5. EFFICIENCY OF GREEN TOTAL FACTOR PRODUCTION: EXPLORING CORE DETERMINANTS

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Abstract

Amid a growing global emphasis on sustainable development and resource efficiency, understanding the core determinants of green total factor production efficiency holds paramount importance for fostering environmentally conscious economic growth. This paper aims to analyze green total factor production (GTFP) and core indicators that could restrict or increase efficiency. The panel data of 285 Chinese cities were selected to construct the unexpected output-ultraefficiency SBM model of the consumption of energy and environmental pollution from 2003 to 2019, first using the GML index for measuring and decomposing the GTFP, subsequently using spatial autocorrelation analysis, and finally using the Tobit model for scrutinizing the key determinants. The findings allow concluded that the GTFP showed a stable trend between 2004 and 2019. However, there were still large differences, and there were certain spatial agglomeration characteristics. The spatial evolution characteristics showed obvious characteristics of "low/high in the west/east accordingly" at the urban level The spatial correlation shows a dynamic change of first weakening and then increasing; the economic foundation, use of energy, and environmental pollution will seriously affect the GTFP.

Keyword: ultra-efficiency SBM model; GML index; spatial autocorrelation; Tobit model.

JEL Classification: Q01; Q56; Q57

1. Introduction

In the face of an increasingly urgent global demand for eco-friendly economic approaches, thoroughly investigating the fundamental drivers behind the effectiveness of green total factor production (GTFP) is of crucial importance (Lee et al., 2022; Cheng et al., 2022; Li et al., 2022). This endeavor stands as a cornerstone in the pursuit of fostering sustainable development (Arefieva et al., 2021; Dźwigoł 2021) and proactively addressing ecological challenges Shpak et al., 2021; Melnyk et al., 2021; Kuzior et al., 2022), thereby contributing to the well-being of both

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current and future generations (Titko et al., 2023; Veckalne et al., 2023). China's 13th national session "further implement the innovation-based development strategy, strengthen the first dynamic role" (National 13th Five-Year Plan for the Development of Strategic Emerging Industries, 2023). It requires exploring the innovation-driven instead of factor input-driven green economy development model as the current economic transformation development and promoting one of the key factors of green economy transformation through the development of green overall factor efficiency (Cheng et al., 2020; Zhao et al., 2020; Chygryn and Miskiewicz 2022; Zhao et al., 2022).

The GTFP brings energy and environment-related aspects into the economic growth nexus, modifying conventional total factor productivity (TFP). It is the core mainspring to change the economic development model under the constraints of environmental resources. In addition, the green growth model emphasizes low resource consumption and pollution emissions, decoupling economic growth from resource consumption (Zhao et al., 2022; Kjaer et al., 2019; Rădulescu et al., 2022) and pollution emissions (Zhang et al., 2016; Kotowicz et al., 2022). Considering the studies (Letunovska et al., 2022; Wang et al., 2021), the growing GTFP has a decisive impact on China's green development. Countries are faced with the problem of "shortage of resources, serious environmental pollution and ecosystem degradation" (Wang et al., 2021; Chai et al., 2021). All countries in the world adopt a low-carbon (i.e., green) development model to solve the current environmental problems. The 19th CPC National Congress's report (Wang, 2004) proposed an improved low-carbon (environmentally friendly) development system by constructing a production model with advanced technical and scientific content that consumes fewer resources.

While analyzing economic growth, the total productivity of the green factor includes "use of energy" and "environmental contamination". It emphasizes the concept of green development of harmonized progress of environment and economic resources, which ultimately improves the traditional overall production of the factor. Therefore, the green factor of the total productivity of energy inputs and environmental pollution has become a new index for quality economic expansion. Improving whole-factor efficiency means a win between economic and environmental performance. Calculating the total productivity of the green factor in China and objectively assessing temporal and spatial differences in the quality of economic growth are conducive to providing a factual basis for transforming China's rapid economic growth from the urban level to high-quality development, having important practical regional as well as global implications.

The marginal contribution of this investigation lies in the following: (1) the research method – using the unwanted production model-ultraefficiency SBM, combined with the Globe-Malmquist–Luenberger index (GML) based on global reference technology, scientifically solve the productivity measure of the total green factor of variable relaxation, effective differentiability of DMU, comparison between periods and other vital issues to ensure robustness of measurement results; (2) data selection – analyzed 285 cities in China, compared with provincial-level data, urban data could more genuinely reflect the spatial heterogeneity of the total productivity of the green factor, the total productivity research of the green factor complements the content of the city level, from the urban level of high-quality development, provides a theoretical basis at the same time. This study provides Chinese solutions to other countries to increase total green factor productivity.

The paper has the following structure: literature review – analysis of the theoretical background on GTFP; material and methods – explanation of variables and their sources, describing the research methods and models; results – outlining the research findings; discussion and conclusions – exploring the core results, comparison with prior studies, policy implications, limitations, and further directions for investigations.

2. Literature Review

The traditional total productivity factor does not consider the impact of energy and resource consumption, which ignores the negative impact of environmental and resource constraints on productivity. On this basis, the assessment of economic performance may be biased. Numerous researchers have increasingly incorporated environmental determinants into efficiency as the economy evolves. Färe et al., (1989) constructed the directional distance function. Based on this, the Malmquist–Luenberger productivity index (ML) was proposed. The index could measure the total productivity of factors in unwanted production. It could also be broken down into high-tech evolution and efficacy indexes. Nevertheless, most of them are limited to radial, angular data envelope analysis (DEA) to calculate the directional distance function. Failure to effectively solve the unorthodoxy instigated by opting radial and angle in the efficiency measuring course. Tone (2001) first suggested a nonangular and nonradial method (SBM), which overcomes the above defects and is widely used in efficiency measurement and evaluation (Färe et al., 1989). Scholars Färe et al., 1989; Tone 2001) further syndicate the DDF (i.e., directional distance function) and Tone's SBM method. It can calculate efficiency from various angles and the influence of nonzero relaxation in input or production to make GTFP more accurate. Therefore, many studies select this methodology to estimate the overall factor thruput, and the research scope is also different. Studies (Färe and Grosskopf 2010; Fukuyama and Weber, 2009; Cui et al., 2017; Ji and Zhou, 2016) have been chosen and analyzed the effect of FDI growth on total factor production.

The research on measuring green factor output primarily focuses on the characteristics of productivity growth trends and the source of productivity growth power. On the one hand, the research conclusions include growth and regression theories. In the "growth theory", there are also significant differences in the geometric average of China's annual growth rate of green total factor productivity. Scholars (Wang et al., 2021; Xiaolao and Hongyang 2017) show that positive green total factor output growth is slowing down in China. The viewpoint of "backwardness theory" mainly comes from the examination of China's industrial green output, which indicates a negative growth phenomenon.

