Dynamic evaluation method of urban green growth level in Anhui province: a comprehensive analysis of 16 cities' panel data from 2013-2017

Junqi Zhu, *Li* Yang*, *Haotian* Zhen, *Shanshan* Li, *Jichao* Geng and *Getnet* Engeda

School of Economics and Management, Anhui University of Science and Technology, Huainan 232001, Anhui, China

Abstract. Considering that green growth development is an increasingly important environmental trend, this paper develops an urban green growth development index and applies it to Anhui Province in China and its 16 cities. Previously, such analyses have taken place mostly at the provincial level, and research on cities is relatively rare. To fill the gap, this paper constructs an urban green growth economy evaluation index based on economic technology, social development, ecological environment, and energy emissions. Using the vertical and horizontal pull-off method to comprehensively evaluate the green growth development levels of 16 cities in Anhui province from 2013 to 2017, the residual expectation coefficient is used to measure and analyze differences in the development levels. The results show that Hefei and Huangshan emit a medium-high level of carbon, and the other 14 cities belong in the high-carbon category. Furthermore, cluster analysis shows that the green growth development levels of the 16 cities fall into four groups. There is a wide disparity between the groups, and the differences between groups are significantly larger than the differences within groups.

1 INTRODUCTION

Green growth is becoming an important trend in the sustainable development of the global economy and society at large. To a significant extent, green growth and a low-carbon economy have important links. The low-carbon economy is a new economic form and development model for the comprehensive development of economic society and the ecological environment. It is guided by the science of sustainable development through technological and institutional innovation, the development of new energy sources, industrial transformation, and other means that will change energy consumption patterns and structures, improve energy efficiency, and minimize greenhouse gas emissions [1,2]. With the rapid development of China's economy since its economic reform, the rural population has migrated to cities, and urbanization has accelerated. In 2017, China's urbanization rate was 58.52%. By 2050, China's urbanization rate is predicted to reach 70% [3,4]. The high urbanization rate will increase energy consumption and emissions of carbon dioxide (CO2). According to Chinese government statistics, cities hold more than half of the world's population but consume 75% of the world's energy and generate 80% of the greenhouse gas emissions [5-6]. In this context, cities shoulder the responsibility of energy conservation and emissions reduction, which are essential to green growth.

Anhui province has abundant energy resources and a large population. The industrial structure is dominated by the second industry. The energy structure is dominated by coal. The recent accelerated increase in the economic development of Anhui has led to a continued increase in energy consumption, significantly raising greenhouse gas emissions. This has intensified the conflict between the environment and energy resources. Anhui should develop green growth economies for the cities to adjust the province's industrial structure, optimize its energy consumption structure, and develop a sustainable economy [7-9].

2 LITERATURE REVIEW

Since the British government published the Energy White Paper in 2003, the concept of green growth has emerged as a frequent topic of discussion among governments and scholars. In researching the development level of green growth, foreign scholars have paid more attention to policies, path choices, models, and carbon emission technologies [10-12]. For example, Kaya Yoichi proposed the KAYA model and Mahony extended the KAYA model, which states that population, energy consumption per unit of energy, energy intensity per unit of GDP, and per capita GDP will affect the carbon emissions of a region or country [13]; Kerkhof, from the perspective of household expenditure, Calculate household carbon dioxide in the Netherlands, Norway, Switzerland, and the United Kingdom in 2000 to identify factors affecting CO2

* Corresponding author: y321212@163.com

emissions within or between countries [14]. In China, scholars have tended to construct an evaluation system and use empirical methods for research [15-17]. The evaluation methods include the analytic hierarchy process, principal component, factor analysis, TOPSIS, and entropy weighting [18-20]. For example, Li Ziliang used a fuzzy analytic hierarchy to construct a comprehensive evaluation system including the overall level of carbon emission, system level of carbon emission, the control level of carbon emission, and an index level of carbon emission to evaluate the green growth in China [21]. Using principal component, factor analysis, and clustering methods, Zheng Shihua constructed and evaluated the provincial green growth development level and divided the development level of China's provincial green growth into four zones: low-carbon, significantly low-carbon, relatively high-carbon, and high-carbon [22]. Yuan Xiaoling constructed a regional green growth evaluation index system from the aspects of low carbon emissions and developmental capability. He applied the TOPSIS method to empirically analyze the 29 provinces and the eastern, central, and western regions of China [23]. Ma Jun considered the development status of the six provinces in the eastern coastal region. Linear weighting was used to calculate the comprehensive green growth value, and the Delphi method was used to determine the weights [24]. Zhang Xin and Wu Wenheng established an urban green growth evaluation index system from the dimensions of economy, society, technology, energy emissions, and the ecological environment, and used factor analysis to empirically study the development level of the green growth in 10 cities in Shaanxi province. The results show that these cities exhibit small- and medium-sized urban distribution patterns [25]. Zhu Xia and Lu Zhengnan implemented the DPSIR (Driving force-Pressure-State-Impact-Response) model and established a green growth evaluation index system with 27 indicators, applying the entropy weight and principal component projection methods to lower a comprehensive evaluation of the level of carbon economic development of the 13 prefecture-level cities in Jiangsu Province [26].

