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Green Total Factor Efficiency in Vegetable Production: A Comprehensive Ecological Analysis of China's Practices

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Abstract: This study undertakes a comprehensive analysis of vegetable production efficiency in China using input–output data from 30 provinces spanning 2011 to 2017. By incorporating environmental pollution costs as undesirable outputs alongside vegetable output value, we employ Data Envelopment Analysis (DEA) with the Banker, Charnes, and Cooper (BCC) model and the Malmquist index model. Our assessment reveals both annual and inter-period efficiency changes. The findings highlight a modest overall efficiency in China's vegetable production and significant regional disparities. Technical progress emerges as a pivotal determinant of total factor productivity (TFP). Recognizing these dynamics, we propose policy recommendations that prioritize technical innovation, sustainable practices, rural infrastructure enhancement, and specialized cultivation methods. Implementing these recommendations could bolster China's position in international trade negotiations due to increased exports and potentially drive broader environmental policy reforms. As vegetable production becomes more efficient and sustainable, there might be a shift in labor needs, potentially leading to migration patterns or changes in employment structures. These insights contribute to the sustainable development of China's vegetable industry, offering a broader understanding of the dynamics of agricultural efficiency in the context of environmental sustainability.

Keywords: vegetable; total factor productivity; Data Envelopment Analysis; technical progress; environmental sustainability

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1. Introduction

Increasing crops while decreasing pesticide and fertilizer use is a global challenge for improving the sustainability of production systems [1]. Vegetables, as a vital functional food for both urban and rural populations, hold significant importance in China's agricultural sector. The government, recognizing the importance of the vegetable industry, has been proactive in its development. As delineated by *The Notice of the General Office of the Ministry of Agriculture and Rural Affairs on Carrying Out the Cultivation of High-Quality Farmers in 2022*, it is vital to ensure a stable supply from the Vegetable-Basket Project in concert with consistent grain and oil expansion. Consequently, the cultivation area for vegetables in China has seen substantial growth, from 19,981,070 hectares in 2017 to 21,872,210 hectares in 2021, at an average annual compound growth rate of 2.3%. Nonetheless, China's agricultural expansion for many years has largely depended on increased inputs [2], and high fertilizer inputs considerably contribute to global agricultural greenhouse gas emissions [3]. These issues are further compounded by the low marginal contribution of land, underdeveloped mechanization, and the overuse of pesticides and fertilizers. For a country like China, grappling with constraints such as relative land scarcity, limited human capital, and ecological pressures, such an extensive growth model, will not only inhibit the long-term development of the vegetable industry but also exacerbate the tensions between industrial development and environmental preservation. In this light, the agricultural supply-side structural reform proposed by China in 2016 marked a shift toward correcting the input structure of vegetable industry factors, while the *No. 1 Central Document in 2023* continued to endorse green agricultural development. The pressing need is to utilize vegetable production resources effectively, reduce dependence on input factors, and ease ecological pressures, thereby enhancing production efficiency. This constitutes an urgent challenge for China's vegetable industry.

Before delving into strategies to improve vegetable production efficiency and resource utilization efficiency, it is pivotal to conduct thorough research on the various factors contributing to the input process in vegetable production. The intricacies and hurdles of vegetable production, particularly regarding material input factors, such as pesticides, fertilizers, agricultural films, irrigation, land, and seeds, are widely recognized in the existing literature.

Pesticide use in vegetable production is a subject of ongoing interest. Lechenet et al. (2017) demonstrated that decreasing pesticide use does not necessarily correlate with reduced crop yield [4]. This insight is pivotal in promoting sustainable farming practices, considering that the long-term use of pesticides harms the environment and ultimately renders the land non-arable, thereby reducing both land and productivity [5]. With a propensity for developing resistant or tolerant strains and the increased awareness of sustainable agriculture, biological control has been considered a valuable alternative to chemical control [6].

Fertilizers are another major input. Tilman et al. (2002) highlighted the environmental harm caused by an over-reliance on synthetic fertilizers [7]. The national greenhouse agriculture area covers about 40 million mu (26,666.7 square kilometers), constituting more than 80% of the world's total greenhouse agriculture area, with over 80% being vegetable cultivation [8]. As plastic-shed vegetable production expands in China, optimizing excessive nitrogen (N) input becomes increasingly crucial [9]. Previous research showed that N_2O emissions from plastic-shed production increase proportionally with the rate of fertilizer N [10–12]. This is due to the fact that N_2O is released during the conversion of some of the N to nitrates when N fertilizers are applied to the soil. Moreover, the GWP of N_2O surpasses CO_2 by a factor of approximately 298 [13,14]. Overall, chemical N fertilizer application increased GHG emissions [15].

The utilization of agricultural mulch films, predominantly plastic mulches, is a topic that has garnered substantial attention in research. These films, acting as a physical barrier to soil, confer numerous benefits including the preservation of soil heat and moisture, the mitigation of weed propagation, the protection of soil structure, and an ultimate increase in crop yields [16,17]. On the other hand, the misuse of plastic mulching materials can engender severe environmental pollution, prompting concerns about their usage [18]. Low-density polyethylene (LDPE) is the most prevalent and effective material for agricultural films due to its ready availability, chemical resistance, mechanical flexibility, and non-toxicity [19]. A study by Tan et al. (2023) indicated that biodegradable films had the least net impact on aquatic pollution and toxicity indicators, while 0.014 mm polyethylene films excelled in mitigating global warming and fossil resource depletion [20]. Sani et al. (2023) presented a discussion on using fruit and vegetable by-products to produce biopolymers as alternatives to synthetic plastic polymers, applying these biopolymers in value-added functional packaging films and coatings [21].

Irrigation, another critical factor in vegetable production, presents both opportunities and challenges. While irrigation boosts yield by supplying ample water, it also leads to elevated N_2O emissions [22,23]. High-yield demands often necessitate significant agricultural inputs, such as nitrogen fertilizers and irrigation, which contribute to an escalation in greenhouse gas emissions [24]. In particular, during vegetable cultivation, large inputs of nitrogen fertilizers and irrigation water augment total N_2O emissions [25]. An optimal irrigation strategy should cater to the water and fertilizer requirements of crops [26–28]. Negative pressure irrigation (NPI) is a subsurface irrigation technique that precisely and continuously supplies water through negative water pressure when soil moisture content diminishes due to evapotranspiration [29–31]. Li et al. (2023) employed two irrigation regimes (negative pressure irrigation and furrow irrigation) to assess two types of soil moisture conditions, with results suggesting that NPI is a more optimal irrigation strategy that can reduce NO emissions while augmenting vegetable yield [32]. Postel et al. (2001) emphasized the importance of efficient water management and the development of sustainable irrigation systems. This was echoed by Raza et al. (2021), who discussed precision irrigation technologies and their potential for resource conservation [33,34].

The significance of land as a factor in vegetable production has been comprehensively documented. Foley et al. (2011) deliberated on the increasing challenges presented by land scarcity, proposing strategies to enhance land-use efficiency [35]. Furthermore, intensive farming practices have been found to diminish soil biodiversity [36–38], an element crucial to ecosystem function [39–41]. Some studies have demonstrated the positive impact of organic farming on soil biota [42]. A study by Yang et al. (2021) suggested that organic vegetable production might experience enhanced soil fertility due to the increased population densities of microbial feeding and omnivorous nematodes, although the threat of plant parasitic nematodes to vegetable production necessitates further attention and the development of control strategies [43].

Lastly, the role of seeds in vegetable production is irreplaceable. High-quality seeds can considerably augment vegetable quality and yield [44,45]. Vernooy et al. (2017) emphasized the significance of seed diversity and its effect on crop resilience [46]. Additionally, the uniformity of vegetable seeds, particularly in terms of size and shape, plays a crucial role in mechanized production, contributing to the implementation of mechanized sowing and enhancing labor productivity [47]. Thakur et al. (2022) furnished an intricate discussion on various seed priming techniques employed to boost the germination rate and vigor in vegetable crops [48].

In conclusion, the extant literature underscores the critical role of these material inputs in vegetable production, emphasizing the escalating focus on sustainable and efficient resource utilization. The prevalent theme in research strategies for optimizing production factor inputs tends to concentrate on providing generalized guidance on resource input behavior [49], such as escalating investment in mechanization, curtailing the use of chemical fertilizers, and reducing agricultural film inputs.

Scholars have conducted extensive research on crop production efficiency, building on the in-depth study of factor inputs in the crop production process. Globally, a considerable amount of research has been undertaken to estimate farm-level efficiency scores [50–57]. Xu et al. (2018) developed a technical efficiency evaluation system for vegetable production aimed at informing decision-making in precision agriculture practices [58]. Akamin et al. (2017) conducted an analysis of the technical efficiency of vegetable growers within selected sites of the humid tropics of Cameroon, focusing on root and tuber-based farming systems [59]. Their findings indicated that farmyard manure was the most productive factor input, which was succeeded by farm equipment and labor. Singbo et al. (2015) employed a sample of vegetable producers in Benin from 2009–2010 to analyze technical efficiency and the value of the marginal product of production input, particularly in relation to pesticide use [60]. The study aimed to measure the distribution efficiency of pesticide use and production inputs. Their findings indicated that in terms of pesticide use, vegetable producers demonstrated less efficiency compared to other input uses.