GTFP considers unwanted production and environmental factors such as pollution emissions. It is parallel to the innovative perception of green advances in the present era (Zhao et al., 2022). On the one hand, based on the dimension of the efficiency of green factors, Chung et al., (1997) took the lead in adding pollution emissions to the measurement framework of the total productivity of factors based on the directional distance function (DDF) and index (ML); Tone (2001) established the distance function based on the relaxation variable, which effectively reduced the measurement bias. On the other hand, the literature focuses on environmental regulation (Yang et al., 2015) and carbon emissions (Cui et al., 2017; Chung et al., 1997; Xie et al., 2017) within research on the increasing influence of the total productivity of the green factor. Most scholars (Bing et al., 2010; Yuanfeng and Daiyan, 2012) outline that the total growth of the green productivity factor is mainly because of technological progress. Rezek and Perrin (2014) applied the SFA-Malmquist Luenberger index to calculate the whole agricultural factorial yield based on the surplus logarithmic function. Bing et al., (2010) measured the total productivity of the environmental factor by uniting the SBM steering DF (distance function) with the Luenberger production index. Chen and Zhang (2016) used Kumbhakar's research method to establish a C-D production function to study the overall productivity change of the green factor. Liu et al., (2016) merged biyearly conservational technology and a nonradial DDF (directional distance function). The BNDDM function was built. It claimed that the productivity index method based on the BNDDM does not compute the total green yield. Song et al., (2018) proposed the RSBM model to estimate the overall productivity of environmental factors. Liu et al., (2021) calculate the total productivity of China's factors considering unexpected production at the macro level. Compared with the total productivity of the element, the key to the total productivity of green factors is to ponder ecological effluence, reflect environmental pollution-induced reduced benefits, and better reflect the requirements of high-quality economic development. Therefore, studying the total productivity of green factors is useful for analyzing the net effect of economic development, which has vital practical importance. Currently, most research in the field is conducted from a regional perspective in China, with few investigations conducted from an urban perspective. This article studies the productivity of the green factor in 285 cities above the level of city hall. The status of the total productivity of green factors at the municipal level is discussed from a more macroscopic perspective. Finally, this paper analyzes the spatial effect of green productivity to analyze the current situation of neighboring cities, presents the governmental policy of environmental regulation, fully considers the overlap and interaction in the formulation of policies, makes full use of favorable factors, avoids adverse factors, maximizes the total productivity of green factors, and improves the efficiency of economic development.

3. Materials and Methods

3.1 Data Source

The data selected in this paper span from 2003 to 2019, with the target of 285 cities in China (due to the availability of data, Tibet, Hong Kong, Macao, and Taiwan lack data), and the data are mainly derived from the China Statistical Yearbook, the Urban Statistical Yearbook, and the official websites of the National Bureau of Statistics and the Local Government Statistics Bureau. This paper selects the index data of input, expected output and unexpected output of 285 cities in China to construct the index system of green total factor productivity in China.

The input indexes selected in this paper include capital input, labor input and energy input. Capital stock expresses capital investment and is calculated by the perpetual inventory method. According to formula 1:

$$\mathrm{K_{it}} = \mathrm{I_{it}} + (1 - \delta_{\mathrm{it}}) \times \mathrm{K_{it-1}} \tag{1}$$

where $\mathrm{K_{it}}$ – the current capital stock, $\mathrm{K_{it-1}}$– the previous capital stock; $\mathrm{I_{it}}$ – the investment, selecting the total amount of fixed assets formed in each city to express; and δ_{it} – a depreciation rate set at 9.6%.

In 2003, the base period was to reduce the capital stock; labor input with employment-population expressed; and energy input using annual electricity consumption as the alternative variable. The energy input uses annual electricity consumption as an alternative variable. Electricity consumption can be used to select variable energy consumption indicators because the GDP elasticity of electricity demand is close to the GDP elasticity of energy demand and data availability and accuracy Bianco et al., 2009.

Expect output. This paper selects GDP to represent and convert nominal GDP to actual GDP as the desired output.

Undesired output. The representative industrial soot and sulfur dioxide discharge, wastewater discharge and comprehensive pollution index in the waste gas were selected as the secondary indexes. The descriptive statistics of the input–output indicators are shown in Table 1.

Table 1. Descriptive statistics of input–output indicators

Variable	Symbols	Unit	N	Mean	St. D.	Min	Max
Investment index							
Capital input	X1	yuan	4845	4.60e+07	6.20e+07	1656720	7.70e+08
Labor input	X2	person	4845	50.32403	75.88684	4.05	986.87
Energy input	X3	Ten thousand kilowatt-hours	4845	984688.5	1597864	2248	1.57e+07
Expect output							
Reality GDP	Y1	Ten thousand yuan	4845	1.39e+07	2.02e+07	215100	2.46e+08
Industrial soot emissions	Y2	Ton	4845	30147.62	109905.9	34	5168812
Unexpected output							
Wastewater discharge	Y3	Ton	4845	6942.579	9478.218	7	154625
Sulfur dioxide emissions	Y4	Ton	4845	50818.71	57183.64	2	683162
Comprehensive pollution index	Y5	Ton	4845	28398.14	55053.6	25.27	2375826

Note: N – number of observations; St. D. – standard deviation; Min – minimum value; Max – maximum value.
Source: developed by the authors.

Table 1 shows the maximum difference between the input, expected output and undesired output of 285 cities in China from 2003 to 2019, which indirectly indicates that there are significant differences in the green development level of 285 cities in China. For the influencing factors of green total factor productivity, combined with the existing research Hussain et al., 2021; Tu et al., 2022; Dacko-Pikiewicz 2019; Veckalne and Tambovceva 2022; Szczepańska-Woszczyna et al., 2022) and data accessibility, the following variables are selected:

(1) Economic basis (*GDP*), measured by each city's per capita GDP. An elevated per capita GDP typically signifies a more robust economic underpinning, suggesting that the city holds the requisite resources and capacities for channeling investments into sustainable and environmentally conscious undertakings.

(2) Capital stock serves (*Cap)* as a measure of the accumulated physical and human capital within a city. The ratio of physical capital stock to human capital stock, as employed by Chen Liming in 2020, provides insights into how well a city has invested in its infrastructure and human resources. A higher capital stock ratio suggests a more robust foundation for innovation, technological advancement, and the implementation of environmentally friendly practices. The ratio of capital stock embodies a narrative of resource allocation that has profound implications for a city's potential to thrive in a rapidly evolving landscape. It underscores the significance of prudent investments in both tangible infrastructure and intangible human capital, acting as a beacon guiding urban planners and policymakers toward a trajectory of sustainable development and enhanced GFTP.

(3) Energy consumption (*Ec*), measured by electricity consumption in each city. Urban centers characterized by elevated energy consumption frequently encounter a multifaceted challenge that revolves around harmonizing the pursuit of robust economic growth with the imperative of embracing sustainable energy practices. This intricate confluence demands a delicate balance, as these cities grapple with the dichotomy of propelling their economies forward while ensuring responsible stewardship of energy resources. The juxtaposition of soaring energy demands against the backdrop of sustainable energy objectives underscores the

intricate tightrope walk that urban planners, policymakers, and industries must navigate. As urbanization propels the growth of these centers, the energy requirements surge in tandem, often raising concerns about the depletion of finite energy resources and the amplification of greenhouse gas emissions.

(4) Environmental pollution (*Ep*), measured by wastewater, waste, waste gas, and PM2.5 in each city. High levels of wastewater, waste, waste gases, and particulate matter (PM2.5) not only pose health risks to the population but also underscore a misalignment between developmental practices and ecological responsibility. GFTP, on the other hand, encompasses the efficiency and effectiveness with which cities utilize resources to generate economic output while minimizing negative environmental externalities. The presence of environmental pollution, as measured by the Ep variables, can act as a counterweight to GFTP by impeding sustainable growth and causing ecological degradation. Pollution levels within urban areas can compromise air and water quality, impacting the health of residents and overall quality of life. These adverse conditions might deter investment, hamper tourism, and potentially lead to a higher prevalence of health-related issues. As a result, GFTP could be stifled, as cities grapple with the repercussions of environmental degradation, struggling to maintain a balance between economic prosperity and the well-being of their inhabitants.