The above literature shows that evaluations of green growth development are mostly at the provincial level; research on cities and dynamic analyses are relatively rare, and most of the data are cross-sectional. Therefore, to fill this gap in the literature, this article dynamically analyzes cities.

3 RESEARCH DESIGN

3.1 Indicator selection

Based on the above principles and systemic ideas for constructing green growth in cities, relevant domestic and foreign indicators are compounded, and the urban green growth evaluation index system is constructed in accordance with the actual situation of 16 cities in Anhui. There are four primary indicators: economic and technological, social development, energy emissions, and ecological environment. Apart from these, there are 17 secondary indicators. See Table 1 for details.

Table 1. Urban green growth development level evaluation index system

Primary indicators	Secondary indicators	Unit	Nature of the indicator
Economic and technological	GDP per capita (y1)	Yuan	Positive [a]
	Tertiary industry proportion of GDP (y2)	%	Positive
	Annual per capita disposable income of urban residents (y3)	Yuan	Positive
	R&D expenditure as a percentage of GDP (y4)	%	Positive
	The comprehensive utilization rate of industrial solid waste (y5)	%	Positive
Social development	Urbanization rate (y6)	%	Positive
	Number of public transport vehicles per 10,000 people (y7)	Number	Negative [b]
	Consumer price index (y8)	%	Positive
	Urban registered unemployment rate (y9)	%	Negative
Ecological environment	Forest coverage (y10)	%	Positive
	Green coverage rate in built-up area (y11)	%	Positive
	Per capita park green area (y12)	Square meter	Positive
	Harmless treatment rate of municipal solid waste (y13)	%	Positive
	Urban sewage treatment rate (y14)	%	Positive
Energy emissions	Unit GDP energy consumption (y15)	Tons of standard coal/10,000 yuan	Negative
	Industrial soot emissions per unit of GDP (y16)	Tons / 100 million yuan	Negative
	Industrial SO2 emissions per unit of GDP (y17)	Tons / 100 million yuan	Negative

[a] Positive indicators are that represent upward or forward development and growth. The larger the value of these indicators, the better the evaluation. The positive indicator is also called the benefit indicator or the large indicator.
[b] For negative indicators, smaller values indicate better evaluations.

3.2 Research method

3.2.1 Vertical and horizontal pull-off method

The vertical and horizontal pull-off method[27-29] is a comprehensive evaluation method for determining index weights based on time-series data tables. Assume n pairs of evaluation objects $S_1,S_2,...,S_n$ and m evaluation indicators $x_1, x_2,...,x_m$ in chronological order $t_1, t_2,..., t_N$ form the original data $\{x_{ij}(t_k)\}$, thus generating a time-series data table. Vertical and horizontal to the open class method was chosen as the evaluation method is simple in principle, have clear intuitive meaning and geometric meaning, and is more suitable for dynamic comprehensive evaluation problem, this method can both in transverse moment t_k ($k = 1,2, ..., N$) the differences between each system, and can reflect the overall distribution of each system on the longitudinal, and both for cross section data, or for sequential solid data, the comprehensive evaluation results are comparable, and is not influenced by subjective factors.

Without loss of generality, the original data here are consistent with dimensionless processing indicators, that is, the evaluation indicators in the original data $x_1, x_2,...,x_m$. After the indicator type is consistently processed, it is a very large indicator. The series $\{x_{ij}(t_k)\}$,is standard data after dimensionless processing.

