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Evaluation and Analysis of the County-Level Sustainable Development Process in Guangxi, China in 2014–2020

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Abstract: Sustainable development has become a scientific and decision-making consensus in countries and regions around the world. The current research on sustainable development mainly focuses on urban areas with a high level of economic development and intensive land use. Small-scale research, especially for underdeveloped areas, is required to reveal the spatial patterns and differences within administrative units. This study focuses on 1241 towns in Guangxi to assess the sustainable development process and variations at the township scale from 2014 to 2020 by using the entropy method, the coupled coordination degree method, and cluster analysis. The results show that the average sustainable development goal composite index (SDGCI) of towns in Guangxi is around 0.12, and their overall sustainable development level is low. The SDGCI of towns in the central region shows an increasing trend, while that in the northern and southern regions shows a decreasing trend. Then, the SDGs are divided into three systems, namely people, planet, and prosperity. The prosperity system contributes the most to the overall SDGCI, and the low values of the people and planet systems are the reason for the low level of sustainable development in Guangxi. The coupling degree of the SDGCI among the three systems is at a high level, and the level of coupling coordination degree is good, which indicates high consistency and close linkage of the towns in Guangxi when pursuing the SDGs. The results of hierarchical cluster analysis show that towns in Guangxi can be divided into three categories to adapt to different features based on SDGCI values. The assessment of SDG process in towns in Guangxi could guide local governments to refine their development policy, formulate and adjust development strategies in a targeted manner, and promote balanced and sustainable development under townships.

Keywords: township; sustainable development goals composite index; coupled coordination degree model; cluster analysis; Guangxi

1. Introduction

In order to address the imbalance of regional development in different parts of the world, the United Nations adopted the "Transforming our World: The 2030 Agenda for Sustainable Development" in 2015, which consists of 17 Sustainable Development Goals (SDGs) and 169 targets [1], providing the world with a global framework to tackle significant global challenges such as climate change, poverty, hunger, inequality, environmental damage, and social instability. Those have always been hot issues of widespread concern in the scientific community, i.e., (1) how to measure and analyze the process of global human social development by scientific methods and (2) how to reveal the spatial disparity of human social development in the world and its dynamic evolution characteristics. For example, Decancq et al. [2], McGillivray et al. [3], and Jordáet et al. [4] used the

human development index (HDI) as the primary measure of the level of human social development and studied in depth the imbalance of human social development worldwide. Böhnke et al. [5] applied a combined objective–subjective evaluation model to evaluate the level of human welfare and analyze the factors influencing its inequality in various countries worldwide. Goff et al. [6] explored the main factors influencing the inequality of human social welfare based on a measure of life satisfaction data. Sustainable development, which emphasizes balance and coordination among the economy, society, and environment, provides a crucial theoretical basis for realizing sustainable prosperity for humankind. The concept of sustainability dates back to the environmental protection movement in the 1960s. Milestone events were the "The Limits to Growth" report by the Club of Rome [7] and the United Nations Conference on the Human Environment held in Stockholm in 1972. Then, the World Commission on Environment and Development (WCED) published the report "Our Common Future" to first define sustainable development as "meeting the needs of the present without compromising the ability of future generations to meet their own needs" [8]. The United Nations Conference "Earth Summit" held in 1992 was another breakthrough, which marked the formulation of Agenda 21 and the start of the United Nations Framework Convention on Climate Change [9]. The Commission on Sustainable Development was launched later. In 2000, specific goals and targets were proposed as the Millennium Development Goals (MDGs) to address worldwide concerns such as poverty, hunger, disease, illiteracy, environmental degradation, and discrimination against women. Following the MDGs, the United Nations expanded the scopes of the goals and introduced the world's Sustainable Development Goals (SDGs) for 2030 in 2015 [1]. The proposal of SDGs has provided a practical methodology and measurement index for analyzing global human social development, bringing together the concerns and contributions of the worldwide community on sustainable development.

The sustainable development process varies from region to region due to policies, geographic location, environmental conditions, and other factors [10,11]. In China, the eastern part of the country is highly developed, while the western part is underdeveloped [12]. The persistence of regional imbalance affects economic efficiency, social welfare and harmony [13]. Research on Chinese regional sustainable development began in the 21st century, and the relevant studies are categorized into single-indicator assessment, multi-indicator assessment, and comprehensive assessment. For single-indicator assessment, Xu et al. [14] used SDG11 indicators to assess the sustainable development of 27 cities in the Yangtze River Delta, China. Wu [15] combined SDG11.4 with remote sensing data to quantitatively assess the ecological environment quality of typical natural heritage sites, such as Mount Huang, Mount Wuyi, and so on. Zhang et al. [16] monitored and assessed SDG11 indicators in 18 cities and counties in Hainan Province. Scientists are increasingly inclined to evaluate multiple indicators in a spatiotemporal manner. As the assessment of sustainable development tends to be more systematic, some scholars assess the indicator system from various aspects. Xu et al. [17] focused on the 17 goals and 119 indicators of SDGs to evaluate the process of sustainable development at the national and provincial levels in China based on the statistical data. Jia et al. [18] proposed an evaluation index system for ecological development in Qinghai Province based on economic development, social progress, and ecological protection. Ding et al. [19] measured the pattern of the coupled coordination degree of the three major systems of land use, high-quality economic development, and carbon emission in 282 prefectural-level cities in China from the perspective of spatial and temporal changes in 2006–2019. Since 2018, the Chinese government has successively set up several National Sustainable Development Agenda Innovation Demonstration Zones, such as Taiyuan, Guilin, Shenzhen, Chenzhou, Lincang, and Chengde.

The imbalance of the sustainable development process also exists between urban and rural areas. Assessing the process of sustainable development goals at a small scale [20] is the basis for clarifying regional development issues and promoting synergistic urban–rural sustainable development. Studies on the European urban system considered that towns are especially important for the development of sustainability potential, i.e., (1) towns located

in the proximity of large cities are subject to the "borrowing-size" effect and (2) towns embedded in a specialized agricultural area (rural towns) have a bidirectional relationship with the surrounding rural settlements [21]. In China, rural revitalization and synergistic urban–rural development are always top priorities for the government [22]. Towns serve as an important transition area between urban and rural areas and an essential hub for the interactive development of urban and rural areas. The current township research mainly focuses on specific aspects of sustainability, such as land utilization, tourism development, cultural protection, and village patterns. For example, Zeng [23] established a sustainable land utilization evaluation index system for Nancheng County, Jiangxi Province, to assess the sustainability of its land resources. Huang [24] analyzed the current situation of rural tourism development in Mashan County, Guangxi, by combining literature research and a field survey. Pi [25] constructed the evaluation index system for sustainable tourism development in traditional villages by using the hierarchical analysis method in Guangxi, with eight subsystems and 36 indexes belonging to the four aspects of economy, society, culture, and ecology based on an expert questionnaire. Zeng et al. [26] tried to evaluate the sustainable development capacity by using principal component analysis (PCA) in Changtang Town, Guangxi.

