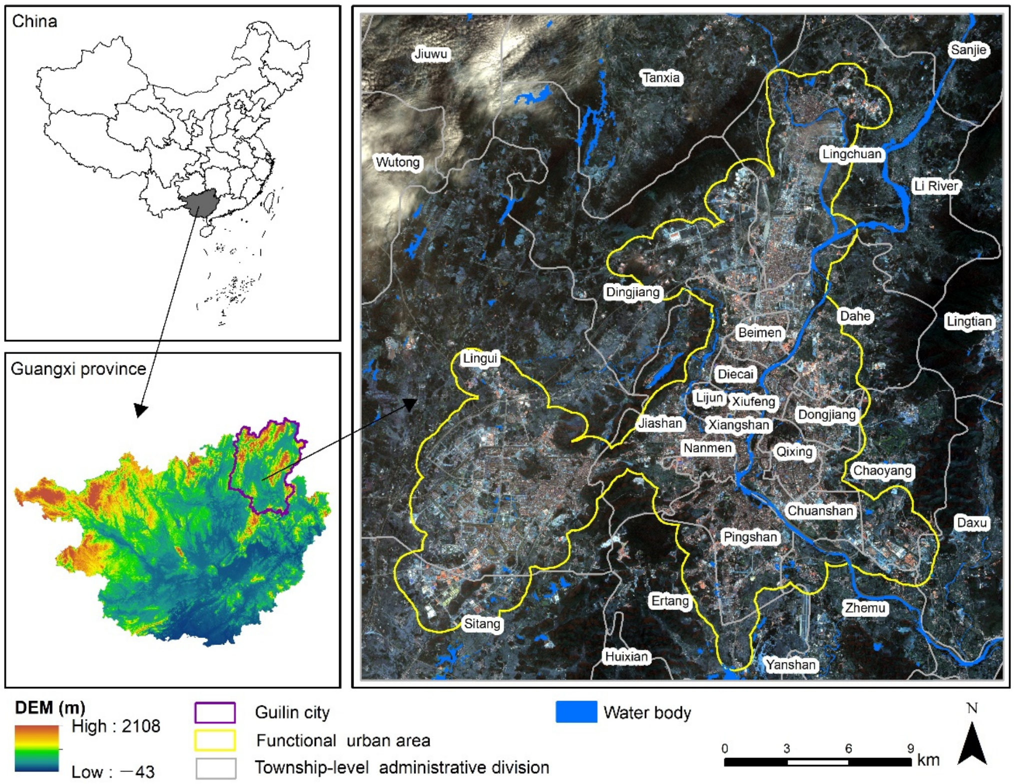

Figure 1. Geographic location of the study area.

4. Materials and Methods

4.1. Datasets

In this study, three SDG11 indicators were measured within the urban functional boundary of Guilin from 2013–2020. High-resolution remote sensing images of Chinese Gaofen-1/6 satellites and geospatial big data were mainly used (Table 2). Since the Gaofen-1 satellite was launched in 2013 and the high-resolution satellite images acquired by Gaofen-1 have been available since then, this study selected 2013–2020 as our study period. The Gaofen-1/6 satellites carry two 2 m panchromatic and 8 m multi-spectral high-resolution cameras with four bands (PMS). After preprocessing, image fusion was employed to fuse the multispectral images and panchromatic images, and 2 m resolution multi-band data was finally obtained for land use classification in the study area. Point of interest (POI) data including bus stations and train stations in 2015 and 2020 were collected from the AutoNavi electronic navigation map (https://ditu.amap.com, accessed on 10 April 2021). Due to the low quality of historical data, the road networks were only obtained for the year 2020. LandScan global population data, produced by the U.S. Department of Energy's Oak Ridge National Laboratory (ORNL) (https://landscan.ornl.gov/, accessed on 1 June 2021), was used to measure the number of populations. This dataset used spatial data, high-resolution imagery analysis techniques, and a dasymetric modeling approach to disaggregate census population numbers within administrative boundaries. LandScan is the finest resolution global population distribution data available representing an ambient population. The LandScan data covering the study area were retrieved in 2013, 2015, and 2020 for the SDG indicator measurement.

Table 2. Geospatial datasets used in this study.

