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Total factor productivity of land urbanization under carbon emission constraints: a case study of Chengyu urban agglomeration in China

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ABSTRACT

In consideration of energy and environmental inefficiency brought about by urban construction, sustainable urbanization has become a hot issue in recent years. In the process of land urbanization, the source of economic growth can be attributed to technical progress and efficiency improvement. To explore the driving factors of land urbanization efficiency and its dynamic changes, the total factor productivity (TFP) and its components of land urbanization was introduced. The spatial-temporal variations of land urbanization of Chengyu urban agglomeration in Western China were estimated by using the Malmquist-Luenberger (ML) productivity index with undesirable output in this study. Results demonstrate that: (1) the average TFP of land urbanization (LUTFP) of Chengyu urban agglomeration in China over time with carbon emissions (1.029) is 1.2 percent lower than that without carbon emissions (1.041). Furthermore, the LUTFP with CO_2 emissions is lower than the LUTFP without CO_2, demonstrating that land urbanization generates social and economic benefits at the cost of resource consumption. (2) LUTFP of Chengyu urban agglomeration under carbon emission constraints presents a generally rising trend in the past ten years and technical progress is the major source of such growth. Efficiency has become a major barrier against the improvement of productivity. (3) LUTFP indexes in Chongqing City and Chengdu plain economic region are generally higher than those of the south and northeast Sichuan economic zones. However, LUTFP of different cities tends to be in equilibrium gradually.

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1. Introduction

Urbanization is an important driving force to the human civilization development and progress. Land urbanization is the carrier of urban development. Urbanization can produce positive effects with coordinated development between economy and

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society. But threats can be brought about if urban land spreading and expanding disorderly, and occupying farmland resources continuously.

Many countries in the world have suffered excessive suburbanization which causes considerable resource waste and ecological damage. For example, the American government proposed the philosophy of 'smart growth' that emphasized the intensive development of land utilization (Daniels, 2000). The disordered development and mismatching of land urbanization not only cause loss of economic efficiency (Zhang & Yu, 2019), but also brings environmental stress, thus influencing economic development quality. China's urbanization highlighted many 'city diseases' while achieving remarkable successes, such as fast expansion of urban scale, relatively high housing price, traffic jam, environmental pollution, etc. Hence, attention should be given to a transformation from the land urbanization characterized by the expansion of industrial development zone depending on land finance to 'urbanization of people'.

Besides, land urbanization carries social and economic activities, causing intensification carbon emission effect. In 2018, China's carbon emissions have reached 0.95 billion tons and 85 percent of the net growth of global carbon emissions were produced in China, India and America (IEA, 2019). In 2019, the Intergovernmental Panel on Climate Change (IPCC) emphasized the connection between land use and carbon emissions in the special report of '*Climate Change and Land*' (Bianco, 2020). Some studies demonstrated that land use and cover influenced the carbon emission pattern in a region and even the whole world. Since the industrial revolution, the global carbon emissions caused by land cover changes reached 177 Pg (Yang et al., 2019) and the built-up regions are one of the major carbon emission sources in urban areas. At present, countries that produce about 70% of global carbon emissions have promised to realize the goal of net zero emission by 2050 (IEA, 2021). Hence, efficient land utilization is not only the key to urban spatial development and improvement of land urbanization efficiency, but also the core content of city's low-carbon economic and sustainable development. Regular monitoring and measurement of energy environmental efficiency can provide benchmark for policies concerning carbon emission improvement and references for policy formulation (Kocijel et al., 2020; Tachega et al., 2021).

Studies on total factor productivity (TFP) from the perspective of land urbanization are important. When land utilization participates in the urban social and economic production activities, the fundamental driving force of economic growth can be divided into two parts: production efficiency and technical progress. The contributions of this study are introduced as follows. The spatial-temporal evolutions of land urbanization TFP are discussed in consideration of the carbon emission constraints of cities in Chengyu urban agglomeration in China. Research conclusions will recognize the contributions of technologies, management, institutions, and other intangible production factors to urban development during the process of land urbanization.

The reminder of this study is organized as follows. In Sec. 2, a detailed review of the literatures on land urbanization and TFP is provided. In Sec. 3, the research methods of Malmquist-Luenberger index based on DDF are introduced. Moreover, the data sources and index system are demonstrated. In Sec. 4, empirical results and spatial-temporal variations of land urbanization TFP in Chengyu agglomeration are analyzed. In Secs. 5 and 6, an integrated discussion is developed, followed by the conclusions and the future research prospects.

2. Literature review

2.1. International context of land urbanization

Land urbanization is a process that land utilization transforms from the rural land pattern to the urban land pattern (Zhang et al., 2020). Studies have systematically analyzed land urbanization issues, finding that the spatial distribution of land urbanization is far from an equilibrium state, and the 'discoordination and hysteresis' of population urbanization along with land expansion. Fast land urbanization brings changes in land utilization and cover, accompanied with reductions of open space, forest vegetation, water area and farmland (Jain et al., 2021), and loss of cultivated lands as well as increase of urban buildings like houses and infrastructures (Doan et al., 2019). Land expansion has been a major path for urbanization in China for a long period. Many scholars found that land urbanization and carbon emissions presented in an inverted U-shaped trend (Dong et al., 2018; Zhou et al., 2021), and green economy can promote economic and social benefits (Ntsama et al., 2021). Land urbanization is one of the major causes of increased carbon emission. On the contrary, it is demonstrated that high-level urbanization in developed countries can promote reduction of carbon emissions by intensive land use arrangement and residents' low-carbon consumption (Muñoz et al., 2020).