For time $t_k\ (k = 1,2, ..., N)$, the comprehensive evaluation function is:

$$y_i(t_k) = \sum_{j=1}^{m} w_j\, x_{ij}(t_k),$$

$$k = 1,2, ..., N; i = 1,2, ..., n \quad (1)$$

The principle of determining the weight w_j is to maximize the difference between the evaluation objects in the time-series data table. The difference $y_i(t_k)$ can be expressed by the sum of the squares of the total deviations:

$$\delta^2 = \sum_{k=1}^{N}\sum_{i=1}^{m} (y_i(t_k) - y)^2 \quad (2)$$

Since the raw data is standardized,

$$\overline{y} = \frac{1}{N}\sum_{k=1}^{N} (\frac{1}{n}\sum_{n=1}^{n}\sum_{j=1}^{m} w_j\, x_{ij}(t_k)) = 0 \quad (3)$$

Thus,

$$\delta^2 = \sum_{k=1}^{N}\sum_{i=1}^{n} (y_i(t_k) - \overline{y})^2 = \sum_{k=1}^{N}\sum_{i=1}^{n} (y_i(t_k))^2 = \sum_{k=1}^{N} [w^t H_k^w] = w^t \sum_{k=1}^{N} H_k^w = w^t H_w \quad (4)$$

Where $w = (w_1, w_2, ..., w_m)^T$; $H = \sum_{k=1}^{N} H_k$ are $m \times m$ order symmetric matrices;

$H_k = A_k^T A_k\ (k = 1,2, ..., N)$, and

$$A_k = \begin{bmatrix} x_{11}(t_k) & \cdots & x_{1m}(t_k) \\ \vdots & \ddots & \vdots \\ x_{n1}(t_k) & \cdots & x_{nm}(t_k) \end{bmatrix}, \quad (k = 1,2, ..., N).$$

If $w^T w = 1$, when w is the eigenvector corresponding to the largest eigenvalue $H_k = \lambda_{max}\ (H)$, of the matrix H, δ^2 takes the maximum value, and $max\ w^T H_w = \lambda_{max}\ (H)$.

If $H_k > 0$, it must be that H >0, and there is a positive (normalized) weight coefficient vector w.

If one of the components w sought is negative, w can be found by the following planning problem. Choose w to make $max\ w^T H_w$.

$$s.t. \|w\| = 1, w > 0 \quad (5)$$

3.2.2 Requirement coefficient

The residual expectation coefficient[30] is a new indicator reflecting the degree of regional disparity. It overcomes the shortcomings of the Searle index and can compare data of different regions at different times while retaining the decomposability of the Xaar index.

Assume that the probability of an occurrence of event A is $P(A)=P$. It is generally believed that the lower the probability of occurrence of an event, the greater is the amount of information generated. Therefore, the amount of information generated from event A occurring is defined as $\log(1/p)$. If there are n events with probabilities of occurrence $P_1, P_2,..., P_n$, the corresponding expected information is calculated as:

$$E = \sum_{i=1}^{N} p_i \log(1/p) \quad (6)$$

The closer the values of the probabilities $P_1,P_2,...,P_n$, the greater the value of E. If $P_1 = P_2 = ... = P_n = 1/n$, then $E(max) = \log(n)$. Define the residual expectation coefficient:

$$u = 1 - \sum p_i \log(1/p_i)/\log(n) = 1 + \sum p_i \log(p_i)/\log(n) \quad (7)$$

According to the principle of decomposition of the Xaar index, the overall difference is divided into the differences between the parts and within the parts, and the difference within each part is equal to the weighted sum of the differences within each part.

$$u_T = u_G + u_W = u_G + \sum f_i\, u_i \quad (8)$$

4 EMPIRICAL RESEARCH

4.1 Data collection and processing

The indicator data studied in this paper are sourced mainly from the statistical yearbooks and bulletins of Anhui and the 16 cities from 2013 to 2017. Some data are calculated, such as R&D expenditure as a percentage of GDP, industrial output, soot emissions, and industrial SO2 emissions per unit of GDP. Due to the different dimensions and magnitudes of each evaluation index, there is incommensurability, and the indicators need to be standardized.

Positive indicator:

$$x_{ij}^* = x_{ij} - min\{x_j\}/max\{x_j\} - min\{x_j\} \quad (9)$$

Negative indicator:

$$x_{ij}^{*} = max\{x_j\} - x_{ij}/max\{x_j\} - min\{x_j\} \quad (10)$$

4.2 Calculation and analysis

According to the steps of the vertical and horizontal pull-off method, the symmetric matrix $H_k = A_k^T A_k \ (k = 1,2,3,4,5)$ and $H = \sum_{k=1}^{N} H_k \ (k = 1,2,\ldots,N)$ are calculated with Matlab7.0 software. The maximum eigenvalue $\lambda_{max} = 412.8230$ and its corresponding eigenvector of the 17-dimensional feature vector H (after normalization) is w^T = (0.0405, 0.0440, 0.0347, 0.0472, 0.0738, 0.0524, 0.0457, 0.0321, 0.0627, 0.0406, 0.1019, 0.0636, 0.758, 0.0452, 0.0815, 0.0805, 0.0777).

