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Citrus Industry Agglomeration and Citrus Green Total Factor Productivity in China: An Empirical Analysis Utilizing a Dynamic Spatial Durbin Model

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Abstract: In the context of increasingly severe resource and environmental constraints, examining the impact of citrus industry agglomeration on the green total factor productivity (GTFP) of citrus is of great importance for the sustainable development of the citrus industry and is crucial for promoting the green, high-quality growth of China's agricultural sector. In this study, the global Malmquist–Luenberger productivity index (GMLPI) model was used to measure the GTFP of mandarins and tangerines based on inter-provincial panel data from China's major citrus-producing regions between 2007 and 2022. The dynamic spatial Durbin model was employed to empirically analyze the effects of citrus industry agglomeration on the GTFP of mandarins and tangerines, including the disaggregation of its spatial spillover effects. The results indicate that, in terms of temporal dynamics, the GTFP, technical progress index (GTC), and technical efficiency index (GEC) of mandarins and tangerines significantly fluctuated, especially during the period from 2007 to 2015. Regional disparities in GTFP and the GTC are more pronounced for mandarins than for tangerines, while the GEC shows greater regional disparities for tangerines than for mandarins. The intensification of citrus industry agglomeration has had a significant positive impact on the GTFP of mandarins and tangerines, both locally and in neighboring regions. The spatial correlation of the green total factor productivity of mandarins and tangerines fluctuated; mandarins showed significant spatial aggregation in some years, while tangerines showed significant spatial dispersion in several years. The local Moran scatterplot further reveals the significant negative spatial autocorrelation of mandarin and tangerine green total factor productivity from 2007 to 2022. The direct, indirect, and total effects of citrus industry agglomeration on the GTFP of mandarins and tangerines are significant and positive in both the short- and long-term, with short-term benefits exceeding long-term effects. Consequently, enhancing regional cooperation and exchange while advancing citrus industry agglomeration is essential for sustained productivity growth.

Keywords: mandarin; tangerine; industrial agglomeration; green total factor productivity; dynamic spatial Durbin model

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1. Introduction

China's No. 1 Central Document for 2024 emphasizes the importance of "promoting agricultural development through industrialization, focusing on quality and green agriculture." The greening of agriculture is not only integral to building a strong agricultural nation, but also essential for accelerating the modernization of agriculture and rural areas. Amid increasingly severe resource and environmental constraints, the citrus industry is transitioning from expansion driven by quantity to a phase focused on balancing economic and ecological benefits through green development. Since the reform and opening-up, as the population's food consumption structure has improved, citrus—which is rich in dietary fiber and vitamins—has played a crucial role in meeting the nutritional needs of urban and rural residents. In 2022, China's citrus planting area reached 2.996 million hectares, with production totaling 6.04 million tons, surpassing apples to become the largest fruit crop by area and output. However, the environmental challenges associated with citrus production cannot be overlooked. Research has shown that citrus cultivation in China involves high nitrogen fertilizer input and low nitrogen use efficiency, particularly in the Chinese citrus production system [1–3]. Compared to other major citrus-producing countries, China's citrus industry faces not only high nitrogen inputs but also relatively low yields and high greenhouse gas emissions [4,5]. At the National Promotion Conference on High-Quality Development of the Characteristic Fruit Industry on 21 September 2023, China's Ministry of Agriculture and Rural Affairs emphasized the need to adhere to a systematic approach and green development principles, aiming to improve fruit quality, industrial efficiency, and sustainable development capabilities. In recent years, China's No. 1 Central Document has repeatedly stressed the importance of winning the battle against agricultural and rural pollution, continuing to promote reduced and more efficient fertilizer and pesticide use, and strengthening agriculture's capacity for emission reduction, carbon sequestration, and climate adaptation. Given mounting environmental pressures, tightening resource constraints, rising production costs, and the demands of rapid, high-quality socio-economic development, the citrus industry must focus on enhancing total factor productivity and reducing carbon emissions to achieve sustainable green development. Therefore, improving the green total factor productivity of citrus has become a critical issue for the high-quality, eco-friendly advancement of the specialty fruit industry.

As the new core issue of economic geography, industrial agglomeration has attracted the attention of many scholars. Marshall first mentioned this phenomenon in his Principles of Economics, where he used the term "localization" to describe the spatial agglomeration of industries; that is, "An industry concentrated in certain localities is commonly, though perhaps not quite accurately, described as a localized industry" [6]. Weber [7] was the first to introduce the term "agglomeration" into the traditional location theory. In introducing new economic geography, Krugman [8] discussed the dynamic change between the industrial agglomeration of economic activities and the convergence of regional economic growth, pointing out that economies of scale can reduce costs, promote technological innovation, and improve management efficiency, thus contributing to urban expansion and the rise in regional centers. Since then, many scholars have carried out extensive research on the connotation and extension, formation mechanism, and economic effect of industrial agglomeration. Researchers have argued that agricultural industry agglomeration can effectively solve problems such as small market scales and scattered production and management in rural areas, promote the appreciation of the value of agricultural products, and foster the development of the rural economy [9–11]. Clearly, the role of agricultural industry agglomeration in promoting agricultural development is becoming increasingly significant [12,13].

Scholars have presented differing views on whether agricultural industry agglomeration enhances total factor productivity. Some argue that agricultural industry agglomeration contributes to improved production efficiency. For instance, using the SBM-Undesirable model to measure China's green agricultural development efficiency, Xue et al. concluded that agricultural industry agglomeration exerts a significant positive spatial spillover effect that is approximately four times greater than the direct effect [14]. Han et al. employed the spatial Durbin model and empirically found that agricultural industry agglomeration promotes the growth of green total factor productivity (GTFP) through significant direct effects and spatial spillovers [15]. Similarly, Wang et al. determined that the intensification of grain industry agglomeration has a long-term positive impact on the GTFP of grain in both local and neighboring regions, with long-term effects exceeding short-term ones [16]. Conversely, other scholars have contended that industrial agglomeration hampers improvements in agricultural production efficiency. Using the SBM-GML model to assess agricultural GTFP, Yin et al. found that agricultural industry agglomeration has a significant negative impact, with spatial spillover effects that restrict productivity improvements in neighboring regions [17]. Chen et al. suggested that low levels of financial support hinder the positive effects of forestry industry agglomeration on green total factor productivity in forestry [18]. Some scholars have argued that the relationship between industrial agglomeration and productivity is not linear. For example, Wang et al. proposed that economic agglomeration has a nonlinear effect on agricultural GTFP [19]. Specifically, in the initial stage, agglomeration subtly promotes GTFP through the trickle-down effect; in the growth stage, it inhibits GTFP via the siphoning effect; in the mature stage, it significantly boosts GTFP through the radiation effect; and, in the decline stage, it restrains GTFP through the crowding effect. Luo et al. suggested an inverted U-shaped relationship between agricultural production agglomeration and GTFP in China, with a more pronounced effect in provinces within the Yangtze River Economic Belt [20]. In addition, some scholars have discussed the influence of agricultural industry agglomeration on agricultural green development and agricultural non-point source pollution from the perspective of spatial effects and concluded that agricultural industry agglomeration has a nonlinear U-shaped influence on agricultural green development after considering spatial spillover effects [21–23]. However, no unanimous conclusion has been reached on the impact of agricultural industrial agglomeration on agricultural green TFP. The key debate is whether the impact of agricultural industrial agglomeration on agricultural green TFP is positive or negative, and what the impact is after considering the spatial spillover effect. Therefore, it is necessary to further analyze the complex relationship between agricultural industrial agglomeration and agricultural green total factor productivity.

In light of this, to clarify the impact of industrial agglomeration on the green total factor productivity (GTFP) of the citrus plantation industry, balanced panel data from China's major citrus-producing provinces between 2007 and 2022 were utilized with spatial econometric models to examine the effect of citrus industry agglomeration on citrus GTFP. The marginal contributions of this study are threefold. First, it extends the research on the relationship between industrial agglomeration and GTFP specific to the citrus plantation industry, refining the research focus beyond that of previous studies on agriculture, forestry, and animal husbandry. Second, recognizing the potential lagged effects in GTFP changes, a lagged term of GTFP variables is incorporated into the spatial Durbin model, and a dynamic spatial Durbin model is constructed to assess the impact of citrus industry agglomeration on citrus GTFP. This provides a theoretical foundation for guiding industrial development. Third, the spatial spillover effects of the dynamic spatial Durbin model are further decomposed into short- and long-term effects, allowing for a more in-depth analysis of the spatial spillover effects of industrial agglomeration on GTFP. This analysis identifies key areas for improving and formulating regional industrial policies.

2. Theoretical Analysis and Research Hypothesis

China's vast territory exhibits significant regional heterogeneity in natural endowments and socio-economic conditions, which strongly influence the localized characteristics of agricultural production. However, neighboring regions often share similar natural environments and socio-economic contexts, leading to a high degree of homogeneity in agricultural production conditions, crop types, and development patterns. Additionally, the rapid advancement of modern transportation networks and information and communication technologies has strengthened the connectivity of agricultural production activities across these regions. This connectivity facilitates spatial spillover effects in green agricultural practices, where green production models and technologies from one region can transcend geographical boundaries and positively impact neighboring regions.