3.2. Model design

(1) Based on the method proposed by Li and Shi (2014), this paper employs the ultraefficient SBM model, which takes into account the consideration of undesired outputs, to evaluate green total factor production:

$$\begin{cases} \rho = \min\limits_{\lambda,\bar{x},y^g,y^b} \dfrac{\sum_{i=1}^{m}\frac{\overline{x_t}}{x_{io}}}{\frac{1}{s_1+s_2}\left(\sum_{r=1}^{s_1}\frac{\overline{y_r^g}}{y_{r0}^g}+\sum_{k=1}^{s_2}\frac{\overline{y_k^b}}{y_{k0}^b}\right)} \\ s.t. X \geq \sum_{\substack{j=1\\ j\neq 0}}^{L} \lambda_j\, x_j \\ \overline{Y^g} \leq \sum_{\substack{j=1\\ j\neq 0}}^{L} \lambda_j\, y_j^g \\ \overline{Y^b} \geq \sum_{\substack{j=1\\ j\neq 0}}^{L} \lambda_j\, y_j^b \\ \bar{X} \geq x_0, \overline{Y^g} \leq y_0^g, \overline{Y^b} \geq y_0^b \\ \overline{Y^g} \geq 0, \overline{Y^b} \geq 0, L \leq e\lambda \leq \mu, \lambda_j \geq 0 \\ \overline{x_t} = x_{i0} + s^-(i,\ldots,m) \\ \overline{y_r^g} = y_{r0}^g - s^g(r=1,\ldots,s_1) \\ \overline{y_k^b} = y_{k0}^b - s^b(k=1,\ldots,s_2) \end{cases} \tag{1}$$

where $X=(x_1,x_2,\ldots,x_L)\in R_+^m$ – dimensional m input vector; $Y^g=(y_1^g,y_2^g,\ldots,y_L^g)\in R_+^{s_1}$ and $Y^b=(y_1^b,y_2^b,\ldots,y_L^b)\in R_+^{s_2}$ – the expected and unexpected output vectors of s_1 and s_2 dimensions, respectively, s_1 – expected output; s_2 – unexpected outputs; $\bar{x}$,$\overline{y_r^g}$,$\overline{y_k^b}$ – the projection value of the input and output of the evaluated unit, that is, the target value; $x_{i0}, y_{r0}^g, y_{k0}^b$ – the corresponding original values.

Referring to formula (1) for measuring the green productivity index (GML) and its decomposed components, where the total number of research periods is represented as T, and utilizing the input and output values from each city during period t, a feasible production set is constructed according to equation (2):

$$\begin{cases} D(k,l,e,g_y,g_b) = max\beta \\ s.t. \sum_{n=1}^{N}\lambda_n k_n \leq k' \sum_{n=1}^{N}\lambda_n l_n \leq l' \sum_{n=1}^{N}\lambda_n e_n \leq e' \sum_{n=1}^{N}\lambda_n y_n \leq y' + \beta g_y \\ \sum_{n=1}^{N}\lambda_n b_n \leq b' - \beta g_b \\ \sum_{n=1}^{N}\lambda_n = 1 \quad \lambda_n \geq 0 \quad \beta \in [0,1] \end{cases} \tag{2}$$

where D – a directional distance function; β – maximizing expected output, mini input and undesired output; k, l, e – represented capital, labor and energy inputs; y – expected output; b – undesired output; $g = (g_y, g_b)$ – direction vector; λ_n – weight assigned to the decision unit when building the production function with a sum of 1 with the variable returns to scale.

The decomposed indicators of the GML index are calculated using the following formulas:

the Technical Efficiency Change Index (GEC):

$$GEC = \frac{1+\overrightarrow{D^t}(k^t,l^t,e^t,y^t,b^t)}{1+\overrightarrow{D^{t+1}}(k^{t+1},l^{t+1},e^{t+1},y^{t+1},b^{t+1})} \tag{3}$$

the Technology Progress Index (GTC)

$$GTC = \frac{GML}{GEC} \tag{4}$$

$$\mathrm{GML} = \frac{1+\overrightarrow{\mathrm{D}^{\mathrm{G}}}(\mathrm{k^t,l^t,e^t,y^t,b^t})}{1+\overrightarrow{\mathrm{D}^{\mathrm{G}}}(\mathrm{k^{t+1},l^{t+1},e^{t+1},y^{t+1},b^{t+1}})} \tag{5}$$

where GML index is the GTFP index, which indicates that each period of GTFP is based on the growth rate of the previous period; when $GML > 1$, productivity increases; otherwise, productivity remains unchanged or decreases. If $GEC > 1$, technical efficiency drives productivity improvement; if $GEC \leq 1$, technical efficiency suppresses productivity improvement. If $GTC > 1$, productivity improvement is driven through technological progress; if $GTC \leq 1$, technological progress suppresses productivity improvement.

(2) Spatial autocorrelation is mainly used to represent the aggregation characteristics of the research object in the whole system and is generally calculated using the Moran index:

$$I_I = \frac{n\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(GTFP_{it}-\overline{GTFP})(GTFP_{jt}-\overline{GTFP})}{S^2\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}} \tag{6}$$

where n – 285 cities in China; w_{ij} – the spatial weight matrix; $GTFP_{it}$ – the green total factor productivity value; and $GTFP_{jt}$ – the green total factor productivity value of the first t year.

(3) The Tobit model is used to analyze the influencing factors of GFTP:

$$y_{it} = \begin{cases} \beta^T x_{it} + e_{it}, & 0 \leq \beta^T x_{it} + e_{it} \leq 1 \\ 0 & \beta^T x_{it} + e_{it} < 0, \beta^T x_{it} + e_{it} > 1 \end{cases} \tag{7}$$

where y_{it} – the independent variable; x_{it} – the dependent variable; e_{it} – the random error of the model; and $\boldsymbol{\beta}$ – the correlation coefficient vector.

Considering the outlined core determinants, formula (7) for investigating their effect on the level of GFTP is rewritten as follows:

$$GTFP_{it} = \beta_0 + \beta_1 GDP + \beta_2 Cap + \beta_3 Ec + \beta_4 Ep + \varepsilon_{it} \tag{8}$$

$GTFP_{it}$ – the total factor efficiency value in year *t* of region i; GDP – GDP per capita; Cap – capital stock; Ec – energy consumption; Ep – environmental pollution.

All variables in formula (8) are standardized to eliminate the influence of differing dimensions across each variable.

4. Results

The empirical results show that the geometric average of the GML index between 2004 and 2019 was 1.0176, indicating that green total factor productivity at the city level in China has achieved positive growth. Among them, 219 cities had a geometric mean GML index greater than 1. The number of cities with increased green total factor productivity accounted for 78.64%. Table 2 shows the temporal trends of green total factor productivity and decomposition breakdown in 285 cities in China between 2003 and 2019.