2.2. Measurement of land utilization performance

Several studies characterized urban land use efficiency with some simple indexes, such as per capital construction land area, the ratio between total output value and urban land area (Wu, Wei, et al, 2017), the ratio between urban construction area and permanent population (Masini et al., 2019), etc. Given such basis, an empirical analysis of influencing factors of urban land utilization was applied. Koroso et al. (2020) believed that if the speed of urban expansion is quicker than urban population growth with a low density of construction areas, the urban land utilization is inefficient. With the increasing attention of climatic change, sustainable development, and urban ecological quality, many scholars have focused on land use performance under the constraints of resources and CO_2 emissions.

Studies on land use efficiency with carbon emissions mainly focused on the following aspects: (1) estimating land use efficiency by using carbon emission as an undesirable output (Kuang et al., 2020). (2) measuring the efficiency of different land use types or land use structure (Yang et al., 2020). (3) measuring the efficiency of rural–urban land conversion (Han et al., 2017; Huang et al., 2018). Earlier studies focused on the land use performance in a country, province, or city, while recently the trends turn to city clusters or economic circles (Yu et al., 2019; Zhao et al., 2018). Based on the literature review above, analyzing urban land use efficiency by applying DEA method is significant.

2.3. Total factor productivity of land urbanization

Frontier models are mainly used for estimating total factor productivity (TFP) (Del Gatto et al., 2011). Stochastic frontier analysis (SFA) accounts for noise and measurement errors, but requires setting the functional form of frontier and parametric assumption of the model (Coelli et al., 2005). As a non-parametric approach, DEA does not require a specific functional form in advance and can deal with multiple inputs and outputs, making it relatively flexible (Jiang et al., 2021). However, DEA method works well in comparing the relative efficiency of each DMU at a particular time, but fails in reflecting the dynamic changes in efficiency (Guo et al., 2009). The Malmquist productivity index is used to describe the dynamic variations and main determinants of resource utilization efficiency. Chung et al. (1997) extended this index by containing undesirable output into production activities so that can use the direction distance function (DDF) to distinguish between desired and undesired outputs. When assessing the environment or energy performance it makes sense to take undesired outputs into consideration. The first typical method is treating bad outputs as inputs and increasing desirable outputs (Rashidi & Saen, 2015; Zhang et al., 2008). However, it contradicts the real production process (Färe et al., 1989). Another popular method treats the undesirable outputs in the non-linear model based on the assumption that undesirable output is weakly disposable (Halkos & Petrou, 2019). Intense research has been focused on DDF for its advantage that aiming at maximizing desirable outputs and minimizing undesirable outputs simultaneously (Du et al., 2018; Wang, 2019).

Traditional studies on TFP ignored environmental changes caused by development (undesirable output). However, resource environment becomes a practical problem that needs to be considered (Benlemlih & Cai, 2020; Li & Chen, 2021). In this study, dynamic productivity changes of land urbanization are measured among different cities in a city cluster to evaluate the performance of sustainable land utilization. Based on previous studies concerning economic efficiency, this study gives more emphasis on the green development by using carbon emission as the undesirable output during land urbanization. Malmquist-Luenberger productivity index is used to analyze the temporal evolution during several periods and disaggregate the driving force of changes in productivity. Similar studies are mainly conducted at the national and provincial level due to the absence of CO_2 emission data at the municipal level. The aim is to enrich the studies about spatial-temporal evolution of land urbanization performance in urban agglomerations under carbon emission constraints.

3. Methodology

3.1. Measurement model for LUTFP

In this study, the total factor productivity of land urbanization (LUTFP), which identifies contributions of intangible production factors (e.g., technology, management, and system) to urban economic and social benefit growths through expansion of land resources were discussed (Huang et al., 2018). Such growths include growths caused by management improvement, organizational optimization, technical and production innovation. LUTFP estimated by the Malmquist-Luenberger (ML) productivity index also considers the undesirable growth of carbon emission while measuring the economic and social output growths in a region, hence reflecting a more reliable ranking of urban development benefits.

3.1.1. Land urbanization environmental technology

According to the environmental technology idea proposed by Färe & Grosskopf (2004), the production process of multiple outputs is called as the 'multi-output production technology'. Production technology follows several assumptions, including weak disposability of undesirable outputs, free disposability of desirable outputs and 'null-joint' relationship between desirable outputs and undesirable outputs (Chung et al., 1997). Land urbanization environmental technology reflects a set of all production possibility, in which inputs can produce desired and undesired outputs under the constraint of carbon emissions.