Theoretically, citrus industry agglomeration can promote the growth of green total factor productivity (GTFP) in the citrus sector through three positive effects. The first is the scale economy effect. Industrial agglomeration optimizes the allocation of citrus resources, enables the intensive use of production factors, and allows agricultural infrastructure and pollution control costs to be shared across the cluster. This effectively reduces unit production costs, thereby enhancing citrus GTFP [24]. The second is the knowledge spillover effect. Research has shown that agricultural industry agglomeration generates significant knowledge spillovers within the agglomeration area [25], facilitating the rapid dissemination of agricultural knowledge and technology. This process fosters mutual learning among production entities, accelerates the adoption and application of advanced production technologies and management practices, and enhances overall productivity [26]. Additionally, factor flows and resource sharing between provinces lead to spatial interactions, where neighboring regions often imitate and learn from each other [27]. Thus, citrus industry agglomeration not only improves GTFP within a region but also generates spatial spillover effects on GTFP in neighboring regions. The third is the positive competition effect. Citrus industry agglomeration stimulates healthy competition within and beyond the industry. On one hand, this competition encourages enterprises to innovate by investing in the research and development of new technologies and products, thereby enhancing market competitiveness [28]. On the other hand, competition motivates farmers and enterprises to adopt more environmentally friendly and efficient production methods to meet the growing market demand for high-quality green products. This serves as a key driver for the transformation of the citrus industry toward sustainable, green, and efficient development, contributing to the sustained growth of citrus GTFP.

However, the impact of citrus industry agglomeration on green total factor productivity (GTFP) is complex, and its potential negative externalities should not be overlooked. The first is the environmental crowding effect. In the process of industrial agglomeration development, a "crowding effect" arises; that is, when there is a large number of production factors in a short time, the negative externality of industrial agglomeration will be greater than the positive externality [29]. In the citrus industry, the excessive input of production factors can lead to diminishing returns in scale, resulting in congestion. This strains the region's resources and environmental capacity, ultimately hindering improvements in citrus GTFP. The second is the path-locking effect. As citrus industry agglomeration intensifies in a region, it absorbs a large concentration of input factors, creating a lock-in effect. This can result in a siphoning effect, drawing resources away from neighboring areas, weakening their industrial development potential, and impeding the growth of their green total factor productivity [30]. The third is the confinement effect. In the initial stages of citrus cultivation, large-scale inputs of land, capital, and labor are required. However, operators with low economic returns may find it difficult to exit due to the substantial sunk costs incurred during these early stages, continuing to consume large amounts of resources [31]. This, in turn, restricts improvements in GTFP within the agglomeration area.

Based on the above theoretical analysis, the following research hypotheses are proposed:

Hypothesis 1: *There is spatial autocorrelation in the green total factor productivity (GTFP) of citrus within a region.*

Hypothesis 2: *The effect of citrus industry agglomeration on citrus GTFP is uncertain. Specifically, the impact of citrus industry agglomeration on GTFP can be either positive or negative.*

Hypothesis 3: *Citrus industry agglomeration exerts spatial spillover effects on citrus GTFP.*

3. Methods and Data Description

The National Agricultural Cost–Benefit Information Compilation in China distinguishes between mandarin and tangerine statistics; thus, this study also separates the two for analysis. Specifically, balanced provincial panel data from seven major mandarin-producing provinces (including districts and cities) and seven major tangerine-producing provinces (including districts and cities) spanning the period from 2007 to 2022 were selected for study. The seven major mandarin-producing provinces are Fujian, Jiangxi, Guangdong, Hubei, Hunan, Guangxi, and Chongqing, and the seven major tangerine-producing provinces are Zhejiang, Fujian, Jiangxi, Guangdong, Hubei, Hunan, and Chongqing. Over the past 20 years, these eight major citrus-producing provinces have been responsible for more than 80% of the national citrus production, making this study highly representative. All data concerning prices are adjusted using the Producer Price Index for Agricultural Products, with 2007 as the base year for deflation.

3.1. Variable Selection

(1) Explained variables. The explained variable in this study is the green total factor productivity (GTFP) of citrus. In the context of environmental pollution associated with citrus cultivation, carbon emission pollution is incorporated into the analytical framework for GTFP, and citrus GTFP is measured based on existing studies [32]. The selected input variables are labor cost, land cost, fertilizer cost, pesticide cost, and other material and service costs for both mandarins and tangerines. Specifically, labor cost is measured as cost per acre and includes both family labor and hired labor. Land cost is defined as cost per acre and encompasses the rent for transferred land and self-camping areas. Other material and service costs include expenses for seeds, films, rental operations, fuel and power, technical services, tools and materials, repairs and maintenance, and various other costs. The data on input variables are sourced from the National Farm Product Cost–Benefit Survey for 2008–2023, while the agricultural product price index is obtained from the China Rural Statistical Yearbook.

The desired output variable is measured using mandarin and tangerine yields per acre, with data sourced from the National Farm Product Cost–Benefit Survey for 2008–2023.

The non-expected output variable is measured as carbon emissions per mu from citrus production. Agricultural carbon emissions do not include nutrients such as nitrogen and phosphorus, which are considered "real pollutants" [33]. Based on existing studies [34] and the characteristics of citrus cultivation, fertilizers, pesticides, agricultural films, diesel fuel, tilling, and irrigation are selected as sources of carbon emissions. Fertilizer use per acre for mandarins and tangerines is expressed in terms of pure application, with data obtained from the National Farm Product Cost–Benefit Survey. Due to the limited availability of statistical data on pesticides, agricultural films, diesel, and irrigation specifically for citrus production, an estimation method is employed by referencing previous research methodologies [35]. This method involves multiplying the proportion of citrus planting area to the total crop sowing area in each region by the original data for each of the indicators: pesticides, agricultural films, diesel, and irrigation. The data utilized for this estimation are sourced from the China Rural Statistical Yearbook. Tillage data are used as an indicator of citrus acreage in each province. According to the study by Li B. et al., the carbon emission factors are as follows: for fertilizer, 0.8956 kg·kg^{-1}; for pesticide, 4.9341 kg·kg^{-1}; for agricultural film, 5.18 kg·kg^{-1}; for diesel, 0.5927 kg·kg^{-1}; for irrigation, 25 kg·Cha^{-1}; and, for tilling, 312.6 kg/kg (C) [36].

Carbon emissions are calculated as follows:

$$C = \sum_{i=1}^{6} C_i = \sum_{i=1}^{6} P_i \eta_i \tag{1}$$

In Equation (1), C represents total carbon emissions, C_i denotes carbon emissions produced by carbon source i, P_i indicates the amount of carbon emission source i, and η_i is the carbon emission coefficient of carbon source i. As the input–output variables in this study are all measured in mu, carbon emissions are also measured in mu. Specifically, carbon emissions per mu of mandarins and tangerines are calculated as total carbon emissions divided by the area of citrus planted in each province. The descriptive statistics of the input–output variables of mandarins and tangerines are shown in Table 1.

(2) Explanatory variables. The explanatory variable in this study is citrus industry agglomeration (Agg). To analyze the characteristics of citrus industry agglomeration and clarify the current layout of citrus plantations, the location entropy index is employed to measure the degree of citrus industry agglomeration in each region, following the practices established by scholars such as Tang L.Y. et al. [37].

Table 1. Descriptive statistics of input–output variables of mandarin and tangerine green total factor productivity.

Classification	VarName	Obs	Mean	SD	Min	Median	Max
Mandarin	Gross value of production	112	2338.98	1518.30	261.34	2183.11	6613.85
	Labor cost	112	954.38	545.68	272.37	776.73	3077.39
	Land cost	112	105.19	57.26	29.39	95.86	397.85
	Fertilizer cost	112	319.98	196.19	45.62	306.65	958.52
	Pesticide cost	112	289.06	286.00	33.05	206.41	1312.49
	Other material and service expenses	112	286.24	215.93	61.28	173.71	958.87
	Carbon emissions	112	32.92	11.75	17.68	29.64	73.75
Tangerine	Gross value of production	112	2053.10	1052.84	573.13	1803.01	5412.06
	Labor cost	112	776.48	474.01	242.51	673.69	3528.28
	Land cost	112	134.38	71.85	31.04	122.24	299.25
	Fertilizer cost	112	243.94	128.72	9.58	234.37	687.62
	Pesticide cost	112	181.11	153.86	4.62	121.36	580.21
	Other material and service expenses	112	221.47	178.23	26.01	159.01	1070.17
	Carbon emissions	112	34.30	12.04	17.68	33.70	73.75

The formula is as follows:

$$Agg_{it} = \frac{e_{it}/e_{jt}}{E_{it}/E_{jt}} \tag{2}$$

In Equation (2), i denotes the province; j denotes the country; t denotes the year; Agg_{it} is the citrus industry agglomeration of province i in year t; e_{it} is the output value of mandarins (tangerines) of province i in year t; e_{jt} is the national output value of mandarins (tangerines) in year t; E_{it} is the total agricultural output value of province i in year t; and E_{jt} is the national total agricultural output value in year t. Generally speaking, when $Agg_{it} > 1$, the region's citrus industry has a comparative advantage in the country and shows strong agglomeration ability to a certain extent; meanwhile, when $Agg_{it} < 1$, the region has weak agglomeration ability in the country [38].

