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Abatement costs of emissions from burning maize straw in major maize regions of China: Balancing food security with the environment

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ABSTRACT

This paper estimates the shadow price of CO_2 from burning maize straw in the Chinese agricultural sector and explores the related policy implications for decision makers. Using a quadratic directional distance function, we evaluate the production inefficiency and shadow prices of CO_2 reduction for the seven major maize-producing provinces in China for 1996–2014. In general, the efficiency improves over time. Shandong province ranked as the top one with full efficiency considering both economic and environmental impacts as of 2014. The mean shadow price for the CO_2 emission was 0.45 yuan/kg (US$75/t), whereas the province-specific shadow prices varied within the interval bounded by 0 and 0.913 yuan/ha (US$152/t). The marginal abatement cost curve was downward-sloped and indicated the need for curbing CO_2 emission in areas exhibiting the highest pollution rates. Given the marginal abatement cost patterns, the transaction costs associated with implementation of the conservation practices (tillage) should not exceed 335 yuan/ha in order to ensure the welfare gains. This government-provided payment would compensate farmers for yield reductions in favor of implementing conservation practices that would substantially reduce CO_2 emissions.

1. Introduction

Agriculture is one of the major contributors to global emissions of the greenhouse gases (GHGs) that drive climate change (Chen et al., 2018; Zhao et al., 2017; Wang et al., 2018). World agriculture accounted for an estimated direct emission of 5.1–6.1 Pg CO_2-equivalents per year, contributing 10–12% to the total global anthropogenic emissions of GHGs in 2005 (Smith et al., 2007). This number would increase to about 40% if indirect sources of emissions, such as production of fertilizers, pesticides and machines, were considered. This makes the agricultural sector the world's second-largest emitter, after the energy sector (which includes emissions from power generation and transport). China, endowed with vast rural areas and a large agricultural sector, is one of the most important producers of agricultural emissions in the world. GHGs from Chinese agriculture reached approximately 712 Tg CO_2 in 2014, accounting for 14% of the world (FAO, 2015).

Burning crop residues to clear the field for next season constitutes a major source of CO_2 emissions in the agricultural sector of China. Sun et al. (2016) estimates that in 2013 alone about 193 Tg of CO_2 was emitted by farmers' burning crop residues in farm fields in China, which accounts for about 30% of the total CO_2 emissions from Chinese agriculture. About 2700 Tg of CO_2 have been emitted from burning agricultural residues in China throughout 1996–2013, which was about 45% of the total residential coal consumption over the same period. In Northeast China, more than 80% of crop residues are burned in the fields each year, of which over 2/3 is from maize straw. Burning crop residues not only harms the human respiratory system, but also often results in low visibility that delays air flights and impedes ground transportation.

Conservation tillage offers an opportunity for reducing burning crop residues. Conservation tillage is a range of cultivation techniques (including no tillage and retaining crop residue to field, for example) designed to minimize soil disturbance for seed placement by allowing crop residue to remain in the soil after planting. Conservation tillage also has co-benefits, such as protecting soil from

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wind and water erosion. As indicated in the literature, there exists a risk for reduction of crop yield under conservation practices, especially in the short run (Zheng et al., 2014). In general, farmers lack incentives to adopt conservation tillage. They are unwilling to sustain crop yield reductions and the GHG emissions from burning crop residues create negative externalities with social costs.

Several provinces in China, under the support by the Ministry of Finance and the Ministry of Agriculture, recently piloted the Compensation for Soil Conservation Program (CSCP). The government is eager to know how much investment should be allocated to effectively implement such programs. Insight into market data might render an efficient mechanism to facilitate valuation of the environmental pressures. However, national or international markets do not exist for GHGs in most cases. Furthermore, measuring GHGs emissions at the farm level can be elusive, making cost-benefit analysis rather challenging. Therefore, there is a need to measure the shadow price of the GHG emission in agriculture. As crop production comprises an important facet of food security, a simulation can be carried as a useful tool for providing the government with information about potential impacts of changes in the cropping practices on crop yields. This paper seeks to provide the government with a yardstick to make an evidence-based decision about CSCP.