Data Set	Acquisition Time	Spatial Resolution	Source
Road network	2020		Autonavi electronic navigation map
Point of interest	2015 2020		Autonavi electronic navigation map
Gaofen-1/6 satellite images	2013 2015 2020	2/8 m	Chinese Academy of Sciences
Population grid data	2013 2015 2020	1 km	LandScan
Urban park	2015 2020		Autonavi electronic navigation map

4.2. Methods

The workflow for SDG indicator assessment is shown in Figure 2. The road network data, point of interest data, and LandScan population data were used to perform a dynamic assessment of public transport accessibility and SDG11.2.1 indicators. Secondly, high-resolution satellite images were used for land cover classification to analyze changes in SDG11.3.1 indicators. Finally, high-resolution satellite images were used to extract green space and measure changes in SDG11.7.1 indicators. The LandScan population grid data was used to calculate the number of populations with convenient access to urban open spaces.

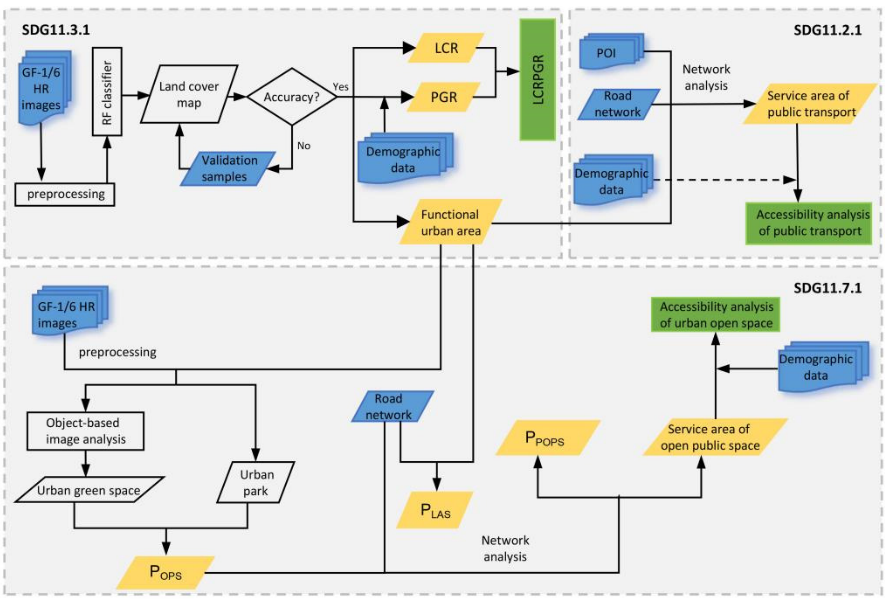

Figure 2. Workflow for SDG indicators assessment in this study.

The notations used for the calculation of three SDG11 indicators, SDG11.2.1, SDG11.3.1, and SDG11.7.1, are summarized in Table 3.

Table 3. Notations used in this study.

Terms	Definition	Unit
P_i	The total population served by public transport service area i.	-
P_{ij}	The number of the population of population zone j (j = 1 . . . n) that fully or partially intersect with a public transport service area i.	-
LCR	Land consumption rate.	-
Urb_t	The total area covered by the urban built-up area in the initial year t.	km^2
Urb_{t+n}	The total area covered by the urban built-up area in the final year t+n.	km^2
LCRPGR	The ratio of land consumption rate to population growth rate.	-
PGR	Population growth rate.	-
$LCPC_{t1}$	The land consumption per capita at time t1.	km^2
Urb_{t1}	The total built up area within the urban boundaries at time t1.	km^2
Pop_{t1}	The total population within the urban boundaries at time t1.	-
$Change\ in\ LCPC_{(t1-t2)}$	The percentage change in land consumption per capita between t1 and t2.	%
Change in Urban Infill	The percentage change rate of urban density.	%
$S_{streets}$	Total area occupied by streets in all locales.	km^2
S_{city}	Total area of all locales.	km^2
S_{OPS}	The total area occupied by open public spaces.	km^2
P_{LAS}	The share of city land occupied by streets.	%
P_{OPS}	The share of urban areas that is allocated to open public spaces.	%
P_{POPS}	The average share of built-up area of cities that is open public space and streets.	%
Subscripts		
i	The service area	
j	The population zone	
t	The initial year	
n	The number of years between the initial year and the final year	
t1	The initial year	
t2	The final year	
Streets	Urban streets	
City	Urban area	
OPS	Open public spaces	
POPS	Built-up area of cities that is open public space and streets	
Symbols		
Σ	The summation symbol	
%	Percentage means the percentage of one number that is the other number, expressed by "%"	
ln	The natural logarithm symbol is the logarithm with constant e as the base, which is recorded as lnN (N > 0)	