(3) Control variables. In this study, urbanization, transportation infrastructure, marketization, labor force, social consumption level, per capita education level of rural residents, fruit planting structure, and agricultural mechanization degree are selected as control variables [14–16,32]. Specifically, urbanization is measured as the proportion of the urban population to the total population at the end of each year in each region. Transportation infrastructure is quantified using the natural logarithm of the number of road miles, while marketization is assessed through the Fan Gang marketization index. The labor force is measured using the natural logarithm of the number of employed persons. The social consumption level is expressed by using the proportion of total retail sales of social consumer goods to the gross regional product, and the per capita education level of rural residents can be calculated using the following formula: the total number of rural residents (who have not attended primary school $\times$ 0 + primary school $\times$ 6 + junior high school $\times$ 9 + senior high school $\times$ 12 + junior college and above $\times$ 16)/the total number of rural residents. The fruit planting structure is expressed as the proportion of the citrus orchard area to the total orchard area, and the degree of agricultural mechanization is expressed as the logarithm of the total power of agricultural machinery. The descriptive statistics of the main regression variables are shown in Table 2.

Table 2. Descriptive statistics of regression variables.

VarName	Obs	Mean	SD	Min	Median	Max
Mandarin GTFP	112	1.003	0.201	0.597	0.996	1.840
Mandarin Agg	112	2.690	1.608	0.391	2.668	7.638
Tangerine GTFP	112	1.001	0.186	0.553	1.000	1.691
Tangerine Agg	112	2.927	2.251	0.704	2.442	15.855
Urban	112	0.568	0.103	0.362	0.564	0.851
TIC	112	11.998	0.344	11.373	12.063	12.619
Market	112	8.719	1.372	6.048	8.737	12.364
Labor	112	7.978	0.420	7.292	7.875	8.864
SCL	112	0.399	0.053	0.296	0.389	0.526
Edu	112	7.773	0.383	6.788	7.802	8.542
FPS	112	0.521	0.208	0.187	0.580	0.824
Machine	112	7.845	0.549	6.757	7.845	8.818

3.2. Methods

(1) Global Malmquist–Luenberger productivity index. To measure total factor productivity that includes undesirable outputs, Chung et al., (1997) [39] pioneered the application of the directional distance function within the Malmquist model, referring to the improved Malmquist index as the ML index. However, Oh, (2010) [40] noted that the ML index is derived from the geometric average of productivity in adjacent periods, lacking transferability and circular cumulative properties. To address this issue, Oh proposed the GML exponential model based on global production techniques, which effectively avoids the problems associated with unsolvable linear programming and technological regression [40]. Consequently, in this study, the approach outlined by Oh, (2010) was adopted by constructing a global ML productivity index for period t to $t + 1$ and decomposing it into a technical efficiency index (GEC) and a technical progress index (GTC).

The formula is as follows:

$$GML_t^{t+1} = \left[\frac{1 + S_V^G(x^t, y^t, b^t; y^t, -b^t)}{1 + S_V^{G+1}(x^{t+1}, y^{t+1}, b^{t+1}; y^{t+1}, -b^{t+1})} * \frac{1 + S_V^{G+1}(x^t, y^t, b^t; y^t, -b^t)}{1 + S_V^{G+1}(x^{t+1}, y^{t+1}, b^{t+1}; y^{t+1}, -b^{t+1})} \right]^{\frac{1}{2}} \quad (3)$$

$$GML_t^{t+1} = GEC_t^{t+1} * GTC_t^{t+1} \quad (4)$$

$$GEC_t^{t+1} = \frac{1 + S_V^G(x^t, y^t, b^t; y^t, -b^t)}{1 + S_V^{G+1}(x^{t+1}, y^{t+1}, b^{t+1}; y^{t+1}, -b^{t+1})} \quad (5)$$

$$GTC_t^{t+1} = \left[\frac{1 + S_V^{G+1}(x^t, y^t, b^t; y^t, -b^t)}{1 + S_V^G(x^t, y^t, b^t; y^t, -b^t)} * \frac{1 + S_V^{G+1}(x^{t+1}, y^{t+1}, b^{t+1}; y^{t+1}, -b^{t+1})}{1 + S_V^G(x^{t+1}, y^{t+1}, b^{t+1}; y^{t+1}, -b^{t+1})} \right]^{\frac{1}{2}} \quad (6)$$

In Equations (3)–(6), GML denotes the global green total factor productivity index, $GML > 1$ denotes an increase in green total factor productivity in period t to $t + 1$, $GML < 1$ denotes a decrease in green total factor productivity in period t to $t + 1$, and $GML = 1$ indicates that the green total factor productivity remains unchanged in period t to $t + 1$. GEC refers to the extent to which actual production is approaching the maximum production frontier, reflecting the rate at which technological laggards are catching up with the advanced. $GEC > 1$ indicates an improvement in technical efficiency that is closer to the production possibility frontier in period t to $t + 1$, $GEC < 1$ indicates a deterioration in technical efficiency, and $GEC = 1$ indicates no change in technical efficiency. GTC reflects the rate of progress of the technological frontier; that is, the dynamic change in the outward shift in the boundary of production possibilities caused by technological progress. $GTC > 1$ indicates the shift in the boundary of production possibilities toward more desired output and less undesired output, which implies technological progress; $GTC < 1$

implies technological degradation; and $GTC = 1$ indicates that the boundary of production possibilities does not change, that is, that technology remains unchanged [41–43].

(2) Spatial correlation index. The spatial correlation of citrus green total factor productivity is examined as a basis for spatial econometric analysis. The global Moran's I index (Moran's I) can reveal the similarity in citrus green total factor productivity between neighboring regions.

The formula is as follows:

$$Moran's\ I = \frac{\sum_{n=1}^{N}\sum_{m=1}^{N} W_{nm}(x_n - \overline{x})(x_m - \overline{x})}{S^2 \sum_{n=1}^{N}\sum_{m=1}^{N} W_{nm}} \tag{7}$$

In Equation (7), x_n and x_m are the index values of variable x in the geographical unit of region n and region m; $\overline{x}$ is the average of the index values in each region; W_{nm} is the spatial weight matrix, with $W_{nm} = 1$ when n and m provinces are contiguous and 0 otherwise; N is the total number of measured areas; and S^2 is the sample variance. In general, the range of Moran's I index is from -1 to 1; that is, high values are adjacent to high values, and low values are adjacent to low values. An index of less than 0 indicates negative spatial autocorrelation; that is, high values are adjacent to low values. An index close to 0 indicates that the spatial distribution is random and there is no spatial autocorrelation.

(3) Dynamic spatial Durbin model. This study recognizes the potential spatial relationship between industrial agglomeration and green total factor productivity, indicating that traditional empirical model tests may yield biased results. Therefore, a spatial econometric model is utilized. The primary spatial measurement models include the spatial lag model (SAR), the spatial error model (SEM), and the spatial Durbin model (SDM). The SDM, which accounts for the spatial lag correlation of both explanatory and response variables, allows for a more comprehensive analysis of the impact of citrus industry agglomeration on citrus green total factor productivity (GTFP) and the degree of synergy in GTFP growth. Furthermore, to address the potential time lag effect associated with changes in GTFP, this study incorporates a lagged variable of GTFP into the spatial Durbin model, resulting in the following dynamic spatial Durbin model formula:

$$\begin{aligned} GTFP_{i,t} = \alpha + \tau GTFP_{i,t-1} + \rho \sum_{j=1}^{N} W_{i,j} GTFP_{j,t} + \delta \sum_{j=1}^{N} W_{i,j} GTFP_{j,t-1} + \\ \beta_1 Agg_{i,t} + \beta_2 \sum_{j=1}^{N} W_{i,j} Agg_{j,t} + \theta Control_{i,t} + \gamma \sum_{j=1}^{N} W_{i,j} X_{j,t} + \mu_i + \lambda_t + \varepsilon_{i,t} \end{aligned} \tag{8}$$

In Equation (8), $GTFP_{it}$ is the mandarin (tangerine) green total factor productivity. Agg_{it} is the mandarin (tangerine) industry agglomeration. i is the province; t is the year; and j is a neighboring province of province i. $Control_{it}$ is a set of control variables; α is a constant term; τ is the coefficient of the time lag term; ρ, β_2, γ are the coefficients of the spatial lag terms of the corresponding variables; δ is the coefficient of the spatiotemporal lag term; $W_{i,j}$ is the spatial weight matrix; β_1, θ are the coefficients of the corresponding variables; μ_i is the spatial effect; λ_t is the temporal effect; and $\varepsilon_{i,t}$ is the random error term.

4. Analysis of Research Results

4.1. Characterization of Citrus GTFP

Figures 1 and 2 illustrate the changes in the global Malmquist–Luenberger productivity index for mandarin and tangerine production in China from 2007 to 2022. As depicted in Figure 1, the green total factor productivity (GTFP) of mandarins exhibits significant volatility, in contrast to the smoother trajectories of the technical progress index (GTC) and the technical efficiency index (GEC). Specifically, the trajectory of mandarin GTFP reveals a distinctive inverted "W" pattern, with notable peaks in 2010 and 2014, recording growth rates of 1.2871 and 1.3290, respectively. This is followed by a decline to a low point of 0.9173 in 2015, followed by a recovery to 1.0387 in 2020 after several years of improvement, before slipping slightly to 0.9569 in 2022. This fluctuating trend reflects the complex interplay between intrinsic adjustments within the industry and external shocks, highlighting the challenges associated with the process of green transformation. The GTC follows a "down–up–down–up" pattern, reaching its lowest point of 0.8782 in 2008, climbing to a peak of 1.2077 in 2010, and then falling to 0.9927 in 2022, albeit with some fluctuations. This phenomenon underscores the critical role of technological innovation in promoting the greening of the mandarin industry while also indicating the need for continuous innovation to sustain and enhance productivity. The GEC shows a more stable, fluctuating upward trend, peaking at 1.2611 in 2014 and then experiencing a pronounced decline to 0.9262 in 2017, before displaying a modest upward trend again.

