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Variation in Total Factor Productivity of Corn in 19 Main Producing Areas under the Constraint of Carbon Emissions

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ABSTRACT

To realize the sustainable development of the corn industry, the key lies in improving the total factor productivity (TFP) of corn under the constraint of carbon emissions. Based on the panel data of 19 main corn producing areas in China, this paper creates a corn TFP measurement model, applies the model to measure the corn TFPs in each main producing area from 2008 to 2018, and analyzes the features and causes of the variation in corn TFP in China with constraint of carbon emissions. The results show that: After 2015, the corn TFP in China was on the rise with constraint of carbon emissions, and the corn production was moving towards low-carbon mode, but exhibited huge regional difference; The policies on corn structure adjustment in the Sickle Band areas have effectively promoted the low-carbon production of corn in these areas, and improved the corn TFP; The growth of corn TFP in China is mainly bottlenecked by the slow technical progress. Finally, several policy suggestions were put forward to promote the low-carbon production and TFP of corn and other crops.

1. INTRODUCTION

To cope with climate change and promote low-carbon sustainable agriculture, countries around the world are competing to improve the total factor productivity (TFP) of agriculture under the constraint of carbon emissions [1]. As the largest food crop in China, corn can be consumed as our daily food, animal feed, and raw materials of energy. It provides an important guarantee for the food security [2] and energy security of China. In 2015, the Chinese Ministry of Agriculture issued the *Guiding Opinions on the Adjustment of Corn Structure in the Sickle Bend*, highlighting the importance of increasing the TFP of corn to the sustainable development of the corn industry.

Yang and Lu [3] effectively measured and decomposed the TFP of corn by the traditional approach for TFP measurement. But, for the following reasons, some of their judgements and interpretations are incorrect: first, their research emphasizes the adaptation between inputs and outputs over the coordination among inputs, outputs, and environment; second, their research only considers desirable outputs like corn yield, failing to take account of undesirable outputs like carbon emissions [4].

The Malmquist-Luenberger (ML) index, which is based on the directional distance function (DDF), can measure the agricultural TFP under environmental constraints, and include both desirable and undesirable outputs into the analysis framework [5]. Some scholars [5, 6] have adopted the ML index to measure the TFP of China's agriculture under the constraint of environmental protection, and examine the growth and changes of its components. However, the measured results varied with the measurement calibers and selected indices. Considering undesriable outputs, some scholars [7-11] also relied on the ML index to measure the TFPs in industry, macroeconomy, and public transport. Some other scholars [12-14] employed similar methods to measure the TFPs of logisitcs, ports and cattle farms in different regions with theconstraint of carbon emissions. In the context of sustainable development, Houshyar et al. [15] adopted data envolopment analysis (DEA) to measure the corn TFP in Iran, but did not discuss the corn TFP in China. Furthermore, a number of scholars held that the TFP under undesirable constraints can be improved by suitable policies, including liberalization of argicultrual market [16], green building policy [17], and agricultural structure [18].

In this paper, a corn TFP measurement model is established and used to measure the TFP indices (2008-2018) of corn and its components in main corn producing areas of China. Then, the features and causes of the variation in corn TFP were analyzed through temporal comparison between the situations before and after 2015 and spatial comparison between the areas in and out of the Sickle Bend. On this basis, policy suggestions were provided to promote the low-carbon production and increase the TFP of corn and other crops.

2. METHODOLOGY

2.1 Model construction

Our corn TFP measurement model was constructed, according to the findings of Färe et al. [19] and Tone [20, 21], as well as Li [22] and Tian et al. [23] are ML index method for TFP measurement, which couples DDFs of slacks-based measure (SBM). The constructed model can be expressed as:

$$
\begin{aligned}
& TFP\left(x^{t+1}, \mathrm{p}^{t+1}, \mathrm{n}^{t+1}; x^{t}, \mathrm{p}^{t}, n^{t}\right) \\
& =\left(\frac{\overrightarrow{S_c^t}\left(x^{t+1}, p^{t+1}, n^{t+1}\right)}{\overrightarrow{S_c^t}(x^t, p^t, n^t)} \times \frac{\overrightarrow{S_c^{t+1}}\left(x^{t+1}, p^{t+1}, n^{t+1}\right)}{\overrightarrow{S_c^{t+1}}\left(x^t, p^t, n^t\right)}\right)^{1/2} \\
& =\frac{\overrightarrow{S_c^{t+1}}(x^{t+1}, p^{t+1}, n^{t+1})}{\overrightarrow{S_c^t}(x^t, p^t, n^t)} \times \left(\frac{\overrightarrow{S_c^t}(x^{t+1}, p^{t+1}, n^{t+1})}{\overrightarrow{S_c^{t+1}}(x^{t+1}, p^{t+1}, n^{t+1})} \times \frac{\overrightarrow{S_c^t}(x^t, p^t, n^t)}{\overrightarrow{S_c^t}(x^t, p^t, n^t)}\right)^{1/2} \\
& = EFFCH(x^{t+1}, p^{t+1}, n^{t+1}; x, p, n) \times TECH(x^{t+1}, p^{t+1}, n^{t+1}; x, p, n)
\end{aligned} \tag{1}
$$

where, *TFP* is the *TFP* from period *t* to period *t*+1 (if *TFP*>1, the productivity increases; otherwise, the productivity decreases); *EFFCH* is the technical efficiency of corn (if *EFFCH*>1, the efficiency increases; otherwise, the efficiency decreases); TECH is the technical advancement of corn (if TECH>1, the technology progresses; otherwise, the technology regresses); *x* is the input variables, including labor input x_1 and four capital inputs, namely, seed input x_2, fertilizer input x_3, pesticide input x_4, and mechanical operation input x_5; *P* is the desirable output variable (corn yield); *n* is the undesirable output variable (carbon emissions).

The four SBM DDFs in the above model correspond to four linear programs to be solved. The undesirable output should be considered to measure the corn TFP with constraint of carbon emissions, and need not to be considered to measure the corn TFP without that constraint.

2.2 Data description

The main corn producing areas of China were taken as the study area. Considering data availability, the authors selected the panel data (2008-2018) on corn inputs and outputs in 19 main producing areas.

The carbon emissions can be computed by $n=T\times\delta$, where *n* is the carbon emissions per hectare; T is the pure consumption of fertilizer per hectare; δ is the carbon emission coefficient. Referring to the results of Oak Ridge National Laboratory [24], the δ value was set to 0.8956.

The relevant data were calculated according to *China Rural Statistical Yearbooks* and *China Agricultural Product Cost-Benefit Statistics*. The descriptive statistics of the inputs and outputs in corn production are listed in Table 1.

Table 1. The descriptive statistics of the inputs and outputs in corn production in China from 2008 to 2018

DMU	Type of index	Name of index	Number of observations	Mean	SD	Min	Max
19 main corn producing areas	Desirable output *p*	Corn yield *p* (kg/hm^2)	209	7,153.92	1,330.89	3,448.20	11,228.85
	Undesirable output *n*	Carbon emissions *n* (kg/hm^2)	209	325.23	53.34	209.30	461.73
	Inputs *x*	Standard man days x_1 (day/hm^2)	209	115.91	51.18	35.85	269.7
		Seed cost x_2 (yuan/hm^2)	209	557.65	112.87	329.55	866.32
		Fertilizer cost x_3 (yuan/hm^2)	209	1,976.89	387.91	1,291.90	3,163.99
		Pesticide cost x_4 (yuan/hm^2)	209	186.32	70.19	33.48	344.47
		Mechanical operation cot x_5 (yuan/hm^2)	209	1,079.09	561.29	7.5	2,309.5

Note: DMU, SD, min, and max is short for decision-making unit, standard deviation, minimum, and maximum, respectively.

3. TEMPORAL ANALYSIS

3.1 Global analysis

Based on our corn TFP measurement model, the global corn TFPs of the 19 main producing areas in 2008-2018 were evaluated on MaxDEA. The evaluation was carried out with and without the constraint of carbon emissions. The global TFPs were further decomposed into the TECH and EFFCH. The evaluation results are listed in Table 2.