The topic of enhancing crop production efficiency has gained considerable traction in academic research. Various strategies have been employed by scholars to improve the productivity of texture-contrast soil, including the use of deep-rooting primer species and crop rotation [61,62], as well as surface and subsurface drainage to mitigate intermittent waterlogging [63].

Crucially, optimizing water and fertilizer inputs is instrumental in enhancing resource use efficiency. Techniques such as deficit irrigation can conserve water while sustaining or even augmenting yields by reducing water use in irrigation [64,65]. Furthermore, applying fertilizers at or near plant roots during peak crop demand and in smaller, more frequent applications, can potentially minimize losses while maintaining or increasing yield and quality [66].

However, it is important to note that optimal water and fertilizer inputs can vary based on the fertigation method and crop type. For instance, Sun et al. (2013) demonstrated that under furrow irrigation, the optimal factor input for tomato cultivation is 300 mm of irrigation water and 150 $kgNha^{-1}$ in autumn and winter, or 300 mm of irrigation water and 250 $kgNha^{-1}$ in spring and summer [67]. Meanwhile, Kuscu et al. (2014) established that the optimal factor input under drip irrigation is 75% of the pan evaporation irrigation regime and a 180 $kgNha^{-1}$ supply [68].

Moreover, some researchers argue that specific production modes or systems can boost vegetable productivity, thus aiding countries in achieving self-sufficiency goals. For example, Song et al. (2022) reported that Singapore's self-sufficiency in green leafy vegetables could reach 80% if vertical farming with natural lighting (Vnat) is employed as the primary local production system [69].

Other studies have indicated a significant correlation between grafting and increased fruit yield in many fruits and vegetables, irrespective of the presence of certain soil-borne diseases [70]. Similarly, Carlos et al. (2021) found that regardless of the transplant time for chicory, intercropping it with collard greens yielded greater crop output and land use efficiency index (LUE) compared to their monocultures, reaching a maximum value (52% higher) when chicory was transplanted 42 days after collard greens [71].

In light of the ongoing degradation of natural ecosystems, researchers are increasingly focusing on the environmental harm and resource wastage caused by agricultural practices. Some argue that the large scale use of pesticides, synthetic fertilizers, and other intensive management practices in vegetable farms often leads to environmental issues, like soil degradation [72,73]. Beacham et al. (2019), for instance, discovered that vertical farms utilizing artificial lighting tend to consume substantial energy, given their need for electricity to power lighting. They maintain growth temperature, ventilation, and other environmental controls [74].

Furthermore, the interplay between agricultural income and environmental considerations has been investigated using diverse methodologies [75–82]. For example, Barbosa et al. (2015) estimated that while hydroponic systems in heated greenhouses could yield 11 times more lettuce than traditional soil farming, they required 82 times more energy due to their reliance on electricity [83].

Recently, the concept of environmental efficiency, which entails the production of more goods and services with fewer resources while minimizing waste and pollution, has ascended the research agenda. Numerous scholars worldwide are dedicated to measuring environmental efficiency [84–89]. Farms with high productivity and high input usage can adopt an "ecologization" strategy to decrease inputs while maintaining productivity levels [1].

Upon reviewing the body of research to date, it is evident that significant progress has been made, providing a relatively mature theoretical framework for the analysis presented in this paper. However, there are still areas requiring supplementation and enhancement.

1. Most of the existing literature on the efficiency of vegetable production factor allocation spans a relatively short time span, with some studies relying solely on cross-sectional data. The results derived from data with an extended temporal span would possess greater universality and practical significance;
2. A significant number of studies neglect the pollution caused by vegetable cultivation. While some researchers have used stochastic frontier analysis to investigate the use of pesticides in agriculture and their impact on farm-level technical efficiency, demonstrating that excessive pesticide application by farmers results in diminished farm efficiency [90], very few have incorporated pollution from vegetable cultivation into the system of calculating vegetable factor productivity. This neglect does not accurately reflect the real efficiency of vegetable production in China;

3. Most studies only employ either the Data Envelopment Analysis with the Banker, Charnes, and Cooper model (DEA-BCC) model or the DEA Malmquist index model, lacking comparative analysis from both static and dynamic perspectives of vegetable production efficiency.

The main contributions of this paper are as follows:

1. This study endeavors to account for environmental pollution costs in the process of vegetable cultivation, treating them as undesirable outputs. These costs are integrated with the vegetable output value within our calculation system. By constructing a joint output indicator, we aim to provide a more comprehensive reflection of the true efficiency of China's vegetable production. This approach offers practical recommendations for enhancing the efficiency of the industry;
2. We enhance the precision of the Data Envelopment Analysis (DEA) outcome measurements by improving the evaluation indicator system for vegetable production efficiency, building on previous studies. Utilizing the BCC model and the Malmquist index model of the DEA method, we calculate both the annual efficiency and inter-period efficiency changes of vegetable production for each region;
3. Our research delivers an exhaustive examination of the spatiotemporal characteristics of China's vegetable production efficiency, scrutinizing it from both static and dynamic perspectives. This dual approach allows for a more nuanced understanding of the efficiency trends in China's vegetable production.

In the rapidly evolving field of vegetable production efficiency, many studies have provided insights into various aspects of the industry. However, this research introduces a novel approach by integrating environmental pollution costs directly into the analysis, treating them as undesirable outputs. This unique perspective not only offers a more holistic understanding of the true efficiency of vegetable production but also bridges a critical gap in the literature. By considering the environmental implications alongside production metrics, we aim to present a more comprehensive picture of the industry's sustainability and efficiency, setting our work apart from conventional studies.

2. Materials and Methods

Figure 1 presents a structured flow of the research methodology employed in this study. It begins with the "Identification and selection of input and output factors", which forms the foundation for the subsequent analysis. The second level, "Calculation of production efficiency", utilizes the DEA-BCC model, and the "Dynamic assessment" employs the DEA Malmquist index to evaluate the temporal changes in efficiency. Based on the insights derived from these analyses, the final level outlines the "Policy implications for optimizing vegetable production", providing actionable recommendations for stakeholders.

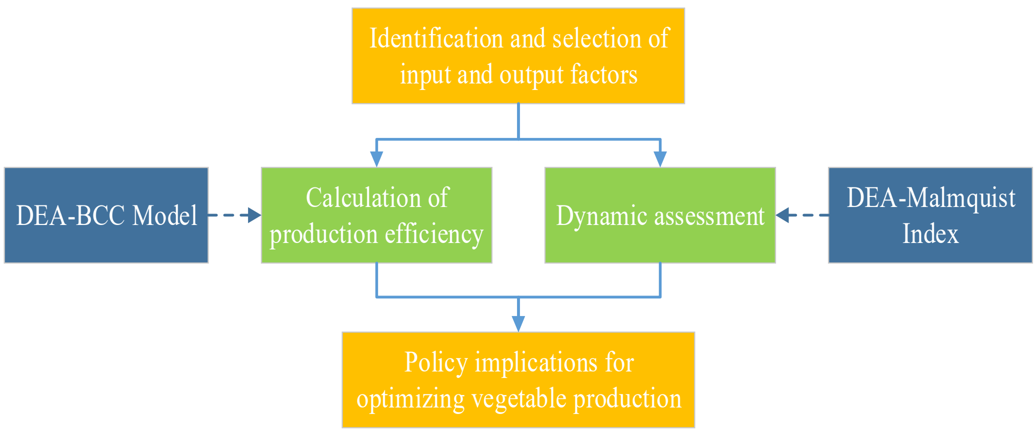

Figure 1. Flowchart of the research methodology employed in this study.

2.1. Static and Dynamic Analysis Models

2.1.1. DEA-BCC Model

Efficiency measurement in production systems has been traditionally approached using various methodologies, with stochastic frontier analysis (SFA) and Data Envelopment Analysis (DEA) being the most prominent. While both methods have their merits, they cater to different analytical needs and data structures.

SFA, a parametric method, assumes a specific functional form for the production frontier and requires the specification of an error structure. It is particularly useful when there is a need to account for statistical noise and when the dataset is large.

While SFA is a robust technique, it requires a specific functional form to be assumed for the production function, which might not accurately represent the complex, multifaceted processes involved in vegetable production across diverse contexts in China. Additionally, SFA often necessitates more stringent assumptions about the distribution of efficiency and error terms, which might not align with the empirical realities of our dataset. In contrast, DEA-BCC is a non-parametric linear programming method that does not impose any functional form on the production frontier. It envelops data points to form an efficiency frontier, making it especially suitable for datasets where the functional form of the production process is not well-defined or is complex. Furthermore, DEA's ability to handle multiple input and output variables without requiring a priori weightings makes it a versatile tool for efficiency analysis in diverse settings.

Given the nature of our dataset, the complexities associated with vegetable production, and the multiple variables we aimed to consider, DEA-BCC emerged as the most suitable method for our study. Its flexibility in handling multiple inputs and outputs, without the need for explicit assumptions about their distribution or functional form, provided a robust framework for our analysis.

For readers interested in the technical intricacies and mathematical formulations of DEA-BCC, we have provided a detailed exposition in Appendix A.1.

2.1.2. DEA Malmquist Index

The DEA-BCC model is a static measurement, which calculates the comprehensive efficiency value of each DMU in each period. If one wants to analyze the dynamic efficiency trend of each DMU over n periods, the DEA Malmquist index is required.