4.2.1. SDG11.2.1

SDG indicator 11.2.1 measures proportion of population that has convenient access to public transport. For SDG 11.2.1, public transport is considered "convenient" for people who live within 500 m walking distance from the nearest low-capacity station and 1 km from the nearest high-capacity station. According to the definition of low-capacity public transportation and high-capacity public transportation, the 500 m service area of the bus stations and the 1 km service area of the railway stations were created using network analysis [34]. A network service area was created along the road network at each public transport stop or around each public transport route per applicable walking distance thresholds. The use of network distance can reflect the configuration of the road network, and identify the existence of obstacles that hinder direct access to public transport facilities. All individual service areas are then merged to create continuous service area polygons. The service area and the population data are overlaid to calculate the population with access to each public transport stop. The number of populations served by the public transport service was calculated by:

$$P_i = \sum_{j=1}^{n} P_{ij}, \tag{1}$$

where P_{ij} is the population served by the public transport service in buffer i of population zone j (j = 1 . . . n) that completely or partially intersect with the service area i, and P_i refers to the total population served by public transport stations in service area i.

The SDG11.2.1 indicator was calculated as percentage of population with convenience assess to public transport. The higher the percentage of the population with convenient access to public transportation services, the better the accessibility, and vice versa. This indicator reflects the service status of the regional road network and transportation stations. The SDG 11.2.1 indicators in 2013, 2015, and 2020 were calculated to analyze the changes in public transportation accessibility in the study area.

4.2.2. SDG11.3.1

SDG indicator 11.3.1 measures the ratio of land consumption rate to population growth rate [40,41,48,52]. Using the remote sensing images of Gaofen-1 in 2013 and 2016 and Gaofen-6 in 2020, a random forest classifier was used to classify the land cover of the study area into five categories: built-up land, forest, cultivated land, water body, and bare land. Based on the classification results, changes in the urban functional boundaries and land use were analyzed for each period. The land consumption rate (LCR) was calculated using the following equation:

$$LCR = \frac{ln(\frac{Urb_{t+n}}{Urb_t})}{n}, \tag{2}$$

where Urb_t is the total area covered by the urban built-up area in the initial year (km^2); Urb_{t+n} is the total area covered by the urban built-up area in the final year (km^2); n is the number of years between the two periods.

The global population grid data was used to calculate the population in the study area in the corresponding year, and the population growth rate (PGR) was calculated using similar method. Combining the changes in built-up land and population, the ratio of land consumption rate to population growth rate (LCRPGR) in the functional urban area was calculated using equation:

$$LCRPGR = \frac{LCR}{PGR}, \tag{3}$$

To capture the urbanization process more comprehensively, two secondary indicators were also calculated. The per capita land consumption (LCPC) at t_1 was derived according to Equation (4), and the percentage change rate of per capita land consumption (Change in LCPC) and the percentage change rate of urban density (Change in Urban Infill) between t_1 and t_2 were calculated according to Equations (5) and (6).

$$LCPC_{t1} = \frac{Urb_{t1}}{Pop_{t1}}, \tag{4}$$

$$ChangeinLCPC_{(t1-t2)} = \frac{LCPC_{t2} - LCPC_{t1}}{LCPC_{t1}}, \tag{5}$$

$$ChangeinUrbanInfill = \frac{Urb_{t2} - Urb_{t1}}{Urb_{t1}} \times 100, \quad (6)$$

where Urb_{t1} refers to the total built-up area within the urban boundary at time t_1 (km^2); Pop_{t1} refers to the total population within the urban boundaries at time t_1; Urb_{t2} refers to the total built-up area at time t_2 within the same urban boundary (km^2).

4.2.3. SDG11.7.1

SDG Indicator 11.7.1 measures the average share of the built-up area of cities that is open space for public use. The road network data and the boundaries of the urban functional area were used to calculate the land allocated to streets (Equation (7)). Using an object-based image analysis method, green space was extracted using the high-resolution satellite images. The urban parks were extracted using the Autonavi electronic navigation map (AMAP). Then, the proportion of open public spaces was calculated using Equation (7). As for the core indicator, the proportion of public open space in the city was expressed as the proportion of the total open space area of streets and open public spaces in the urban area [49].

$$\begin{cases} P_{LAS} = \frac{S_{streets}}{S_{city}} \times 100\% \\ P_{OPS} = \frac{S_{OPS}}{S_{city}} \times 100\% \\ P_{POPS} = \frac{S_{streets}+S_{OPS}}{S_{city}} \times 100\% \end{cases}, \quad (7)$$

where P_{LAS} represents the share of city land occupied by streets (%), $S_{streets}$ represents the total area occupied by streets in all locales (km^2), and S_{city} represents the sum area of all locales (km^2); P_{OPS} represents the share of urban areas that is allocated to open public spaces (%), S_{OPS} represents the total area occupied by open public spaces (km^2); P_{POPS} represents the average share of built-up area of cities that is open space for public use for all (%).