Without the constraint of carbon emissions, the corn TFP decreased by 2.85% annually, the TECH degraded by 3.99% annually, and EFFCH improved by 1.53% annually from 2008 to 2018. With constraint of carbon emissions, the corn TFP decreased by 3.02% annually, the TECH degraded by 4.80% annually, and EFFCH improved by 2.63% annually in the same period.

Taking 2015 as the dividing line, the corn TFP decreased first and then increased. The corn TFP declined from 2008 to 2015, as TECH regressed faster than the improvement of EFFCH; the corn TFP grew from 2015 to 2018, for the TECH progressed faster than the deterioration of EFFCH.

Table 2. Global corn TFPs and components in 2008-2018

Period	Without constraint of carbon emissions			With constraint of carbon emissions		
	TECH$_1$	EFFCH$_1$	TFP$_1$	TECH	EFFCH	TFP
2008-2009	0.8840	1.0862	0.9577	0.8534	1.1215	0.9492
2009-2010	0.8880	1.0400	0.9202	0.8678	1.0660	0.9167
2010-2011	0.9456	0.9771	0.9261	0.9648	0.9544	0.9248
2011-2012	0.9453	1.0833	1.0230	0.9465	1.1103	1.0457
2012-2013	0.9440	0.9804	0.9240	0.9099	1.0004	0.9030
2013-2014	0.9895	1.0345	1.0183	0.9624	1.0443	0.9986
2014-2015	0.9387	1.0077	0.9462	0.9313	1.0126	0.9441
2015-2016	0.9830	1.0004	0.9835	0.9667	1.0173	0.9835
2016-2017	1.0350	0.9938	1.0293	1.0565	0.9814	1.0338
2017-2018	1.0475	0.9490	0.9872	1.0610	0.9550	0.9990
Mean	0.9601	1.0153	0.9715	0.9520	1.0263	0.9698
2008-2015	0.9336	1.0299	0.9593	0.9194	1.0442	0.9546
2015-2018	1.0218	0.9811	1.0000	1.0281	0.9846	1.0054

Fare et al. [25] suggested that the carbon intensity of production can be determined by comparing the magnitude of the TFP with constraint of carbon emissions and that (TFP_1) without the constraint of carbon emissions. When all input factors are the same, $TFP>TFP_1$ means the desirable output grows faster than the undesirable output, indicating that the DMU realizes low-carbon production; otherwise, the DMU realizes high-carbon production. On this basis, it can be judged that China's corn production was in high-carbon mode in 2008-2015, and low-carbon mode in 2015-2018.

3.2 Regional analysis

Similarly, the corn TFP of each of the 19 main producing areas was measured and decomposed. The measurement results are listed in Tables 3-5.

With constraint of carbon emissions, the mean TFPs in four regions, namely, Hebei, Inner Mongolia, Guangxi, and Shaanxi, were greater than 1, while those of the other 15 main producing areas were smaller than 1. The fastest growing TFP belongs to Hebei, whose mean TFP was 1.0160; the fastest declining TFP belongs to Hubei, whose mean TFP was 0.9120.

The corn TFPs in four regions (including Hebei) increased, as their EFFCHs improved faster than the regression of TECHs. By contrast, the corn TFPs in 15 regions decreased. Among them, the decrease in 4 regions, namely, Heilongjiang, Henan, Hubei, and Ningxia, results from the EFFCH deterioration and TECH regression; the decrease in the other 11 regions occurred as their EFFCHs improved slower than the regression of TECHs. Overall, under the constraint of carbon emissions, the growth of corn TFP in China is mainly dragged down by the slow TECH progress.

As shown in Tables 4 and 5, from 2008 to 2015, the corn production was in high-carbon mode in 13 main producing areas, and in low-carbon mode in 6 main producing areas; from 2015 to 2018, the corn production was in high-carbon mode in 8 main producing areas, and in low-carbon mode in 11 main producing areas. Therefore, the corn production in China is moving towards low-carbon mode.