For readers interested in the technical intricacies and mathematical formulations of the DEA Malmquist index, we have provided a detailed exposition in Appendix A.2.

2.2. Selection of Variables

In order to reflect the true performance of vegetable industry development and avoid decision-making errors, this study considers resource elements and environmental elements closely related to the sustainable development of the vegetable industry when selecting input–output indicators for vegetables. The specific content is as follows (Table 1), in our study, we categorize the input factors affecting vegetable production efficiency in China into three distinct but interrelated layers. The first layer, "Resource Factors", comprises land [91] and water [92], which serve as the foundational elements for agricultural production. The second layer, "Labor and Management Factors", includes labor [92] and management costs [93]. These factors are influenced by the availability and quality of resources from the first layer and, in turn, impact the third layer. The third layer, "Technological and Material Factors", consists of basic agricultural inputs [94] like seeds, fertilizers, and pesticides, as well as fixed assets [92], such as tools and materials. This layer is both influenced by and exerts influence on the labor and management layer, as technological choices can affect labor efficiency and management decisions. By structuring our input factors in this manner, we aim to offer a nuanced understanding of the multiple components and their interdependencies that contribute to vegetable production efficiency in China. The comprehensive output indicator is obtained by subtracting the environmental pollution cost from the vegetable output value. The usage of pesticides and fertilizers has been on the rise in recent years, resulting in significant harm to the water environment, such as frequent algae blooms in some lakes and rivers, affecting the drinking water safety of the surrounding population. Based on the principle of accountability, we referred to the government document "Notice on the Pollutant Discharge Standard for the Use of Ammonia Nitrogen and Total Phosphorus in the Taihu Lake Basin". According to the document, the agricultural key pollution source pollutant discharge units' standard for the use of ammonia nitrogen is CNY 6000/year per ton, and the standard for the use of total phosphorus discharge is CNY 23,000/year per ton. We converted the environmental pollution cost accounting into the sum of the usage fees for the amount of nitrogen and phosphorus discharged during the vegetable cultivating process. Based on this, this paper translates the accounting of environmental pollution costs into the sum of paid usage fees for the amount of nitrogen and phosphorus emissions discharged during the process of vegetable cultivation.

Table 1. Selection and composition of input–output indicators for vegetables.

First-Level Indicators	Second-Level Indicators	Composition of Indicators (per Mu)	Symbol	Reference
Input Indicators	Land Input	Rental Cost of Transferred Land + Opportunity Cost of Own Land	Land	[91]
	Labor Input	Opportunity Cost of Family Labor + Hired Labor Cost	Labor	[92]
	Water Input	Irrigation Expenses (Including Water Charges)	Water	[92]
	Basic Agricultural Input	Seed + Fertilizer + Farmyard Manure + Pesticides + Plastic Film Cost + Machinery Operation Cost + Technical Service Fee + Fuel Power Fee + Other Direct Costs	Basic	[94]
	Fixed Assets Input	Depreciation of Fixed Assets + Tools and Materials Fee + Repair and Maintenance Fee	Assets	[92]
	Management Input	Insurance Fee + Management Fee + Financial Fee + Sales Fee	Manage	[93]
Comprehensive Output Indicators	Value of Vegetable Production	Value of Main Product + Value of By-products	Output	[95]
	Environmental Pollution Cost	Pollutants (Nitrogen and Phosphorus) Equivalent × Paid Use Charge Standard		[94]

Note: "Mu" is a traditional Chinese unit of area, and 1 Mu equals 666.67 square meters.

2.3. Data Source

The data for each input and expected output indicator come from the *National Compilation of Cost and Benefit Data of Agricultural Products* (hereinafter referred to as the "Compilation") for the years 2012–2018. The primary vegetables counted in the "Compilation" are open-field/greenhouse tomatoes, open-field/greenhouse cucumbers, open-field/greenhouse eggplants, open-field/greenhouse peppers, open-field Chinese cabbages, open-field round cabbages, open-field string beans, and open-field radishes. Starting in 2012, vegetable data statistics classified by province began to appear. When selecting the research objects, because of differences in the input of basic information, technical means, scale configuration, and management levels between greenhouse cultivation and open-field cultivation, if we only use vegetables as the research object and do not explore the differences in vegetable production efficiency under different models, it will obviously lack depth and detail. Therefore, we excluded Chinese cabbages, round cabbages, string beans, and radishes. Furthermore, considering issues, such as the large variety in vegetable production and discontinuity in regional samples, we excluded eggplants and peppers, which only a few provinces plant in facilities. Finally, we selected tomatoes and cucumbers because these two types of vegetables, whether grown in open-fields or facilities, cover a wide area, evenly spanning most provinces in the country. Moreover, both the cultivation area and output of tomatoes and cucumbers in China rank first in the world. Related literature often involves tomatoes and cucumbers as research objects, indicating their representativeness and persuasive power.

Taking cucumbers and tomatoes from thirty provinces, autonomous regions, and municipalities directly under the central government during the period from 2011 to 2017 as samples, six major regions were divided: Northeast China, North China, East China, Central South China, Southwest China, and Northwest China according to the national administrative division standards. To address a few cases of missing and abnormal data, we used the mean replacement method. For instance, if the wage of hired labor for open-field cucumbers is missing for just one year, we substitute the missing value with the arithmetic mean of the adjacent two years. The descriptive statistics of each variable are presented in Table 2.

Table 2. Descriptive statistical analysis of input–output variables of vegetables in China (unit: yuan).

Classification	Variables	Mean	Standard Deviation	Minimum	Maximum	Sample Size
Overall Vegetables	Output	9588.10	2198.42	3838.00	16,921.00	210
	Land	341.01	152.74	90.00	1040.00	210
	Labor	3342.70	984.73	1252.00	6060.00	210
	Water	64.01	48.48	5.00	347.00	210
	Basic	1462.10	493.41	594.00	3123.00	210
	Assets	445.23	237.61	41.00	1183.00	210
	Manage	126.62	96.07	4.00	606.00	210
Greenhouse Vegetables	Output	12,693.00	2269.49	7429.84	18,352.09	147
	Land	409.23	157.07	172.79	1040.36	147
	Labor	4211.20	1185.73	1403.83	6937.92	147
	Water	96.42	60.28	6.99	347.47	147
	Basic	2058.80	590.84	1052.22	3661.36	147
	Assets	853.87	409.49	235.09	2064.65	147
	Manage	163.54	137.05	8.19	651.13	147
Open-field Vegetables	Output	7457.90	1911.02	3838.25	15,686.92	189
	Land	276.55	107.07	90.34	724.48	189
	Labor	2839.20	828.34	1053.92	5350.64	189
	Water	49.62	35.55	0.42	151.09	189
	Basic	1040.40	409.88	594.21	3037.64	189
	Assets	180.47	93.20	28.56	447.50	189
	Manage	96.34	80.61	4.17	590.36	189

Note: overall vegetables refer to open-field tomatoes, greenhouse tomatoes, open-field cucumbers, and greenhouse cucumbers. Greenhouse vegetables refer to greenhouse tomatoes and greenhouse cucumbers. Open-field vegetables refer to open-field tomatoes and open-field cucumbers.

3. Results and Discussion

To assess the adherence of the constructed DEA model in this study to the concept of "isotonicity" (output expansion with input growth) between input and output variables, a Pearson correlation coefficient test was employed using SPSS 18.0 software (SPSS Inc., Chicago, IL, USA) on vegetable input–output indicators across China. The test outcomes revealed that the Pearson coefficient values between diverse inputs and output indicators were satisfactory, with the majority meeting the criterion at the 0.05 significance level (Table 3). This signifies that the choice of indicators is sound, and the data primarily comply with the "isotonicity" condition. Subsequently, DEAP 2.1 software was utilized to carry out the DEA-BCC efficiency computation and DEA Malmquist index analysis on the input and output data of vegetables across distinct regions of China from 2011 to 2017, generating technical efficiency and total factor productivity change and their decomposition values over the years.

Table 3. Pearson correlation of input–output indicators for vegetables in China.

Indicators	Output	Land	Labor	Water	Basic	Assets	Manage
Output	1						
Land	0.418 **	1					
Labor	0.530 **	0.452 **	1				
Water	0.359 **	0.202 **	0.446 **	1			
Basic	0.425 **	0.629 **	0.391 **	0.398 **	1		
Assets	0.500 **	0.340 **	0.412 **	0.612 **	0.577 **	1	
Manage	0.090	0.222 **	0.147 *	0–0.040	0.201 **	0.032	1

Note: *, ** indicate significant correlations at the 0.1, 0.05 levels, respectively.

3.1. Calculation Results of Production Efficiency Based on the DEA-BCC Model

3.1.1. Overview of General Traits

Considering resource and environmental constraints, the average production efficiency for vegetable production in China from 2011 to 2017 stood at 0.747 on a national scale (Figure 2). This modest level indicates considerable potential for enhancement, suggesting that China could potentially curtail its vegetable production inputs by nearly 25% while maintaining an equivalent output. The efficiency of overall vegetable production, as well as open-field vegetable production, showed a general ascendant trend despite intermittent fluctuations. The apex of average production efficiency for overall vegetables (0.838) was noted in 2016. In contrast, greenhouse vegetables, despite possessing superior production efficiency, displayed a stagnant trend with significant fluctuations.