Substituting the calculated weight coefficient in formula (2), the comprehensive scores of green growth development levels of the 16 cities are obtained. The results are shown in Table 2.

Table 2. Comprehensive scores and rankings of green growth development levels in 16 cities in Anhui province from 2013 to 2017

City	2013		2014		2015		2016		2017	
	Score	Ranking	Score	Ranking	Score	Ranking	Score	Ranking	Score	Ranking
Hefei	0.734	1	0.747	1	0.783	1	0.773	1	0.718	2
Wuhu	0.570	5	0.509	11	0.614	6	0.625	4	0.581	9
Bengbu	0.631	3	0.659	3	0.661	2	0.683	3	0.650	4
Huainan	0.504	12	0.449	14	0.399	16	0.461	16	0.473	16
Maanshan	0.482	15	0.408	16	0.545	13	0.599	6	0.537	14
Huaibei	0.524	8	0.539	7	0.547	12	0.558	12	0.612	5
Tongling	0.558	7	0.554	5	0.564	10	0.625	5	0.481	15
Anqing	0.520	10	0.443	15	0.579	8	0.583	10	0.570	10
Huangshan	0.725	2	0.708	2	0.660	3	0.695	2	0.719	1
Fuyang	0.434	16	0.548	6	0.551	11	0.519	14	0.557	12
Suzhou	0.486	14	0.533	8	0.564	9	0.597	7	0.610	6
Chuzhou	0.513	11	0.504	12	0.533	15	0.515	15	0.537	13
Lu'an	0.522	9	0.484	13	0.534	14	0.561	11	0.678	3
Xuancheng	0.500	13	0.532	9	0.597	7	0.587	8	0.586	7
Chizhou	0.568	6	0.530	10	0.626	4	0.585	9	0.586	8
Bozhou	0.628	4	0.571	4	0.618	5	0.556	13	0.563	11

The green growth evaluation rating standards are shown in Table 3. Refer to the domestic and international literature on green growth evaluation grade standards for more details [18, 24, 31-35].

Table 3. Urban green growth development levels

Green growth development level comprehensive score	Class
Above 1.165	Low carbon
1.0—1.165	Medium to a low carbon
0.875—1	Medium carbon
0.675—0.875	Medium to high carbon
0.42—0.675	High carbon
Below 0.42	Ultra-high carbon

According to Tables 2 and 3, the development level of the green growth in Hefei and Huangshan in 2013-2017 is comprehensive. The scores are all above 0.675, but none exceed 0.875, which corresponds to medium-high carbon emissions. The other 14 cities exhibit green growth development within the range of 0.42-0.675 in these five years, and, thus, they are all classified as high-carbon.

For further analysis, the scores of the green growth development level of the 16 cities in 2013-2017 are used as clustering variables, and system clustering analysis is conducted using SPASS22.0 software. System cluster strategy is to each object as a cluster, and then merge these atomic clusters for more and more variety, until all objects in a cluster, or an end conditions are met. The clustering method is easy to define the similarity of distance and rules, and has few restrictions. There is no need to specify the cluster number in advance; in addition, the hierarchical relationship of the classes can be visually demonstrated through the pedigree chart. The 16 cities can be divided into four groups, as shown in Figure 1.