Table 3. Regional corn TFPs and components in 2008-2018

Main producing areas	Without constraint of carbon emissions			With constraint of carbon emissions		
	$TECH_1$	$EFFCH_1$	TFP_1	TECH	EFFCH	TFP
Hebei	0.9847	1.0513	1.0335	0.9713	1.0558	1.0160
Shanxi	0.9557	1.0225	0.9736	0.9508	1.0265	0.9709
Inner Mongolia	0.9736	1.0338	1.0018	0.9673	1.0498	1.0069
Liaoning	0.9570	0.9989	0.9491	0.9421	1.0020	0.9349
Jilin	0.9807	1.0011	0.9792	0.9803	1.0026	0.9783
Heilongjiang	1.0103	0.9906	1.0004	0.9979	0.9874	0.9844
Jiangsu	0.9691	1.0192	0.9837	0.9596	1.0380	0.9880
Anhui	0.9781	1.0053	0.9767	0.9736	1.0217	0.9740
Shandong	0.9693	1.0137	0.9817	0.9637	1.0169	0.9795
Henan	0.9649	0.9763	0.9365	0.9620	0.9758	0.9302
Hubei	0.9526	0.9673	0.9229	0.9435	0.9643	0.9120
Guangxi	0.9637	1.0323	0.9943	0.9541	1.0538	1.0037
Sichuan	0.9480	1.0205	0.9602	0.9450	1.0348	0.9667
Guizhou	0.8991	1.0435	0.9472	0.9064	1.0771	0.9823
Yunnan	0.9065	1.0582	0.9496	0.8831	1.0919	0.9447
Shaanxi	0.9594	1.0377	0.9903	0.9545	1.0653	1.0016
Gansu	0.9313	1.0356	0.9576	0.9124	1.0549	0.9406
Ningxia	0.9577	0.9820	0.9412	0.9448	0.9908	0.9357
Xinjiang	0.9795	1.0000	0.9795	0.9763	1.0000	0.9763

Table 4. Production modes of main corn production areas in 2008-2015

Main producing area	TFP_1 (without constraint of carbon emissions)	TFP (with constraint of carbon emissions)	Production mode
Hebei	1.0448	1.0221	High carbon
Shanxi	0.9599	0.9579	High carbon
Inner Mongolia	0.9746	0.9714	High carbon
Liaoning	0.9294	0.9062	High carbon
Jilin	0.9574	0.9520	High carbon
Heilongjiang	0.9954	0.9734	High carbon
Jiangsu	1.0180	1.0381	Low carbon
Anhui	1.0139	1.0217	Low carbon
Shandong	0.9573	0.9536	High carbon
Henan	0.9312	0.9170	High carbon
Hubei	0.9045	0.8762	High carbon
Guangxi	1.0008	1.0157	Low carbon
Sichuan	0.9448	0.9531	Low carbon
Guizhou	0.8994	0.9355	Low carbon
Yunnan	0.9248	0.9078	High carbon
Shaanxi	0.9826	0.9957	Low carbon
Gansu	0.9454	0.9237	High carbon
Ningxia	0.8849	0.8616	High carbon
Xinjiang	0.9582	0.9542	High carbon

Table 5. Production modes of main corn production areas in 2015-2018

Main producing area	TFP_1 (without constraint of carbon emissions)	TFP (with constraint of carbon emissions)	Production mode
Hebei	1.0073	1.0017	High carbon
Shanxi	1.0057	1.0010	High carbon
Inner Mongolia	1.0652	1.0897	Low carbon
Liaoning	0.9951	1.0019	Low carbon
Jilin	1.0298	1.0398	Low carbon
Heilongjiang	1.0120	1.0102	High carbon
Jiangsu	0.9036	0.8713	High carbon
Anhui	0.8901	0.8628	High carbon
Shandong	1.0387	1.0397	Low carbon
Henan	0.9489	0.9611	Low carbon
Hubei	0.9659	0.9955	Low carbon
Guangxi	0.9791	0.9757	High carbon
Sichuan	0.9960	0.9985	Low carbon
Guizhou	1.0586	1.0914	Low carbon
Yunnan	1.0077	1.0310	Low carbon
Shaanxi	1.0082	1.0154	Low carbon
Gansu	0.9861	0.9798	High carbon
Ningxia	1.0727	1.1086	Low carbon
Xinjiang	1.0291	1.0279	High carbon