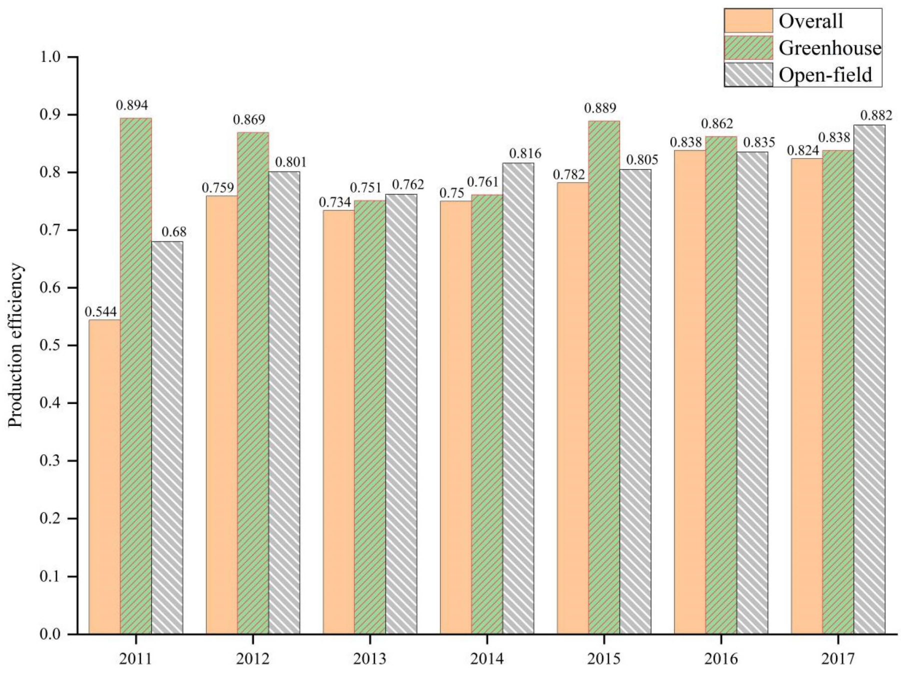

Figure 2. Average production efficiency of the overall vegetables, greenhouse vegetables, and open-field vegetables in China from 2011 to 2017.

Upon analyzing variances in cultivation techniques, a divergence is observed in the production efficiencies of greenhouse and open-field vegetables. Table 4 reveals that the average production efficiency of greenhouse vegetables (0.838) from 2011 to 2017 outperformed open-field vegetables (0.797). When scrutinizing specific vegetable categories, the ranking sequence was as follows: greenhouse cucumbers (0.872) > open-field tomatoes (0.815) > open-field cucumbers (0.777) > greenhouse tomatoes (0.769). This demonstrates that while greenhouse vegetables generally exhibit higher production efficiency than open-field vegetables, certain greenhouse crops lag behind their open-field counterparts. This discrepancy may be ascribed to the nascent stage of greenhouse tomato production, with producers, driven by the mindset of "high input, high output", engaging in production without sufficient caution, leading to resource squandering. Hence, when factoring in resource and environmental constraints, the production efficiency of greenhouse tomatoes trails behind that of open-field tomatoes and open-field cucumbers.

Table 4. Mean production efficiency of the greenhouse/open-field overall vegetables, greenhouse/open-field cucumbers, and greenhouse/open-field tomatoes from 2011 to 2017.

Cultivation Patterns	Production Efficiency		
	Overall Vegetables	**Cucumbers**	**Tomatoes**
Greenhouse	0.838	0.872	0.769
Open-field	0.797	0.777	0.815

3.1.2. Investigation of Regional Variations

An exploration from the vantage point of six major regions (Figure 3) unveils marked regional discrepancies in the production efficiency of overall vegetables in China. Southwest China exhibited the pinnacle of average production efficiency at 0.799, while the Northeast region displayed the nadir, barely reaching 0.653. The ranking of average production efficiency for overall vegetables from 2011 to 2017 emerged as follows: Southwest China > Northwest China > South Central China > North China > East China > Northeast China. Southwest China consistently held the top spot for both greenhouse and open-field cultivation when analyzing distinct cultivation methods. The starkest differences in vegetable production efficiency between the two cultivation methods were observed in East China and Northwest China. East China topped the chart in terms of average production efficiency for open-field vegetables, and it languished at the bottom for greenhouse vegetables. Similarly, Northwest China secured the second spot for greenhouse vegetable production efficiency but held the penultimate spot for open-field vegetable production efficiency.

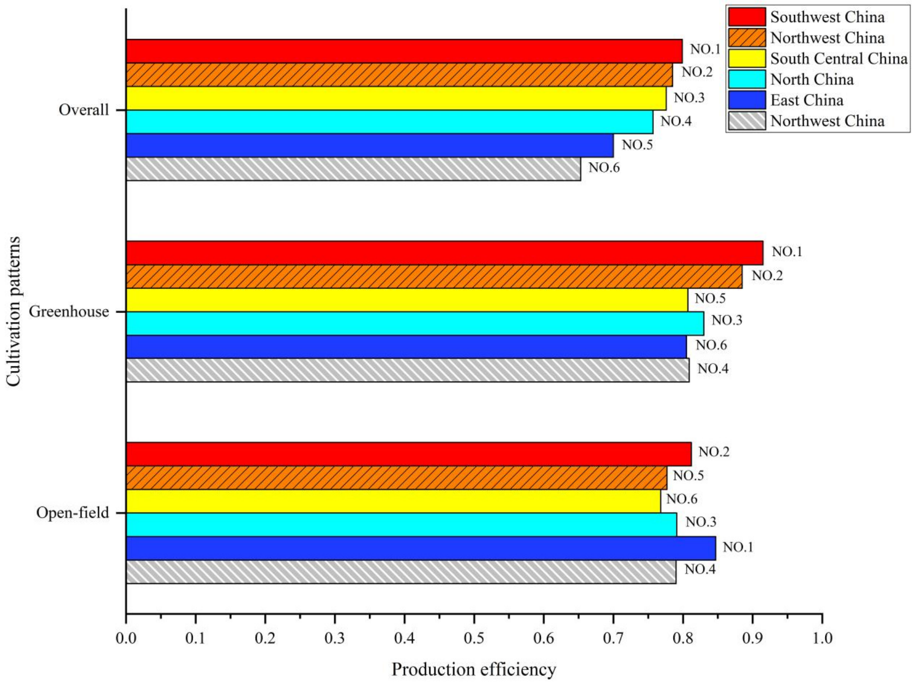

Figure 3. Average production efficiency of the overall vegetables, greenhouse vegetables, and open-field vegetables in the six major regions of China from 2011 to 2017, along with their respective regional rankings.

3.1.3. Examination of Provincial Disparities

According to the data depicted in Figure 4, the quintet of regions in China with the highest average overall vegetable production efficiency from 2011 to 2017 are Guangdong (0.995), Jiangxi (0.966), Chongqing (0.943), Tianjin (0.927), and Shaanxi (0.926). Conversely, the quintet of regions trailing the rest are Jiangsu (0.539), Henan (0.557), Jilin (0.560), Beijing (0.606), and Inner Mongolia (0.607). More than half of the regions (16 out of 30) register an average overall vegetable production efficiency beneath the national average, highlighting a deficiency in coordinated development that concurrently safeguards resources and the environment and escalates the vegetable production value.