Summarily, the above studies are mostly based on statistical data or interview surveys. Due to the limited number of data sources, the assessment of the efforts to achieve the Sustainable Development Goals is mainly performed at the provincial or municipal level. These studies therefore cannot effectively reveal the spatial patterns and differences within administrative units, such as the urban–rural relationships. At a small scale, current township research mainly focuses on specific aspects of sustainability. The evaluation indicators are formed by highly subjective questionnaires with certain types of indicators, and some of them are difficult to quantify. There is, therefore, an urgent need for more granular data to assess the efforts to achieve the Sustainable Development Goals at an acceptable (township) scale.

Monitoring the indicators of the Sustainable Development Goals is paramount, and Earth observation technologies such as remote sensing (RS) are essential tools. With the rapid development of aerospace technology, remote sensing techniques are significantly advancing. Several Earth observation systems have been successfully built with global coverage, which can rapidly and accurately acquire Earth observation data at a wide range of spatial, temporal, and spectral resolutions, thus providing excellent data support for assessing SDGs. As early as 30 years ago, Rao et al. [27] foresaw the potential of RS technology in sustainability-related research. With the introduction of the SDGs, some scholars have proposed concepts such as "sustainability remote sensing" [28] and "sustainability seen from space" [29], and the Group on Earth Observations (GEO) has launched the Earth Observations for the Sustainable Development Goals (EO4SDG) initiative [30]. In addition, big Earth data, including remote sensing data, have been widely used in urban monitoring [31] and air quality monitoring [32] for SDG11, climate change research [33] for SDG13, land cover monitoring and ecosystem assessment [34] for SDG14, and hydrological and water resources research [35] for SDG6. The accurate and dynamic monitoring capability of big Earth data provides an essential tool for sustainable development evaluation [36]. Guo et al. [37] introduced the realization of big Earth data in assessing SDG indicators to comprehensively analyze the process of SDGs 2, 6, 11, 13, 14, and 15 in China for 2010–2020. Han et al. [38] confirmed that the SDG 11 indicator assessment framework based on satellite imageries and geospatial data has excellent application in Guilin, Guangxi, and could be applied to other cities for targeted planning and assessment. Remote sensing emerges as a crucial monitoring tool, bridging the spatial coverage and temporal frequency gaps evident in existing observational data [30,39]. The advantages of remote sensing data, characterized by high spatial and temporal resolution, make them invaluable for SDG monitoring. Furthermore, remote sensing data facilitate examining and identifying priority areas for sustainable management [40]. Applying remote sensing data to township-level

studies could effectively improve the efficiency and quality of evaluating the sustainable development process on a regional scale.

This paper mainly focuses on three aims in order to achieve the research objectives: (1) to assess the spatial and temporal variations of sustainable development goals at the township scale; (2) to analyze sustainable development process in towns under different dimensions by dividing the indicator data into different subsystems; and (3) to classify the types of towns based on their process of sustainable development goals as to support decision-making by adaption to the local conditions of different townships. Located in southwestern China and connected to the Association of Southeast Asian Nations (ASEAN), Guangxi has rich natural ecological resources and diversified cultural backgrounds, and is characterized by diverse karst landscapes, widespread mountainous terrain, and severe rocky desertification. Its geographic fragility and cultural complexity constrain local socio-economic development, and unbalanced regional development is a prominent problem in Guangxi, which makes it a valuable area for sustainable development assessment. In this study, we establish an SDG composite index (SDGCI) by using the entropy method to integrate 25 SDG-related factors. Then, the spatial and temporal changes in the SDGCI at the scale of townships (1241 towns) in Guangxi were evaluated in 2014–2020. Furthermore, the SDG indicators were divided into the systems of people, planet, and prosperity under the United Nations classification. Lastly, the towns were clustered into different types based on their SDGCI values, so as to provide guidance for the local government on the fine-tuning of the development policy, and to promote the balanced and sustainable development of the townships.

2. Study Area and Data

2.1. Overview of the Study Area

The Guangxi Zhuang Autonomous Region (GZAR) is located in southwestern China, between latitudes of 20°54′ and 26°24′ N and longitudes of 104°26′ and 112°04′ E, with a total landmass area of about 237,600 km². The geographical features of Guangxi include mountains, plains, rivers, and coastlines, which could be roughly divided into the karst landscape area in the south and the mountains and plains area in the north, as shown in Figure 1. Guangxi has a warm climate with abundant rainfall and ample sunlight, with an average annual temperature ranging from 17.5 to 23.5 °C. The precipitation varies between 800 and 2000 mm. The climate in Guangxi exhibits distinct seasonal differences, with hot and rainy summers and warm and dry winters.

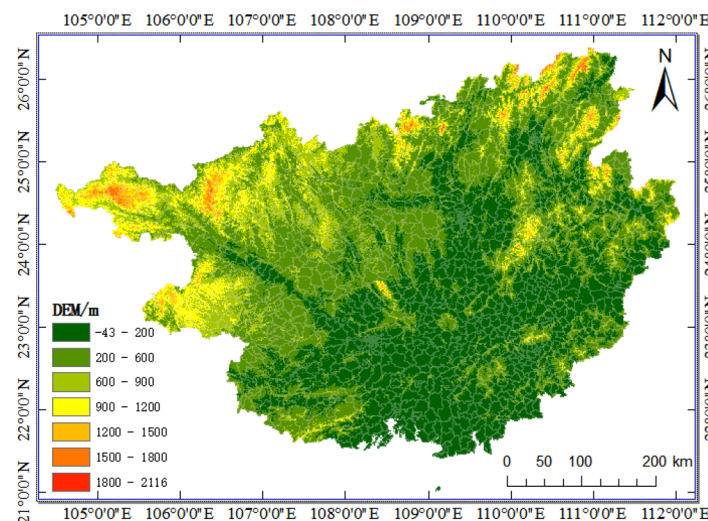

Figure 1. Spatial distribution of terrain in the GZAR.

According to the 2021 statistics, the GZAR is governed by 14 prefecture-level administrative units, 109 county-level units, and 1241 townships. At the end of 2021, the total

resident population of the region was 50.47 million, of which 28.09 million were urban residents, accounting for 55.66% of the resident population.