The above analysis reveals the corn TFP in China, and the sptial and temporal features of its components. Referring the Fare et al.'s criteria, the low-carbon technology innovators (LCTIs) that dominate the efficient frontier of China's annual corn production must satisfy:

$$MLTECH_{t}^{t+1} > 1 \tag{2}$$

$$\overrightarrow{D_0^t}\left(x^{t+1}, y^{t+1}, b^{t+1}; y^{t+1}, -b^{t+1}\right) < 0 \tag{3}$$

$$\overrightarrow{D_0^{t+1}}\left(x^{t+1},\ y^{t+1},\ b^{t+1};\ y^{t+1}, -b^{t+1}\right) = 0 \tag{4}$$

Formula (2) indicates that the efficient frontier expands towards more good outputs and fewer bad outputs; formula (3) indicates that the technical structure of period t is not applicable to period t+1; formula (4) ensures that the LCTIs fall on the efficient frontier. The regions that satisfy all three conditions are the LCTIs that dominate corn production in China (Table 6).

According to the above meaurement, from 2008 to 2018, nine main corn producing areas were the LCTIs that domianting the efficient frontier of China's corn production, including Hebei for 4 years, Heilongjiang for 4 years, Inner Mongolia for 3 years, and Sichuan for 3 years. This means these four regions have attached importance to environmental protection and the efficiency of resource utilization.

Figure 1 presents the variations in corn TFP, TECH, EFFCH with 2008 as the base year. It can be seen that, under the constraint of carbon emissions, China's corn TFP exhibited a declining trend, except for the rises in 2012 and 2017, showing an annual decline of 6.39%. The TECH of China's corn production regressed from 2008 to 2016 at an annual rate of 6.66%, and progressed 3.20% annually from 2016 to 2018. The EFFCH of China's corn production increased with slight fluctuations; the annual increase was about 0.96%.

The above results indicate that, on average, the technical efficiency of China's corn production has improved, and promoted the TFP of corn under the constraint of carbon emissions. However, the technical progress is slower than the regression of advanced technology, causing the corn TFP in China to decline with the constraint of carbon emissions.

Table 6. The LCTIs that dominate corn production in China (2008-2018)

Year	LCTIs
2008-2009	Hubei
2009-2010	Heilongjiang, Gansu
2010-2011	Heibei, Heilongjiang, Hubei
2011-2012	Hebei, Guangxi, Sichuan
2012-2013	Inner Mongolia, Helongjiang, Sichuan, Xinjiang
2013-2014	Inner Mongolia, Heilongjiang, Xinjiang
2014-2015	None
2015-2016	Heibei, Shanxi, Sichuan
2016-2017	Heibei, Heilongjiang, Guangxi, Xinjiang
2017-2018	Inner Mongolia, Xinjiang
Total: Heibei (4), Inner Mongolia (3), Shanxi (1), Heilongjiang (4), Hubei (2), Guangxi (2), Sichuan (3), Gansu (1), Xinjiang (2)	

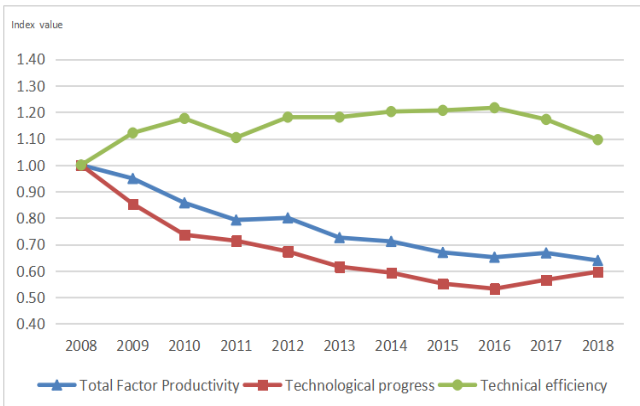

Figure 1. Variations in corn TFP and its components under the constraint of carbon emissions