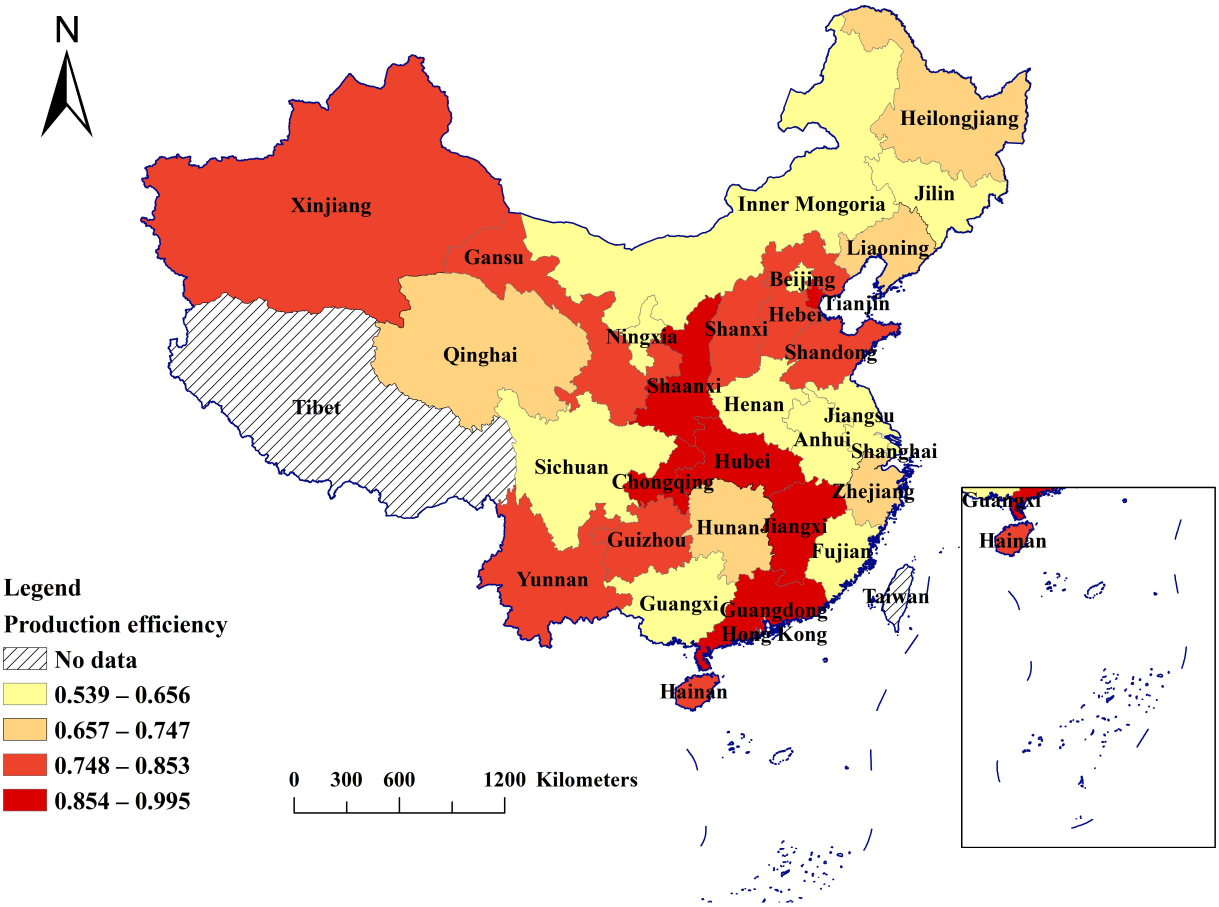

Figure 4. Average production efficiency of each province in China from 2011 to 2017.

3.2. Dynamic Assessment via the DEA Malmquist Index

3.2.1. Analysis of Aggregate Characteristics

The national trajectory (Figure 5) illustrates that the Tfpch of the overall vegetable cultivation in China registered an increase of 3.9% in 2011–2012, 0.7% in 2014–2015, and 3% in 2016–2017. However, there were varying degrees of TFP contraction between 2013 and 2015, with a precipitous plunge of 9.7% in 2012–2013. The aggregate TFP value of vegetables equates to 0.99, falling short of 1, suggesting an overarching downward trend with an annual contraction rate of −1%. Upon dissecting the Malmquist productivity index's components, the yearly modifications in Effch and Techch of overall vegetables averaged between 1.082 and 0.915, respectively. Technical efficiency increased positively with an annual growth rate of 8.2%, while technical progress contributed negatively, with an annual decline rate of −8.5%. These findings denote that exclusive reliance on technical efficiency to propel TFP expansion is inadequate, and the dearth of technical progress serves as the principal bottleneck in China's overall vegetable TFP progression.

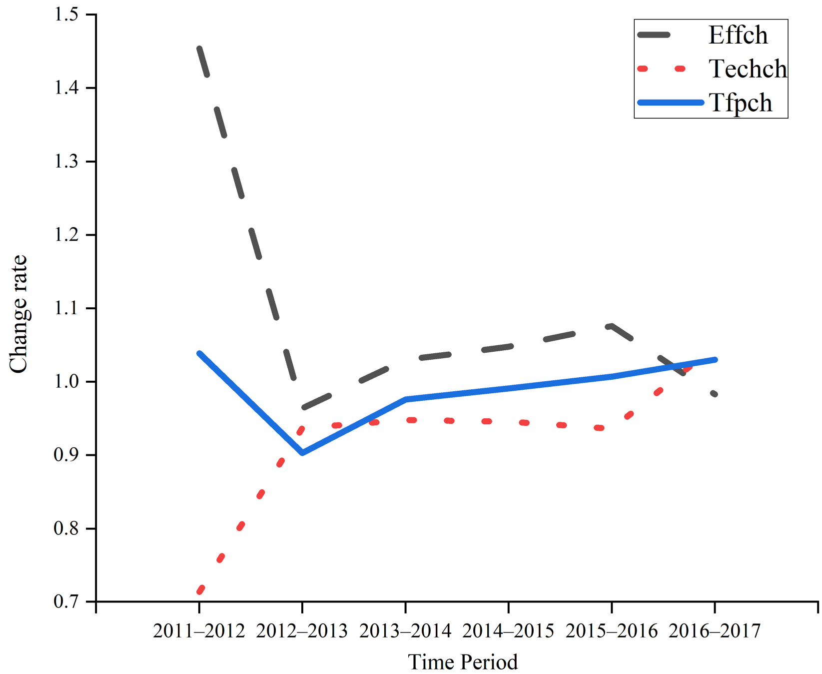

Figure 5. Average value of efficiency change (Effch), technical change (Techch), and total factor productivity change (Tfpch) of the overall vegetables in China from 2011 to 2017.

From a temporal viewpoint (Figure 6), overall vegetables and greenhouse vegetables in China initially manifested high TFP, with the steepest decrease occurring from 2012 to 2013, succeeded by an oscillatory recovery. Contrarily, open-field vegetables initiated with a lower TFP unveiled a robust growth trend, particularly from 2013 to 2015, with the Tfpch escalating from −7.1% to 4.3%.

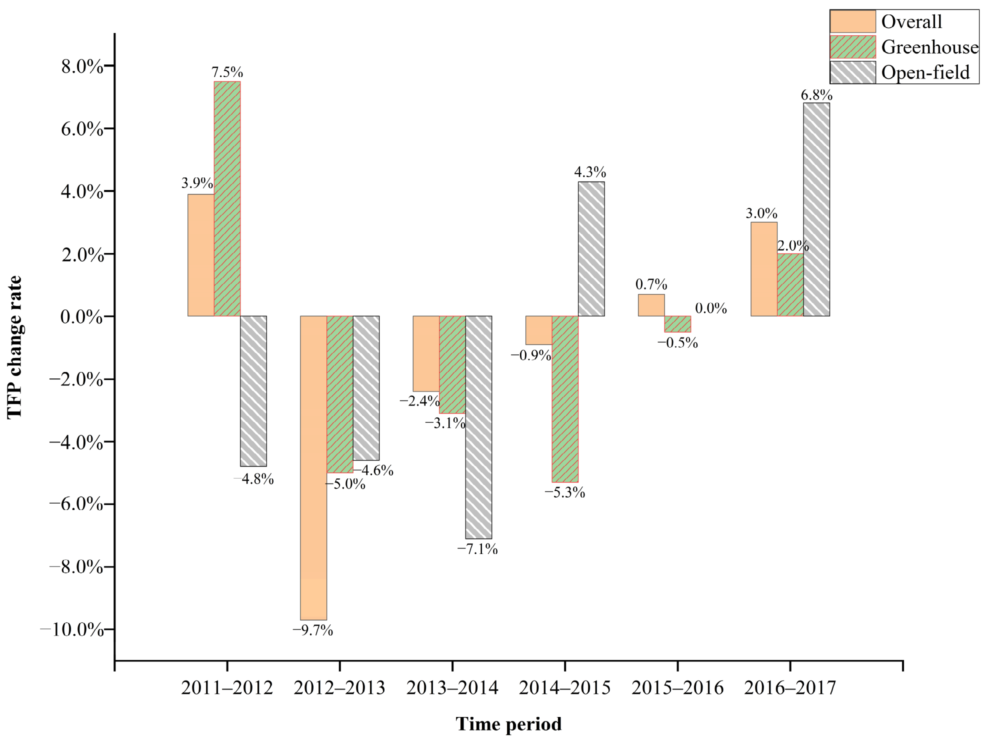

Figure 6. Total factor productivity change (Tfpch) of the overall vegetables, greenhouse vegetables, and open-field vegetables in China from 2011 to 2017.

Evaluating greenhouse vegetables (Table 5), the mean TFP, efficiency, and technical change indices were 0.992, 0.989, and 1.003, respectively. This indicates that a deficiency in technical efficiency predominantly incites the decline in greenhouse vegetable TFP. Conversely, for open-field vegetables (Table 5), the mean TFP, efficiency, and technical change stood at 0.991, 1.056, and 0.945, respectively, suggesting that inadequate technical progress chiefly catalyzes the decrement in TFP.

Table 5. Average TFP change (Tfpch) and decomposition of China's greenhouse vegetables and open-field vegetables from 2011 to 2017.

Classification	Effch	Techch	Tfpch
Greenhouse Vegetables	−10.1%	0.3%	−0.8%
Open-field Vegetables	5.6%	−5.5%	−0.9%

Note: Effch is the abbreviation of efficiency change, Techch is the abbreviation of technical change, Tfpch is the abbreviation of total factor productivity change.

From this analysis, it is clear that the strategic focus for open-field vegetable development should gravitate toward augmenting technical investment and innovation, fostering sustained technical progress. In contrast, greenhouse vegetables, currently displaying advanced technical status, should prioritize optimizing operational scale and bolstering operational efficiency.