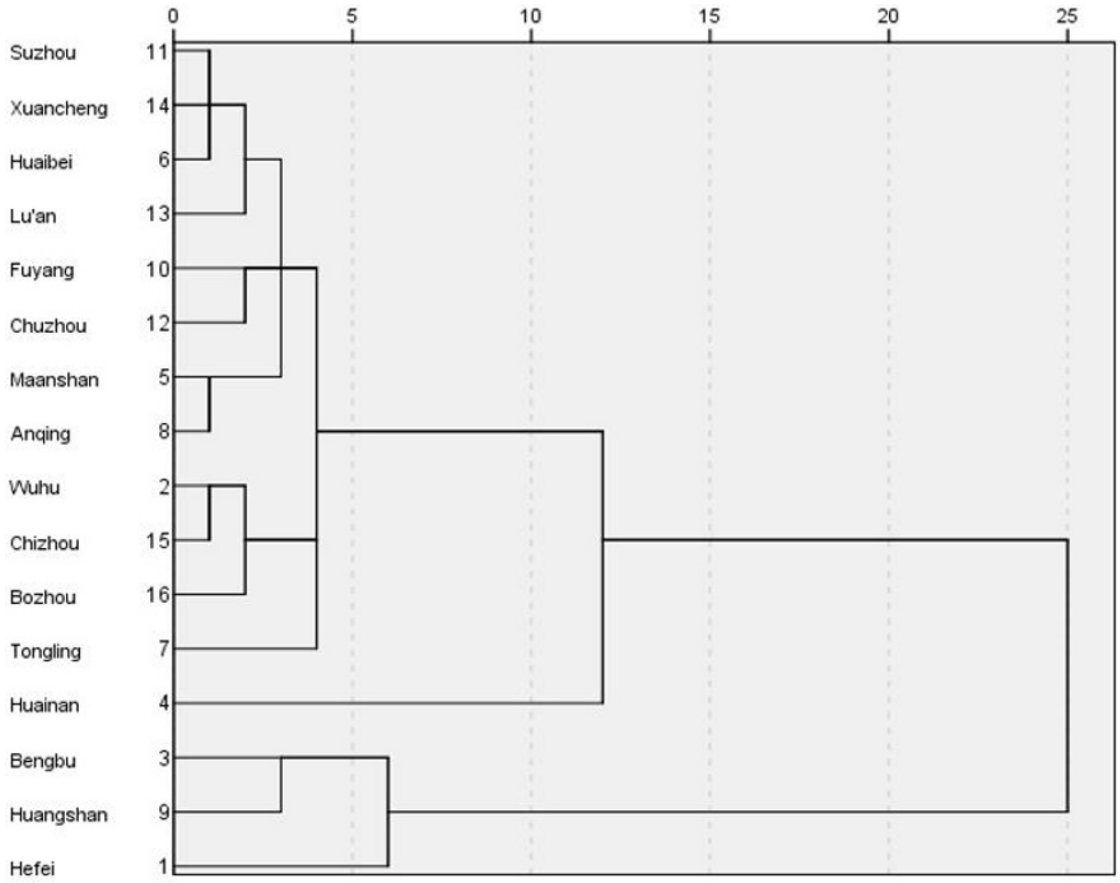

Figure 1. Tree analysis of the green growth development level in 16 cities in Anhui province

The first group of cities – high-carbon cities with a high level of green growth development – represents Hefei, Huangshan, and Bengbu. The development of the green growth in Hefei and Huangshan ranked first, second or third in each of these five years, and the low-carbon development level is greater than 0.65. Hefei is the capital of Anhui, with a developed economy, highly ranked colleges and universities, and advanced technology. Most of the indicators are developing well, and the low-carbon development level is high. Forest resources in Huangshan are abundant, tourism and tertiary industries are developed, carbon emissions are the low, and ecological environment and energy emission indicator values have remained strong. At the same time, the ecological environment indicators and energy emission indicators of Bengbu are developing very well.

The second group of cities have a moderately high level of green growth development. The specific cities are Bozhou, Wuhu, Tongling, and Chizhou. Their low-carbon economies rank between 4 and 10, and their green growth scores are around 0.56. Some of the green growth indicators in these cities are too low, such as the forest coverage rate and the green area of per capita parks of Wuhu; the proportion of R&D expenditures in Bozhou and Chizhou; and the proportion of Tongling's tertiary industry in GDP.

The third group of cities – Huaibei, Xuancheng, Suzhou and Lu'an–exhibit a moderately low level of green growth development. Green growth rankings are relatively low, with levels in the middle and lower ranges. The green growth indicators of these five cities are uneven, most of the indicators are low, and they only trend well in one dimension.

The fourth group of cities – Chuzhou, Fuyang, Huainan, Anqing and Maanshan – exhibit a low level of green growth development, and have done so historically. The economy and technology of these cities are underdeveloped except for Maanshan, and they are below average in economic technology, social development, ecological environment, and energy emissions. There is a sizeable disparity between this group and the other three groups and Maanshan's energy emission indicators have been at the bottom in these five years.

4.3 Calculation and analysis of the differences in the development levels of green growth economies

The residual expectation coefficient is an index describing the difference and mutual relationship between the two levels of urban green growth economies. Based on the above classification results, this paper compares the differences in the development levels of urban green growth economies from the differences between and within groups.

We define the differences between groups u_G and the differences within the groups u_W according to equations (7) and (8). The results are shown in Table 4.