It is promised that, by 2030, China will reduce CO_2 intensity (as measured in tons per dollar of GDP) by 60–65% compared to 2005 (NEA, 2015; He et al., 2018). Although it has been estimated that China's agricultural sector has the potential to reduce GHGs by 20% (Zhang, 2015), allocation of the abatement targets among sectors is still a critical question to policy makers. Theoretically, the optimal abatement scheme is to maximize the total GDP given the constraint of abatement mission (Wang et al., 2016; Zhou and Wang, 2016). This would render abatement level where marginal cost of each sector is equal. Therefore, it is important to estimate the abatement cost for each sector from this perspective (Song and Wang, 2018; Thoidou, 2017). Furthermore, the productive activities associated with environmental pressures need to be streamlined within each sector (Fang et al., 2018; Qi and Li, 2017).

There have been a number of studies on estimating abatement cost of undesirable outputs, such as CO_2, following the concept of shadow prices. However, there is little literature to estimate the shadow prices of agricultural emissions in China. Zhou et al. (2014) conducted a systematic review of the studies on estimating shadow prices of undesirable outputs by applying frontier models. These studies were primarily focused on energy generation. The shadow price of undesirable output can be interpreted as the opportunity cost of abating one additional unit of undesirable output in terms of the loss of desirable output given the same amount of inputs. A prevalent practice is to use the distance function (e.g. Shephard or directional distance function) to derive the shadow price. This approach can be implemented by means of parametric or nonparametric frontier models. Empirically, earlier studies estimated shadow prices of GHGs at the plant, sector and even regional economic levels. Wei et al. (2013) estimated the shadow price of CO_2 and explored its determinants for thermal power enterprises in China. The mean CO_2 shadow price was $249 in 2004 using the linear programming approach. They also found that the shadow price was a negatively related to firm size, age, and coal share, whereas a positive correlation with the technology level was established. Du et al. (2015b) investigated the technical inefficiency, shadow price and substitution elasticity of CO_2 emissions of China based on a provincial panel data from 2001 to 2010. They showed that China's technical inefficiency increased over the period implying further scope for CO_2 emissions reduction in the medium and longer term at best by 4.5% and 4.9%, respectively. The shadow price of CO_2 abatement increased from around 120 US$/t in 2001 to 308 US$/t in 2010.[1]

The present paper is the first one to estimate the shadow price of CO_2 associated with the practice of burning crop residue in China. The directional distance function in quadratic form is used to gauge the efficiency and CO_2 shadow price for the seven major maize-producing provinces during 1996–2014. Furthermore, the paper simulates the changes in efficiency and abatement cost of CO_2 under a scenario of adopting soil conservation practices. By comparing the two cases, i.e. baseline technology and conservation technology, we are able to approximate the investments the government should allocate to promote soil conservation practices.

From a policy perspective, the results of our research are to be of practical use to provide a decision support tool. Indeed, for policy makers, the research provides the CO_2 shadow price estimates in the framework of burning crop residues which have not been available to date. This paper also contributes to the literature on abatement costs of agricultural emissions. Being able to assess the marginal abatement costs is an important step in tackling the environmental policy issues, since these costs can be used when fixing carbon tax rates and ascertaining initial market price for a trading system (Färe et al., 1993; Wei et al., 2013). In the agricultural sector, these issues are important from the support rate perspective.

The paper unfolds as follows: Section 2 presents the data used. Section 3 describes the methods to evaluate efficiency and shadow prices using a directional distance function. Section 4 reports the results of production inefficiency and shadow prices of CO_2. Section 5 discusses and concludes the paper.