4. SPATIAL ANALYSIS

Since 2015, China has made Sickle Bend areas the focus of corn structural adjustment. The Sickle Bend mainly covers 13 main producing areas, namely, Hebei, Shanxi, Inner Mongolia, Liaoning, Jilin, Heilongjiang, Guangxi, Guizhou, Yunnan, Shaanxi, Gansu, Ningxia, and Xinjiang. Here, the other 6 main corn producing areas are collectively referred to non-Sickle Bend areas.

Table 7. Corn TFPs in and outside the Sickle Bend and their components with constraint of carbon emissions

Period	Sickle Bend areas			Non- Sickle Bend areas		
	TECH	EFFCH	TFP	TECH	EFFCH	TFP
2008-2015	0.9197	1.0440	0.9521	0.9189	1.0447	0.9599
2015-2018	1.0185	1.0147	1.0288	1.0489	0.9193	0.9548

Table 8. Production modes of corn in and outside the Sickle Bend and their components with constraint of carbon emissions

Period	Sickle Bend areas			Non-Sickle Bend areas		
	TFP_1 (constraint of carbon emissions)	TFP (constraint of carbon emissions)	Mode	TFP_1 (constraint of carbon emissions)	TFP (constraint of carbon emissions)	Mode
2008-2015	0.9583	0.9521	High carbon	0.9616	0.9599	High carbon
2015-2018	1.0197	1.0288	Low carbon	0.9572	0.9548	High carbon

As shown in Table 7, with constraint of carbon emissions, the corn TFPs of the areas in and outside the Sickle Bend were both declining from 2008 to 2015, and the decline in the Sickle Bend was faster than that outside; from 2015 to 2018, the corn TFPs in Sickle Bend areas were on the rise, while those in non-Sickle Bend areas were still on the decline.

As shown in Table 8, in 2008-2015, the corn production was in high-carbon mode in and outside the Sickle Bend; when it comes to 2015-2018, the corn production shifted to the low-carbon mode in Sickle Bend areas, but remained in high-carbon mode in non- Sickle Bend areas.

To sum up, in 2015-2018, the Sickle Bend areas achieved low-carbon production of corn and improved the corn TFP. The progress can be attributed to the favorable policies implemented by the government in the Sickle Bend on corn structural adjustment, which promote the sustainable development of agriculture. The specific polices include: (1) encourage technical innovation and strengthen technical support; (2) build a industrial layout suitable in time and space, reduce corn planting in non-dominant regions, and increase corn planting in dominant regions; (3) promote eco-friendly farming systems like grain and bean rotation, and establish a land-use model that uses land while improving soil; (5) set up a novel planting and breeding structure that benefits both crop yield and vegetation cover, combines agriculture and animal husbandry, and supports cyclic development.

5. CONCLUSIONS

The following conclusions were drawn through measurement and analysis of the corn TFP in China:

(1) After 2015, the corn TFP in China was on the rise with constraint of carbon emissions, and the corn production was moving towards low-carbon mode, but exhibited huge regional difference.

(2) The policies on corn structure adjustment in the Sickle Band areas have effectively promoted the low-carbon production of corn in these areas, and improved the corn TFP.

(3) The growth of corn TFP in China is mainly bottlenecked by the slow technical progress.

Based on these findings, several suggestions were put forward:

(1) The policies on corn structure adjustment should be promoted to main corn producing areas outside the Sickle Band, as well as the main producing areas of other crops.

(2) The Chinese government should facilitate the exchange of low-carbon corn production experience, which could benefit the planting of other crops across the country.

(3) The Chinese government should also promote the technical progress on corn and other crops, which is the key to elevating crop TFPs.

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