Table 4. Urban green growth development level residual expectation coefficient (2013–2017)

Years	Overall difference	Difference between groups (u_G)	U1	U2	U3	U4	Difference within groups (u_W)
2013	0.00321	0.00213	0.00207	0.00080	0.00035	0.00127	0.00108
2014	0.00359	0.00180	0.00119	0.00068	0.00066	0.00341	0.00179
2015	0.00498	0.00235	0.00303	0.00059	0.00064	0.00481	0.00263
2016	0.00384	0.00231	0.00139	0.00086	0.00030	0.00273	0.00153
2017	0.00473	0.00340	0.00099	0.00217	0.00108	0.00123	0.00133

From the overall difference, we see that the gap between the development levels of green growth in various cities and towns in 2013-2017 has basically maintained an upward trend, and the extent of the increase is accordingly expanding. This shows that the gap between the green growth development levels of various cities and towns is expanding as a whole.

From the differences between and within groups, we observe that change basically maintained in a small fluctuation range before rebounding sharply in 2017. From the perspective of intra-group differences, the trend of change is basically the opposite of the difference between groups, rising until 2016 before beginning to decline. Again, from the data in Table 3, there is a certain gap between groups and within groups. The differences between groups are almost greater than the differences within groups from 2013 to 2017. The impact of differences between groups also indicates that the total difference in the development levels of green growth economies in different cities is caused mainly by differences between groups. In the future, exchanges, learning, and cooperation should be strengthened between cities at various levels.

5 CONCLUSIONS AND SUGGESTIONS

5.1 Conclusions

Based on the relevant literature and the actual situation of each city, this research constructs an evaluation index of urban green growth development levels. Using the vertical and horizontal pull-off method to comprehensively evaluate the green growth development levels of 16 cities in Anhui province from 2013 to 2017, the residual expectation coefficient is used to measure and analyze differences in the development levels.

The results show that of the 16 cities in Anhui, the green growth development level of Hefei and Huangshan from 2013 to 2017 is characterized as medium-high carbon, and the other 14 cities belong in the high-carbon category. Furthermore, the green growth development levels of the 16 cities are clustered into four groups. From the overall difference, the disparity between the green growth development levels of the 16 cities from 2013 to 2017 was expanding. There is a wide disparity between the groups, and the differences between groups are significantly larger than the differences within the groups.

5.2 Suggestions

The industrial structures and economic development models of the 14 cities that emit high levels of carbon should be revised to promote the transition to green growth. Considering the challenges cities and towns face, they should adjust and optimize the industrial structure, promote technological innovation, and adopt a new model of economic development.

Targeted strategies should be adopted according to local conditions. The cities with a less developed green growth economy should improve the income guarantee and welfare system, and develop new energy sources and a green circular economy. The strategies for the third and fourth groups of cities should help them form the characteristics of the urban industrial structure while increasing investment in environmental protection and improving environmental quality.

The relevant decision-makers in these cities should broaden the opportunities for green growth exchanges. Various cities in Anhui can conduct symposiums and seminars and host expert field visits on the development of the green growth economy; exchange experiences and lessons from developing the green growth in all levels of cities; and promote the green growth in all levels of Anhui. The disparity in development levels indicates the need for common development.

Cities should establish and improve a green growth system. The economic system may be one of the most important factors as Anhui develops green growth, such as with the establishment of a carbon emission restraint mechanism, the construction of a green growth energy technology development mechanism, and the improvement of the taxation system and laws related to the development of the green growth.

6 CONTRIBUTIONS AND LIMITATIONS

With green growth development is increasingly important considering recent environmental trends, This study develops an urban green growth development index and applies it to Anhui Province in China and its 16 cities. Previously, such analyses have taken place mostly at the provincial level, few studies investigate the dynamic nature of such indices, and research on cities is relatively rare. At the same time, considering

the imbalance of regional development, there may be some inadequate explanations of some issues. Future research needs to further consider the uncertainties existing in the calculation process, such as the uncertainty of weight, the uncertainty of normalized treatment, the uncertainty of clustering method, etc., and build more detailed aspects of the model to cover further aspects of issues associated with green growth.

ACKNOWLEDGMENTS

This article was supported by the National Natural Science Foundation of China (No. 71971003), the Major of National Social Science Foundation of China(20ZDA084), the Program of Humanities and Social Sciences in Colleges and Universities of Anhui Province, China (No. SK2020A0209), the MOE (Ministry of Education in China) Project of Humanities and Social Sciences (No. 19YJCZH037), Key Research Fund for Young Teachers of Anhui University of Science and Technology (No. QNSK201801).