Based on the output-oriented setting, the production possibility indicates that each DMU uses inputs vector $x = (x_1, x_2, \ldots, x_N \in R_N^+)$ can produce desirable output vector $y = (y_1, y_2, \ldots, y_M \in R_M^+)$ and undesirable output vector $b = (b_1, b_2, \ldots, b_I \in R_I^+)$. The environmental technology production possibility set is shown in Eq. (1):

$$P^t(x^t) = \left\{ \left(y^t, b^t\right) : x^t \text{ can produce } \left(y^t, b^t\right), x^t \in R_N^+, t = 1, 2, 3 \ldots, T \right\} \tag{1}$$

3.1.2. Directional distance function

The directional distance function can be used to seek for the largest feasible increase in desirable outputs which are compatible with the largest feasible reduction in undesirable outputs and can solve the efficiency evaluation problem that involves 'bad output'. By setting a direction variable $g = (g_y, -g_b)$, the desired output y and undesired output b can be adjusted from the opposite direction proportionally under the input x and the land urbanization environmental technology structure $P(x)$. In this case, DDF based on the output perspective can be defined as Eq. (2) (Färe & Grosskopf, 2000).

$$\overrightarrow{D}\left(x, y, b; g_y, -g_b\right) = \sup\left[\beta : \left(y + \beta g_y, b - \beta g_b\right) \in P(x)\right] \tag{2}$$

where β means the maximum proportion that the output vector (y,b) can scale along the direction vector g simultaneously. If $\beta \geq 0$ and the higher value of β, the longer distance from DMU to the production frontier.

3.1.3. ML productivity index based on DDF

According to Chung et al. (1997), the Malmquist-Luenberger productivity index is used to measure LUTFP of Chengyu urban agglomeration that uses carbon emissions as the undesirable output. TFP estimates the productivity of different DMUs according to their distances to the best production frontier. In this study, changes of TFP indicate that land urbanization productivity of cities moves toward or further away from the best practitioners. The ML productivity index, which examines the changes in efficiency between periods t and $t+1$ is shown in Eq. (3).

$$ML^{t,t+1} = \left[\frac{1+\overrightarrow{D^t}\left(x^t, y^t, b^t; y^t, -b^t\right)}{1+\overrightarrow{D^t}\left(x^{t+1}, y^{t+1}, b^{t+1}; y^{t+1}, -b^{t+1}\right)} \times \frac{1+\overrightarrow{D^{t+1}}\left(x^t, y^t, b^t; y^t, -b^t\right)}{1+\overrightarrow{D^{t+1}}\left(x^{t+1}, y^{t+1}, b^{t+1}; y^{t+1}, -b^{t+1}\right)}\right]^{\frac{1}{2}} \tag{3}$$

where $ML > 1$ implies increased efficiency productivity performance while $ML < 1$ implies decreased efficiency productivity performance, and $ML = 1$ signifies no change. ML index can be divided into technical efficiency change (*MLeffch*) and technical change (*MLtech*) (Lovell, 2003).

$$MLeffch^{t,t+1} = \frac{1+\overrightarrow{D^t}\left(x^t, y^t, b^t; y^t, -b^t\right)}{1+\overrightarrow{D^{t+1}}\left(x^{t+1}, y^{t+1}, b^{t+1}; y^{t+1}, -b^{t+1}\right)} \tag{4}$$

$$MLtech^{t,t+1} = \left[\frac{1+\overrightarrow{D^{t+1}}\left(x^t, y^t, b^t; y^t, -b^t\right)}{1+\overrightarrow{D^t}\left(x^t, y^t, b^t; y^t, -b^t\right)} \times \frac{1+\overrightarrow{D^{t+1}}\left(x^{t+1}, y^{t+1}, b^{t+1}; y^{t+1}, -b^{t+1}\right)}{1+\overrightarrow{D^t}\left(x^{t+1}, y^{t+1}, b^{t+1}; y^{t+1}, -b^{t+1}\right)}\right]^{\frac{1}{2}} \tag{5}$$

MLeffch measures whether the observed DMU moves closer or farther from the best production frontier over time, which decided by the performance of resources allocation and management level in the process of land urbanization in this study. Efficiency improves if $MLeffch > 1$, thus remains at the same level if $MLeffch = 1$ and decrease if $MLeffch < 1$. *MLtech* evaluates the dynamic change in the production possibility frontier between t and $t+1$, which refers to the technical level in land urbanization. $MLtech > 1$ means technical progress, $MLtech = 1$ implies no change, and $MLtech < 1$ denotes technical regression.

3.2. Study area

According to the Development Plan of Chengyu Urban Agglomeration published by China in 2016, the Chengyu urban agglomeration covers 27 districts (counties) in Chongqing City and 15 cities of Sichuan Province, including Chengdu, Zigong, Luzhou, Deyang, Mianyang, Suining, Neijiang, Leshan, Nanchong, Meishan, Yibin, Guang'an, Dazhou, Ya'an, and Ziyang. In consideration of the available data, 16 municipalities and cities in Chengyu urban agglomeration were chosen as the research areas. In order to analyze regional differences, 16 chosen cities were grouped into four clusters according to the '13th Five-Year Plan', which differ in natural environment and geological conditions, social economic development level, industrial orientation, and land use characteristics. The four zones include Chongqing Zone, Chengdu Plain economic region, southern Sichuan economic zone, and northeastern Sichuan economic zone. Seizing the opportunities of New-type Urbanization, The Belt and Road, and The Yangtze River Economic Belt strategies, Chengdu-Chongqing region is becoming an influential economic center.

Table 1. Input-output index system of LUTFP.