A network analysis was performed to generate an urban open space service area with a road network distance of 400 m. First, a network dataset was create using road network data, and then a road network-based service area was created around each public open space using a 400 m threshold. All people living in the service area are deemed to have convenient use of open public space. Finally, combined with the grid population data, the population in the service area of the open space was calculated in each period in the study area.

5. Results

5.1. Spatiotemporal Variation of Population with Access to Public Transport Stops (SDG 11.2.1)

The public transportation service area of Guilin in 2015 and 2020 was shown in Figure 3. The service area of public transport stations was increasing and covers most of the population in the main functional areas of the city, but there were also some densely populated areas that were not covered by the service area.

Figure 4 shows the changes in population with convenient access to public transport services from 2013 to 2020. The level of public transport services continued to improve from 2013 to 2020. The total population with access to public transport stops increased from 458,861 in 2013 to 489,379 in 2015 and 573,957 in 2020. The accessibility indicator increased from 42.08% in 2013 to 52.31% in 2020.

The changes in SDG 11.2.1 indicators were further evaluated at the township level (Figure 5). The indicators of most towns showed a trend of improvement over time. Among them, the population in Xiangshan, Xiufeng, Qixing, and Lijun has been fully covered by public transportation services. However, in towns such as Dingjiang, Lingchuan, and Lingui, less than 40% of the population has access to convenient public transport. The construction of public transportation facilities in these areas was weak, and investment on public transportation infrastructures is highly needed in these areas.

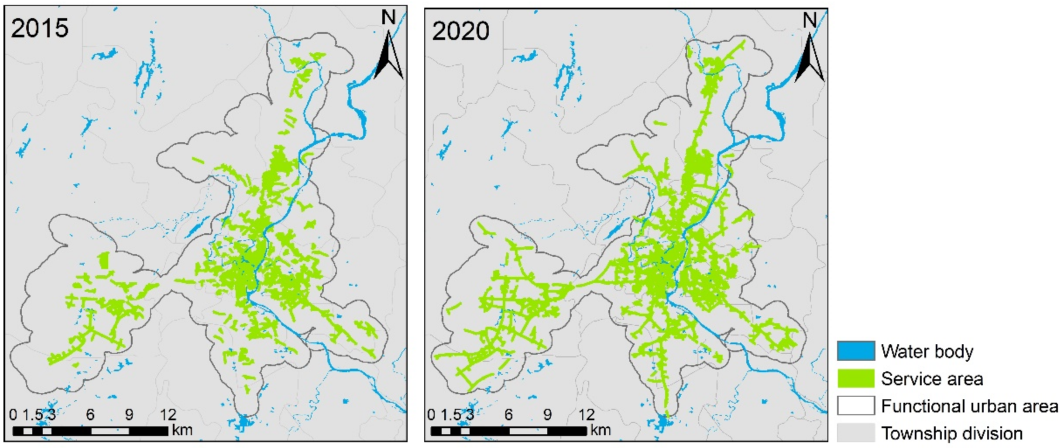

Figure 3. Service area of public transport stops in Guilin in 2015 and 2020.

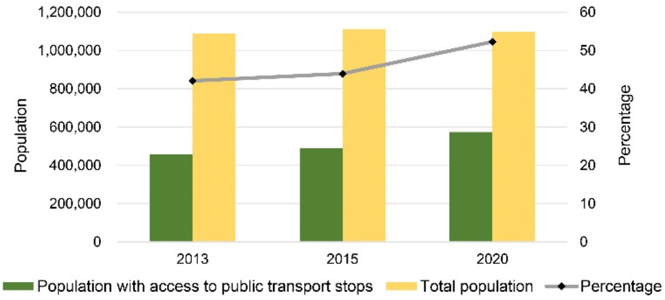

Figure 4. Number and percentage of the population with access to public transport stops from 2013 to 2020 in Guilin.