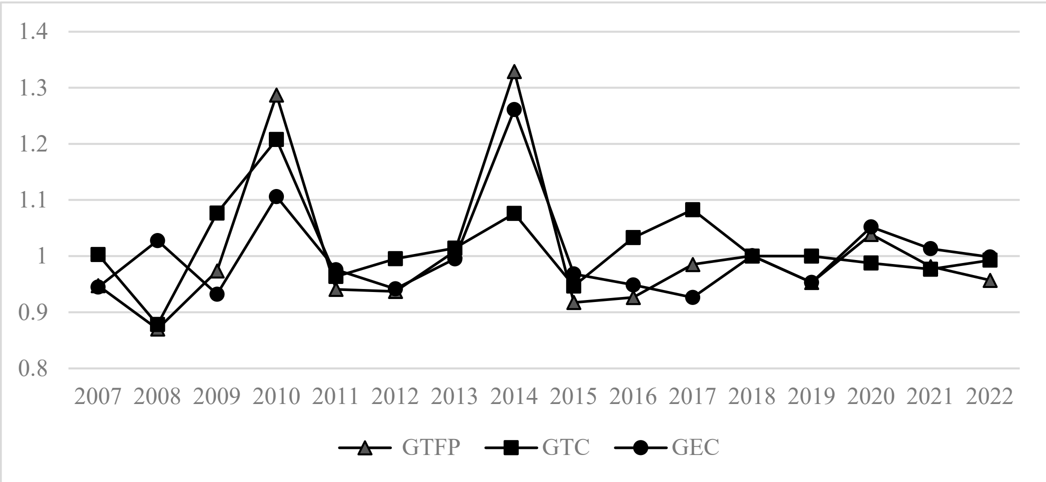

Figure 1. Changes in GTFP and the decomposition of its components for China's mandarin production from 2007 to 2022.

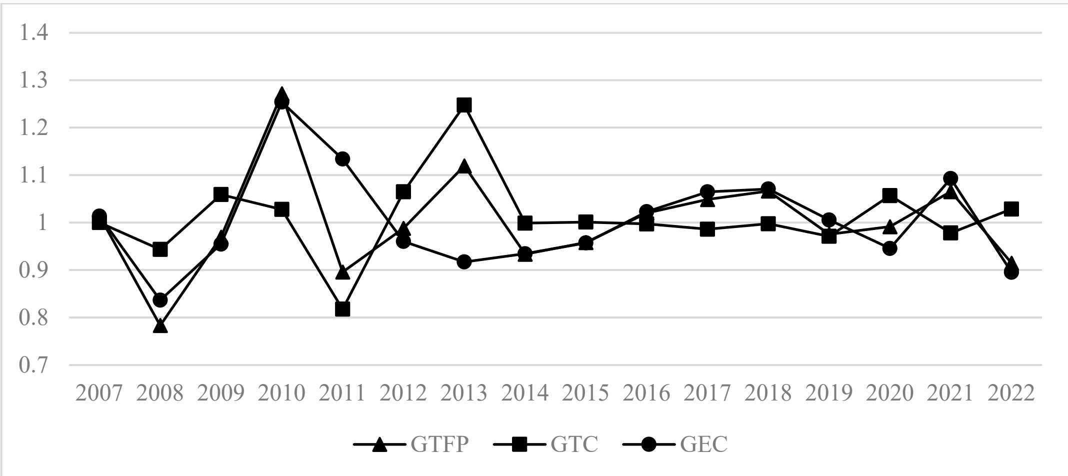

Figure 2. Changes in GTFP and the decomposition of its components for China's tangerine production from 2007 to 2022.

In summary, the GTC of mandarins was the driver of mandarin GTFP, and its fluctuating trend was highly correlated with significant changes in GTFP, further indicating that technological innovation plays a decisive role in promoting the green transformation and sustainable development of the citrus industry.

As shown in Figure 2, for tangerines, the GTFP and GTC change more than the GEC. The tangerine GTFP in 2007–2014 showed a large "decline–rise–decline–rise–decline" trend, reaching a minimum value of 0.7831 in 2008 and a maximum value of 1.2716 in 2010, experiencing a small annual increase from 2014 to 2018, and undergoing a fluctuating decrease from 2019 to 2022. The tangerine GTC fluctuated widely from 2007 to 2014, reaching a minimum value of 0.8178 in 2011 and a maximum value of 1.2475 in 2013, with a small fluctuating upward trend from 2015 to 2022. The tangerine GEC changes are small, with an overall "decline–rise–decline–rise–decline" trend. The fluctuations from 2007 to 2012 are more intense, reaching a minimum value of 0.8364 in 2008 and a maximum value of 1.2539 in 2010; it then underwent a small increase from 2013 to 2018, fell back to 0.9455 in 2020, rebounded to 1.0927 in 2021, and fell to 0.8951 in 2022. Taken together, both the GTC and the GEC of tangerines were increasing and decreasing during the sample period and had similar fluctuation patterns; thus, they are both drivers of tangerine GTFP.

Table 3 presents the average GTFP and its composition for the major mandarin- and tangerine-producing provinces in China from 2007 to 2022. The GTFP values of most major mandarin- and tangerine-producing provinces (cities) are close to or equal to 1, indicating that mandarin and tangerine production in these provinces (cities) is efficient on the whole and has some growth potential. The highest green total factor productivity (GTFP) for mandarins and tangerines occurred in Jiangxi (1.0428) and Chongqing, respectively. This suggests that Jiangxi and Chongqing have high green productivity in mandarin and tangerine production, respectively, which may be due to technological advancement, managerial efficiency, or the optimization of resource allocation. In contrast, the lowest green total factor productivity (GTFP) for mandarins and tangerines was observed in Fujian (0.9848) and Zhejiang (0.9866), respectively, suggesting that there is still room for improvement in citrus green production efficiency in Fujian and Zhejiang. In terms of the GTC, the highest values were in Fujian for tangerines (1.0364) and Hubei for mandarins (1.0291). The tangerine technical progress index is higher than the mandarin technical progress index as a whole, reflecting that tangerines are more advantageous in terms of planting technology, the introduction of new varieties, the mechanization of agriculture, etc. This also indicates that mandarin production needs to further increase its investment in technological innovation. In terms of the GEC, Hunan mandarins and Hubei tangerines had the highest values (1.0337 and 1.0339, respectively), indicating that these regions excel in management efficiency and resource allocation in citrus production. In contrast, Fujian had the lowest mandarin technical efficiency index (GEC) (0.9848), and Hunan had the lowest tangerine technical efficiency index (GEC) (0.9884), suggesting that there is still room for these two provinces to improve their production efficiency.

Table 3. Average GTFP and its composition for the major mandarin- and tangerine-producing provinces in China from 2007 to 2022.

Mandarin				Tangerine			
Major Producing Regions	**GTFP**	**GTC**	**GEC**	**Major Producing Regions**	**GTFP**	**GTC**	**GEC**
Fujian	0.9848	1.0000	0.9848	Zhejiang	0.9866	1.0154	0.9999
Jiangxi	1.0428	1.0703	1.0002	Fujian	0.9993	1.0364	0.9972
Hubei	1.0070	1.0291	1.0120	Jiangxi	0.9872	1.0034	0.9891
Hunan	0.9959	0.9956	1.0337	Hubei	1.0194	1.0137	1.0339
Guangdong	1.0017	1.0000	1.0017	Hunan	0.9884	1.0000	0.9884
Guangxi	0.9942	1.0049	0.9919	Guangdong	1.0002	1.0072	0.9921
Chongqing	0.9968	1.0022	0.9950	Chongqing	1.0247	1.0000	1.0247

4.2. Spatial Correlation Analysis

4.2.1. Global Moran's I

We employed the Stata 17 software to compute global Moran's I indices for both mandarins and tangerines based on their green total factor productivity panel data spanning from 2007 to 2022. The findings are presented in Table 4. The mandarin global Moran's I indices showed negative values in most years, indicating the stronger spatial correlation and the clustering of dissimilar attributes of mandarin green total factor productivity. In 2009, 2013, and 2018, the mandarin global Moran's I indices were significant and positive, indicating that, in these years, mandarin green total factor productivity showed a more significant spatial correlation of similar attributes. Similar to mandarin values, tangerine global Moran's I indices were also negative in most years, with negative and statistically significant global Moran's I indices in 2013, 2016, 2017, and 2021, suggesting the strong spatial correlation and clustering of spatially dissimilar attributes of tangerine green total factor productivity. Overall, the spatial correlation of green total factor productivity for citrus in China is somewhat volatile, but mandarin GTFP shows significant spatial aggregation in some years, while tangerine GTFP shows significant spatial dispersion in multiple years, with some spatial spillover effects.

Table 4. Global Moran's I of mandarin and tangerine GTFP from 2007 to 2022.