2.2. Data

In this study, we use various big Earth data, covering 15 target indicators of SDGs and 25 datasets (Table 1), to transform the gridded data into township-scale irregular spatial unit data using a zonal statistical method, and then to carry out township-scale sustainable development assessment. For data with a spatial resolution of 10 km, the approximate nearest neighbor resampling method was used to obtain zonal statistics. For data with a higher spatial resolution, the mean resampling method was used; especially particular, for preparing the percentage of cultivated land area, surface water area, forest area, the sum resampling method was used. The research period of this study was 2014–2020. To address the issue of insufficient or missing data in specific years, the analysis primarily relied on data from the preceding year. The correspondence between the SDG indicators and the datasets is shown in the table below.

Table 1. SDG indicators and datasets.

SDG Indicators	Datasets (Unit)	Period	Spatial Resolution	Data Sources	Incline
2.4.1 Proportion of agricultural area under productive and sustainable agriculture	Maize cultivation area (1 km^2)	2000–2019	1 km	Luo et al., 2020 [41]	+
	Rice cultivation area (1 km^2)	2000–2019	1 km	Luo et al., 2020 [41]	+
	Percentage of cultivated land area (%)	1990–2020	-	Yang and Huang, 2021 [42]	+
3.8.1 Coverage of essential health services	Distance to hospital (1 km)	2014–2021	1 km	Open Street Map (OSM)	−
3.9.1 Mortality rate attributed to household and ambient air pollution	Near-surface CO concentration (mg/m^3)	2013–2020	10 km	Wei et al., 2023 [43]	−
	Near-surface SO$_2$ concentration (μg/m^3)	2013–2020	10 km	Wei et al., 2023 [43]	−
4.a.1 Proportion of schools offering basic services, by type of service	Distance to school (1 km)	2014–2021	1 km	Open Street Map (OSM)	−
6.6.1 Change in the extent of water-related ecosystems over time	Precipitation (mm/year)	2001–2020	1 km	Zhao et al., 2022 [44]	+
	Potential evapotranspiration (mm/year)	1990–2021	1 km	Peng, 2022 [45]	−
	Percentage of surface water area (%)	1990–2020	-	Yang and Huang, 2021 [42]	+
	Distance to river (1 km)	2014–2023	1 km	Open Street Map (OSM)	−
7.1.1 Proportion of population with access to electricity	Nighttime lighting index (-)	2000–2020	1 km	Zhong et al., 2022 [46]	+
7.3.1 Energy intensity measured in terms of primary energy and GDP	Actual electricity consumption (kWh)	1992–2019	1 km	Chen et al., 2022 [47]	+
	Distance to energy-consuming industrial heat sources (1 km)	2012–2022	1 km	Ma and Xie, 2022 [48]	+
8.1.1 Annual growth rate of real GDP per capita	Gross domestic product (million dollars)	1992–2019	1 km	Chen et al., 2022 [47]	+
9.1.1 Proportion of the rural population who live within 2 km of an all-season road	Distance to road (1 km)	2014–2023	1 km	Open Street Map (OSM)	−
11.6.2 Annual mean levels of fine particulate matter	PM2.5 concentration (μg/m^3)	2000–2021	1 km	Wei et al., 2021 [49]	−
	PM10 concentration (μg/m^3)	2000–2021	1 km	Wei et al., 2021 [50]	−
13.2.2 Total greenhouse gas emissions per year	Fossil fuel emission (Tons of carbon)	2000–2021	1 km	Oda et al., 2018 [51]	−
	O$_3$ concentration (μg/m^3)	2013–2020	10 km	Wei et al., 2022 [52]	−
15.1.1 Forest area as a proportion of total land area	Percentage of forest area (%)	1990–2020	-	Yang and Huang, 2021 [42]	+
15.2.1 Progress towards sustainable forest management	Vegetation index (-)	2000–2021	1 km	NASA MOSDIS Land Processes DAAC (MOD13Q1)	+
15.4.1 Coverage by protected areas of important sites for mountain biodiversity	Distance to natural attractions (1 km)	2014–2021	1 km	Open Street Map (OSM)	+
	Ecosystem quality index (-)	2001–2021	500 m	Xu et al., 2021 [53]	+
15.5.1 Red List Index	Rare plant and animal biodiversity (-)	2018	10 km	BiodiversityMapping.org	+

3. Method

3.1. SDGCI Calculation and Change Analysis

Given that the entropy method could objectively weight the data and avoid subjectivity, this study established an SDG composite index (SDGCI) to integrate 25 SDG-related factors by employing the entropy method. The detailed calculation process was as follows.

In the initial step, positive and negative indicators were normalized to eliminate masking effects and differences in magnitude among the data.

$$\textit{Positive Indicator} \quad Z_{ij} = \frac{X_{ij} - \min X_{ij}}{\max X_{ij} - \min X_{ij}} \tag{1}$$

$$\text{Negative Indicator} \quad Z_{ij} = \frac{\max X_{ij} - X_{ij}}{\max X_{ij} - \min X_{ij}} \tag{2}$$

where X_{ij} represents the value of indicator j in township i; Z_{ij} is the normalized value of X_{ij}, and if Z_{ij} is 0, it is replaced by 0.0001; and $\max X_{ij}$ and $\min X_{ij}$ represent the maximum and minimum values of X_{ij}, respectively.

In the second step, the weights of the indicators were calculated based on the calculation of entropy.

$$p_{ij} = \frac{Z_{ij}}{\sum\limits_{i=1}^{n} Z_{ij}} \tag{3}$$

$$e_j = -\frac{1}{\ln(n)} \times \sum_{i=1}^{n} p_{ij} \ln(p_{ij}) \tag{4}$$

$$w_j = \frac{1 - e_j}{m - \sum_{j=1}^{m} e_j} \tag{5}$$

where p_{ij} is the proportion of indicator j to the sum of all the indicator values for township i, n is the number of townships, e_j is the entropy value of indicator j, w_j is the weight of indicator j, and m denotes the number of indicators.

The third step was to calculate the SDG composite index (SDGCI) of each town for each year. The SDGCI is a weighted sum of all the SDG indicators. It represents the combination measurement of SDG indicators, which is calculated by multiplying the standardized value of the indicators by their weights and then summing the products by all the indicators.

$$U_i = \sum_{j=1}^{m} w_j Z_{ij} \tag{6}$$

3.2. Classification and Cluster Analysis of SDG Indicator System

Existing research indicates a synergistic and balanced relationship between the partial and holistic goals. Classification and cluster analysis could simplify the complex relationships between goals and improve the SDG's intersectoral management [54]. In this study, we adopted the United Nations SDG classification [1] to categorize SDG indicators of towns in Guangxi into three systems: people (SDG1~7), planet (SDG8~12), and prosperity (SDG13~15). The SDGCI values for these three systems could be calculated according to the method in Section 3.1.