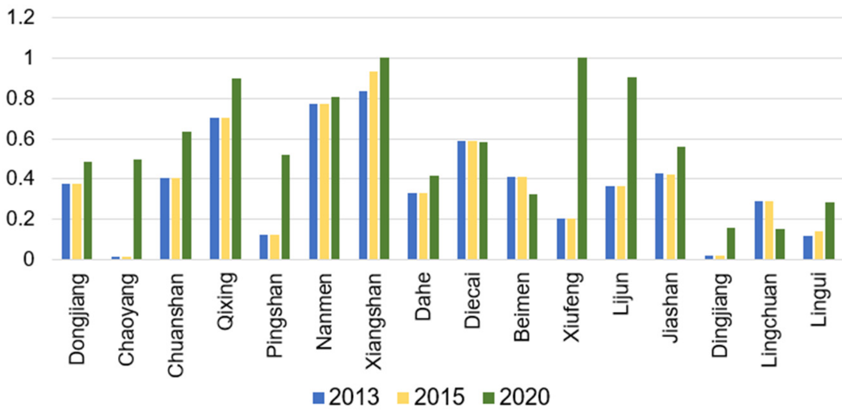

Figure 5. The proportion of populations with access to public transport stops from 2013 to 2020 in the townships of Guilin.

5.2. Spatiotemporal Variation of Land Consumption vs. Population Growth (SDG 11.3.1)

The accuracy of the land use classification results in the study area was evaluated using ground truth samples. The overall classification accuracy and kappa coefficient of the classification results of each period were higher than 90%. Based on the land use classification results, the temporal variations in LCR, PGR, and LCRPGR indicators and the corresponding secondary indicators (i.e., change in LCPC and change in urban infill) were measured in the study area (Table 4). The results showed that the urban expansion and population growth rates of Guilin were not well coordinated from 2013 to 2020. The urban expansion rate was faster than the population growth rate, and the per capita urban built-up area continued to increase at an accelerating rate. This indicates a sprawling urban growth pattern in the study area.

Table 4. SDG11.3.1 indicators from 2013 to 2015 in Guilin.

Time Span	LCR	PGR	Change in LCPC	Change in Urban Infill	LCRPGR
2013–2015	0.0525	0.0179	7.16%	4.77%	2.9343
2015–2020	0.0320	−0.0007	17.78%	23.30%	−45.7867

At the township level, the built-up area expanded more than 12 times faster than the population growth rate in Dingjiang, followed by Dahe, Pingshan, and Chuanshan from 2013 to 2015 (Figure 6). During the period 2013 to 2015, a large number of construction projects were started. However, those towns hardly attracted many people inflow. The towns of Diecai, Xiufeng, Lijun, Xiangshan, and Nanmen experienced a population decline. From 2015 to 2020, the expansion rates of built-up areas in Lingchuan, Lingui, and Dingjiang were still far greater than the population growth rate, which might be due to new settlement planning in these towns. The growth rate of built-up area in Lingui new area accelerated tremendously after 2015.

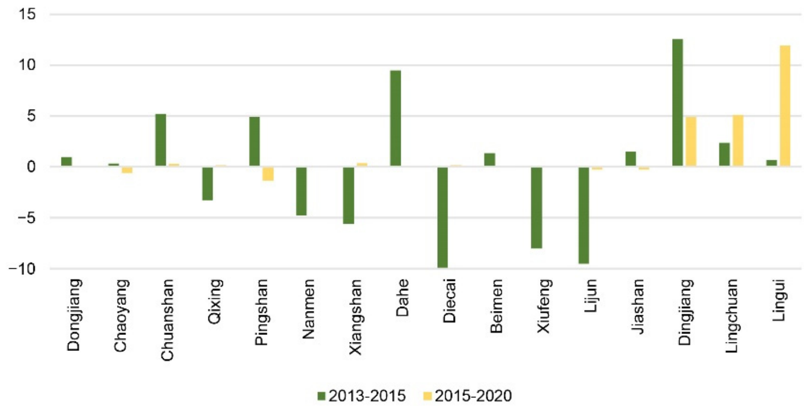

Figure 6. Ratio of land consumption rate to population growth rate(LCRPGR) from 2013 to 2020 in townships of Guilin.