Table 2. Average GTFP and its decomposition for 285 cities above the prefecture level in China from 2004 to 2019

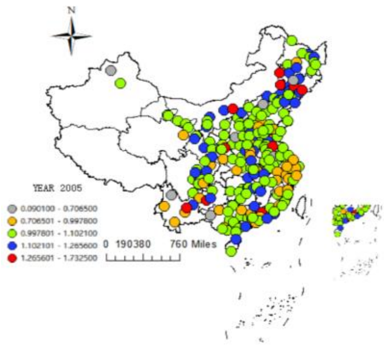
Year	GML	GEC	GTC	Year	GML	GEC	GTC
2004	1.0700	1.0665	1.0044	2013	0.9632	1.0549	0.9128
2005	1.0483	0.9956	1.0545	2014	1.0314	1.0931	0.9439
2006	1.0542	1.0870	0.9703	2015	1.0257	1.0116	1.0137
2007	1.0423	0.9633	1.0829	2016	1.0110	0.9927	1.0174
2008	1.0577	1.0505	1.0072	2017	0.7875	0.7995	0.9802
2009	1.0412	1.0713	0.9815	2018	1.0356	1.0268	1.0080
2010	1.0200	1.0491	0.9787	2019	1.0331	0.9977	1.0383
2011	1.0189	1.0195	0.9997				

Source: developed by the authors.

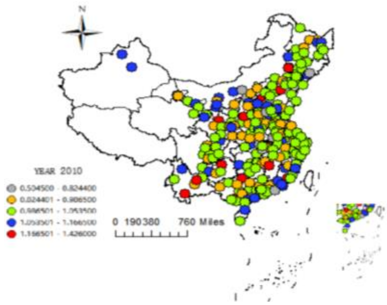
As shown in Table 2, the overall development of GTFP in China is stable. However, there are still significant changes, and there is a downward trend in a few years. Specifically, the 2003-2004 green total factor productivity GML index of 1.0700 has a downward trend, affecting the green technology progress index. Because of China's economic growth since 2003, the main characteristic of economic development is a heavy industrial structure. The development model has extensive characteristics that hinder the rise of green total factor productivity. The GML index declined by 2% from 2004 to 2005, which was the main influencing factor. From 2005 to 2006, the green total factor productivity GML index increased by 5.7%. This was mainly due to the change in green technology efficiency in the 11th Five-Year Plan period, which prompted enterprises to increase research and development investment, actively implement environmental protection technology and optimize resource allocation efficiency.

In 2016-2017, the green total factor productivity GML index declined and reached the lowest point, affected by the decline in green technology efficiency, mainly because China's economy experienced a cyclical downturn and economic growth from high to medium speed. China's investment scale has reached 50 trillion yuan, and its GDP investment scale is immense. Continuing to expand the investment scale will be subject to space limitations. Continuing to stimulate the growth of traditional labor-intensive industries, the strong constraints of the international market and domestic demand will eventually lead to traditional labor-intensive industry surplus, and structural adjustment is facing difficulties. In 2017-2019, the green total factor productivity GML index rebounded. Green technology progress has driven green total factor productivity, mainly because since 2018, China's economic development has also entered a new normal, and China's economy has changed from a stage of high-speed growth to a stage of high-quality development. Adhering to supply-side structural reform as the main line has promoted stable economic growth to a large extent, adjusted the industrial structure layout, vigorously promoted reform and innovation, improved macroeconomic regulation and control policies, and achieved remarkable results in pollution prevention and control. The results of the spatial aggregation and spatial evolution characteristics for 285 prefecture-level cities in 2005, 2010, 2014, and 2019 are shown in Figure 1.

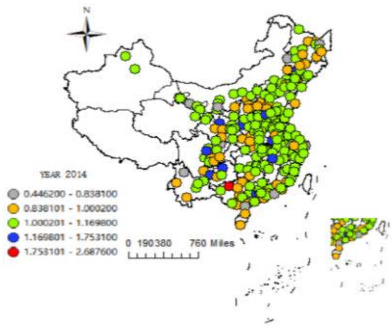
Figure 1. Spatial distribution diagram of the GTFP of 285 Chinese cities in (a) – 2005, (b) – 2010, (c) – 2014, and (d) – 2019



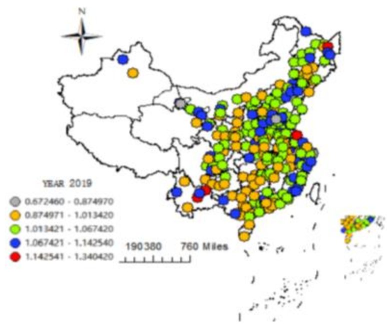
(a)



(b)



(c)



(d)

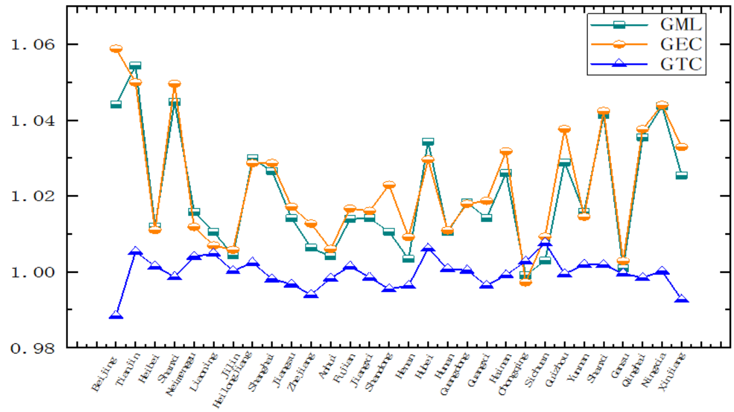
Source: developed by the authors.

Color depth reflects the degree of GFTP, and the gray icon represents urban green, the lower the total factor productivity. The red icon represents higher GFTP. According to the color of GFTP, productivity is divided into five categories.

From a time point of view, there are an increasing number of cities with dark colors, showing an increasing trend from 2005 to 2019, which shows that China's cities' GTFP has generally improved significantly, especially in central and southern China and East China. Figures 1 a, b, c and d show that the areas with high GFTP are relatively stable, mainly in Beijing, Jiangsu, and Zhejiang, and the GTFP is low in northwestern China. However, over time, total green factor productivity in northwestern China is slowly improving because of the "western development" strategy and improved national attention driving a new round of economic development.

In 2019, the number of cities in the blue region increased, mainly in China's central cities of Jiangsu, Zhejiang and Shanghai, and gradually spread to other regions. The reason for explaining this phenomenon is the dual problem of GFTP and its high-quality development in recent years. Urban environmental pollution control has achieved remarkable results. From the perspective of the spatial dimension, the areas with high GTFP are adjacent. The GTFP of 285 cities in China shows specific spatial correlation and spatial aggregation characteristics. The GTFP shows a prominent feature of "the east is high and low in the west", gradually decreasing from east to west. From the results of the calculation by province, except for Yunnan Province, the GML index of the GTFP in other provinces in China is higher than 1, indicating that the GTFP of all provinces in China increased from 2004 to 2019 compared to before (Figure 2).

Figure 2. GML index and its decomposition in China from 2004 to 2019

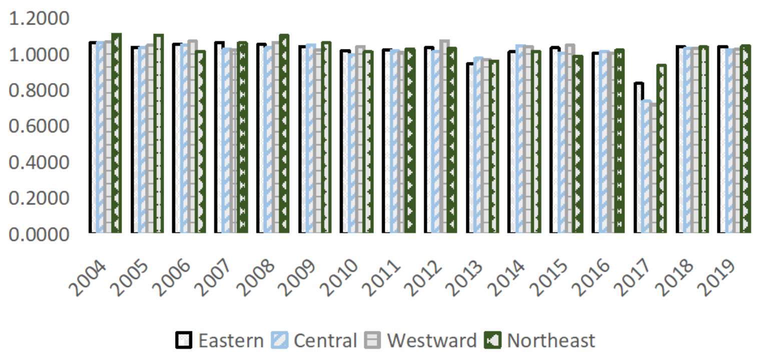


Source: developed by the authors.