Type	Factor	Indicator	Unit
Input indexes	Land	Area of built districts	1000 m^2
	Labor	Number of employed persons in the secondary and tertiary industries	10,000 people
	Capital	Capital stock of cities	100 million CNY
Desirable output indexes	Economic benefits	Per capital total value of the secondary and tertiary industries	100 million CNY
	Social benefits	Urban resident population	10,000 people
	Ecological benefits	Green coverage area in urban built districts	1000 m^2
Undesirable output index	Negative impact on the environment	Carbon emissions from the secondary and tertiary industries	10,000 tons

Source: Created by authors.

3.3. Variable selection and data description

Based on the theory of factors of production, input elements in the land urbanization process mainly include land, capital, and labor force. In this study, urban construction area, capital stock over years, and number of practitioners in the secondary and tertiary industries were chosen as the input indexes for estimation of land urbanization TFP (Table 1). Following the example of Xie and Cao (2018), land urbanization was assumed to achieve integrative and eco-friendly development of urban and rural areas by improving the economic, social, and ecological benefits to meet the goals of the new type of urbanization. Thus, the output indexes are selected from the three perspectives above. As a systematic and comprehensive assessment tool, the global power city index (GPCI) provides a framework to assess and compare the performance of cities around the world (Kourtit et al., 2014). The CPCI indicators were followed in choosing the output measures. Consequently, per capital total value of the second and tertiary industries, resident population in urban area, and green coverage area in urban construction area are desirable output indexes, while carbon emissions from urban construction land is the undesirable output index in this study. Table 1 lists all the variables used in this study.

Original data of all indexes were obtained from *Sichuan Statistical Yearbook* and *Chongqing Statistical Yearbook* over years. Few missing data were supplemented through interpolation method and regression imputation.

3.3.1. Input indexes

1. Land urbanization refers to urban land expansion. Urban built area provides huge space and potential for industrial development, people living, infrastructure construction, and other various human activities. The total built-up area is highly relative to urban land allocation and utilization, which reflects the efficiency of regional land institutions and management performance in the process of land urbanization.
2. Since socioeconomic activities in urban areas, including the secondary and tertiary industries, mainly take place in the built-up districts transformed from rural lands, employed persons engaged in the secondary and tertiary industries were used to represent the labor indicator.

3. Capital stock is used as a proxy for capital input which is estimated by the perpetual inventory model (PIM) according to the example presented by Coe and Helpman (1995) based on the total investment in fixed assets by region from 2007 to 2017. First, the capital stock of each city in 2007 was calculated as benchmark, as shown in Eq. (6). The capital stock from 2008 to 2017 can be estimated following the procedure suggested by Zhang et al. (2004), as shown in Eq. (7).

$$K_0^i = \frac{I_0^i}{(g + \delta)} \tag{6}$$

$$K_t^i = \frac{I_t^i}{P_t^i} + (1-\delta)K_{t-1}^i \tag{7}$$

where i refers to zones and t is the year. K_0^i and K_t^i denote the capital stock of the ith city in the first year of the set period and year t, respectively. I_0^i and I_t^i are the total investments in fixed assets at base and current price, respectively. g is the geometric rate of average annual growth of the investment in fixed assets from 2007 to 2017, δ is the depreciation rate of the fixed asset. P_t^i refers to the price index in period t. This study followed the research of Zhang et al. (2004) in setting the value of δ as 9.6%. The data were obtained from the public information sources including *Sichuan Statistical Yearbook* (2007–2017), *Chongqing Statistical Yearbook* (2007–2017), and *China Statistical Yearbook* (2007–2017).

3.3.2. Output indexes

Per capital total value of the second and tertiary industries refers to the economic performance on urban built area. Urban resident population implies the level of population urbanization characterized by new type of urbanization, and reflects the performance of harmonious development and the degree of equitable basic public service. Green coverage area in urban built districts refers to ecological benefits and welfare.

In an urban constructed area, electricity and heat generation, transportation, industry production, and other production or living activities are the primary sources of CO_2 emissions. CO_2 emission data of each city is not available from the published official information in China. In this study, energy consumption in the secondary and tertiary sectors of each city is estimated by multiplying energy consumption per unit of GDP by GDP of the secondary and tertiary industries.

4. Results and analysis

4.1. LUTFP analysis with CO_2 consideration

Table 2 shows the TFP index and its components of Chengyu urban agglomeration from 2007 to 2017. The left side demonstrates a scenario without consideration of undesirable output while the right side presents another scenario with consideration of CO_2 emissions. The geometric mean value of LUTFP over time with emissions

Table 2. LUTFP and its components in Chengyu urban agglomeration from 2007 to 2017.

	M index and its components without considerations of undesirable output					ML index and its components with considerations of undesirable output				
Years	M	effch	tech	pech	sech	ML	effch	tech	pech	sech
2007–2008	1.074	1.013	1.060	0.997	1.016	1.058	1.013	1.045	0.996	1.017
2008–2009	1.041	1.018	1.022	1.011	1.007	1.029	1.010	1.019	1.007	1.002
2009–2010	1.029	0.998	1.031	0.998	1.000	1.022	0.999	1.023	0.992	1.007
2010–2011	1.061	0.987	1.075	0.981	1.006	1.043	0.991	1.052	0.994	0.997
2011–2012	1.043	1.007	1.036	1.027	0.981	1.031	1.009	1.022	1.015	0.994
2012–2013	1.025	0.993	1.032	0.989	1.004	1.018	0.997	1.021	0.996	1.001
2013–2014	1.018	1.005	1.013	1.008	0.997	1.012	1.002	1.011	1.011	0.991
2014–2015	1.045	0.998	1.047	1.042	0.957	1.030	0.994	1.037	1.020	0.974
2015–2016	1.038	0.997	1.041	0.995	1.002	1.027	1.002	1.025	1.005	0.997
2016–2017	1.036	1.001	1.036	1.013	0.988	1.024	0.996	1.028	0.998	0.998
Annual average	1.041	1.002	1.039	1.006	0.996	1.029	1.001	1.028	1.003	0.998
Annual average growth rate (%)	4.077	0.154	3.917	0.588	−0.431	2.924	0.116	2.805	0.331	−0.215

Note: M and ML index of land urbanization in the table are expressed by geometric means of zones in different years.
Source: Authors' processing in MaxDEA.