From 2013 to 2015, the fastest growing area in per capita land consumption (LCPC) was in Dahe, up to 24.72% (Figure 7). The LCPC in Dingjiang, Lingchuan, Chuanshan, and Pingshan continued to grow, and the LCPC of other regions were decreasing. From 2015 to 2020, the LCPC of Jiashan, Lijun, Xiufeng, and Nanmen increased sharply due to the loss of population, while the per capita land consumption area of most of the remaining townships showed a downward trend. The changes in LCPC (Figure 7) indicates that land use efficiency continued to decrease, especially in Lingui, Lingchuan, and Dingjiang, where disorderly expansion occurred. In the townships where the expansion of built-up land was much faster than the population growth, the planning and management of land development should be strengthened to avoid low-density sprawl of urban land.

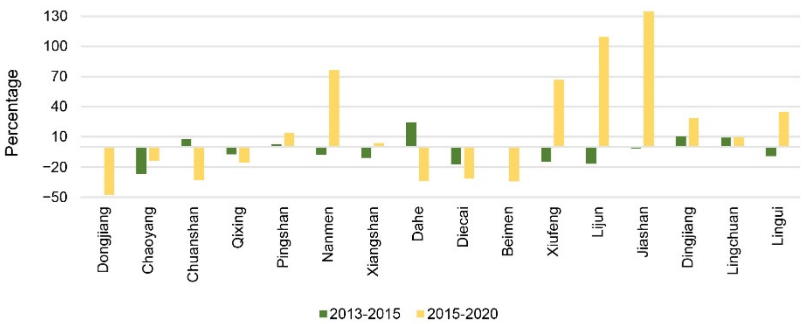

Figure 7. Changes in per capita land consumption (LCPC) from 2013 to 2020 in townships of Guilin.

5.3. Spatiotemporal Variation of Open Public Space (SDG 11.7.1)

For SDG11.7.1 indicator, the land of streets in the area was 16.18 km^2, which accounts for 5.13% of total urban area (Figure 8). The area of green space was 160.28 km^2, 123.10 km^2, and 59.32 km^2 in 2013, 2015 and 2020, respectively, showing a rapidly decreasing trend. The corresponding areal proportion of urban green space (POPS) accounted for 50.83%, 33.91%, and 18.81% of the urban area, respectively. The proportion of the overall open public space has gradually decreased from 55.97% in 2013 to 39.04% in 2015 and 23.95% in 2020.

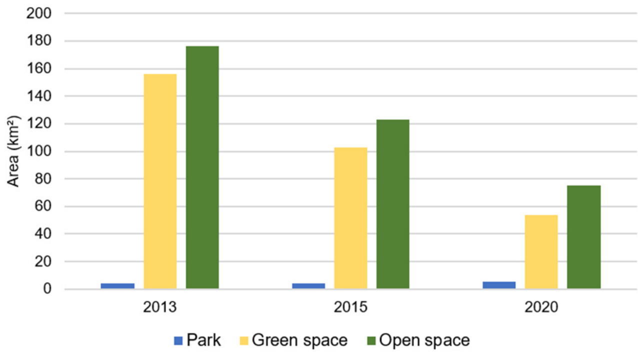

Figure 8. Area of open public space from 2013 to 2020 in Guilin.

The 400 m service area of parks and green spaces were shown in Figure 9. In 2013, 2015, and 2020, the service areas were 151.34 km^2, 96.09 km^2, and 81.76 km^2, respectively. The proportions of the population in the service area of open public space in Guilin were 73.2 %, 64.0%, and 59.3% in 2013, 2015, and 2020, respectively (Table 5). With the rapid decrease of green spaces, the service area has decreased over time. The total number of residents served by green open spaces also showed a rapid downward trend. Most of the green areas were converted into urban built-up land. From 2013 to 2020, the area of green space in the urban functional area dropped sharply, while the number of urban parks has only increased by 6 km^2 with a total area of 1.24 km^2. Most of them were distributed in the new urban areas in the west, however, the number and area cannot meet the needs of citizens due to rapid increase in population.