In order to further measure the contribution of each system to the overall SDGCI and their interrelationship, this study invoked the coupling coordination degree method to analyze the coupling coordination degree among systems, and the formula is as follows:

$$C = \frac{3 \bullet \sqrt[3]{U_{people} \times U_{planet} \times U_{prosperity}}}{U_{people} + U_{planet} + U_{prosperity}} \tag{7}$$

$$D = \sqrt{C \times T} \tag{8}$$

where Upeople, Uplanet and Uprosperity represent the SDGCI values of the three systems, respectively. C is the coupling degree. D is the coupling coordination degree. $T = \left(U_{people} + U_{planet} + U_{prosperity} \right)/3$, which represents the average of the SDGCI values of the three systems.

In order to analyze the distribution of SDGCIs for the three systems and explore the differences and correlations among different townships, this study carried out cluster analysis by using SDGCIs of the three systems as inputs. The hierarchical clustering method is based on the similarity of distance among data points. The advantages of the hierarchical clustering method are that (1) the similarity of distances is easy to define with few restrictions, and (2) the number of clusters does not need to be given in advance [55]. The number of clusters was determined according to the elbow rule [56], and the cluster distribution of each town in Guangxi under the United Nations SDG classification was finally obtained.

4. Results

4.1. Spatial and Temporal Changes of SDGCI

Figure 2 shows the spatial distribution of SDGCI in Guangxi townships from 2014 to 2020. The spatial pattern of SDGCI in Guangxi is characterized as "high in the southern and central region and low in the surrounding areas". From 2014 to 2020, the average value of the SDGCI of towns in Guangxi is around 0.12. The maximum value of the SDGCI of townships fluctuates at about 0.45, indicating that the comprehensive sustainable development level of townships in Guangxi is relatively low. The towns with an SDGCI value of more than 0.3 are mainly distributed in the urban centers and the flat areas, and there are significant regional differences. As shown in Table 2, from 2014 to 2020, about 35% of the towns in Guangxi have an SDGCI of 0.1 or less; about 57% of the towns have an SDGCI between 0.1 and 0.2; about 7% of the townships have an SDGCI between 0.2 and 0.3; and the proportion of townships with an SDGCI greater than 0.3 is about 1%. The number of townships in Guangxi with an SDGCI greater than 0.3 ranges from 11 to 19, with the least being observed in 2018 and 2020, the most in 2015, and a decrease in 2020 compared to 2014.
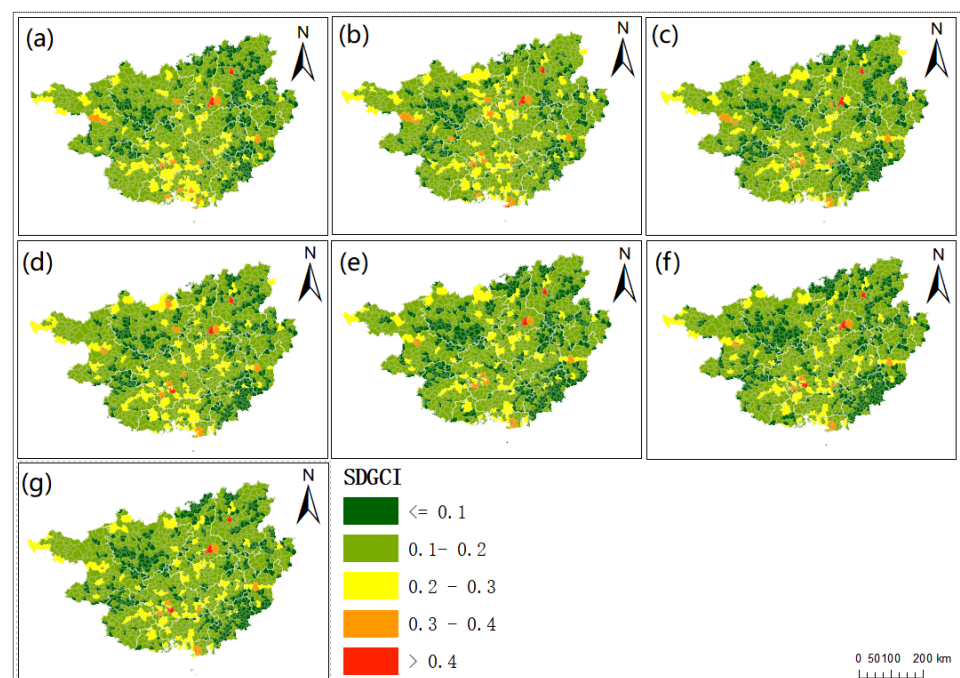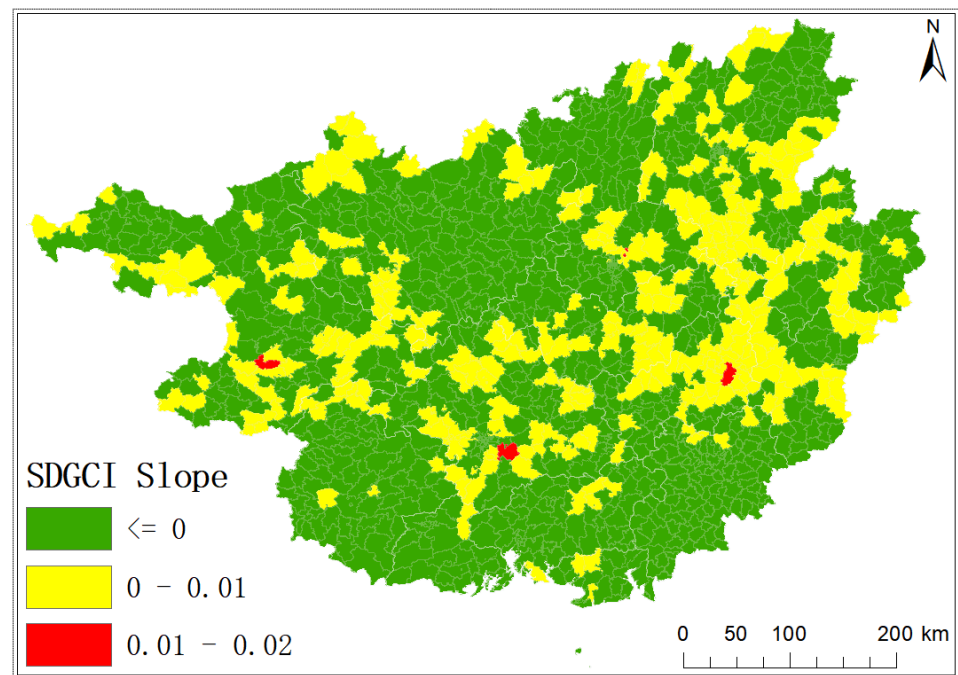

Figure 2. Spatial distribution of SDGCI in Guangxi in 2014–2020: (**a**) 2014, (**b**) 2015, (**c**) 2016, (**d**) 2017, (**e**) 2018, (**f**) 2019, (**g**) 2020.