REFERENCES

[1] Song, M., Fisher, R., & Kwoh, Y. 2019. Technological challenges of green innovation and sustainable resource management with large scale data. *Technological Forecasting and Social Change*, **144**, 361-368.

[2] Chen, J., Xu, C., Cui, L., Huang, S. & Song, M. 2019. Driving factors of CO2 emissions and inequality characteristics in China: A combined decomposition approach. *Energy Economics*, **78**, 589-597.

[3] Schroeder, P. M., and R. B. Chapman.2014. Renewable energy leapfrogging in China's urban development? current status and outlook. *Sustainable Cities and Society*. **11**, 31-39. doi: 10.1016/j.scs.2013.11.007.

[4] Song, M., Zhu, S., Wang, J., & Zhao, J. 2020. Share green growth: Regional evaluation of green output performance in China. *International Journal of Production Economics*, **219**, 152-163.

[5] Zeng, S., and J. Chen. 2016. Forecasting the Allocation Ratio of Carbon Emission Allowance Currency for 2020 and 2030 in China. *Sustainability*. **8** (7), 650. doi: 10.3390/su8070650

[6] Jin, P., Peng, C., & Song, M. 2019. Macroeconomic uncertainty, high-level innovation, and urban green development performance in China. *China Economic Review*, **55**, 1-18.

[7] Yang, J., J. Wu, T. He, L. Li, D. Han, and Z. Wang.2016. Energy gases and related carbon emissions in China. *Resources, Conservation & Recycling*. **113**, 140-148. doi: 10.1016/j.resconrec.2016.06.016.

[8] Yang, L., K. Wang, and J. Geng. 2018. China's regional ecological energy efficiency and energy saving and pollution abatement potentials: an empirical analysis using epsilon-based measure model. *Journal of Cleaner Production*, **194**, 300-308. doi: 10.1016/j.jclepro.2018.05.129.

[9] Song, M., Zhu, S., Wang, J., & Wang, S. 2019. China's natural resources balance sheet from the perspective of government oversight: Based on the analysis of governance and accounting attributes. *Journal of environmental management*, **248**, 109232.

[10] Cassen, C., M. Hamdi-Cherif, G. Cotella, J. Toniolo, P. Lombardi, and JC. Hourcade. 2018. Low Carbon Scenarios for Europe: An Evaluation of Upscaling Low Carbon Experiments. *Sustainability*. **10** (3), 848. doi: 10.3390/su10030848.

[11] Deakin, M., and A. Reid. 2018. Smart cities: Under-gridding the sustainability of city-districts as energy efficient-low carbon zones. *Journal of Cleaner Production*. **173**, 39-48. doi: 10.1016/j.jclepro.2016.12.054.

[12] Uchida, K., M. Fujii, S. Ashina, S. Maki, T. Hanya, K. Aizawa and T. Fujita. 2017. Field Trial toward Low-carbon Society in Indonesia. *Fujitsu Scientific & Technical Journal*. **53**(3), 62-72.

[13] Mahony, T. O. 2013. Decomposition of Ireland's carbon emissions from 1990 to 2010: an extended KaYa identity. *Energy Policy*. **59**(4-5), 573-581. doi: 10.1016/j.enpol.2013.04.013.

[14] Kerkhof, A.C., M. René, J. Benders, and H. C.Moll. 2009. Determinants of variation in household CO2 emissions between and within countries. *Energy Policy*. **37** (4), 1509-1517. doi: 10.1016/j.enpol.2008.12.013.

[15] Shi, B., H. Yang, J. Wang, and J. Zhao. 2016. City Green Economy Evaluation: Empirical Evidence from 15 Sub-Provincial Cities in China. *Sustainability*. **8** (6), 551. doi: 10.3390/su8060551.

[16] Sun, L., H. Li, L. Dong, K. Fang, J. Ren, and Y. Geng. 2017. Eco-benefits assessment on urban industrial symbiosis based on material flows analysis and energy evaluation approach: a case of Liuzhou city, China. *Resources, Conservation & Recycling*. **119**, 78-88. doi: 10.1016/j.resconrec.2016.06.007.

[17] Yang, X., R. Li. 2018. Investigating Low-Carbon City: Empirical Study of Shanghai. *Sustainability*. **10**(4),1054. doi: 10.3390/su10041054.