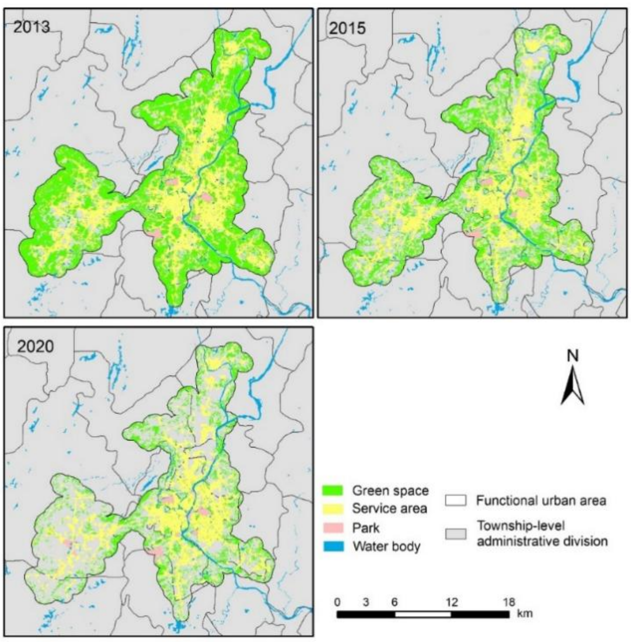

Figure 9. Open public spaces and service areas from 2013 to 2020 in Guilin.

Table 5. Population with access to open public spaces from 2013 to 2020 in Guilin.

	2013	2015	2020
Population with access to public open space	817,366	731,600	664,953
Total population	1,117,265	1,142,848	1,121,568
Proportion (%)	73.16	64.02	59.29

Figure 10 shows the changes in the proportion of the population in the green space service area of each town in the functional area of Guilin. At the township level, the service areas were relatively large for Xiufeng, Xiangshan and Qixing. The proportions of served population in most towns have decreased over time. The fastest decline was observed in Lingui, which has dropped from 50% to 24%. In 2020, the proportions of served population in Dingjiang, Lingui, Lingchuan, Dahe, Chaoyang, and Jiashan were lower than 40%. In addition, the entire area of Xiufeng was fully covered by the service area of open public space from 2013 to 2020, and all residents have convenient access to urban green space.

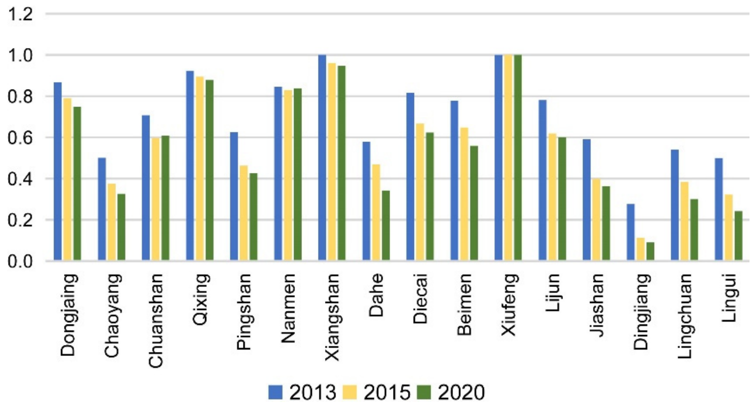

Figure 10. Proportion of population with access to open public space from 2013 to 2020 in townships of Guilin.

6. Discussion

The SDG11.2.1 evaluation results show that the public transport convenience of the regional central towns in Guilin is better than that of the peripheral towns. The research results of Tiznado-Aitken, Muñoz and Hurtubia [36] are consistent with our study. Building an integrated transportation network that meets the needs of social and economic development is very important for achieving sustainable development. The transportation links between the bordering towns and the central towns should be strengthened to promote the in-depth development of regional economics [53]. Meanwhile, intensive use of urban resources and livable environment should be maintained to build a modern town in Guilin with a good ecological environment during the road network construction. This study confirms that the application of high-resolution Earth observation data can improve the lack of information on SDG11.3.1 at a fine scale [48]. The growth rate of the built-up area exceeded the growth rate of the population in the same time period, increasing imbalance between rapid urban expansion and population growth. The uncoordinated population and land growth have been reported in small and medium-sized cities in China [22,46,54]. One possible reason is that low land acquisition costs and rapid industrial development have transformed a large number of agricultural land markets into non-agricultural land markets, which has resulted in the growth of LCR [54]. The proportion of land use types used for built-up areas in Guilin was increasing, while the land used to provide urban green spaces was decreasing. The benefits provided by the urban green space cannot meet the needs of the increasing population. The realization of the SDGs depends on the balance and cohesion of all the elements related to land [55]. It is necessary to balance the growth of urban built-up areas and green spaces to promote sustainable development. In the undergoing densification of urban areas, adequate and accessible green public spaces should be planned to solve the scarcity of green space and to sustain the quality of urban environments and social systems, and human wellbeing [56].