At the same time, the GEC value of other provinces except Yunnan Province is than 1, indicating that the technical efficiency of productivity is significant. In terms of the GTC value, the GTC value of 15 provinces in China is less than 1, indicating that the driving effect of technological progress on the higher yield rate is still relatively weak.

Finally, based on the regional calculation outcomes, the GTFP growth rate exhibited fluctuations in both eastern and central China. Specifically, the central region experienced fluctuations from 2003 to 2008 (depicted in Figure 3).

Figure 3. Growth trend chart of regional GTFP in China from 2004 to 2019



Source: developed by the authors.

Subsequently, between 2008 and 2015, there was a period of low growth rate and overall development instability.

To effectively portray the overarching pattern of spatial correlation, the global Moran's I index was calculated (Table 3).

Table 3. Results of the spatial autocorrelation calculations

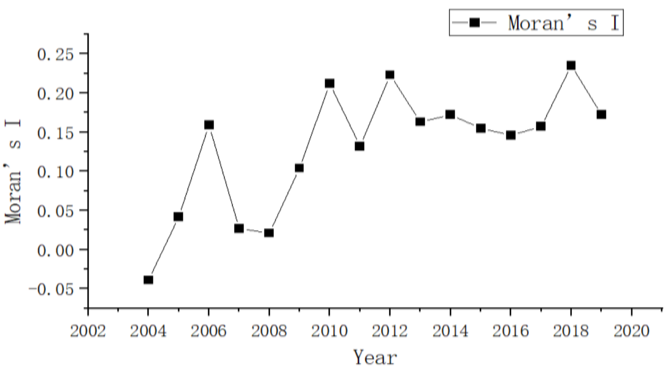
Year	Moran's I	E[I]	Mean	Sd	P Value	Year	Moran's I	E[I]	Mean	Sd	P Value
2004	-0.039	-0.004	-0.006	0.043	0.220	2012	0.223**	-0.004	-0.005	0.039	0.030
2005	0.042	-0.004	-0.004	0.048	0.150	2013	0.163**	-0.004	-0.006	0.047	0.072
2006	0.159*	-0.004	-0.003	0.044	0.078	2014	0.172**	-0.004	-0.003	0.039	0.015
2007	0.027	-0.004	-0.003	0.047	0.300	2015	0.155**	-0.004	-0.004	0.047	0.093
2008	0.021	-0.004	-0.004	0.047	0.235	2016	0.146**	-0.004	-0.008	0.044	0.089
2009	0.104*	-0.004	-0.004	0.043	0.100	2017	0.157**	-0.004	-0.003	0.044	0.079
2010	0.212**	-0.004	-0.003	0.004	0.025	2018	0.235**	-0.004	-0.005	0.043	0.022
2011	0.132**	-0.004	-0.003	0.044	0.017	2019	0.172**	-0.004	-0.005	0.047	0.053

*Note: *, * *, and * * * indicate significance levels of 10%, 5%, and 1%; E[I] – expectation; Sd – standard deviation.*

Source: developed by the authors.

The GML index of total green factor productivity calculated in this work reflects the growth rate of each period based on the previous period. It does not reflect the overall level of growth for the current period. Therefore, the cumulative green total factor productivity tests the spatial correlation. Ma *et al.* (2019) assume that the GTFP index of GML in 2003 is the value of base period 1. Next, the GTFP index of GML factors in 2004 is the value of the base period 2003 multiplied by the GML index 2004. Thus, the following studies' green index of total factor productivity GML refers to the cumulative value. The adjacent spatial weight matrix was used to comprehensively explore the spatial distribution pattern of China's GTFP. Based on the calculations presented in Table 3, the Moran index for the cumulative GML index of GTFP in 2006 exhibited a positive value and successfully passed the significance test at the 10% level. For the years spanning 2009 to 2019, the test was passed at a higher significance level of 5%. This outcome highlights a robust and positive spatial correlation in GTFP among the 285 cities. Figure 4 illustrates that China’s GTFP's Moran index follows a general pattern of initial increase, subsequent decline, a subsequent rise, and eventual gradual change.

Figure 4. The dynamic trend of the Moran index in GTFP from 2004 to 2019



Source: developed by the authors.

Specifically, the period from 2004 to 2016 witnessed an increase from -0.05 in 2004 to 0.159 in 2006, with fluctuations post-2010. On the whole, the spatial correlation among China’s GTFP exhibits dynamic changes, initially weakening before later strengthening.

Based on the calculation of GTFP in 285 cities using the superefficient SBM model and the GML index, the results of GDP, Cap, Ec, and Ep impact on the GML index and its decomposition are shown in Table 4.

Table 4. Tobit model regression results

Variable	**GML**	**GEC**	**GTC**
GDP	2.13e-10*	-1.79e-10*	1.12e-10*
	(0.056)	(0.077)	(0.000)
Cap	1.03e-08*	-2.78e-09	-7.99e-10
	(0.017)	(0.453)	(0.455)
Ec	-5.73e-10*	9.57e-10***	-1.63e-10*
	(0.030)	(0.000)	(0.016)
Ep	-1.32e-07*	-2.34e-07***	-8.28e-09
	(0.068)	(0.000)	(0.642)
constant	1.091868***	1.077205***	1.005603***
	(0.000)	(0.000)	(0.000)

*Note: *, * *, and * * * indicate significance levels of 10%, 5%, and 1%, respectively.*

Source: developed by the authors.

The data presented in Table 4 reveal a significant correlation between GDP per capita and the overall productivity of green factors. However, it adversely impacts technological efficiency while positively influencing technological progress. All of these relationships pass the 10% significance test, suggesting that the level of regional economic development exerts a driving effect on all aspects of GFTP. Both capital stock and technological progress show a positive correlation with the total productivity of green factors, passing the 10% significance test. On the other hand, technical efficiency exhibits a negative correlation and fails to pass the test. This suggests that the conversion process of labor-intensive enterprises entails substantial capital investment and environmental pollution, along with heightened technical requirements. This scenario enables rapid development in technological progress. Energy consumption demonstrates a positive correlation with technological efficiency but a negative correlation with both total factor productivity and technological progress. This implies that excessive energy consumption hampers technological progress, thereby affecting the overall productivity of green factors. Moreover, environmental pollution displays negative correlations with the total productivity of green factors, technological efficiency, and technological progress. This underscores the profound impact of environmental pollution on green economic development.

5. Discussion and Conclusions

This investigation uses the GML index model and the unexpected output ultraefficiency model to measure the GTFP in 285 cities in China. It analyzes the trend of the temporal and spatial evolution of total green factor productivity and its decomposition items. The results of the study show that the development of China's 285 cities' GTFP from 2004 to 2019 was stable. However, there were still significant changes, and a few years showed a downward trend, and they showed specific spatial correlation and spatial aggregation characteristics. Similar conclusions were obtained in previous studies (Feng et al., 2023; Hu et al., 2023). As in studies (Wang et al., 2021; Chai et al., 2021; Wang 2004), this investigation shows that China's city-level GTFP is obviously "high and low in the west", gradually decreasing from the east to the western region at the provincial level; with technical efficiency and technological advancement, China's growth rate has increased. From the perspective of spatial autocorrelation, the GTFP in 285 cities has a solid and positive spatial correlation. The spatial correlation shows a dynamic change of first weakening and then strengthening, which is consistent with the results of previous studies (Zhao et al., 2020; Zhang et al., 2016; Wang et al., 2021; Chai et al., 2021). From the perspective of influencing factors, economic foundation, energy consumption, and environmental pollution significantly affect the development of GTFP. It should be noted that scholars (Wu, 2023; Kuzior et al., 2022; Dzwigol et al., 2021; Jiakui et al., 2023; Li and Chen 2021) outline that green finance, digitalization, and innovations are the crucial factors of green economic growth.