(1.029) is 1.2 percent lower than that without emission (1.041), indicating that high level of carbon dioxide restricts the improvement of land urbanization efficiency to some extent. The average technical and efficiency changes with CO_2 emissions are 1.028 and 1.001, respectively. Besides, the annual average growth rate of technical progress reaches 2.805% and technical efficiency is only 0.116%. This gap reveals that technical advance is more crucial to the TFP than the efficiency change in Chengdu-Chongqing area. In addition, the uneconomic way of development, including high-energy-intensive industries and extensive utilization of resources, drove economic and social progress but led to inefficiency in land urbanization during the past ten years.

Figure 1 visualizes the changes of LUTFP between 2007 and 2017. In view of time series analysis, the average LUTFP score fluctuates, with peaks in 2007, 2010, and 2014, and valleys in 2009 and 2013. In this period, scale efficiency declines significantly, indicating that the mode of production based on urban expansion in Chengyu urban agglomeration changes accordingly. From 2008 to 2010, TFP under the carbon emission constraint decreases significantly due to economic downturn caused by global financial crisis, leading to low economic efficiency and depressed investment environment.

Technical efficiency index can be decomposed into pure technical efficiency change and scale efficiency change. The improvement of pure technical efficiency is mainly brought about by the progress in land utilization, production technology, and urban planning, reflecting the efficiency level of optimizing existing resources. Scale efficiency reflects the efficiency produced by new space and resources during land urbanization. Table 2 shows the annual average growth rates of pure technical efficiency and scale efficiency are 0.331% and −0.215%, thus the promotion of pure technical efficiency offsets the bad effect produced by decreasing scale efficiency, contributing to the slight growth of technical efficiency.

4.2. Spatial-temporal pattern of LUTFP in Chengyu urban agglomeration

Table 3 visualizes the M and ML index for all 16 cities in the Chengyu urban agglomeration. The biggest difference between M index and ML index was observed

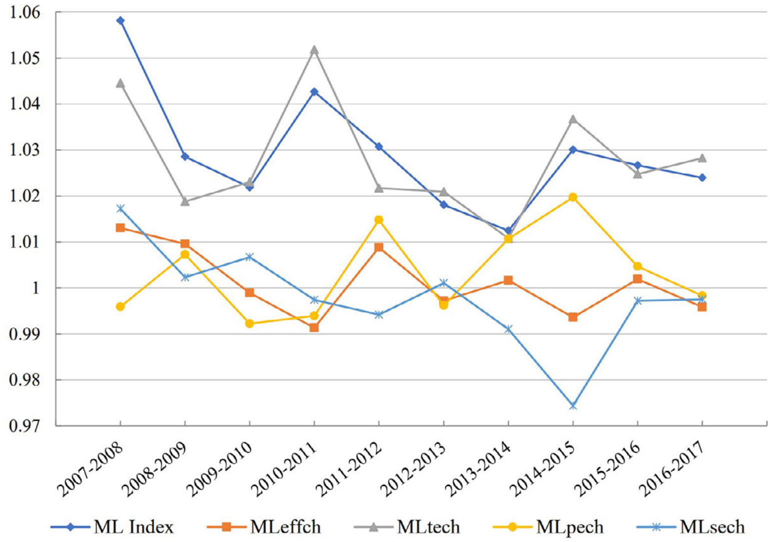

Figure 1. The annual variation trend of LUTFP and its components with considerations of carbon emissions from 2007 to 2017.
Source: Created by authors based on calculations.

in Ziyang, followed by Chongqing. Consequently, the LUTFP was overestimated under the condition leaving CO_2 out. Deyang, Mianyang, and Leshan showed the smallest differences in ML and M index, hence these cities find a basic equilibrium between urbanization and emissions control to some extent. LUTFP with CO_2 emissions in Chongqing and Chengdu Plain economic zone were higher than the average level of the whole cluster, showing the differences in performance of administration and urban land deployment. On the contrary, the relatively low level of LUTFP in southern and northeast Sichuan economic zones reflected a lower development quality.

In view of decomposition of ML index, TFP of the most samples in Chengyu urban agglomeration is mainly attributed to technical progresses. Technical efficiency in Chongqing, Chengdu, Mianynag, Ziyang, Suining, Ya'an, Dazhou, Nanchong, Neijiang, and Zigong show insignificant improvement. The promotion of technical progress offset the decline in technical efficiency resulting in the rise of total productivity in Luzhou, Meishan, and Guang'an, thus technical improvement and innovations are major driving factors of efficiency growth in these cities during land urbanization. With the urban economic development transformation, the land, labor-, and capital-intensive industries changed gradually toward environmental-friendly innovative industries. Deyang, Leshan, and Yibin benefited from the collaborative effect of technological progress and efficiency, hence these cities paid high attention to land resource utilization while pursuing technological progresses by controlling land supply and land utilization in the urbanization process.