3.2.2. Examination of Regional Disparities

An analysis of the six major regions (Figure 7) reveals that Southwest China, North China, and Northeast China experienced an upward trend in average Tfpch from 2011 to 2017, registering growth rates of 5.60%, 3%, and 1%, respectively. Conversely, Northwest China, Central South China, and East China demonstrated a decline in Tfpch, with annual contraction rates of 1.40%, 2.4%, and 4.30%, respectively. In all six regions, the mean Effch surpassed 0%, while the mean Techch value fell below 0%. This regional comparison bolsters the notion that inadequate technical progress forms the primary hurdle to the growth of overall vegetable TFP in China.

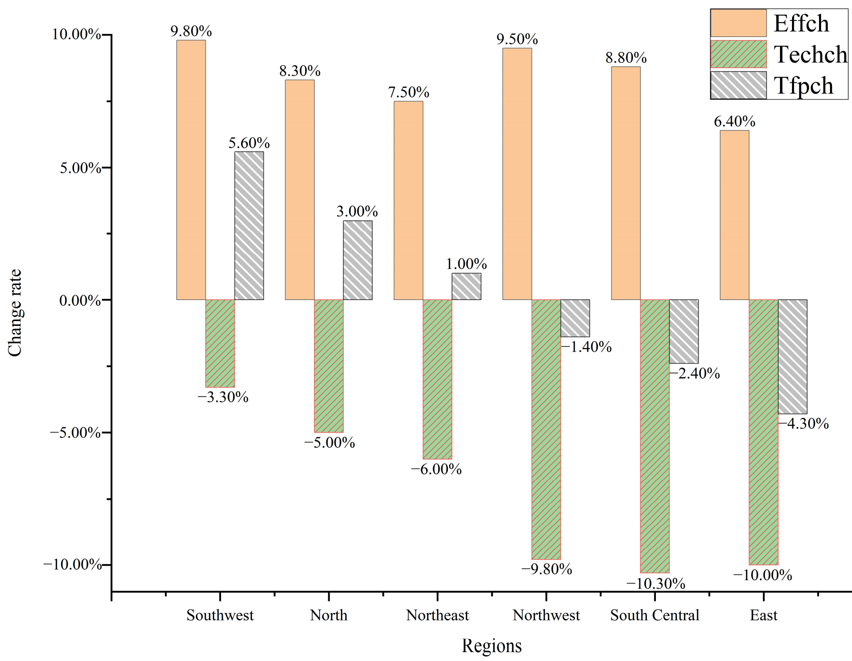

Figure 7. Average efficiency ahange (Effch), technical change (Techch), and total factor productivity change (Tfpch) of the overall vegetables in the six major regions of China from 2011 to 2017.

While technical progress has been identified as the main hindrance to TFP growth, it may also be inferred that the rate of adoption of new technologies and practices is equally crucial. Education, training, and technology promotion practices contribute to productivity enhancement [96]. When considering that these regions likely have access to similar vegetable production technologies, it raises questions about why some regions perform better than others. East China has robust scientific research strength in agricultural colleges and universities, yet it ranks the lowest in Techch. This discrepancy might indicate that Southwest China, for example, Guizhou province, has performed better in promoting vegetable production technology. Guizhou province recently established a provincial-level agricultural technology experiment demonstration base in Weining Autonomous County. The initiative introduces new high-quality vegetable varieties, such as cabbages, from inside and outside the province. It integrates accompanying cultivation technology, promotes new varieties and techniques throughout the county, fosters the rapid transformation of advanced agricultural technology, and enhances the public service capability of the grassroots agricultural technology promotion system. Consequently, we propose that regions that are more open to change and those that have established mechanisms for technology transfer may exhibit more significant advancements.

Further comparing the fluctuations in technical efficiency and technical progress between greenhouse and open-field vegetables in Southwest China (Figure 8) reveals that the mean values for both Effch (3.1%) and Techch (4.1%) of greenhouse vegetables exceed 0%. For open-field vegetables, the mean Effch (8.5%) surpasses 0%, and the mean Techch (0.972) falls short of 0%. Clearly, greenhouse vegetables in Southwest China outperform open-field vegetables in terms of technical innovation. However, there persists a significant problem of insufficient technical progress in Southwest China's open-field vegetables.

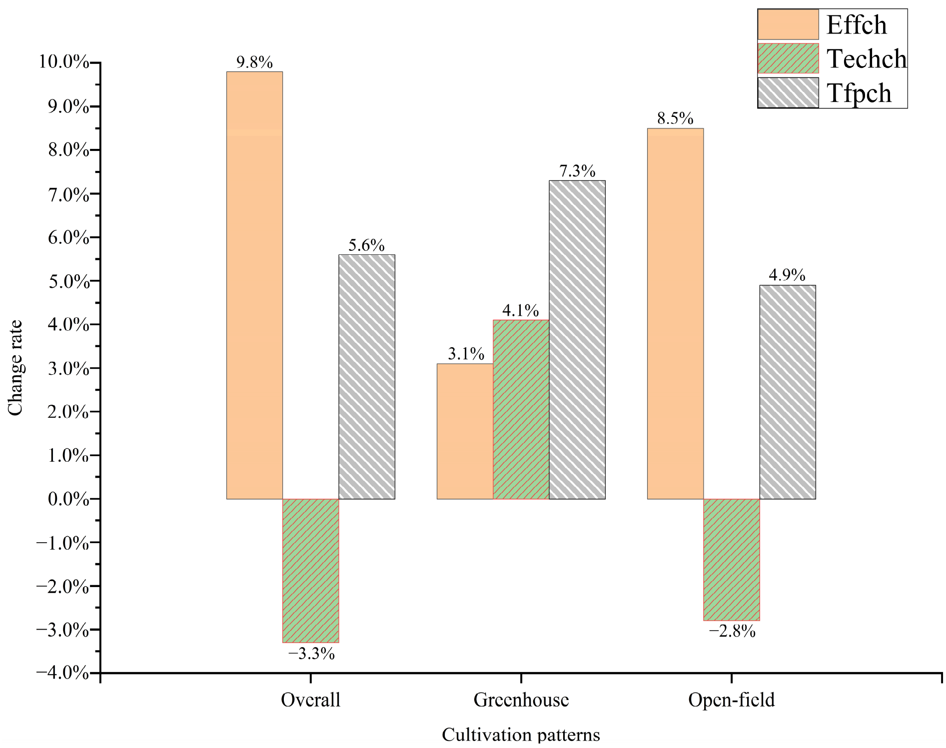

Figure 8. Average efficiency change (Effch), technical change (Techch), and total factor productivity change (Tfpch) of the overall vegetables, greenhouse vegetables, and open-field vegetables in Southwest China from 2011 to 2017.

3.2.3. Analysis of Interprovincial Variations

Reviewing the provinces (Figure 9), 13 provinces in China observed an increase in average overall vegetable TFP. The top five provinces are Tianjin (20.6%), Guizhou (10.2%), Chongqing (9.5%), Guangxi (4.4%), and Zhejiang (4.4%). Conversely, provinces with negative TFP growth include Guangdong (−18.6%), Shanghai (−12.9%), Beijing (−9.3%), Heilongjiang (−8.8%), and Jiangsu (−8.1%). Henan, Hunan, and Sichuan witnessed a stagnation in average overall vegetable TFP. Evaluating the TFP change components, all regions except Hainan accomplished growth in technical efficiency, while all regions barring Tianjin, Shanxi, and Chongqing failed to register growth in technical progress. This further ratifies that insufficient technical progress constitutes the primary obstacle to the growth of the overall vegetable TFP in China.