Year	Mandarin			Tangerine		
	Moran's I	**z**	***p***	**Moran's I**	**z**	***p***
2007	−0.102	0.522	0.301	−0.324	−0.681	0.248
2008	−0.148	0.081	0.468	0.067	1.030	0.152
2009	0.191 **	1.879	0.030	0.067	1.276	0.101
2010	−0.386	−0.961	0.168	−0.367	−0.929	0.176
2011	−0.226	−0.345	0.365	−0.135	0.176	0.430
2012	−0.130	0.198	0.421	−0.220	−0.312	0.378
2013	0.235 **	2.114	0.017	−0.451 *	−1.353	0.088
2014	−0.366	−0.831	0.203	−0.174	−0.035	0.486
2015	−0.199	−0.184	0.427	−0.395	−1.212	0.113
2016	−0.484 *	−1.532	0.063	−0.356	−0.858	0.195
2017	−0.262	−0.473	0.318	−0.470 *	−1.503	0.066
2018	0.375 ***	2.485	0.006	0.066	1.077	0.141
2019	−0.120	0.308	0.379	0.102	1.230	0.109
2020	−0.269	−0.439	0.330	0.186 *	1.584	0.057
2021	−0.176	−0.042	0.483	−0.471 *	−1.418	0.078
2022	−0.082	0.398	0.345	−0.364	−1.087	0.138

*, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

4.2.2. Local Moran's I

Figures 3 and 4 are Moran's I scatterplots for mandarin and tangerine GTFP in 2007, 2012, 2017, and 2022, which are used to further reflect the spatial distribution characteristics of the green total factor productivity of mandarins and tangerines. In the four selected representative years, the linear fitting curves of Moran's I index of green TFP of mandarins and tangerines all showed significant negative correlations in geographical space, indicating that there were certain spatial differences in the green TFP of mandarins and tangerines at the overall level. There are many reasons for this result. For example, the cultivation of mandarins and tangerines has high requirements for sunshine, precipitation, and temperature differences, which is closely related to differences in resource endowment among provinces and is also influenced by various provincial policies on fruit planting and market access, as well as factors such as planting technology levels and infrastructure construction.

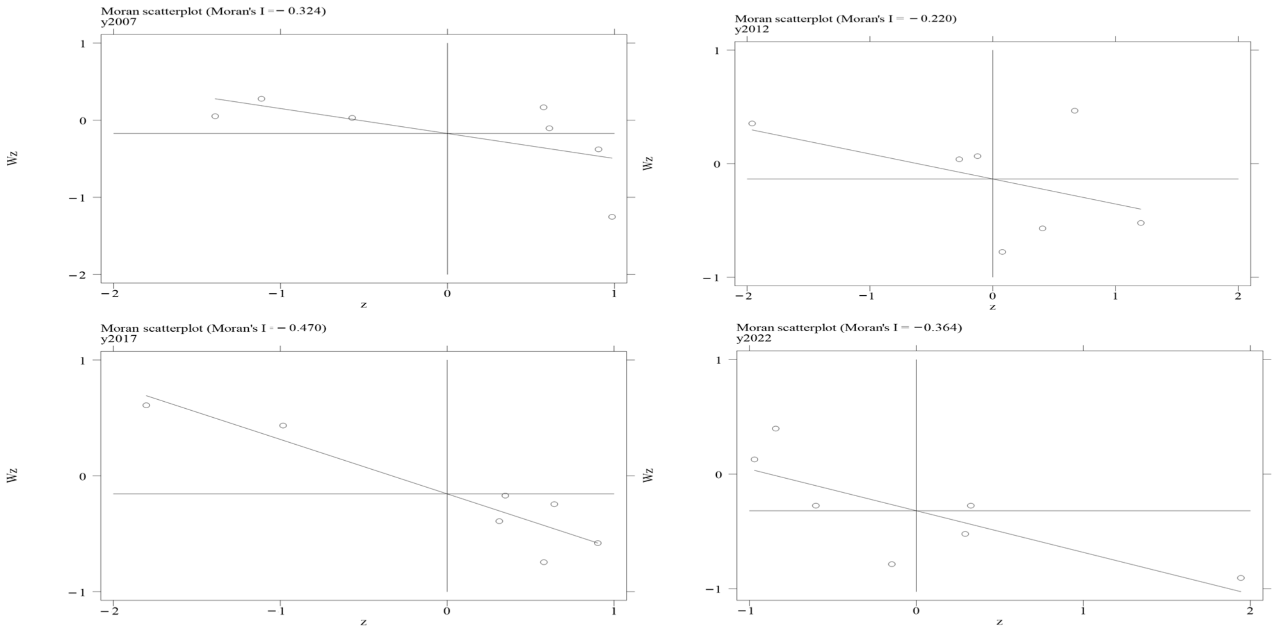

Figure 3. Moran's I scatterplot of mandarin green total factor productivity for 2007, 2012, 2017, and 2022.

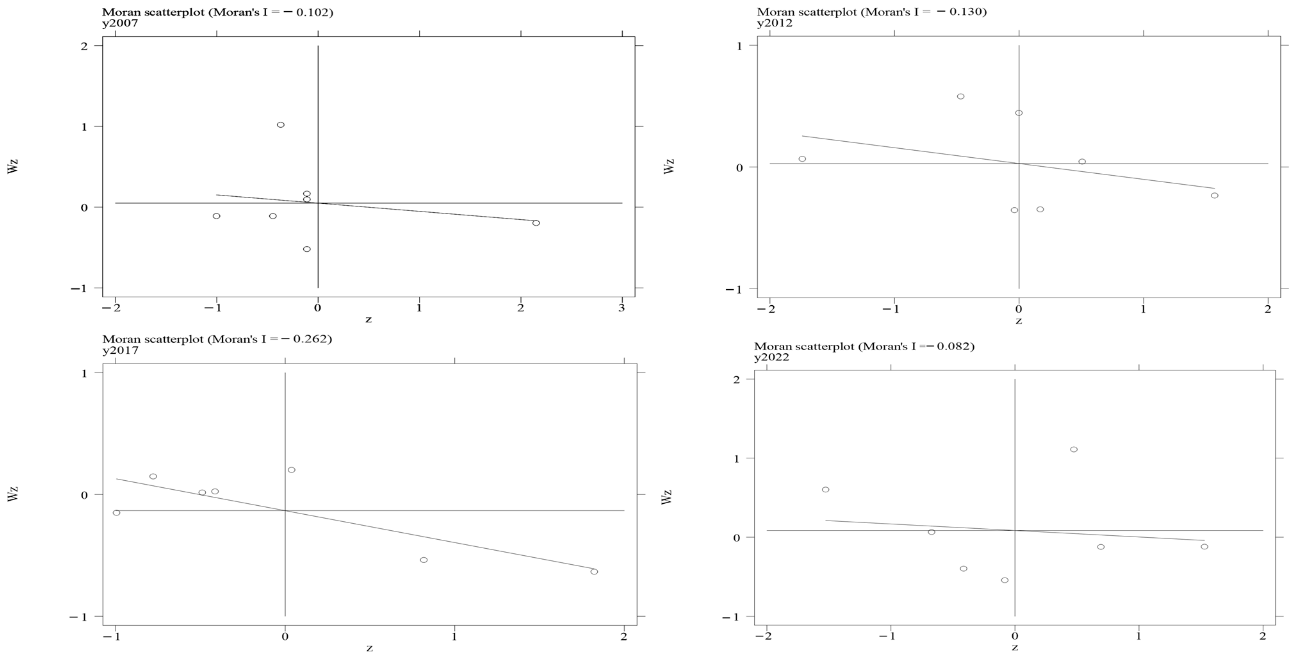

Figure 4. Moran's I scatterplot of tangerine green total factor productivity for 2007, 2012, 2017, and 2022.

As shown in Figure 3, among the four quadrants formed by the local Moran's I scatterplot of mandarin green total factor productivity in a representative year, most provinces with mandarin as the main citrus production are located in the second or fourth quadrant, indicating that there is spatial agglomeration characterized by a "low–high" or "high–low" combination of mandarin green total factor productivity. The "low–high" combination means that provinces with lower green TFP have neighboring provinces with higher green TFP. The "high–low" combination means that provinces with higher green TFP have neighboring provinces with lower green TFP. The results show that while most provinces in the main mandarin-producing areas focus on improving green total factor productivity, some provinces with low green total factor productivity have limited improvements, and the gap between them and their neighboring provinces has widened.

As shown in Figure 4, in the four quadrants formed by the local Moran's I scatterplot of tangerine green total factor productivity in the representative year, most of the major tangerine-producing provinces are located in the second or third quadrant. This shows that tangerine green total factor productivity has spatial agglomeration characterized by a "low–high" or "low–low" combination. The "low–high" combination means that provinces with lower tangerine green TFP have neighboring provinces with higher tangerine green TFP. The "low–low" combination means that provinces with low tangerine green TFP will have neighboring provinces that also have low tangerine green TFP. It is worth noting that, in 2022, the distribution of provinces in mainly tangerine-producing areas diverges, indicating that the correlation among provinces is enhanced, and tangerine green TFP begins to converge, which is also a manifestation of tangerine green TFP improvement.