Table 2. SDGCI interval statistics of townships in Guangxi in 2014–2020.

Year	SDGCI			Number (Percentage) of Towns for Different SDGCI Intervals				
	Mean	Median	Max	≤0.1	(0.1,0.2]	(0.2,0.3]	(0.3,0.4]	>0.4
2014	0.129	0.117	0.415	403 (32.5%)	729 (58.7%)	93 (7.5%)	14 (1.1%)	2 (0.2%)
2015	0.134	0.122	0.472	344 (27.7%)	774 (62.4%)	104 (8.4%)	16 (1.3%)	3 (0.2%)
2016	0.127	0.115	0.474	441 (35.5%)	701 (56.5%)	85 (6.8%)	12 (1.0%)	2 (0.2%)
2017	0.129	0.117	0.481	406 (32.7%)	725 (58.4%)	96 (7.7%)	11 (0.9%)	3 (0.2%)
2018	0.123	0.111	0.502	480 (38.7%)	669 (53.9%)	81 (6.5%)	9 (0.7%)	2 (0.2%)
2019	0.122	0.110	0.481	497 (40.0%)	649 (52.3%)	83 (6.7%)	9 (0.7%)	3 (0.2%)
2020	0.125	0.114	0.479	442 (35.6%)	697 (56.2%)	91 (7.3%)	8 (0.6%)	3 (0.2%)
Mean	0.127	0.115	0.472	430 (34.7%)	706 (56.9%)	90 (7.3%)	11 (0.9%)	3 (0.2%)

We calculated the annual changes in the SDGCI in Guangxi townships in 2014–2020 (Figure 3). Summarily, the towns with a negative change in SDGCI are mainly distributed in the northern and southern regions, and those with a positive change are mainly distributed in the central part of Guangxi. Developing townships in the northern and southern regions need more attention and strengthening.

Figure 3. Spatial distribution of SDGCI changes in Guangxi in 2014–2020.

4.2. SDGCI Changes and Relationship Analysis for Different Systems

4.2.1. SDGCI Changes Based on United Nations SDG Classification

Figure 4 illustrates the spatial distribution of SDGCI of the three systems based on the United Nations SDG classification in 2015 and 2020. Overall, the SDGCI of the prosperity system contributes the most to the overall results. The average SDGCI value of the prosperity system is greater than the sum of the values of the people and planet systems (Table 3). Most towns have Upeople and Uplanet values below 0.2, while the value of Uprosperity is larger than 0.2. The SDG indicators of the prosperity system in Guangxi have been well developed, and the underdevelopment of Upeople and Uplanet constrains the improvement of the overall SDGCI of towns. It is necessary to strengthen the development of people and planet system indicators, such as strengthening the utilization and protection of cultivated land, controlling pollution emissions strictly, reducing the production of urban particulate matter, and strengthening infrastructure construction.
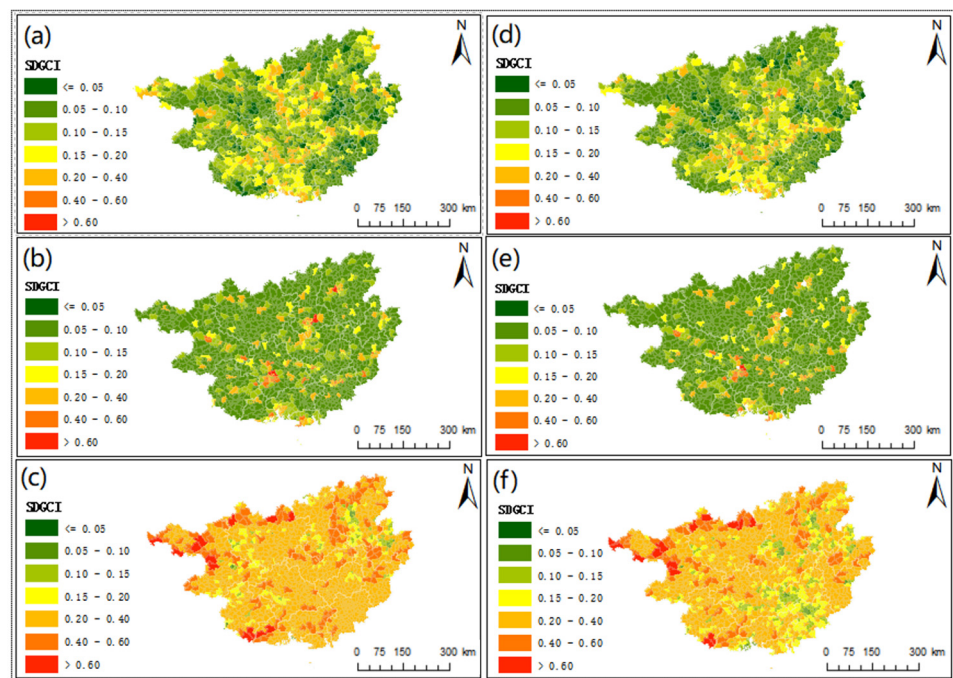
Figure 4. Spatial distribution of the SDGCI across three systems of the United Nations SDG classification in 2015 and 2020: (**a**) Upeople, (**b**) Uplanet, and (**c**) Uprosperity in 2015; and (**d**) Upeople, (**e**) Uplanet, (**f**) Uprosperity in 2020.

Table 3. SDGCI interval statistics of townships in Guangxi for three systems based on the United Nations SDG classification in 2015 and 2020.

Year	Systems	SDGCI			Number (Percentage) of Towns for Different SDGCI Intervals			
		Mean	Median	Max	≤0.2	(0.2,0.4]	(0.4,0.6]	>0.6
2015	people	0.107	0.091	0.468	1161 (93.6%)	78 (6.3%)	2 (0.2%)	0 (0.0%)
	planet	0.117	0.085	0.982	1111 (89.5%)	99 (8.0%)	27 (2.2%)	4 (0.3%)
	prosperity	0.280	0.269	0.795	269 (21.7%)	845 (68.1%)	114 (9.2%)	13 (1.0%)
2020	people	0.103	0.089	0.489	1172 (94.4%)	67 (5.4%)	2 (0.2%)	0 (0.0%)
	planet	0.112	0.078	0.984	1120 (90.2%)	93 (7.5%)	24 (1.9%)	4 (0.3%)
	prosperity	0.238	0.222	0.785	497 (40.0%)	658 (53.0%)	72 (5.8%)	14 (1.1%)