2. Data

In order to estimate the environmental efficiency and shadow prices of CO_2 resulting from burning the maize straw, this paper combines a provincial level panel data of inputs and output for producing maize in seven provinces in China for 1996–2014 with a field survey dataset on farmers' utilization of maize straw. Maize is one of the major crops in China's agricultural production. According to the national statistics, the percentage of area sown under maize to total area sown increased by 11 percentage points from 21.8% in 1996 to 32.9% in 2014. The seven provinces featured in this study the major maize production regions accounting for about 60% maize production of the whole country in 2014. They include Heilongjiang, Jilin and Liaoning in Northeast China, and Hebei, Henan, Shandong and Anhui in the North China Plain (Fig. 1).

The dataset of inputs and outputs is constructed based on Compiled Materials of Costs and Profits of Agricultural Products of China (CMCP, 1996–2014), published by the State Development and Planning Commission. CMCP documents the cost and revenue per hectare of major products for each province in each year. The shadow pricing model used in this paper treats each province in each year as a decision making unit, which uses inputs to produce desirable and undesirable outputs. In our case, we assume each province uses a single integrated input (i.e. total cost/ha) to produce maize (kg/ha) and one undesirable output (i.e. CO_2 equivalent emission from burning maize straw per ha). Total cost per ha includes both labor and materials costs per ha. Materials costs include costs for machinery depreciation or rental, fuels, seeds, fertilizers and organic manure, irrigation, pesticides, etc. Labor cost includes both family labor and employed labor cost, which is calculated by multiplying the labor days by average wage for rural labor. Maize yield is directly documented in CMCP. To eliminate the influence of

[1] The exchange rates are 1US$ = 8.277 in 2001 and 1US$ = 6.827 in 2010, respectively.

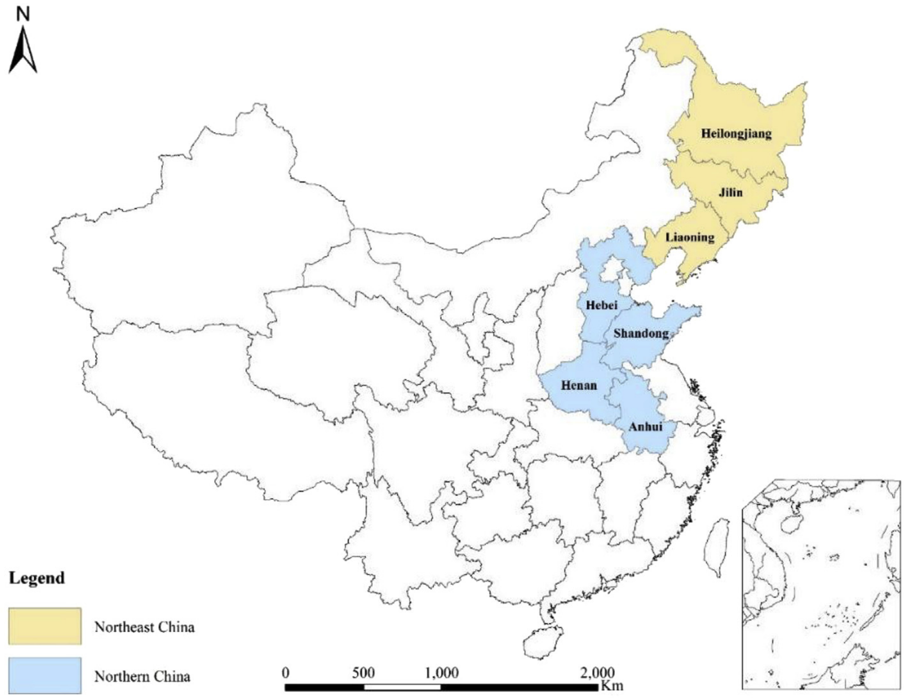

Fig. 1. Map of study areas.

inflation, we deflate grain price and total costs to the 2010 price. Consumer price index of rural residents from China Statistical Yearbook is used (NBSC, 2011).