Figure 2 illustrates the cross-sectional data of ML index in four years. LUTFP was relatively high in 2007, with five cities having an average score of at least 1.06, hence a rapid progress of land urbanization efficiency. By 2017, ML index of most cities had stabilized between 1 and 1.04, except for Guang'an, Zigong, and Luzhou with a

Table 3. LUTFP and its components of 16 cities in Chengyu urban agglomeration.

		M index and its components without considerations of undesirable output					ML index and its components with considerations of undesirable output				
Area / City		M	effch	tc	pec	se	ML	effch	tc	pec	se
Chongqing		1.083	1.000	1.083	1.000	1.000	1.055	1.000	1.055	1.000	1.000
Chengdu Plain Economic Zone	Deyang	1.051	1.009	1.042	0.998	1.011	1.046	1.016	1.029	1.010	1.006
	Leshan	1.048	1.010	1.038	1.003	1.006	1.045	1.017	1.027	1.014	1.004
	Chengdu	1.051	1.000	1.051	1.061	0.943	1.036	1.000	1.036	1.051	0.952
	Suining	1.052	1.000	1.052	1.000	1.000	1.036	1.000	1.036	1.000	1.000
	Ya'an	1.041	1.000	1.041	1.000	1.000	1.029	1.000	1.029	1.000	1.000
	Mianyang	1.025	1.000	1.025	0.997	1.003	1.020	1.000	1.020	0.990	1.010
	Ziyang	1.057	1.028	1.028	1.036	0.992	1.020	1.000	1.020	1.000	1.000
	Meishan	1.031	0.994	1.037	0.999	0.995	1.022	0.993	1.029	0.988	1.005
	Regional average	1.044	1.005	1.039	1.012	0.994	1.032	1.004	1.028	1.006	0.997
Northeast Sichuan Economic Zone	Nanchong	1.027	1.000	1.027	1.000	1.000	1.022	1.000	1.022	1.000	1.000
	Guang'an	1.029	0.984	1.046	0.985	0.999	1.021	0.989	1.032	0.982	1.007
	Dazhou	1.015	1.000	1.015	1.000	1.000	1.011	1.000	1.011	1.000	1.000
	Regional average	1.024	0.995	1.029	0.995	1.000	1.018	0.996	1.022	0.994	1.002
Southern Sichuan Economic Zone	Zigong	1.047	1.000	1.047	1.000	1.000	1.033	1.000	1.033	1.000	1.000
	Yibin	1.039	1.014	1.024	1.019	0.996	1.032	1.015	1.017	1.023	0.992
	Luzhou	1.035	0.987	1.048	0.998	0.989	1.025	0.988	1.037	0.998	0.990
	Nejiang	1.024	1.000	1.024	1.000	1.000	1.017	1.000	1.017	1.000	1.000
	Regional average	1.036	1.000	1.036	1.004	0.996	1.027	1.001	1.026	1.005	0.996
Regional average in Chengyu urban agglomeration		1.041	1.002	1.039	1.006	0.996	1.029	1.001	1.028	1.003	0.998

Note: M and ML index of land urbanization in the table are expressed by geometric means of years in different zones.
Source: Authors' processing in MaxDEA.

range between 1.04 and 1.06. Therefore, land urbanization efficiency of cities in the Chengyu urban agglomeration under carbon emission constraint become more stable.

In order to find the regional characteristics of LUTFP under the constraints of carbon emissions, we use Figure 3 to demonstrate the relationship between LUTFP and carbon emissions: (1) carbon emissions of Chongqing, Chengdu, Deyang, Yibin and Leshan were relatively high with a high score of LUTFP. These cities are the core cities in Chengyu economic circle and the major carbon emission zones, due to the mature industries and population scale of urban construction areas. Nevertheless, high productivity was achieved because of the advanced production technologies, management level, and optimal industrial structure. While consuming considerable energy sources, these cities reduced carbon emissions by improving technologies and implementing emission-cutting measures. (2) Neijiang and Dazhou generated large amount of carbon emissions, but their LUTFP score ranked low among the 16 sampled cities, hence urban development in these two cities was achieved at the cost of relatively high energy consumption and carbon emissions. Dazhou and Neijiang are important secondary industry bases. The promotion of social economic development in a short term brings great burdens to ecological environment. (3) Carbon emissions of Ya'an, Zigong, and Suining ranked low, but their LUTFP value was relatively high. Low-carbon lifestyle, green industries along with resource-saving and sustainable way of development were promoted in these cities to maintain the existent natural and ecological conditions. (4) Meishan, Nanchong, Guang'an, and Ziyang have small changes of carbon emissions, and the TFP was relatively low. Some of