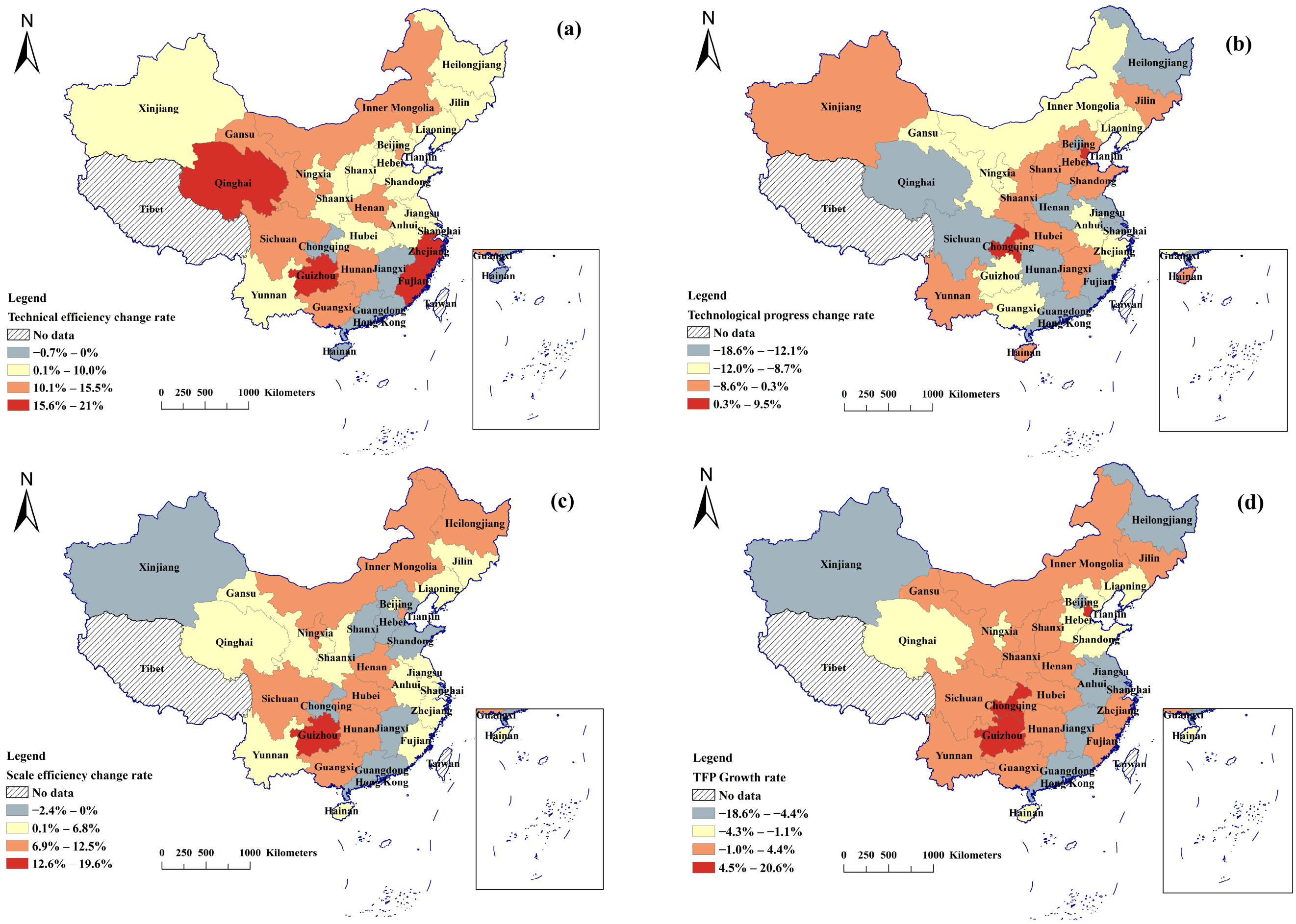

Figure 9. Average Effch (**a**), Techch (**b**), Sech (**c**), and Tfpch (**d**) of the overall vegetables in each province of China from 2011 to 2017.

The role of external environmental factors, such as climate change and regional biodiversity, could have a notable influence on vegetable production efficiency. Climate change is challenging vegetable production, and variations in seasonal patterns or extreme events (e.g., heat waves, droughts, excessive rain, change in seasonal patterns) threaten both yield and quality [97]. Tianjin and Guizhou lead in Effch, Techch, Sech, and Tfpch among all provinces. Tianjin, located in the North Temperate Zone and affected by monsoon circulation and experiences a monsoon climate with hot, rainy summers and cold, dry winters. On the other hand, Guizhou belongs to the Subtropical Monsoon Climate Zone, which is characterized by small temperature changes, no severe cold in winter, no extreme heat in summer, and rich biodiversity. We surmise that regions with high biodiversity and suitable climate conditions may exhibit superior overall efficiency due to the symbiotic relationships within the local ecosystems and favorable weather conditions.

3.3. Discussion

The findings of this study offer a comprehensive understanding of the vegetable production efficiency landscape in China from 2011 to 2017. Several key insights emerge from the analysis that have significant implications for policy formulation.

(1) The research underscores the pivotal role of technological innovation in shaping the trajectory of the TFP in China's vegetable industry. The observed modest average production efficiency, particularly in open-field vegetables, is largely attributed to a lack of technological progress. This insight suggests that for a substantial improvement in TFP, there is an urgent need to prioritize and invest in technological advancements tailored to the unique challenges in the vegetable sector.

This emphasis on technological innovation resonates with findings from other studies. For instance, modernizing practices, such as adopting drip irrigation systems, have been shown to efficiently deliver water directly to plant roots, thereby reducing water wastage and enhancing crop productivity [98–100]. Furthermore, a plethora of research has delved into the impact of various production technologies on the efficiency of agricultural products. Techniques such as alternate partial root-zone irrigation [101], aerated irrigation [102], and the use of treated wastewater for irrigation [103] have been explored for their effects on yield, quality, water productivity, and greenhouse gas emissions across different crops, including vegetables. The application of organic fertilizers [104] and specific planting methods [105] have also been studied for their potential benefits. Notably, subsurface drip irrigation has been identified as a significant technological advancement, leading to increased yields, enhanced irrigation water productivity, and overall water productivity in crops, vegetables, and fruits [106].

In light of these findings from the broader literature, it becomes evident that the trajectory of the TFP in China's vegetable industry can be significantly influenced by embracing a range of technological innovations. By integrating these advancements, there is potential not only for improved production efficiency but also for addressing environmental concerns and ensuring sustainable growth in the sector.

(2) The stark regional differences in vegetable production efficiency, with Southwest China outperforming other regions, highlight the uneven distribution of resources, expertise, and technological adoption across the country. Such disparities suggest that a one-size-fits-all policy approach may not be effective. Instead, region-specific interventions, considering the unique challenges and strengths of each region, could yield better results.

This observation is in line with findings from Ito et al. (2023) [107], who noted differential agricultural output growth across regions between 2001 and 2020. Specifically, the eastern region experienced the lowest growth at 1.94%, while the western region saw the highest at 3.98%. Notably, TFP growth accounted for about 40% of the annual output growth across all regions, with technical change being the predominant contributor. This pattern aligns with other empirical studies on Chinese agriculture [108–110].

Furthermore, the significant role of research and development (R&D) in bolstering agricultural productivity is well-documented in various countries, and similar trends are evident in Chinese agriculture [111–113]. Huang and Yang (2017) [114] emphasize that China's central government has substantially increased its investment in agricultural R&D since the mid-2000s. This surge in investment is further evidenced by the OECD (2018) [115] report, which indicates that China's agricultural R&D expenditure in 2013 was nearly four times that of 2000, adjusted for inflation. Given this backdrop, it is plausible to attribute the technological progress observed between 2001 and 2020 to the government's robust commitment to scientific innovation in agriculture. This perspective is further supported by studies, such as Diao et al., 2018 [109] and Wang et al., 2019 [116], who highlight the rapid advancement of agricultural technology in the western region, thereby reducing the technological disparities between regions.

(3) The integration of environmental pollution costs in the analysis underscores the significance of sustainable practices in vegetable production. The environmental implications of vegetable cultivation, if not addressed, could offset the gains from any improvements in production efficiency. This emphasizes the need for policies that not only boost efficiency but also ensure the environmental sustainability of the industry.

Our observations concerning the environmental implications of vegetable cultivation are further accentuated by the broader challenges posed by climate change. For instance, greenhouse gas (GHG) emissions, which are exacerbated by certain agricultural practices, threaten the long-term productivity of crops, such as rice [117]. This global perspective on environmental sustainability resonates with our findings and underscores the urgency of addressing these challenges.

Moreover, our findings align with studies from Uruguay [1] and worldwide [118], which question the necessity of using large amounts of synthetic pesticides to achieve high yields. This is particularly relevant given the growing body of literature advocating for a transition to more sustainable agricultural systems [119–122]. As Scarlato et al. (2022) [1] suggest, promoting sustainable agricultural production fundamentally requires a systemic redesign at both the crop and farm levels. This involves engaging farmers in a collaborative effort to modify deeply ingrained practices.

Furthermore, the debate between Agroecological Crop Protection (ACP) and Integrated Pest Management (IPM) approaches is worth noting in the context of our study. While IPM often centers around the reduced use of pesticides, ACP offers a more holistic approach. ACP emphasizes the ecological health of agroecosystems by optimizing interactions between various living communities, both below and above ground. This approach is anchored in two main pillars: biodiversity and soil health [123].

(4) This study determined that the production efficiency of overall greenhouse vegetables surpasses that of open-field vegetables. This observation aligns with findings from other scholars, notably Moursy et al. (2023) [124]. Specifically, Moursy et al. (2023) [124] highlighted the advantages of greenhouse cultivation, noting its positive impact on total yield [125], benefit–cost ratio, applied irrigation water, and water productivity, using eggplants as a case study. These findings contrast with our observation regarding tomatoes, where greenhouse cultivation exhibited lower production efficiency compared to open-field cultivation. A potential explanation for this discrepancy lies in the inherent characteristics of greenhouse cultivation. Due to its enclosed environment, greenhouse cultivation predominantly depends on irrigation as the sole water source for tomato growth [126]. This reliance becomes particularly pronounced given that tomatoes, when grown in greenhouses, are among the most water-intensive vegetables and necessitate consistent irrigation throughout their growth cycle [127].

4. Conclusions

4.1. Conclusions

This study, utilizing the DEA-BCC and DEA Malmquist index models, analyzed the comprehensive and temporal efficiency of China's vegetable production from 2011 to 2017. The findings indicate considerable variations in efficiency across different time periods, regions, and cultivation methods. Also, the research explored the external factors affecting comprehensive efficiency, yielding valuable insights into the sector's efficiency dynamics. The main conclusions are as follows:

(1) It was revealed that despite the constraints of resources and the environment, the average production efficiency of vegetable production in China remains modest at 0.747. Furthermore, this study underscored the pivotal role of technological progress (or the lack thereof) in shaping the trajectory of the TFP for vegetables in China. While both greenhouse and open-field vegetable cultivation suffered from limitations in this respect, the effect was most acute for open-field vegetable cultivation due to an acute lack of technological progress;

(2) A pivotal revelation of this research was the role of technological innovation, or rather the absence of it, in the development of China's vegetable TFP. It was observed that a stark lack of technical progress, particularly in open-field vegetables, proved to be a significant hindrance in the growth of TFP. This insight into the connection between technological innovation and productivity growth could significantly guide future policy decisions and strategies;
(3) Interestingly, the research showed stark regional differences in vegetable production efficiency. Southwest China demonstrated the most efficient performance, followed by Northwest, Central South, North, East, and Northeast China. However, the TFP trend was not uniformly positive across these regions, with only Southwest, North, and Northeast China experiencing an upward trend, while others experienced varied levels of deterioration.