4.3. Spatial Panel Modeling Analysis

4.3.1. The Rationality of the Model

The spatial correlation for mandarin (tangerine) green total factor productivity (GTFP) was further analyzed through regression using spatial econometric models. In order to determine which spatial measurement model is more suitable, the Lagrange multiplier test, Hausman test, LR test for model selection, and LR test for fixed effects were conducted. The results are shown in Table 5. First, the LM test was used to verify whether there is spatial autocorrelation. The LM or robust LM test results for mandarins and tangerines show that there is spatial autocorrelation. Further, the Wald test and LR test for model selection were used to determine suitable spatial panel models. While the LR test results for model selection were significant for mandarins, the Wald test results and LR test results for model selection were significant for tangerines. Some studies have shown that if the LM test, Wald test, and LR test statistics for model selection are inconsistent, the SDM should be chosen [44]. Therefore, based on all of the test results, the SDM was considered more suitable for this study. In addition, the results of the Hausman test and LR test for fixed effects show that it is more reasonable to use the SDM with bidirectional fixed effects in time and space for regression analysis.

Table 5. Selection of a spatial model.

Test		Mandarin	Tangerine
Spatial error	LM	5.6110 ** (0.0180)	8.9100 *** (0.0030)
	Robust LM	1.3470 (0.2460)	7.4070 *** (0.0060)
Spatial lag	LM	4.8390 ** (0.0280)	1.6270 (0.2020)
	Robust LM	0.5750 (0.4480)	0.1240 (0.7250)
Hausman		17.7300 ** (0.0385)	121.4600 *** 0.0000
Wald test for SAR		9.3800 (0.4030)	17.2900 ** (0.0156)
Wald test for SEM		7.6000 (0.5750)	37.5500 *** (0.0000)
LR test for Ind		59.2700 *** (0.0000)	54.9100 *** (0.0000)
LR test for time		4.3200 ** (0.0377)	10.6900 *** (0.0000)
LR test for SAR		11.3100 ** (0.0456)	29.8800 *** (0.0005)
LR test for SEM		12.4400 ** (0.0292)	29.6000 *** (0.0005)

, and * indicate statistical significance at the 5%, and 1% levels, respectively.

4.3.2. Regression Result Analysis

Table 6 reports the effect of mandarin (tangerine) industry agglomeration on mandarin (tangerine) green total factor productivity based on the dynamic spatial Durbin model (DSDM).

Table 6. Spatial panel model regression results.

Variable	Mandarin		Tangerine	
	DSDM		DSDM	
	Main	**Wx**	**Main**	**Wx**
L.GTFP	−0.4042 ***	−0.2670 *	−0.3650 ***	−0.2477
	(0.0454)	(0.1443)	(0.0918)	(0.1725)
Agg	0.1192 ***	0.1187 ***	0.0872 ***	0.1149 **
	(0.0227)	(0.0336)	(0.0107)	(0.0524)
Urban	−0.0354	−0.5633	0.0169	1.1611
	(0.2761)	(0.4834)	(0.3875)	(1.0319)
TIC	−0.0432	0.2948	−0.6361 **	−2.8442 ***
	(0.3677)	(0.6207)	(0.2879)	(0.5910)
Market	0.0738	0.4360 *	−0.0712	−0.3290 **
	(0.0798)	(0.2629)	(0.0641)	(0.1594)
Labor	0.1462	−1.4986	1.1743 ***	4.2700 ***
	(0.3620)	(0.9962)	(0.3037)	(0.6337)
SCL	−0.9261	−1.1663	0.0093	0.1138
	(1.0832)	(2.6114)	(0.5092)	(1.6052)
Edu	−0.0058	−0.0544	0.0018	−0.1444
	(0.0822)	(0.3162)	(0.0924)	(0.3924)
FPS	−1.6880 ***	−2.8741 **	0.7243	1.5123
	(0.2952)	(1.1729)	(0.5210)	(1.4504)
Machine	−0.1578	−0.0173	0.0008 ***	0.0012 *
	(0.1407)	(0.5580)	(0.0001)	(0.0006)
Spatial rho	0.6476 ***	—	0.5615 ***	—
	(0.1335)		(0.0579)	
Variance	0.0132 ***	—	0.0123 ***	—
sigma2_e	(0.0022)	—	(0.0024)	
R^2	0.0893	—	0.0024	—
AIC	−54.5253	—	−63.2455	—
BIC	75.5188	—	66.7985	—
N	105	—	105	—

*, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

First, there is a significant time lag effect in the growth of mandarin (tangerine) green total factor productivity in different regions, and the coefficient of the time lag term is significant and negative at the 1% level. A negative coefficient is a form of negative time inertia, which is manifested by the fact that green total factor productivity growth in the previous period has a negative impact on the current period. In other words, there is a "diminishing marginal effect" on the growth of green total factor productivity in mandarins (tangerines). This may be due to the gradually diminishing marginal effects of the optimal allocation of resources, such as technological progress and management efficiency improvement, leading to insignificant growth in the green total factor productivity of mandarins (tangerines) caused by the continuous increase in the same input; the impact may even be negative due to the excessive concentration of resources or market saturation. Therefore, in order to continuously promote the growth of mandarin (tangerine) green total factor productivity, it is necessary to continuously explore new growth drivers, such as technological innovation, institutional innovation, and structural optimization, to overcome the negative impacts of the diminishing marginal effect. At the same time, it is also necessary to focus on balancing the distribution of resources and avoiding over-concentration in a certain field or region so as to fully utilize the comparative advantages of various regions and fields and achieve a steady increase in the green total factor productivity of mandarins (tangerines).

Second, mandarin (tangerine) industry agglomeration has a significant positive effect on mandarin (tangerine) green total factor productivity, and the regression coefficients are significantly positively correlated at the 1% level, indicating that mandarin (tangerine) industry agglomeration helps to enhance mandarin (tangerine) green total factor productivity. This finding is consistent with the conclusion drawn from existing research that agricultural industry agglomeration can promote the growth of agricultural green total factor productivity [26]. In the DSDM, the spatial impact of mandarin (tangerine) industry agglomeration is more significant. The main reason for this may be that, on one hand, due to economies of scale, industrial agglomeration means that mandarin (tangerine) growers in the same region or related enterprises can share infrastructure, market information, technical resources, and so on, in order to reduce production costs and improve production efficiency. Economies of scale are reflected not only in the expansion of production scale but also in the sharing of technology and management experience. On the other hand, moderate industrial agglomeration is conducive to the promotion of technological spillover and knowledge sharing. Within the same region, advanced planting techniques, pest control methods, water-saving irrigation techniques, and other approaches can be adopted more quickly by other farmers or enterprises, resulting in a technological spillover effect. Additionally, it also helps to establish a regional brand effect. When the mandarin (tangerine) industry in a region forms agglomerates, the region's products are often more easily recognized and accepted by consumers, thus broadening the market space. The brand effect and market expansion can incentivize farmers and enterprises to adopt more environmentally friendly and efficient production methods to meet the market demand for high-quality green products, further enhancing mandarin (tangerine) green total factor productivity. Furthermore, moderate industrial agglomeration can form a synergistic effect of environmental protection policies. In the industrial agglomeration area, it is easier for the government to implement unified environmental protection policies and regulatory measures, such as the promotion of organic fertilizers, a reduction in pesticide use, and the implementation of water-saving irrigation. These policies can be more effectively enforced and supervised within the agglomeration area, thus facilitating the popularization of green production methods and enhancing the green total factor productivity of mandarins (tangerines).

4.4. Decomposition of Spatial Spillover Effects

The spatial spillover effects of the DSDM were decomposed into short-run and long-run effects using the partial differential method [45], allowing for a further analysis of the impact of mandarin (tangerine) industry agglomeration on mandarin (tangerine) green total factor productivity. Table 7 reports the estimates of short-run direct effects, short-run indirect effects, short-run total effects, long-run direct effects, long-run indirect effects, and long-run total effects for the DSDM. As shown in Table 4, both in the short and long run, mandarin (tangerine) industry agglomeration has significant positive direct, indirect, and total effects on mandarin (tangerine) green total factor productivity.

In the short run, every 1 percentage point increase in mandarin (tangerine) industrial agglomeration can directly promote the green total factor productivity of mandarins and tangerines in the region by 0.1893 and 0.1325 percentage points, respectively. Additionally, it can potentially promote the green total factor productivity of mandarins and tangerines in the neighboring regions by 0.4860 and 0.3283 percentage points, respectively. In total, this promotion of mandarin and tangerine green total factor productivity amounts to 0.6753 and 0.4608 percentage points, respectively, showing a strong direct promotion effect and spatial spillover effect. The spatial spillover effects of mandarin and tangerine account for 71.96% and 71.25% of the total effects, respectively.

In the long run, every 1 percentage point increase in citrus industry agglomeration can directly promote the green total factor productivity of mandarins and tangerines in the region by 0.0950 and 0.0718 percentage points, respectively. Furthermore, it can potentially promote the green total factor productivity of mandarins and tangerines in the neighboring regions by 0.1375 and 0.1204 percentage points, so in total, the green total factor productivity will be promoted by 0.2325 and 0.1922 percentage points, respectively. This suggests that the positive contribution of mandarin (tangerine) industrial agglomeration to mandarin (tangerine) green total factor productivity is a long-lasting process, and the proportion of spatial spillovers to the total effect tends to decrease in the long run. The mandarin and tangerine spatial spillovers accounted for 59.14% and 62.64% of the total effect, respectively, and were larger in effect size in the short run than in the long run. This may be due to the fact that the spatial spillover effect diminishes over time, or that the development of the citrus plantation industry in the long run is subject to disruption by other factors (e.g., technological advances or market changes). Additionally, citrus industry agglomeration itself may encounter bottlenecks (e.g., resource constraints or environmental pressures), which could also contribute to the diminishing impact.