Improving the GTFP is crucial to achieving "quantitative" economic growth and "qualitative" improvement. On the one hand, government departments should strengthen investment in R&D and formulate more effective environmental policies. Intense levels of technological innovation with technical efficiency and progress go hand in hand. Meanwhile, strengthening the management of environmental regulations, energy-intensive enterprises implement strict restriction punishment measures and environmental management of pollution sources, reduce unexpected production, improve the total green productivity of China and achieve sustainable economic development.

The conclusions drawn from this investigation into the efficiency of the GTFP and its core determinants hold significant policy implications for China's sustainable development and environmental management:

1. Recognizing the "high and low in the west" spatial pattern in GTFP underscores the need for targeted policies that promote sustainable economic growth in the western regions. Implementing region-specific strategies, such as investing in green technologies and infrastructure, could help bridge the development gap and foster balanced progress across the country.
2. The observed importance of technical efficiency and technological advancement in driving GTFP growth calls for policies that encourage research, development, and adoption of green technologies. Offering incentives and support for businesses and industries to embrace innovative eco-friendly practices can contribute to enhancing overall GTFP.
3. The fluctuating spatial correlation of GTFP suggests the importance of dynamic spatial planning. Policymakers should consider the evolving patterns of green productivity and tailor interventions based on the changing strengths and weaknesses of different regions.
4. The significant impact of economic foundation, energy consumption, and environmental pollution on GTFP highlights the need for integrated environmental policies. Stricter regulations, incentives for energy-efficient practices, and investments in pollution control technologies promote both economic growth and environmental preservation.
5. While economic foundation, energy consumption, and environmental pollution play crucial roles, policymakers should also explore additional drivers such as green finance, digitalization, and innovations (Wu 2023; Kuzior et al., 2022; Dzwigol et al., 2021; Jiakui et al., 2023; Li and Chen, 2021; Ratajczak 2022). Diversifying the sources of green economic growth led to a more resilient and robust sustainable development trajectory.
6. Given the positive spatial correlation found, encouraging collaboration and knowledge sharing (Kharazishvili et al., 2021) among cities leads to collective advancements in GTFP. Establishing platforms for sharing best practices, technologies 4.0 (Gajdzik et al., 2021; Nyenno et al., 2023) and experiences can accelerate the adoption of efficient and environmentally friendly production methods.

Incorporating these policy implications into China's development strategies contributes to the enhancement of green total factor production, promotes sustainable economic growth, and addresses pressing environmental challenges in a comprehensive and effective manner.

While this study offers valuable insights into the determinants of green total factor production efficiency, there are certain limitations that should be acknowledged. The paper focuses on core indicators such as economic foundation, energy consumption, and environmental pollution. Other potentially relevant variables, such as policy frameworks, technological innovation, green finance, digitalization, innovations, and social factors, could provide a more comprehensive understanding of green total factor production efficiency. In addition, the study could not fully address the causal relationships between the identified determinants and green total factor production efficiency. Further research might be needed to explore the direction of causality and potential feedback loops.

Reference

19th National Congress Reaffirms China's Commitment to Climate Action, Sustainable Development. Available online: https://sdg.iisd.org/news/19th-national-congress-reaffirms-chinas-commitment-to-climate-action-sustainable-development/ [Accessed in 10 January 2023].

Arefieva, O., Polous, O., Arefiev, S., Tytykalo, V., and Kwilinski, A., 2021. Managing sustainable development by human capital reproduction in the system of company's organizational behavior. In *IOP Conference Series: Earth and Environmental Science* (Vol. 628, No. 1, p. 012039). IOP Publishing. http://doi.org/10.1088/1755-1315/628/1/012039.

Baltgailis, J., and Simakhova, A., 2022. The technological innovations of fintech companies to ensure the stability of the financial system in pandemic times. *Marketing and Management of Innovations*, 2, pp.55-65. http://doi.org/10.21272/mmi.2022.2-05.

Bianco, V., Manca, O., and Nardini, S., 2009. Electricity consumption forecasting in Italy using linear regression models. *Energy*, *34*(9), pp.1413–1421.

Bing, W., Yanrui, W., and Pengfei, Y., 2010. Regional environmental efficiency and environmental total factor productivity growth in China. *Economic Research*, *5*, pp.95–109.

Chai, B., Gao, J., Pan, L., and Chen, Y., 2021. Research on the impact factors of green economy of China—from the perspective of system and foreign direct investment. *Sustainability*, *13*(16), 8741. https://doi.org/10.3390/su13168741.

Chen, Y., and Zhang, J., 2016. Carbon emission, green total factor productivity and economic growth. J. Quant. Tech. Econ, *8*, pp.47–63.

Cheng, C., Yu, X., Hu, H., Su, Z., and Zhang, S., 2022. Measurement of China's Green Total Factor Productivity Introducing Human Capital Composition. *International Journal of Environmental Research and Public Health*, *19*(20), 13563. https://doi.org/10.3390/ijerph192013563.

Cheng, Z., Li, L., and Liu, J., 2020. Natural resource abundance, resource industry dependence and economic green growth in China. *Resources Policy*, *68*, 101734. https://doi.org/10.1016/j.resourpol.2020.101734.

Chung, Y., Färe, R., and Grosskopf S., 1997. Productivity and undesirable outputs: a directional distance function approach. *Journal of Environmental Management*, *51*(3), pp.229–240. https://doi.org/10.1006/jema.1997.0146.

Chygryn, O., and Miskiewicz, R., 2022.New Trends and Patterns in Green Competitiveness: A Bibliometric Analysis of Evolution. *Virtual Economics*, *5*(2), pp.24-42. https://doi.org/10.34021/ve.2022.05.02(2).

Cui, Y., Huang, H., and Zhang, Q., 2017. Add pricing and scale reward effect in total factor productivity. *Quantitative, economic, Technical and economic research*, *34*(10), pp.128–143.

Dacko-Pikiewicz, Z., 2019. Building a family business brand in the context of the concept of stakeholder-oriented value. *Forum Scientiae Oeconomia*, *7*, pp.37-51. https://doi.org/10.23762/FSO_VOL7_NO2_3

Dzwigol, H., 2020. Innovation in marketing research: Quantitative and qualitative analysis. *Marketing and Management of Innovations*, 1, pp.128-135. http://doi.org/10.21272/mmi.2020.1-10

Dźwigoł, H., 2021. The Uncertainty Factor in the Market Economic System: The Microeconomic Aspect of Sustainable Development. *Virtual Economics*, 4 (1), pp.98-117. https://doi.org/10.34021/ve.2021.04.01(5)

Dzwigol, H., Trushkina, N., and Kwilinski, A., 2021. The Organizational and Economic Mechanism of Implementing the Concept of Green Logistics. *Virtual Economics*, *4*(2), pp.41-75. https://doi.org/10.34021/ve.2021.04.02(3)

Färe, R., and Grosskopf, S., 2010. Directional Distance Functions and Slacks-based of Efficiency. *European Journal of Operational Research*, 2, pp.320–322.https://doi.org/10.1016/j.ejor.2010.02.033.