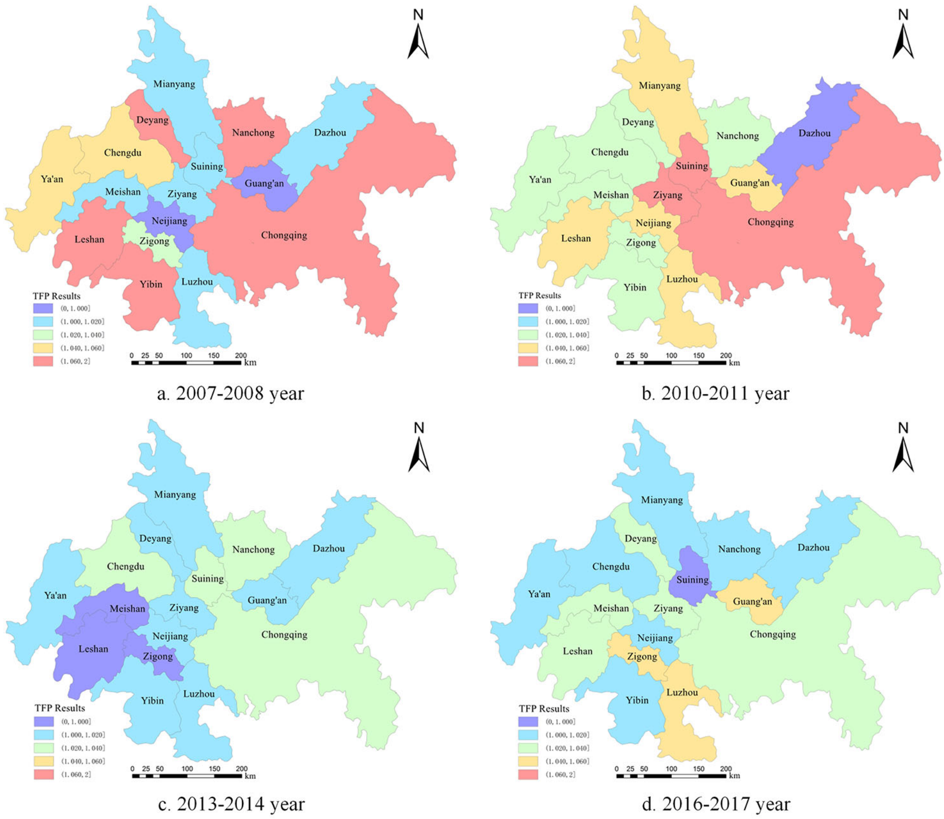

Figure 2. Spatial-temporal evolution pattern of LUTFP in Chengyu urban agglomeration under carbon emission constraints from 2007–2017.
Source: Created by authors based on calculations.

these cities were in the middle and northeast regions of Sichuan which are the ecological barrier regions in the middle and upper reaches of the Yangtze River. Central and local governments' regulation and control over high-energy intensity and highly pollutive industries in this area restricted the economic and social development to some extent. Another reason is that agricultural or emerging industries are based pillars of the economy which generate low carbon emissions.

5. Discussions

5.1. Driving force behind the land urbanization

ML index of land urbanization is lower than the M index in Chengdu-Chongqing city cluster. Färe et al. (2001) once proved that when the inputs are fixed, the expected output grows at a lower pace than the unexpected output if the ML index is smaller than M index. In other words, the production pattern is not environmental-friendly. Besides, this study believes that technical progress is the fundamental reason for LUTFP in the Chengyu urban agglomeration, known as the 'monorail track' model (Wu, Liu, et al., 2017), while technical efficiency has become a bottleneck

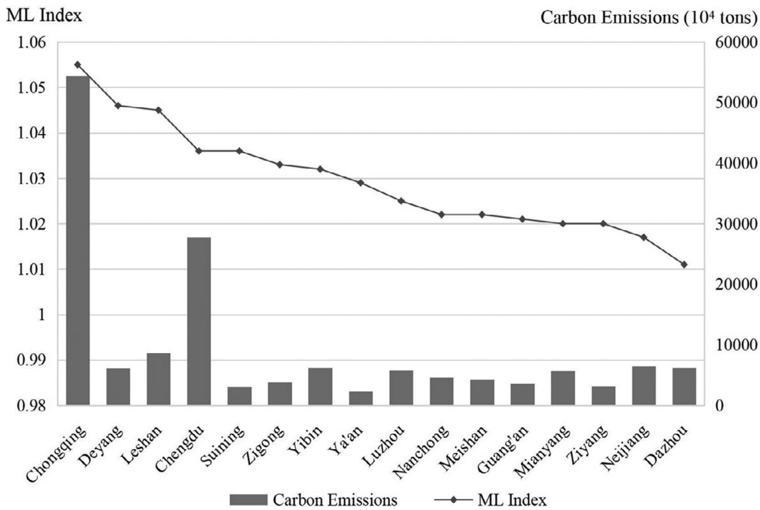

Figure 3. ML index of land urbanization and carbon emissions of 16 cities in Chengyu urban agglomeration from 2007 to 2017.
Source: Created by authors based on calculations.

against the growth of TFP (Wang & Wang, 2017). However, Li (2017)'s empirical results demonstrated that changes of TFP in western China from 2001 to 2014 are mainly attributed to changes of technical efficiency. This shows that different input and out variables might cause significant differences in TFP.