Table 7. Decomposition of spatial spillover effects.

Classification	Variable	In the Short Run			In the Long Run		
		Direct Effect	Indirect Effect	Total Effect	Direct Effect	Indirect Effect	Total Effect
Mandarin	Agg	0.1893 ***	0.4860 **	0.6753 **	0.0950 ***	0.1375 ***	0.2325 ***
		(0.0589)	(0.2416)	(0.2984)	(0.0206)	(0.0523)	(0.0689)
	Urban	−0.2449	−1.4541	−1.6990	−0.0635	−0.5214	−0.5849
		(0.3517)	(1.2238)	(1.4711)	(0.1891)	(0.4358)	(0.4816)
	TIC	0.0521	0.6618	0.7139	−0.0119	0.2577	0.2458
		(0.6326)	(2.0325)	(2.6382)	(0.2959)	(0.6360)	(0.8950)
	Market	0.2467	1.2001	1.4468	0.0830	0.4151	0.4981
		(0.2178)	(0.9730)	(1.1862)	(0.0849)	(0.2983)	(0.3767)
	Labor	−0.3556	−3.4825	−3.8380	0.0067	−1.3279	−1.3212
		(0.6726)	(3.1746)	(3.7692)	(0.2640)	(1.0015)	(1.1474)
	SCL	−1.5573	−4.3809	−5.9381	−0.7541	−1.2900	−2.0441
		(2.1466)	(7.9631)	(10.0477)	(0.9353)	(2.7025)	(3.5430)
	Edu	−0.0266	−0.1443	−0.1709	−0.0079	−0.0510	−0.0588
		(0.1901)	(0.8682)	(1.0506)	(0.0747)	(0.3027)	(0.3659)
	FPS	−3.1059 ***	−9.8410 **	−12.9469 **	−1.4245 ***	−3.0323 ***	−4.4568 ***
		(1.0202)	(4.9299)	(5.9313)	(0.2319)	(1.0137)	(1.1943)
	Machine	−0.2005	−0.2963	−0.4968	−0.1164	−0.0546	−0.1710
		(0.1656)	(1.2723)	(1.3892)	(0.0854)	(0.4766)	(0.4568)
Tangerine	Agg	0.1325 ***	0.3283 ***	0.4608 ***	0.0718 ***	0.1204 *	0.1922 ***
		(0.0076)	(0.0982)	(0.1046)	(0.0139)	(0.0616)	(0.0713)
	Urban	0.3406	2.3460	2.6866	0.0808	1.0399	1.1207
		(0.7149)	(2.5213)	(3.2127)	(0.3348)	(0.9319)	(1.2304)
	TIC	−1.5215 ***	−6.4157 ***	−7.9372 ***	−0.6416 ***	−2.6693 ***	−3.3109 ***
		(0.5538)	(2.0846)	(2.5921)	(0.2027)	(0.6617)	(0.7760)
	Market	−0.1733 *	−0.7395 **	−0.9128 **	−0.0725 **	−0.3083 ***	−0.3808 ***
		(0.0970)	(0.3734)	(0.4529)	(0.0364)	(0.1142)	(0.1156)
	Labor	2.5376 ***	9.8788 ***	12.4164 ***	1.1268 ***	4.0525 ***	5.1793 ***
		(0.3245)	(0.6444)	(0.9247)	(0.3916)	(1.1130)	(1.4823)
	SCL	0.0423	0.2386	0.2808	0.0136	0.1035	0.1171
		(0.8832)	(3.5213)	(4.3208)	(0.4324)	(1.4750)	(1.7929)
	Edu	−0.0378	−0.2872	−0.3250	−0.0071	−0.1285	−0.1356
		(0.1511)	(0.8030)	(0.9261)	(0.0690)	(0.3413)	(0.3659)
	FPS	1.2551	3.8458	5.1009	0.6292	1.4985	2.1277
		(0.9277)	(3.3706)	(4.2438)	(0.4555)	(1.5078)	(1.8910)
	Machine	0.0013 ***	0.0034 **	0.0046 **	0.0007 ***	0.0013 ***	0.0019 ***
		(0.0003)	(0.0015)	(0.0019)	(0.0001)	(0.0004)	(0.0005)

*, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

4.5. Robustness Test and Endogeneity Problem

4.5.1. Robustness Test

To ensure the reliability of the research conclusions, two primary methods were employed to assess robustness. First, a robustness test was conducted by substituting different models; specifically, regression analyses were performed using the SEM, the SAR model, and the static SDM. The findings are presented in Table 8, which indicates that after model substitution, mandarin (tangerine) industry agglomeration positively influences the green total factor productivity of oranges. Secondly, subsamples from the overall dataset were utilized for robustness testing by adjusting the sample time span to 2010–2019 for regression analysis. The results are shown in the DSDM column. The results revealed that the estimated coefficients for mandarin (tangerine) industry agglomeration were significant at both 5% and 1%, aligning closely with previous test outcomes and suggesting that these conclusions are relatively robust.

4.5.2. Endogeneity Problem

The dynamic spatial Durbin model can be used to account for the spatial lag term, time lag term, and endogeneity caused by missing variables. However, the dynamic spatial Durbin model cannot solve the simultaneous endogeneity problem caused by the interaction between explanatory and explained variables [46]. In fact, industrial agglomeration can promote the improvement of green total factor productivity, which may further promote industrial agglomeration. Therefore, considering the potential endogeneity problem between mandarin and tangerine industry agglomeration and green total factor productivity, appropriate instrumental variables were selected and used with the systematic GMM method to further deal with the endogeneity problem of dynamic panel data [47]. The selection of instrumental variables from a geographical perspective has natural advantages. As indicators based on a geographical perspective are naturally formed, they can be considered to meet exogenous conditions. Topographic relief [48] and distance from the nearest port [49] are used as geographical variables. On one hand, these geographical variables are not directly related to other economic variables, which can better meet the requirements of exogeneity. On the other hand, these geographical variables are also important factors affecting population distribution and labor intensity, which meet certain requirements for correlation. Instrumental variables were created by using topographic relief, distance from the nearest port, and year dummy variables, mainly because mandarin and tangerine industry agglomeration evolves in two dimensions, time and space, while geographical distance only reflects a change in the spatial dimension and cannot reflect a change in the time dimension, so the year dummy variable was added. It was processed with a lag of one phase.

Table 9 shows the influence of mandarin and tangerine industry agglomeration on mandarin and tangerine green total factor productivity based on a dynamic panel system GMM. The Arellano–Bond AR (1) test statistics of mandarins and tangerines were significant, indicating the existence of first-order autocorrelation, while the Arellano–Bond AR (2) test statistics were not significant, indicating the absence of second-order autocorrelation. The Sargan test statistics of mandarins and tangerines were not significant, indicating that there was no over-recognition of instrumental variables. In addition, the Wald test p value is close to 0, indicating that the model is significant as a whole. It can be seen that the estimated results in Table 8 are reasonable, and the selected instrumental variables are appropriate. When topographic relief and distance from the nearest port are used as instrumental variables, the GMM estimation results of the system are also basically consistent with the results in Table 5, which confirms the robustness of the basic conclusions.

Table 8. Robustness test.