[18] Su, M., C. Liang, B. Chen, S. Chen, and Z. Yang. 2012. Low-Carbon Development Patterns: Observations of Typical Chinese Cities. *Energies*. **5**(2) 291-304. doi: 10.3390/en5020291.

[19] Xie, Z., X. Gao, J. He, and C. Feng. 2016. Evaluating rural low-carbon communities: a study of Guangdong province, China. *Energy & Buildings*, **133**, 777-789. doi: 10.1016/j.enbuild.2016.10.042

[20] Jin, X.. 2017. Low carbon city construction planning for the needs of residents. *Agro Food Industry Hi-Tech*. **28**(1), 2472-2476.

[21] Li, S., and X. Shi. 2012. Study on the Construction of low-carbon economy composite evaluation in Sichuan province. *Science and Technology Management Research*. **32**(21), 61-65. doi: 10.3969/j.issn.1000-7695.2012.21.014.

[22] Zheng, S. 2013. Construction and Empirical Study on Evaluation Index System of Provincial Low Carbon Economy Development. *Urban Problems*. **11**, 61-66 (In Chinese).

[23] Yuan, X., L. Lei, and Y. Zhong. 2013. Construction and Empirical Analysis of Low Carbon Economy Evaluation Index System. *Urban Problems*. **1**, 56-61 (In Chinese).

[24] Ma, J., L. Zhou, and W. Li. 2010. Indicator System Construction for Urban Low Carbon Economy Development. *Science & Technology Progress and Policy*. **27** (22) 165-167. doi: 10.3969/j.issn.1001-7348.2010.22.039.

[25] Zhang, X., and W. Wu. 2017. Comprehensive Evaluation and Coordination Degree of Urban Low-carbon Economy Development Level—Taking Shaanxi Province as an Example. *Development Research*. 38-43 (In Chinese).

[26] Zhu, X., and Z. Lu. 2013. Evaluation on the Low-carbon City Development based on DPSIR Model—The Case of Jiangsu Province. *Journal of Technical Economics & Management*. **1**, 115-118. doi: 10.3969/j.issn.1004-292X.2013.01.027.

[27] Glatzmaier, J., H. Wehrbein, and P. Diedrich. 1995. Die entwicklung eines resorbierbaren implantatsystems zur orthodontischen verankerung. *Das BIOS-Implantatsystem. Fortschritte Der Kieferorthopädie*, **56**(3), 175-181. doi:10.1007/BF02276634.

[28] Elżbieta Horszczaruk, and P. Brzozowski. 2014. Bond strength of underwater repair concretes under hydrostatic pressure. *Construction & Building Materials*, **72**(72), 167-173. doi: 10.1016/j.conbuildmat.2014.08.020.

[29] Lu, X. 2014. Evaluation of China's Provincial Resources and Environment Carrying Capacity and Spatial Statistical Analysis. *Statistics & Decision*. **7**, 116-120 (In Chinese).

[30] Shang, W..2004.A new indicator reflecting the degree of income difference—the residual expectation coefficient. *Statistical Research*. **1**, 35-37. doi:10.3969/j.issn.1002-4565.2004.01.008 (In Chinese).

[31] Wang, Z., F. Yin, Y. Zhang, and X. Zhang. 2012. An empirical research on the influencing factors of regional CO2 emissions: evidence from Beijing city, China. *Applied Energy*. **100**(4), 277-284. doi: 10.1016/j.apenergy.2012.05.038.

[32] .Liming, Y., X. Jiuping, and L. Yifan. 2014. Evaluation of the efficiency of low carbon industrialization in cultural and natural heritage: taking Leshan as an example. *Sustainability*. **6**(6), 3825-3842. doi: 10.3390/su6063825.

[33] Liu, G., Y. Hao, Y. Zhou, Z. Yang, and M. Su. 2016. China's low-carbon industrial transformation assessment based on logarithmic mean divisia index model. *Resources, Conservation and Recycling*. **108**, 156-170. doi: 10.1016/j.resconrec.2016.02.002.

[34] Yang, L., J. Wang, and J. Shi. 2016. Can China meet its 2020 economic growth and carbon emissions reduction targets? *Journal of Cleaner Production*. **142**, 993-1001. doi: 10.1016/j.jclepro.2016.08.018.

[35] de Koning, A., G. Huppes, B. Sprecher, G. van Engelen, and A. Tucker. 2018. Metal supply constraints for a low-carbon economy? *Resources, Conservation & Recycling*. **129**, 202-208. doi: 10.1016/j.resconrec.2017.10.040.