The temporal and spatial trends of LUTFP in Chengyu urban agglomeration are shown in Figures 1 and 2. ML index was generally high before 2011, but relatively low after 2011. This may be due to the process of industry shifting from the primary to the secondary that Chengyu city zone was going through (Yang & Duan, 2019). Land urbanization achieved high productivity as a result of industrial optimization and upgrading. However, such industrial technical progress was accompanied with relatively high carbon emission (Wang et al., 2019). Another driving force was emission-cutting and resources conservation initiatives implemented by governments in 2009 and reinforced in 2010–2011. Most cities experienced technical advance, or adopted alternative energies, whereas the increasing investments and production costs limited the production effectiveness to some extent (Wang et al., 2016). This may be the reason for the decline of technical efficiency during this period. However, this progress in technology would benefit the technical efficiency in the long term (Zheng et al., 2015). Consequently, the transformation of industrial structures and emission-cutting policies play a crucial part in land urbanization. The valley in 2009 may be influenced by financial crisis and the rate of TFP declined sharply due to the collaborative effect of technical changes and technical efficiency (Hu & Sun, 2020).

5.2. Different development patterns and measures for carbon reduction

Considering the ‘inverted U-shaped’ pattern of the relationship between land urbanization and carbon emission, city development modes can be divided into different groups based on varying levels of urbanization and emission (Zhou et al., 2021). This study believes that cities in the Chengyu urban agglomeration can be classified into four types as: 'high carbon emission-high productivity', 'high carbon emission-low productivity', 'low carbon emission-high productivity', and 'low carbon emission-low productivity'. Diversified policies should be 'suited to the case' as the development patterns among cities and regions can be tremendously different (Zhang & Xu, 2017). The 'high carbon emission-high productivity' cities represent key developing cities that dominate economic and social development in the region, relying on large-scale urban sprawl along with high carbon emissions (Zhang et al., 2021). These cities need to transform the industrial structure, upgrade the energy-saving facilities, expand the utilization of renewable and clean energy and improve the urban living environment to achieve a high development quality. 'High carbon emission-low productivity' cities may be in the early stage of accelerated land urbanization process, in which continuous growth of carbon-intensive industries are emerging (Zhou et al., 2019). Land urbanization was accompanied with the extensive land utilization and high energy consumption. Instead of chasing the economic growth at the cost of increased energy consumption and excessive depletion of natural resources, it is critical for these cities to use their unique strengths to upgrade industrial structure, boost lower wastage industries, promote green technologies, and form carbon pricing mechanisms, which follows the transformation from traditional linear economy to circular economy (Kyriakopoulos, 2021). The 'low carbon emission-high productivity' cities have two situations. In one case, these cities have already entered a high-level urbanization stage with higher land use efficiency and a low construction or emission rate (Xu & Zhang, 2016). In another case, carbon emission is at a relatively low level. This proved that cities with mature industrial economies or better ecological environments both enjoyed better carbon emission performance (Afzalinejad, 2021; Wang et al., 2016). 'Low carbon emission-low productivity' cities have lower social and economic levels, which may be restricted by ecological and resource endowments. Backward growth in urban expansion and carbon emissions resulted in the low level of land urbanization (Li et al., 2020). For those cities at an early stage of development facing with insufficient growths of output, intensive-use strategies should be implemented to take full advantage of land or other production factors effectively.

6. Conclusions

In consideration to the carbon emission, the goal of sustainable urban development becomes better with some conclusions drawn in the study: (1) the gap between M index and ML index demonstrates that ignoring carbon emission control led to overestimation of TFP. Land urbanization promotes the economic growth in the short run but brought burdens to the ecological environment. (2) The 'monorail track' model of technical progress is the fundamental reason of increasing LUTFP in most cities in Chengyu area. In contrast, the growth trend of technological efficiency is not obvious. (3) LUTFP of most cities is relatively high in Chongqing and Chengdu plain, but generally lower than the average level in the southern and northeastern Sichuan economic zones. However, the land urbanization efficiencies of different cities tend to be in equilibrium. Currently, land urbanization development underestimates the regional difference. Diversified measures of land utilization should be implemented according to urban features and resource endowment.

Some relevant policies are suggested as follows: Production technical efficiency should be emphasized to transform the 'monorail track' pattern into the 'dual track' pattern. To meet the goal of sustainable urban development, central and local governments must change the development model, control the urban sprawl with intensive land use, adjust industrial restructure in alignment with urban spatial structure, and realize high-efficiency green development. Regulation and supervision over resources utilization and carbon emissions should be strengthened especially in manufacturing sector. Besides, a circular economy principle should be applied in the policies comprehensively, which includes promoting resource conservation, recycling, and reusing the waste materials. The necessary legislation framework should clarify the collective responsibility of producers, consumers, and governments for green moves. This study has some limitations and prospects. To improve TFP based on spatial correlation and transduction mechanisms of urban agglomerations, it makes sense to determine whether variations in TFP are caused by redundant input factors like lands, labor force, and capital, or inadequate output factors like social, economic, and ecological factors. Additionally, the integration of all aspects in development results in a spatial effect among neighboring cities, including urbanization and carbon emissions. Urban agglomeration strategies have strengthened this effect by coordinated development. It is necessary to work out how to fully use these interactions by promoting a regional collaborative emission-cutting mechanism, enhancing cooperation and policy integration, to achieve balanced high-quality urbanization. Moreover, a coordinated system with a wider range of regions should be built to break the obstacles between separated administrative institutions. Specific discussions from the regional perspective and some policy suggestions shall be proposed for further research, thus research conclusions can be more applicable.

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