Var	Mandarin						Tangerine					
	SEM	SAR	SDM		DSDM		SEM	SAR	SDM		DSDM	
	Mian	Main	Main	Wx	Main	Wx	Mian	Main	Main	Wx	Main	W x
L.GTFP	—	—	—	—	−0.3650 ***	−0.2477	—	—	—	—	−0.4093 ***	−0.3358 *
					(0.0918)	(0.1725)					(0.0835)	(0.1755)
Agg	0.0383 **	0.0289 *	0.0575 ***	0.0960 **	0.0872 ***	0.1149 **	0.0332 ***	0.0315 ***	0.0718 ***	0.0906 ***	0.0984 ***	0.1641 ***
	(0.0176)	(0.0162)	(0.0207)	(0.0463)	(0.0107)	(0.0524)	(0.0114)	(0.0112)	(0.0125)	(0.0311)	(0.0120)	(0.0505)
Urban	0.1055	0.1760	0.0346	−0.6026	0.0169	1.1611	−0.1769	−0.2347	0.0708	0.8994	0.8436 ***	1.2144
	(0.4137)	(0.3864)	(0.4213)	(0.7619)	(0.3875)	(1.0319)	(0.4275)	(0.3932)	(0.4628)	(1.0560)	(0.3270)	(1.1761)
TIC	−0.1086	−0.1244	0.1390	0.1789	−0.6361 **	−2.8442 ***	−0.2519	−0.1442	−0.2402	−0.4611	0.4646	0.0654
	(0.3003)	(0.2497)	(0.4645)	(0.9222)	(0.2879)	(0.5910)	(0.2990)	(0.2748)	(0.4252)	(1.2472)	(0.4899)	(1.1489)
Market	0.0020	−0.0084	0.0538	0.2818 *	−0.0712	−0.3290 **	0.0328	0.0247	0.0161	−0.0004	−0.1276	−0.6112 **
	(0.0641)	(0.0630)	(0.0685)	(0.1690)	(0.0641)	(0.1594)	(0.0785)	(0.0763)	(0.0759)	(0.1741)	(0.0872)	(0.2681)
Labor	0.2059	0.1955	0.1173	−0.0471	1.1743 ***	4.2700 ***	−0.1505	−0.3030	1.3047 ***	4.1131 ***	2.0769 **	7.8742 ***
	(0.3072)	(0.2826)	(0.3645)	(0.9643)	(0.3037)	(0.6337)	(0.3379)	(0.3039)	(0.4440)	(1.1092)	(1.0468)	(2.9870)
SCL	−0.4535	−0.3305	−0.9821	−1.4004	0.0093	0.1138	0.8696	0.6546	0.4890	0.2766	−1.5824 *	1.1842
	(0.7041)	(0.6256)	(1.2063)	(2.3868)	(0.5092)	(1.6052)	(0.7860)	(0.7237)	(0.9900)	(2.3104)	(0.9286)	(2.2096)
Edu	−0.0632	−0.0340	−0.0900	−0.2558	0.0018	−0.1444	−0.0157	−0.0127	0.0648	0.0044	−0.2448 ***	0.3804
	(0.1170)	(0.1076)	(0.1338)	(0.2924)	(0.0924)	(0.3924)	(0.1229)	(0.1208)	(0.1137)	(0.2632)	(0.0823)	(0.4665)
FPS	−0.5075	−0.3617	−0.9085	−2.3264	0.7243	1.5123	−0.6115	−0.7170	0.8565	1.7995	0.6425	−3.3581
	(0.5779)	(0.5692)	(0.6489)	(1.7454)	(0.5210)	(1.4504)	(0.6203)	(0.5905)	(0.5877)	(1.5863)	(1.6098)	(4.1003)
Machine	0.0418	0.0345	−0.0744	0.3447	0.0008 ***	0.0012 *	0.0001	0.0000	0.0004	0.0009	1.1454 **	4.2035 **
	(0.1040)	(0.1102)	(0.1419)	(0.4812)	(0.0001)	(0.0006)	(0.0002)	(0.0002)	(0.0003)	(0.0008)	(0.4525)	(1.9352)
Spatial lambda	−0.5906 ***	—	—	—	—	—	−0.2913 *	—	—	—	—	—
	(0.1265)						(0.1490)					
Spatial rho	—	−0.5891 ***	−0.6391 ***	—	0.5615 ***	—	—	−0.2532 **	−0.5434 ***	—	0.4475 ***	—
		(0.1279)	(0.1270)		(0.0579)			(0.1291)	(0.1315)		(0.0915)	
Variance	0.0184 ***	0.0189 ***	0.0173 ***	—	0.0123 ***	—	0.0203 ***	0.0205 ***	0.0145 ***	—	0.0079 ***	—
sigma2_e	(0.0026)	(0.0027)	(0.0025)	—	(0.0024)	—	(0.0028)	(0.0028)	(0.0020)	—	(0.0019)	
R^2	0.0246	0.0248	0.0437	—	0.2159	—	0.0174	0.0215	0.0595	—	0.1133	—
AIC	−96.5096	−58.9106	−49.7010	—	−63.2455	—	−93.9956	−57.7405	−71.1737	—	−31.7283	—
BIC	−66.6061	19.9259	53.6019	—	66.7985	—	−64.0921	21.0960	32.1293	—	73.2853	—
N	112	112	112	—	63	—	112	112	112	—	63	—

*, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 9. SYS-GMM test results based on dynamic panel system.

Var	Mandarin	Tangerine
L.GTFP	−0.2720 *** (−4.3800)	−0.2840 *** (−4.0600)
Agg	0.2100 *** (4.9400)	1.8060 ** (−2.1000)
Wx * Agg	−0.0459 *** (−4.4100)	0.6400 ** (2.120)
Urban	−0.2490 (−0.9100)	−0.9890 *** (−11.4800)
TIC	0.0150 (0.1400)	0.3780 *** (2.7300)
Market	0.0414 ** (2.0500)	−0.0100 (−0.3500)
Labor	0.1150 ** (1.9900)	−0.3710 ** (−2.4900)
SCL	−0.2580 (−1.160)	0.3150 (0.8400)
Edu	−0.1060 ** (−2.1800)	0.0782 (1.1200)
FPS	0.0608 (0.7000)	−0.9280 *** (−3.1700)
Machine	0.0308 (1.110)	0.0279 ** (2.4800)
Sargan test	97.0600 (0.3660)	102.6800 (0.1060)
Hansen test	0.0000 (1.0000)	0.0000 (1.0000)
AR(1) test	−2.0900 ** (0.0370)	−2.1000 ** (0.0350)
AR(2) test	−1.5300 (0.1270)	−1.0800 (0.2780)
Wald test	212.1500 *** (0.0000)	1934.4100 *** (0.0000)

, and * indicate statistical significance at the 5%, and 1% levels, respectively.

5. Conclusions and Implications

5.1. Conclusions

The main research findings of this study are listed below. First, in the time dimension, China's mandarin and tangerine green total factor productivity, technical progress index, and technical efficiency index all experienced significant volatility during the sample period, especially between 2007 and 2015. Overall, the tangerine green total factor productivity, technical progress index, and technical efficiency index were higher than those of mandarins. From the point of view of regional differences, the green total factor productivity values of most citrus-producing provinces (cities) are close to or equal to 1, but there are still significant regional differences. The regional differences in mandarin green total factor productivity and technical progress index are greater than those for tangerine, and the regional differences in tangerine technical efficiency index are greater than those for mandarin. Second, from the perspective of the global Moran index, both mandarins and tangerines have certain spatial spillover effects on green total factor productivity. Mandarin shows significant spatial aggregation in some years, while tangerine shows significant spatial dispersion in several years. From the local Moran scatterplot, the green TFP of mandarin and tangerine showed a significant negative spatial autocorrelation between 2007 and 2022; that is, provinces with high green TFP were spatially dispersed from provinces with low green TFP. Third, the dynamic spatial Durbin model results revealed a significant time lag effect in the growth of mandarin (tangerine) green total factor productivity, and the intensification of mandarin (tangerine) industry agglomeration has a significant positive effect on both local and neighboring mandarin (tangerine) green total factor productivity. Fourth, the results showed that mandarin (tangerine) industry agglomeration has positive spatial spillover effects on mandarin (tangerine) green total factor productivity

(GTFP) in both the short- and long run, where the short-run benefits are greater than the long-run effects.

The results of this study further provide empirical evidence that the industrial agglomeration of mandarins and tangerines can improve their green total factor productivity in local and neighboring regions. However, there are also certain limitations: First, there is a lack of prefecture- and county-level data, and the use of provincial panel data for empirical evidence has limitations. Second, China's macro data do not have clear statistical indicators to measure mandarin and tangerine pesticides, agricultural films, diesel oil, irrigation, and other factors. This study adopted a weighted estimation method to measure mandarin and tangerine pesticides, agricultural films, diesel oil, irrigation, and other factors, which may lead to biased statistical results. In addition, it is also crucial to explore how industrial agglomeration affects mandarin and tangerine green total factor productivity levels. Therefore, future studies can investigate the impact of mandarin and tangerine industry agglomeration on the green total factor productivity of mandarins and tangerines from a micro perspective, such as at the city or firm level.

5.2. Implications

The results of this study can assist in establishing a high-standard and concentrated citrus industry hub and promoting the growth of citrus green total factor productivity (GTFP). The results indicate that the GTFP of mandarins and tangerines is significantly and positively influenced by citrus industry agglomeration in both the region and neighboring areas. Therefore, on one hand, we should pay attention to the external advantages of citrus industry agglomeration and promote the cluster development of citrus-related industries by creating a core citrus production area, combining local characteristics, and further guiding the concentration of production, post-harvest management, commercialization treatment, intensive processing, cold chain logistics, sales, and other resources, according to local conditions. This can assist the formation of a professional production area with the standardized management, precision production, market operation, and brand operation of citrus production. On the other hand, efforts can be made to improve the green and sustainable development ability of the citrus industry by promoting green standardized production technology; using the Internet of Things, cloud computing, drones, and other digital technologies to build smart orchards; guiding fruit farmers toward the zero growth of fertilizer and chemical pesticide application; promoting biopesticides, insecticidal lamps, insect traps, mite predation, and other green prevention and control technologies; forming a green development system combining digital and organic factors; and enhancing citrus green total factor productivity.

Full play should be given to the spatial spillover effect, and cross-regional coordinated development should be strengthened. Citrus industry agglomeration not only has a positive impact on the green total factor productivity in the local area, but also significantly promotes the improvement of green total factor productivity in neighboring areas. Therefore, on one hand, it is necessary to strengthen the cross-regional policy coordination and communication mechanism; actively build an information-sharing platform covering key information, such as advanced planting technology, an environmental management strategy, and market dynamics; cooperate to carry out technology sharing and exchange, such as offline training and on-site guidance; and promote the overflow of experience in citrus planting technology, processing, brand building, and distribution processing. Efforts should also be made to promote the development of the citrus industry in neighboring provinces and improve the quality of the green coordinated development of the regional citrus industry. On the other hand, there is a need to actively break the geographical boundaries of the citrus market, use e-commerce platforms to form efficient product transactions with online and offline connectivity, and promote product spatial docking and coordinated industrial development.

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