The CO_2 emission is measured in kg/ha and estimated by using the following formula (Sun et al., 2016):

$$CO_{2i,t} = Y_{i,t} \cdot R \cdot B_{i,t} \cdot CF \cdot EF$$

where $CO_{2i,t}$ is the CO_2 emissions (kg/ha) in province i in year t, $Y_{i,t}$ stands for maize yield in province i in year t (kg/ha) from CMCP, R stands for residue to maize ratio,[2] $B_{i,t}$ is the percentage of burnt maize straw in province i in year t (based on our survey data), CF stands for the combustion factor, and EF is the emission factor.[3] The percentage of burnt maize straw is derived from a large scale farm survey. We interviewed 60 village leaders face to face in each province on their farmers' utilization of maize straw as a percentage to their villages in 2015, 2010, 2005 and 2000. Then, we interpolate the survey data to all the years from 1996 to 2014 by assuming a constant rate of change between every 5 years. The details of the sample selection procedure is documented in Huang and Ding (2016).

The utilization of maize straw differs largely across the provinces and over time (Fig. 2). The percentage of burning in the North China Plain is lower than that in Northeast China, while the situation is opposite for retaining to field. Retaining to field, also called crop residue retention, refers to a method that apply crop residue to the soil directly or after composting the straws (wheat straw, maize straw and rice stalks) which are not suitable for direct feed. This may be partially because warmer climate in the North China Plain favors adoption of conservation practices and partially due to a stricter policy since the North China Plain is closer to Beijing. The burning percentage in Hebei and Henan decreased from 57% in 2000 to 28% in 2015 and from 67% in 2000 to 45% in 2015, respectively. However, the other two provinces in the North China Plain saw a slight increase in burning percentage, from 47% in 2000 to 56% in 2015 in Shandong and from 63% in 2000 to 71% in 2015 in Anhui. The average percentage of burning in Northeast China is much higher (>80%), although Heilongjiang and Jilin has seen a slightly decreasing trend.

The percentage of retaining to field has been increasing in all provinces since 2000, but the increments are relatively small in Northeast China. It increased by 20% in the North China Plain, while it only increased by less than 10% in Northeast China. For example, Hebei saw an increase in retaining to field from 12% in 2000 to 50% in 2015, while in Liaoning the increase was from just less than 1% to around 11%. It is not surprising to see that a decreasing percentage of maize straw used as livestock feed in all provinces, since livestock production has become more specialized over the past decades. The descriptive statistics for the key variables used in the distance function are presented in Table 1. The data were normalized by sample means prior to calculation of the distance function.

3. Estimating efficiency and shadow prices

The directional distance function is a way of describing production process besides the production function. The advantage of directional distance function over a traditional production function is that it can deal with multiple outputs, including undesirable outputs. Following Färe et al. (2005) and Hou et al. (2015), several essential steps of estimating production efficiency and shadow prices will be presented next.

Firstly, a production possibility is defined to represent a technology that jointly produces desirable and undesirable outputs. In mathematical form, it can be described as:

[2] R = 1.25, which is the median value from the following studies: Yukihiko et al. (2005); Liu et al. (2008); Kim and Dale (2004); Zeng et al. (2014); Lal (2005); Shen et al. (2010); Cui et al. (2008); Song and Wang (2018); Jia and Li (2006); Bi (2010); Renewable Energy Project (2008).

[3] CF = 0.92 and EF = 1.35 from Streets et al. (2003) and Turn et al. (1997).