4.2.2. Spatial and Temporal Variations of SDGCI Coupling Degree (SDGCI_CD) among Different Systems

The spatial distribution of SDGCI_CD among different systems at the township scale in Guangxi is analyzed, as shown in Figure 5. Overall, the SDGCI_CD among the three systems is very high, and the average coupling degree is higher than 0.85 in both 2015 and 2020. Furthermore, according to the classification of the coupling degree level [19], the coupling degree is at a high level. The towns with a high SDGCI_CD in 2015 are mainly distributed in the southwest and northeastern regions of Guangxi. In 2020, the towns with a high SDGCI_CD extend towards the southeastern region. Compared with that in 2015, the SDGCI_CD values of towns in the northwest of Guangxi decrease in 2020, while those in the southeast increase. The value of SDGCI_CD change shows an increasing trend from northwest to southeast. As shown in Table 4, the number of towns with SDGCI_CD > 0.8 increases by 5% (62) in 2020 compared to that in 2015.
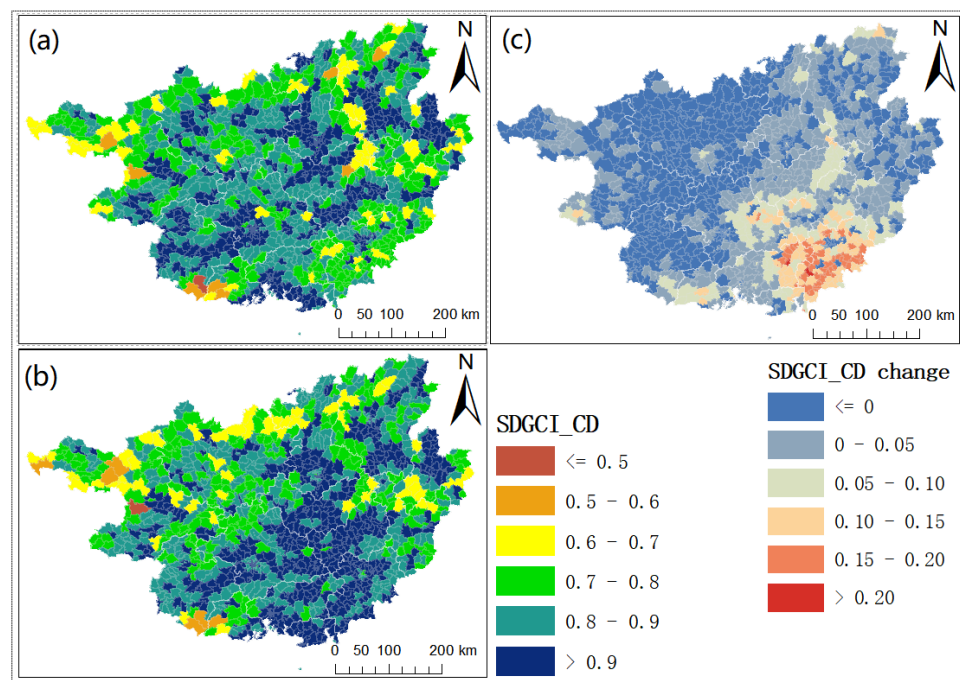
Figure 5. Spatial distribution of SDGCI_CD among different systems in 2015 and 2020 and SDGCI_CD changes between 2015 and 2020: (**a**) 2015, (**b**) 2020, (**c**) changes between 2015 and 2020.

Table 4. Interval statistics of SDGCI_CD for different systems in 2015 and 2020.

Year	SDGCI_CD			Number (Percentage) of Towns for Different SDGCI_CD Intervals			
	Mean	**Median**	**Max**	**≤0.6**	**(0.6,0.7]**	**(0.7,0.8]**	**>0.8**
2015	0.852	0.867	0.9999	9 (0.7%)	63 (5.1%)	263 (21.2%)	906 (73.0%)
2020	0.869	0.886	0.9995	7 (0.6%)	52 (4.2%)	214 (17.2%)	968 (78.0%)

4.2.3. Spatial and Temporal Variations of SDGCI Coupling Coordination Degree (SDGCI_CCD) among Different Systems

The spatial distribution of SDGCI_CCD among different systems at the township scale in Guangxi is analyzed, as shown in Figure 6. The SDGCI_CCD of most towns in Guangxi in 2015 and 2020 ranges between 0.3 and 0.5. The towns with an SDGCI_CCD of more than 0.5 are sporadically distributed in flat areas or close to urban areas, with high coupling coordination. Compared with 2015, the SDGCI_CCD of towns in most regions of Guangxi shows a decreasing trend, while the SDGCI_CCD of the western and eastern regions shows an increasing trend in 2020. The number of towns with decreasing SDGCI_CCD values is more than those whose SDGCI_CCD increases. As shown in Table 5, the number of towns with an SDGCI_CCD greater than 0.4 decreases by 108 in 2020 compared with 2015.

Table 5. Interval statistics of SDGCI_CCD for different systems in 2015 and 2020.

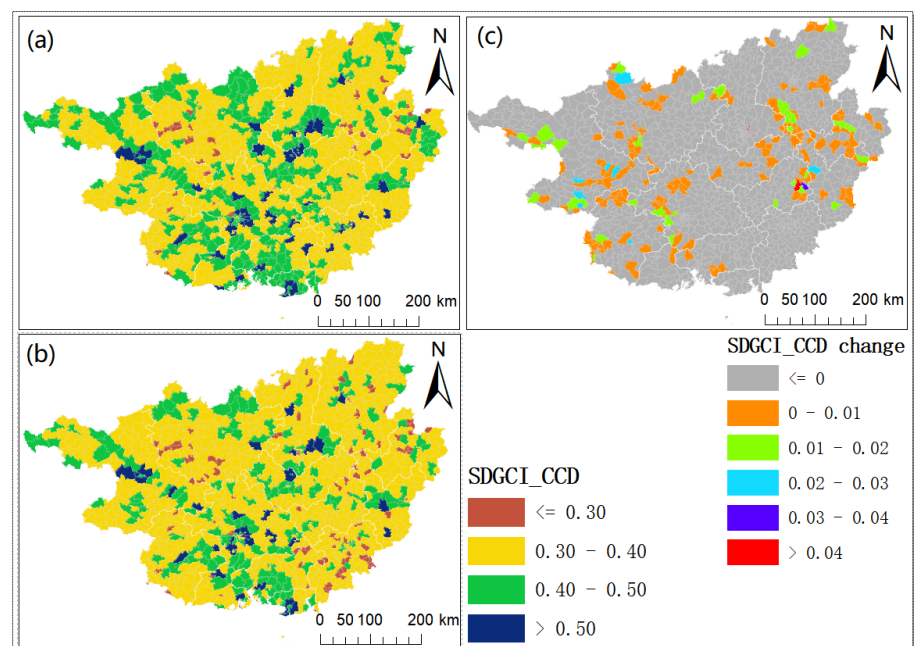| Year	SDGCI_CCD			Number (Percentage) of Towns for Different SDGCI_CCD Intervals			
	Mean	**Median**	**Max**	**≤0.30**	**(0.30,0.40]**	**(0.40,0.50]**	**>0.50**
2015	0.373	0.361	0.682	55 (4.5%)	864 (69.6%)	277 (22.3%)	45 (3.6%)
2020	0.356	0.344	0.668	124 (9.9%)	903 (72.8%)	181 (14.6%)	33 (2.7%)

Figure 6. Spatial distribution of SDGCI_CCD among different systems in 2015 and 2020 and SDGCI_CCD changes between 2015 and 2020: (**a**) 2015, (**b**) 2020, (**c**) changes between 2015 and 2020.