In conclusion, this research ventured into uncharted territories by intertwining environmental costs with vegetable production efficiency. Our innovative approach of treating pollution costs as undesirable outputs has shed light on the true efficiency of the vegetable production landscape in China. This perspective, which diverges from traditional studies, underscores the importance of sustainable practices in the industry. By offering a more rounded view, we hope to pave the way for future research that equally values both production efficiency and environmental sustainability, ultimately driving the industry toward a more responsible and efficient future.

4.2. Policy Implications

Based on the research findings, several policy recommendations are proposed to boost China's vegetable production efficiency, aiming for a robust, efficient, and sustainable development of the industry:

(1) Central to elevating TFP in the vegetable industry is an integrated approach that prioritizes technical innovation and the assimilation of modern agricultural practices. Establishing a collaborative innovation ecosystem, encompassing government, industry, academia, and research, is crucial. This initiative should be complemented by an effective extension service system to promote a culture of innovation within farming communities. Simultaneously, a shift toward scientifically managed, knowledge-intensive farming practices will leverage technical innovations for improved standardization, scalability, and efficiency;
(2) Given the environmental implications of vegetable cultivation, the integration of sustainable practices is vital. This goal encompasses the mitigation of non-point source pollution through measures like the recycling of agricultural waste, the use of low-toxicity pesticides and biological products, and the adoption of water conservation technologies. Complementing these practices, policies promoting circular agriculture (a system that minimizes waste and optimizes the use of resources) and those enhancing regional biodiversity could collectively ensure the environmental sustainability of the vegetable industry;
(3) The government should enhance infrastructure and industry policies. A strategic focus on rural infrastructure development and an efficient insurance system could create a favorable environment for the vegetable industry. Industry policies should aim to alleviate the various natural, social, and economic risks that vegetable producers encounter, subsequently spurring productivity. Furthermore, considering the environmental implications and the global shift toward sustainable energy, we recommend that the government initiate policies to replace diesel-powered machinery with machines powered by clean energy sources. The adoption of machinery powered by renewable energy, such as solar or wind, or at the very least, biofuels, can significantly reduce the carbon footprint of the agricultural sector;
(4) Given the distinct differences between greenhouse and open-field vegetable cultivation, specialized policies and technical support systems could enhance the respective

TFP more effectively. For instance, greenhouse vegetable cultivation could benefit from subsurface drip irrigation (SDI), which is a water-saving irrigation technology.

4.3. Limitations of This Study

The primary data source for this study is the publicly available *National Compilation of Cost and Benefit Data of Agricultural Products*. While this provides a broad overview, it lacks the granularity of targeted field research data, potentially missing nuances of production efficiency at the micro-level for individual vegetable growers. Additionally, our empirical approach might not capture all environmental pollution sources in vegetable cultivation. For instance, harmful gases from straw burning and soil compaction due to improper agricultural film handling were not factored in, possibly leading to an underestimation of the environmental impacts.

Furthermore, the proposed approach, while theoretically sound, has not been empirically validated in real-world scenarios. Testing its effectiveness and practicality using field data from actual vegetable growers would offer a more robust assessment. The study's focus is on specific regions and contexts, and its adaptability and scalability to different settings, both within China and internationally, remain unexplored.

Lastly, while our study provides insights into vegetable production efficiency, there is potential for interdisciplinary collaborations. Integrating perspectives from related research areas could offer a more holistic view of the challenges and solutions in sustainable vegetable production.

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Abbreviations

DEA	Data Envelopment Analysis
BCC	Banker, Charnes, and Cooper model
CCR	Charnes, Cooper, and Rhodes
DMU	Decision-Making Unit
TFP	Total Factor Productivity
Tfpch	Total Factor Productivity Change
Effch	Efficiency Change
Techch	Technical Change
Pech	Pure Efficiency Change
Sech	Scale Efficiency Change

Appendix A

Appendix A.1. DEA-BCC Basics

Using linear programming techniques, DEA provides a suitable way to estimate a multiple inputs/multiple outputs empirical efficient function as described by Farrell (1957) [128,129]. The common theoretical models in DEA include the Charnes, Cooper, and Rhodes (CCR) model and the BCC model. The difference between the two lies in that the CCR model assumes constant returns to scale, while the BCC model assumes variable returns to scale. In actual production, most decision-making units are not in the optimal scale of production, revealing the drawbacks of the CCR model. Since the vegetable industry belongs to the industry with variable returns to scale, it usually strives to maximize output with the least resource input, so the input-oriented BCC model is used to study the production efficiency of vegetable production in China. It is assumed that there are n DMUs, each with m inputs x_{ik} (i = 1, 2, . . . , m) and s outputs y_{jk} (j = 1, 2,. . . , s). The formula for the DEA-BCC model is as follows:

$$min\left[\theta-\varepsilon\left(\sum_{j=1}^{s}s_j^{+}+\sum_{i=1}^{m}s_i^{-}\right)\right]$$

$$s.t.\quad \sum_{k=1}^{n}\mu_k x_{ik}+s_i^{-}=\theta x_{ik_0}$$

$$\sum_{k=1}^{n}\mu_k y_{jk}-s_i^{+}=\theta y_{jk_0}$$

$$\sum_{k=1}^{n}\mu_k=1,\ \ \mu_k\geq 0$$

$$s_i^{-}\geq 0,\ \ s_i^{+}\geq 0 \tag{A1}$$

In Formula (A1), θ $(0<\theta\leq 1)$ is the comprehensive efficiency indicator, μ_k is the weight variable, s_j^{+}, s_j^{-} are slack variables, and ε is the non-Archimedean infinitesimal. The larger the value of θ, the higher the production efficiency of vegetable production. When $\theta=1$, it indicates that the decision-making unit has reached the optimum, that is, it is on the production frontier and is DEA efficient. If $\theta<1$, it implies DEA inefficiency.

Appendix A.2. DEA Malmquist Index Basics

Färe et al. (1992) developed a DEA-based Malmquist productivity index, which measures the productivity change over time [130]. The DEA Malmquist index method, based on the DEA method, allows for reflecting dynamic changes in efficiency over time, thereby avoiding the influence of the arbitrariness of time selection. It decomposes the Malmquist TFP into efficiency change and technical change, as specifically expressed in Formula (A2):

$$M^t\left(x^t,\ y^t, x^{t+1},\ y^{t+1}\right)=Effch\ \times\ Techch \tag{A2}$$

In this equation, M^t represents the Tfpch; $Effch$ represents the efficiency change; and $Techch$ represents technical change. Efficiency change can further be decomposed into Pech and Sech, as follows:

$$Effch=Pech\ \times\ Sech \tag{A3}$$

The specific formulas are as follows [131,132]:

$$M^t\left(x^t,\ y^t, x^{t+1}, y^{t+1}\right)=D^{t+1}\left(x^{t+1}, y^{t+1}\right)/D^t\left(x^t, y^t\right)$$

$$\times\left[\left(D^t\left(x^{t+1}, y^{t+1}\right)/D^{t+1}\left(x^t,\ y^t\right)\times D^t\left(x^t,\ y^t\right)/D^{t+1}\left(x^{t+1}, y^{t+1}\right)\right]^{1/2} \tag{A4}$$

$$D^{t+1}\left(x^{t+1},\ y^{t+1}\right)/D^t\left(x^t,\ y^t\right)=D^t\left(x^{t+1},\ y^{t+1}\right)/D^t\left(x^t,\ y^t\right)\times D^{t+1}\left(x^{t+1},\ y^{t+1}\right)/D^t\left(x^{t+1},\ y^{t+1}\right) \tag{A5}$$

In Formulas (A4) and (A5), $Effch = D^{t+1}(x^{t+1}, y^{t+1})/D^t(x^t, y^t)$, $Techch = \left[(D^t(x^{t+1}, y^{t+1})/D^{t+1}(x^t, y^t)\times D^t(x^t, y^t)/D^{t+1}(x^{t+1}, y^{t+1})\right]^{1/2}$, $Pech = D^t(x^{t+1}, y^{t+1})/$

$D^t(x^t, y^t)$, $Sech = D^{t+1}(x^{t+1}, y^{t+1}) / D^t(x^{t+1}, y^{t+1})$.$x^t$, x^{t+1} represents the input quantity in period t and period $t + 1$; y^t, y^{t+1} represents the output quantity in period t and period $t + 1$; $D^t(x^t, y^t)$, $D^{t+1}(x^{t+1}, y^{t+1})$ represents the input distance function of the decision unit compared with the frontier surface in periods t and $t + 1$, and $D^t(x^{t+1}, y^{t+1})$, $D^{t+1}(x^t, y^t)$ represents the input distance function of the decision unit compared with the frontier surface in periods t and $t + 1$.

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