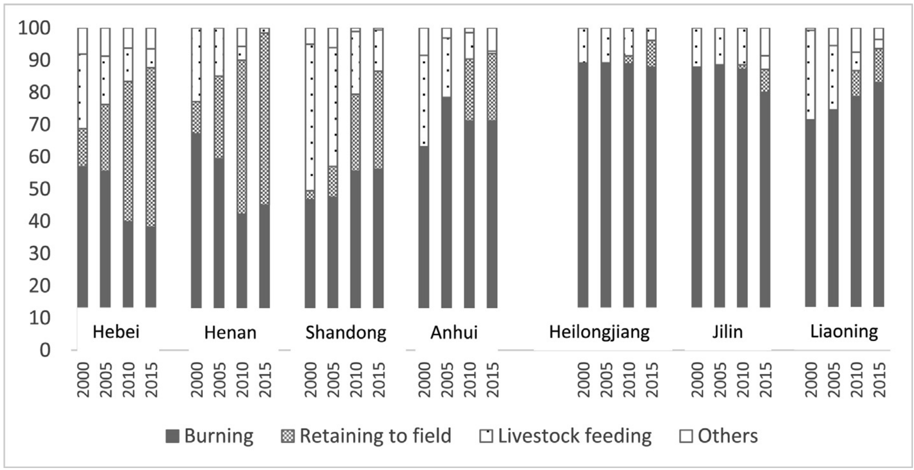

Fig. 2. Utilization of maize straw by province, 2000–2015 (%).

Table 1
Descriptive statistics for the variables used in the distance function.

Variable	Mean	Std. Dev.	Minimum	Maximum
Total cost (yuan/ha)	5757	1940	3249	11,045
Maize yield (kg/ha)	6232	995	3982	8211
CO_2 from burning maize straw (kg/ha)	6605	2035	3241	11,128

$$P(x) = \{(y,\ b) : x \text{ can produce } (y, b)\}, \tag{1}$$

where $x = (x_1, \ldots, x_N) \in \Re_+^N$ is a vector of N inputs, $y = (y_1, \ldots, y_M) \in \Re_+^M$ is a vector of M desirable outputs and $b = (b_1, \ldots, b_J) \in \Re_+^J$ is a vector of J undesirable outputs. The production possibility set is assumed to have the following properties, as presented in Färe et al. (2005), i.e. convexity and compactness, free disposability of good outputs, weak disposability of desirable and undesirable outputs and null-jointness. The production possibility set is constructed by the dots which represent the production combinations given constant inputs (Fig. 3).

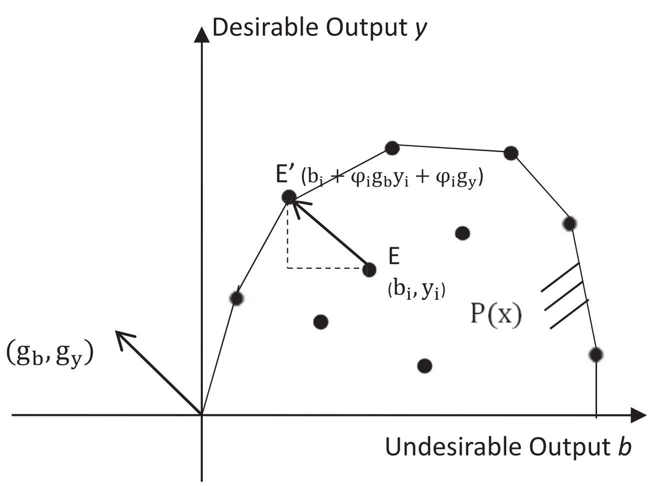

Fig. 3. The Directional Output Distance Function. Note: The dots are sample observations that construct the output possibility set *P(x)*. The resulting boundary is the Pareto efficient frontier spanned by the efficient observations. The arrows denote the directional vector $(g_b,\ g_y)$. All the dots under the frontier curve are inefficient ones, for example, (b_i, y_i). The distance function measures the efficiency. For example, the value of distance function for (b_i, y_i). is the "distance" from point E to point E′ along the direction given by the arrow.