Actions taken at the neighborhood level can lead to positive urban changes and enhance the sustainability of communities [57]. The evaluation of SDG indicators 11.2.1, 11.3.1, and 11.7.1 suggested that the three towns of Lingui, Lingchuan, and Dingjiang should consider increasing their green area andpublic transportation facilities to prevent the low-density development of built-up land. Investments in urban infrastructure to enable a function can often create lock-in situations that last for decades or even centuries [58]. In urban planning, natural landscapes, trunk lines, and urban construction should be integrated, and ecological and livable towns should be built on the basis of existing landscapes. It is worth mentioning, however, that some scholars have found that the construction of extensive road networks across the landscape also destroys natural habitats and increases the pressure on sustainable development policies. For example, human activities have led to ecological degradation in the Qilian Mountains [59]. Monitoring of SDG 11.7.1 indicator aims to ensure that important ecological functional areas such as nature reserves, scenic spots, forest parks, wetlands, and vital water sources within the urban area of Guilin City are not damaged. It also aims to improve the construction of urban open space. According to the township-level analysis results of SDG11.3.1, policymakers in Lingui, Lingchuan, and Dingjiang should plan and consider building new districts based on their population density, resources, and environmental carrying capacity and should not pursue urbanization while ignoring the ecological environment. Due to the lack of conservation and preservation, deforestation in the past ten years was extensive, and the water storage capacity was weakened, which also impacted the water quality in Guilin. Since 2011, Guilin has implemented a series of policies to improve the ecological environment. These policies are encouraging and might help to formulate sustainable development strategies suitable for Guilin in the future.

A well-conceptualized and robust SDG monitoring framework can inform the strategic design of policies and interventions to address the challenges of growing urban areas and uncertainty in a variety of scenarios. SDG11 monitoring framework explicitly considers the linkages between policy, urban development, and the SDGs by integrating interdisciplinary knowledge. Implementing isolated targets without a comprehensive approach will undermine the unique dynamics of each city and endanger sustainable development. The comprehensive evaluation results in our study indicates that the evaluation results of multiple SDG indicators should be considered comprehensively under the local context to gain insights from local ecosystem and development conditions and guide sustainable policies and practices. Since the proposed approach is based on the United Nations' guidelines and uses open geospatial data, it can be easily adopted in cities in other countries or regions to support sustainable urban practices.

One limitation of our study is that the indicator assessment was performed in the years 2013, 2015, and 2020. The study periods highly depend on the availability of open geospatial data. With geospatial data becoming more readily available, an annual evaluation of the SDG indicators can be performed in future studies. Moreover, raw spatial and temporal resolution geospatial data such as gridded population data (1000 m) was used in this study. This may have caused uncertainties and bias in the evaluation results [60,61]. Geospatial data with higher spatiotemporal resolution and thematic accuracy should be used to obtain more reliable assessment results. The sharing of geospatial data should be endorsed, and multi-source data fusion technology should be developed to improve the resolution and accuracy of SDG indicator measurements.

7. Conclusions

Following the guidelines of SDG11 indicators, this study evaluated the spatiotemporal changes in transport accessibility, land consumption, and urban open space in the urban functional area of Guilin from 2013 to 2020. The evaluation results showed that the accessibility of public transport gradually improved from 2013 to 2020, and the SDG11.2.1 indicators increased from 42.08% in 2013 to 52.31% in 2020. However, the expansion of built-up land was faster than the increase in population, and the per capita land consumption continued to increase. The proportion of public open space area also decreased from 56.0% in 2013 to 24.0% in 2020, and the proportion of population with convenient access to open public space decreased from 73.2% to 59.3%. At the township level, the SDG11 indicators of Lingui, Lingchuan, and Dingjiang, which have been rapidly growing in recent years, ranked the lowest among the evaluated towns. Therefore, the construction of public transport facilities should be increased, the low-density sprawl of built-up land should be controlled, and the area of green space should be enlarged in these areas. This study proved the effectiveness of the United Nations Sustainable Development Goal SDG11 indicators in evaluating changes in urban transportation, urban public space, and urban land use efficiency that are closely related to urban sustainability at the neighborhood level. The evaluation framework for SDG11 indicators based on HR satellite images and open geospatial big data proposed in this study can be applied to other cities, thereby contributing to the achievement of the sustainable development goals. Geospatial data with enhanced spatial and temporal resolution should be produced and applied to improve the accuracy and reliability of SDG evaluation results in future studies.

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

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