4.3. Differences and Linkages of SDGCI in Townships: Results of Cluster Analysis

A cluster analysis is carried out on SDGCI of the towns in Guangxi under the United Nations SDG classification, and the number of clusters is determined to be three based on the elbow rule.

As shown in Figure 7 and Table 6, the towns in Guangxi are classified into three categories based on the SDGCI values of the three systems under the United Nations SDG classification in 2015 and 2020. The first type of town (Cluster 1) exhibits high SDGCI values for prosperity system and low values for people and planet systems. These towns are mainly distributed in the marginal regions in 2015 and extend towards the west and central regions in 2020. The second type of town (Cluster 2) exhibits moderate performance for all three systems by considering SDGCI values. These towns are mainly distributed in the central part of Guangxi in 2015 and shrink into the southeast part in 2020. The third type of town (Cluster 3) has high SDGCI values for the planet system and low values for people and prosperity systems. These towns are sporadically distributed in the central and southern regions in 2015 and 2020. Compared with 2015, the number of towns in the first category increases significantly, while that in the second category decreases and that in the third category remains almost the same. Different towns possess different features. The three systems of the second type of town develop in a balanced way. The prosperity system of the first type of town develops prominently, and the planet system of the third type of town develops well. It is necessary to adapt to the local conditions of different towns in formulating policies and implementing planning.

Table 6. Statistics of SDGCI clustering results for the three systems under the United Nations SDG classification in 2015 and 2020.

Year	Systems	SDGCI Intervals for Clustering Results of Towns		
		Cluster 1	Cluster 2	Cluster 3
2015	people	[0.056,0.414]	[0.093,0.434]	[0.113,0.350]
	planet	[0.061,0.322]	[0.134,0.570]	[0.313,0.640]
	prosperity	[0.047,0.849]	[0.200,0.705]	[0.107,0.458]
	Number of towns	531	622	88

Table 6. *Cont.*

| Year | Systems | SDGCI Intervals for Clustering Results of Towns | | |
		Cluster 1	Cluster 2	Cluster 3
2020	people	[0.066,0.523]	[0.135,0.466]	[0.190,0.394]
	planet	[0.059,0.448]	[0.170,0.579]	[0.430,0.669]
	prosperity	[0.253,0.847]	[0.168,0.615]	[0.090,0.342]
	Number of towns	733	414	94

Figure 7. Ternary maps and spatial distribution of SDGCI clustering results of towns in Guangxi in 2015 and 2020, based on the three systems under United Nations SDG classification: ternary maps of clustering results in (**a**) 2015 and (**b**) 2020 and spatial distribution maps of clustering results in (**c**) 2015 and (**d**) 2020.

5. Discussions

Based on existing research, this study applies big Earth data to the assessment of sustainable development indicators, which partly solves the problem of insufficient and missing statistical data, and also achieves the characterization of spatial differences in the sustainable development goals [57]. This study takes Guangxi as an example to assess the sustainable development process at the township scale, which shall provide a reference for assessing sustainable development process at fine scales.

Comparing with the results of existing studies, Xu et al. [17] assessed the SDG process at the provincial scale in China from 2000 to 2015 every five years, and Wang et al. [58] assessed the development of environment-related SDG indicators at the provincial scale in China from 2010 to 2018 for each year. This study further assesses the SDG process at township scale in Guangxi from 2014 to 2020 every year. We extend the SDG assessment to the post-COVID-19 era and focus on the finer scale of townships. Xu et al. found that the overall SDG composite index of Guangxi showed an increasing trend from 2000 to 2015. Wang et al. found that the SDG composite index of Guangxi showed an increasing trend from 2010 to 2016 and illustrated a decreasing trend from 2016 to 2018. This study further discovers that the SDG composite index in Guangxi increased in 2014–2017 and decreased in 2017–2020 at the township scale, which is consistent with the results of existing studies.

To analyze the relationship between SDGCI and SDG indicators further, we calculate the Pearson correlation coefficient (PCC) between SDGCI and 25 variables used in this study for each year (Table 7). The results show that most of the variables (18 in 25) have a linear relationship with SDGCI at a high significance level (** p value < 0.01), in which the gross domestic product, actual electricity consumption, cultivated land area, nighttime lighting index, surface water area, rice cultivation area and maize cultivation area have a strong positive relationship with SDGCI (PCC > 0.5). PM2.5, potential evapotranspiration, PM10 and fossil fuel emission are strongly negatively correlated with SDGCI (PCC < −0.4). Primarily, it can be concluded that SDGCI in towns of Guangxi is highly related to their agriculture, economy, water resources and air pollutant emission. Accordingly, corresponding policy recommendations are proposed:

(1) Protection of cultivated land. The results show that both cultivated land and rice cultivation areas have a strongly positive relationship with SDGCI. While guaranteeing the quantity of cultivated land, we should ensure its spatial production suitability and improve the matching of crops and cultivated land [59].

(2) Protection of the natural environment, especially the surface water environment. Ecosystem quality index and forest area contribute to SDGCI positively at a significant level, while surface water area and potential evapotranspiration have a strong relationship with SDGCI. Ecosystem conservation could integrate biodiversity conservation, ecological restoration, and water resource exploitation and protection, and promote the establishment of comprehensive conservation policies, laws and ecological compensation measures [60,61].

(3) Improvement of infrastructure construction. Although the contribution of the distance to a railway, road, and hospital to SDGCI in Guangxi is low, the relationships between distance to a railway and road and SDGCI are significant (* p < 0.05). Guangxi is famous for its beautiful natural environment and rich tourism resources. The coordinated development of interregional, urban and rural transportation could meet economic and tourism development needs [62].