Secondly, a directional distance function is defined corresponding to the production possibility set. Given the production possibility set P(x), a directional distance function for a given observation (x_i, y_i, b_i) is written as:

$$D_i\left(x_i, y_i, b_i; g_y, g_b\right) = \max\left\{\varphi_i \geq 0 : \left(y_i + \varphi_i g_y, b_i + \varphi_i g_b\right) \in P(x_i)\right\} \tag{2}$$

where $g = (g_y, g_b)$ is a direction function, φ_i is a scalar representing the degree of simultaneous change of desirable and undesirable outputs. The directional distance function says that the observation after expanding y_i by φ_i and reducing b_i by φ_i along the direction (g_y, g_b) still belongs to the production possibility set. Mathematically, $(y_i + \varphi_i g_y, b_i + \varphi_i g_b) \in P(x_i)$. The direction is chosen by the authors. D_i is the maximum φ_i, whereas $(y_i + D_i g_y, b_i + D_i g_b)$ is on the efficiency frontier instead of inside the frontier (for example, Point E′ in Fig. 3).

Corresponding to the assumptions of the production possibility set, the distance function satisfies several properties. For details regarding these properties, please refer to Färe et al. (2005) and Hou et al. (2015). Benefiting from these properties, the directional distance function can be an attractive measure of environment and technical efficiency. For instance, if $D_i(x_i,\ y_i,\ b_i; g_y,\ g_b) \gg 0$, inefficiency occurs, which means considerable scope for increasing desirable outputs and(or) reducing undesirable outputs exists.

Thirdly, we use a profit maximization model to derive the shadow prices of undesirable outputs. The profit function, which contains the adverse effect generated by the undesirable outputs is defined as:

$$R_i\left(\mathbf{x_i}, \mathbf{p_y}, \mathbf{p_b}\right) = \max_{\mathbf{y},\mathbf{b}}\left\{\mathbf{p_y}\mathbf{y}_{\boldsymbol{i}} + \mathbf{p_b}\mathbf{b}_{\boldsymbol{i}} : \ \mathbf{D_i}\left(\mathbf{x_i}, \mathbf{y}_{\boldsymbol{i}}, \mathbf{b}_{\boldsymbol{i}}; \mathbf{g_y}, \mathbf{g_b}\right) \geq 0\right\}, \tag{3}$$

where $R_i(\mathbf{x_i}, \mathbf{p_y}, \mathbf{p_b})$ represents the maximum profit for the i-th observation, $\mathbf{p_y} = (p_{y1}, \ldots p_{yM}) \in \Re^M_+$ represents the prices of desirable output and $\mathbf{p_b} = (p_{b1}, \ldots, p_{bJ}) \in \Re^J_-$ represents the prices of undesirable output. The first order conditions for maximizing problem in Eq. (3) yields are:

$$\nabla_b D_i(\mathbf{x_i}, \mathbf{y_i}, \mathbf{b_i}; \mathbf{g}) = \frac{p_b}{p_y g_y + p_b g_b} \geq 0 \tag{4}$$

and

$$\nabla_y D_i(\mathbf{x_i}, \mathbf{y_i}, \mathbf{b_i}; \mathbf{g}) = \frac{p_y}{p_b g_y + p_b g_b} \leq 0. \tag{5}$$

Thus, given the m-th desirable output price, say p_{ym}, the shadow price of the j-th undesirable output can be recovered by taking the ratio of Eq. (4) and Eq. (5):