Färe, R., Grosskopf, S., Lovell, C. K., and Pasurka, C., 1989. Multilateral productivity comparisons when some outputs are undesirable: a nonparametric approach. *The review of economics and statistics*, 71(1), pp.90–98.

Feng, R., Shen, C., Dai, D., and Xin, Y., 2023. Examining the spatiotemporal evolution, dynamic convergence and drivers of green total factor productivity in China's urban agglomerations. *Economic Analysis and Policy*, *78*, pp.744-764. https://doi.org/10.1016/j.eap.2023.04.014

Feng, Y., Zhong, S., Li, Q., Zhao, X., and Dong, X., 2019. Ecological well-being performance growth in China (1994–2014): From perspectives of industrial structure green adjustment and green total factor productivity. *Journal of cleaner production*, *236*, 117556. https://doi.org/10.1016/j.jclepro.2019.07.031

Fukuyama, H., and Weber W. L., 2009. Output Slacks-adjusted Cost Efficiency and Value-based Technical Efficiency in DEA Models. *Journal of the Operations Research Society of Japan*, *2*, pp.86–104. https://doi.org/10.15807/jorsj.52.86

Gajdzik, B., Grabowska, S., and Saniuk, S., 2021. Key socioeconomic megatrends and trends in the context of the Industry 4.0 framework. *Forum Scientiae Oeconomia*, 9(3), pp.5–22. https://doi.org/10.23762/FSO_VOL9_NO3_1

Hu, Y., Li, Y., Sun, J., Zhu, Y., Chai, J., and Liu, B., 2023.Toward green economy: Environmental performance of belt and road initiative in China. *Environmental Science and Pollution Research*, *30*(4), pp.9496-9513. https://doi.org/10.1007/s11356-022-22804-4

Hussain, H.I., Haseeb, M., Kamarudin, F., Dacko-Pikiewicz, Z., and Szczepańska-Woszczyna, K., 2021. The role of globalization, economic growth and natural resources on the ecological footprint in Thailand: Evidence from nonlinear causal estimations. *Processes*, *9*, 1103. https://doi.org/10.3390/pr9071103

Hussain, S. A., Haq, M. A. U., and Soomro, Y. A., 2020. Factors influencing consumers' green purchase behavior: Green advertising as moderator. *Marketing and Management of Innovations*, 4, pp.144-153. http://doi.org/10.21272/mmi.2020.4-11

Ji, X., and Zhou, S., 2016. Total factor productivity and its impact on Agricultural Economic Growth – is based on an empirical study in Jiangsu Province. *Science and Technology Management Research*, *36*(21), pp.104–108.

Jiakui, C., Abbas, J., Najam, H., Liu, J., and Abbas, J., 2023. Green technological innovation, green finance, and financial development and their role in green total factor productivity: Empirical insights from China. *Journal of Cleaner Production*, *382*, 135131. https://doi.org/10.1016/j.jclepro.2022.135131

Jin, W., Zhang, H. Q., Liu, S. S., and Zhang, H. B., 2019. Technological innovation, environmental regulation, and green total factor efficiency of industrial water resources. *Journal of cleaner production*, *211*, pp.61-69. https://doi.org/10.1016/j.jclepro.2018.11.172

Kharazishvili, Y., Kwilinski, A., Dzwigol, H., and Liashenko, V., 2021. Strategic European Integration Scenarios of Ukrainian and Polish Research, Education and Innovation Spaces. *Virtual Economics*, *4*(2), pp.7–40. https://doi.org/10.34021/ve.2021.04.02(1)

Kjaer, L. L., Pigosso, D. C., Niero, M., Bech, N. M., and McAloone, T. C., 2019. Product/service-systems for a circular economy: the route to decoupling economic growth from resource consumption?. *Journal of Industrial Ecology*, *23*(1), pp.22-35. https://doi.org/10.1111/jiec.12747

Koibichuk, V., Ostrovska, N., Kashiyeva, F., and Kwilinski, A., 2021. Innovation technology and cyber frauds risks of neobanks: Gravity model analysis. *Marketing and Management of Innovations*, 1, pp.253-265. http://doi.org/10.21272/mmi.2021.1-19

Kotowicz, J., Węcel, D., Kwilinski, A. and Brzęczek, M., 2022. Efficiency of the power-to-gas-to-liquid-to-power system based on green methanol. *Applied Energy*, *314*, 118933.

Kuzior, A., and Kwilinski, A., 2022.Cognitive Technologies and Artificial Intelligence in Social Perception. *Management Systems in Production Engineering*, 30 (2), pp.109-115. https://doi.org/10.1016/j.apenergy.2022.118933

Kwilinski, A., 2023. The Relationship between Sustainable Development and Digital Transformation: Bibliometric Analysis. Virtual Economics, 6(3), 56-69. https://doi.org/10.34021/ve.2023.06.03(4)

Lee, C. C., Zeng, M., and Wang, C., 2022. Environmental regulation, innovation capability, and green total factor productivity: New evidence from China. *Environmental Science and Pollution Research*, 29(26), pp.39384-39399. https://doi.org/10.1007/s11356-021-18388-0

Letunovska, N., Abazov, R., and Chen, Y., 2022.Framing a Regional Spatial Development Perspective: The Relation between Health and Regional Performance. *Virtual Economics*, *5*(4), pp.87-99. https://doi.org/10.34021/ve.2022.05.04(5)

Li, C., Qi, Y., Liu, S., and Wang, X., 2022. Do carbon ETS pilots improve cities' green total factor productivity? Evidence from a quasinatural experiment in China. *Energy Economics*, *108*, 105931. https://doi.org/10.1016/j.eneco.2022.105931

Li, H., and Shi, J., 2014. Energy efficiency analysis on Chinese Industrial sectors: An improved super-SBM model with undesirable outputs. *Journal of Cleaner Production*, *65*, pp.97–107. https://doi.org/10.1016/j.jclepro.2013.09.035.

Li, Y., and Chen, Y., 2021. Development of an SBM-ML model for the measurement of green total factor productivity: The case of pearl river delta urban agglomeration. *Renewable and Sustainable Energy Reviews*, *145*, 111131. https://doi.org/10.1016/j.rser.2021.111131

Liu, D., Zhu, X., and Wang, Y., 2021. China's agricultural green total factor productivity based on carbon emission: an analysis of evolution trend and influencing factors. *Journal of Cleaner Production*, *278*, 123692. https://doi.org/10.1016/j.jclepro.2020.123692

Liu, G., Wang, B., and Zhang, N., 2016. A coin has two sides: which one is driving China's green TFP growth?. *Economic Systems*, *40*(3), pp.481-498.