(4) Control of environmental pollution: Atmospheric pollutants such as $PM_{2.5}$, PM_{10}, SO_2, CO, O_3 and fossil fuel emissions negatively correlate with SDGCI in Guangxi. The following suggestions are put forward: vigorously developing green transportation and controlling traffic pollution, regulating high-polluting industries, improving clean production in various industries, and developing clean energy [63].

Table 7. Pearson correlation coefficient between indicator data and SDGCI for 2014–2020. Significance levels: *** p value < 0.001; ** p value < 0.01; and * p value < 0.05.

Factors	2014	2015	2016	2017	2018	2019	2020	R Value Mean	Correlation
Gross Domestic Product	0.666 ***	0.655 ***	0.694 ***	0.652 ***	0.675 ***	0.671 ***	0.666 ***	0.668	Positive
Actual electricity consumption	0.665 ***	0.654 ***	0.691 ***	0.648 ***	0.671 ***	0.665 ***	0.660 ***	0.665	Positive
Percentage of cultivated land area	0.611 ***	0.603 ***	0.596 ***	0.617 ***	0.603 ***	0.636 ***	0.632 ***	0.614	Positive
Nighttime lighting index	0.581 ***	0.574 ***	0.612 ***	0.569 ***	0.598 ***	0.601 ***	0.605 ***	0.591	Positive
Percentage of surface water area	0.522 ***	0.506 ***	0.536 ***	0.546 ***	0.557 ***	0.571 ***	0.563 ***	0.543	Positive
Rice cultivation area	0.396 ***	0.425 ***	0.503 ***	0.557 ***	0.475 ***	0.527 ***	0.531 ***	0.488	Positive
Maize cultivation area	0.457 ***	0.461 ***	0.361 ***	0.400 ***	0.412 ***	0.398 ***	0.397 ***	0.412	Positive
Ecosystem quality index	0.313 ***	0.346 ***	0.336 ***	0.373 ***	0.3523 ***	0.335 ***	0.341 ***	0.342	Positive
Rare plant and animal biodiversity	0.245 ***	0.263 ***	0.267 ***	0.286 ***	0.317 ***	0.308 ***	0.312 ***	0.285	Positive
Percentage of forest area	0.202 ***	0.239 ***	0.229 ***	0.267 ***	0.252 ***	0.226 ***	0.223 ***	0.234	Positive
Distance to natural attractions	0.217 ***	0.179 ***	0.269 ***	0.243 ***	0.242 ***	0.215 ***	0.227 ***	0.227	Positive

Table 7. *Cont.*

Factors	2014	2015	2016	2017	2018	2019	2020	R Value Mean	Correlation
Distance to railway	0.061 *	0.127 ***	0.123 ***	0.113 ***	0.139 ***	0.133 ***	0.131 ***	0.118	Positive
Distance to river	0.077 **	0.072 ***	0.076 *	0.058 *	0.053	0.062 *	0.067 *	0.066	Positive
Distance to road	0.059 *	0.033	0.032	0.012	0.063 *	0.091 **	0.088 **	0.054	Positive
Distance to hospital	−0.013	0.021	−0.041	−0.021	0.049	0.048	0.158 ***	0.029	-
Distance to school	−0.046	0.009	−0.051	−0.035	0.049	0.047	0.052	0.004	-
Vegetation index	−0.048	0.022	−0.014	0.023	0.005	0.024	0.014	0.004	-
Distance to energy-consuming industrial heat sources	−0.012	−0.042	−0.035	0.010	0.010	0.025	0.014	−0.004	-
Precipitation	0.087 **	−0.089 **	−0.068 *	0.047	−0.060 *	−0.147 ***	−0.097 ***	−0.047	-
Near-surface SO_2 concentration	−0.234 ***	−0.265 ***	−0.259 ***	−0.301 ***	−0.291 ***	−0.274 ***	−0.280 ***	−0.272	Negative
Near-surface CO concentration	−0.236 ***	−0.263 ***	−0.262 ***	−0.323 ***	−0.300 ***	−0.290 ***	−0.288 ***	−0.280	Negative
O_3 concentration	−0.264 ***	−0.307 ***	−0.273 ***	−0.294 ***	−0.291 ***	−0.287 ***	−0.290 ***	−0.287	Negative
PM2.5 concentration	−0.412 ***	−0.471 ***	−0.455 ***	−0.499 ***	−0.486 ***	−0.479 ***	−0.467 ***	−0.467	Negative
Potential evapotranspiration	−0.454 ***	−0.470 ***	−0.456 ***	−0.496 ***	−0.478 ***	−0.468 ***	−0.468 ***	−0.470	Negative
PM10 concentration	−0.428 ***	−0.470 ***	−0.454 ***	−0.497 ***	−0.486 ***	−0.495 ***	−0.475 ***	−0.472	Negative
Fossil fuel emission	−0.582 ***	−0.567 ***	−0.597 ***	−0.550 ***	−0.573 ***	−0.570 ***	−0.574 ***	−0.573	Negative

In all, the key to SDGs is to balance the economy and environment under ecological and environmental constraints and promote high-quality and green development of the economy.

The results obtained in this study on the assessment of sustainable development process at the township scale still have certain limitations. The following improvements need to be made in future research: (1) The number of sustainable development goal indicators is still limited, and a more comprehensive range of data still need to be collected. (2) The data sources in this study are diverse, and the data consistency could cause uncertainties. (3) The data with coarse spatial resolution could lead to uncertainties when obtaining zonal statistics for towns with smaller area.

6. Conclusions

This study takes 1241 townships in Guangxi as the study area. We characterized spatial and temporal changes in the sustainable development composite index from 2014 to 2020 at the township scale. The results obtained are as follows:

(1) The average value of SDGCI in Guangxi is around 0.12. The SDGCI level of townships in Guangxi is low, and the development of towns in the northern and southern regions needs to be strengthened.

(2) The SDGCI value of the prosperity system contributes the most to the overall SDGCI. It is necessary to strengthen the development of people and planet system indicators, such as strengthening the utilization and protection of cultivated land, controlling pollution emissions, and strengthening infrastructure construction.

(3) The towns in Guangxi are categorized into three clusters based on SDGCI values of the three systems. Thus, the sustainable development capacity of Guangxi could be improved by adapting to the local conditions of different towns.

Sustainable development is necessary in the towns of Guangxi. While gross domestic product, cultivated land area, and surface water area contribute positively to SDGCI, $PM_{2.5}$, potential evapotranspiration, PM_{10} and fossil fuel emission negatively influence SDGCI in the towns of Guangxi. The key to SDGs is to balance the economy and environment under ecological and environmental constraints. This study could guide local governments to refine their development policy based on the different types of towns, and promote

the balanced, sustainable development of towns to narrow the gaps between them in the process of achieving the SDGs.

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