Ma, L., Long, H., Chen, K., Tu, S., Zhang, Y., and Liao, L., 2019. Green growth efficiency of Chinese cities and its spatiotemporal pattern. *Resources, Conservation and Recycling*, *146*, pp.441-451. https://doi.org/10.1016/j.resconrec.2019.03.049

Melnyk, L., Kubatko, O., Piven, V., Klymenko, K., and Rybina, L., 2021. Digital and economic transformations for sustainable development promotion: A case of OECD countries. *Environmental Economics*, *12*(1), pp.140–148. https://doi.org/10.21511/ee.12(1).2021.12

National 13th Five-Year Plan for the Development of Strategic Emerging Industries. Available online: https://cset.georgetown.edu/publication/national-13th-five-year-plan-for-the-development-of-strategic-emerging-industries/ [Accessed in 10 January 2023]

Nyenno, I., Truba, V., and Tokarchuk, L., 2023. Managerial Future of the Artificial Intelligence. *Virtual Economics*, *6*(2), pp.72-88. https://doi.org/10.34021/ve.2023.06.02(5)

Podhorska, I., Vrbka, J., Lazaroiu, G., and Kovacova, M., 2020. Innovations in financial management: Recursive prediction model based on decision trees. *Marketing and Management of Innovations*, 3, pp.276-292. http://doi.org/10.21272/mmi.2020.3-20

Rădulescu, C. V., Bran, F., Ciuvăț, A. L., Bodislav, D. A., Buzoianu, O. C., Ștefănescu, M., and Burlacu, S., 2022. Decoupling the Economic Development from Resource Consumption: Implications and Challenges in Assessing the Evolution of Forest Area in Romania. *Land*, *11*(7), 1097. https://doi.org/10.3390/land11071097

Ratajczak, S., 2022. Digital leadership at universities – a systematic literature review. *Forum Scientiae Oeconomia*, *10*(4), pp.133–150. https://doi.org/10.23762/FSO_VOL10_NO4_7

Rezek, J. P., and Perrin, R. K., 2014. Environmentally Adjusted Agricultural Productivity in the Great Plains. *Journal of Agricultural and Resource Economics*, 2, pp.346–369.

Shi, X., Li, L., 2019. Green total factor productivity and its decomposition of Chinese manufacturing based on the MML index: 2003–2015. *Journal of Cleaner Production*, *222*, pp.998-1008. https://doi.org/10.1016/j.jclepro.2019.03.080

Shpak, N., Melnyk, O., Horbal, N., Ruda, M., and Sroka, W., 2021. Assessing the implementation of the circular economy in the EU countries. *Forum Scientiae Oeconomia*, *9*(1), pp.25–39. https://doi.org/10.23762/FSO_VOL9_NO1_2

Song, M., Chen, Y., and An, Q., 2018. Spatial econometric analysis of factors influencing regional energy efficiency in China. *Environmental Science and Pollution Research*, *2018*(25), pp.13745–13759. https://doi.org/10.1007/s11356-018-1574-5.

Szczepańska-Woszczyna, K., Gedvilaitė, D., Nazarko, J., Stasiukynas, A., and Rubina, A., 2022.Assessment of Economic Convergence among Countries in the European Union. *Technological and Economic Development of Economy, 28*, pp.1572-1588. https://doi.org/10.3846/tede.2022.17518

Titko, J., Tambovceva, T., Atstāja, D., Lapinskaitė, I., Solesvik, M. Z., Svirina, A., and Uzule, K., 2023. Attitudes Toward Sustainable Entrepreneurship among Students: A Pilot Study in Latvia and Lithuania. *TalTech Journal of European Studies*, *13*(1), pp.107-132. https://doi.org/10.2478/bjes-2023-0006

Tone K., 2001. A slacks-based measure of efficiency in data envelopment analysis. *European journal of operational research*,130(3), pp.498–509. https://doi.org/10.1016/S0377-2217(99)00407-5.

Tu, Y.-X., Kubatko, O., Piven, V., Sotnyk, I., and Kurbatova, T., 2022. Determinants of Renewable Energy Development: Evidence from the EU Countries. *Energies*, *15*, 7093. https://doi.org/10.3390/en15197093

Veckalne, R., and Tambovceva, T., 2022. The Role of Digital Transformation in Education in Promoting Sustainable Development. *Virtual Economics*, *5*(4), pp.65-86. https://doi.org/10.34021/ve.2022.05.04(4)

Veckalne, R., Kapustins, M., and Tambovceva, T., 2023. Smart Cities, Green Diets: How the Lucy Veg App Supports Valencia's Vegan Community and Contributes to SDGs. *Virtual Economics*, *6*(2), pp.7-22. https://doi.org/10.34021/ve.2023.06.02(1)

Wang, M, Xu, M., and Ma, S., 2021. The effect of the spatial heterogeneity of human capital structure on regional green total factor productivity. *Structural Change and Economic Dynamics*, *59*, pp.427-441. https://doi.org/10.1016/j.strueco.2021.09.018

Wang, S., Chen, G., and Han, X., 2021. An Analysis of the impact of the emissions trading system on the green total factor productivity based on the spatial difference-in-differences approach: The Case of China. *International Journal of Environmental Research and Public Health*, *18*(17), 9040. https://doi.org/10.3390/ijerph18179040.

Wang, Y., 2004. Environmental degradation and environmental threats in China. *Environmental monitoring and assessment*, *90*, pp.161-169. https://doi.org/10.1023/b:emas.0000003576.36834.c9

Wu, G., Riaz, N., and Dong, R., 2023. China's agricultural ecological efficiency and spatial spillover effect. *Environment, Development and Sustainability*, *25*(4), pp.3073-3098. https://doi.org/10.1007/s10668-022-02169-x

Xiaolao, W., and Hongyang, L., 2017. The impact of different executive R & D inputs on total factor productivity—is based on the perspective of the Sino-US comparison. *Scientific Research*, *35*(06), pp.853–862. https://doi.org/10.3390/agriculture13091846

Xie, R., Yuan, Y., and Huang, J., 2017. Different types of environmental regulations and heterogeneous influence on "green" productivity: evidence from China. *Ecological Economics*, *132*, pp.104–112. https://doi.org/10.1016/j.ecolecon.2016.10.019

Yang, L., Ouyang, H., Fang, K., Ye, L., and Zhang, J., 2015. Evaluation of regional environmental efficiencies in China based on superefficiency-DEA. *Ecological Indicators*, *51*, pp.13–19. https://doi.org/10.1016/j.ecolind.2014.08.040

Yuanfeng, K., and Daiyan, P., 2012. Analysis of Environmental production efficiency and Environmental Total factor Productivity in China. *Economic Research*, 7, pp.62–74.

Zhang, K. M., and Wen, Z. G. 2008. Review and challenges of policies of environmental protection and sustainable development in China. *Journal of environmental management*, *88*(4), pp.1249-1261

Zhang, Z., Xue, B., Pang, J., and Chen, X., 2016. The decoupling of resource consumption and environmental impact from economic growth in China: spatial pattern and temporal trend. *Sustainability*, *8*(3), 222.

Zhao, J., Zhang, Y., Chen, A., and Zhang, H., 2022. Analysis on the Spatio-Temporal Evolution Characteristics of the Impact of China's Digitalization Process on Green Total Factor Productivity. *Int. J. Environ. Res. Public Health* , *19*, 14941. https://doi.org/10.3390/ijerph192214941

Zhao, P. J., Zeng, L. E., Lu, H. Y., Zhou, Y., Hu, H. Y., and Wei, X. Y., 2020. Green economic efficiency and its influencing factors in China from 2008 to 2017: Based on the super-SBM model with undesirable outputs and spatial Dubin model. *Science of the Total Environment*, *741*, 140026. https://doi.org/10.1016/j.scitotenv.2020.140026

Zhao, X., Ma, X., Shang, Y., Yang, Z., and Shahzad, U., 2022. Green economic growth and its inherent driving factors in Chinese cities: Based on the Metafrontier-global-SBM superefficiency DEA model. *Gondwana Research*, *106*, pp.315-328. https://doi.org/10.1016/j.gr.2022.01.013