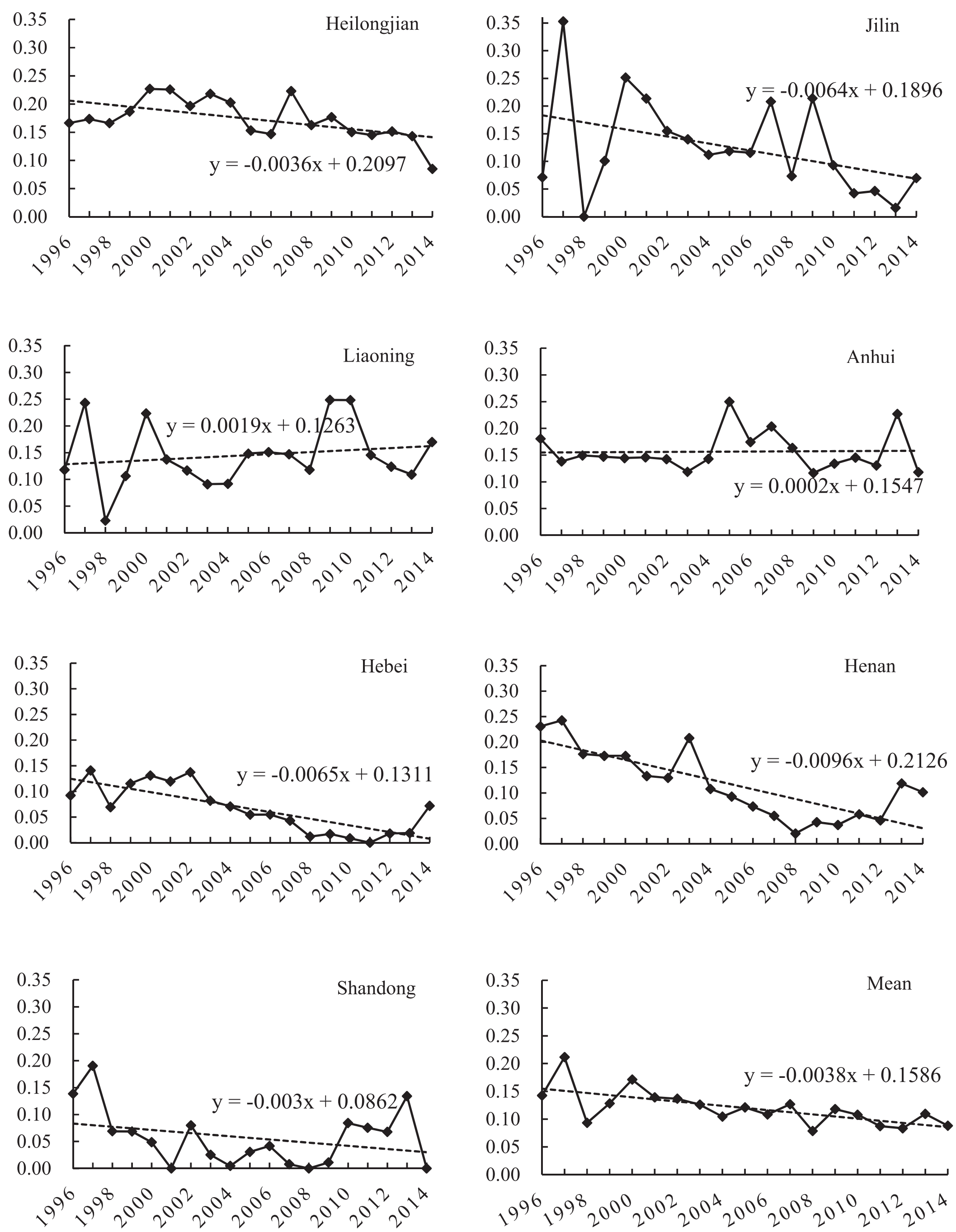

Fig. 4. Inefficiency scores for the seven provinces, 1996–2014.

$$p_{bj} = p_{ym}\left(\frac{\partial D_i(\mathbf{x_i}, \mathbf{y_i}, \mathbf{b_i}; \mathbf{g})/\partial b_j}{\partial D_i(\mathbf{x_i}, \mathbf{y_i}, \mathbf{b_i}; \mathbf{g})/\partial y_m}\right). \quad (6)$$

Eq. (6) implies that the profit is maximized where marginal rate of transformation between an undesirable output and a desirable output equals the price ratio of the two. Therefore, the shadow prices of undesirable outputs are interpreted as the opportunity cost of abating one additional unit of undesirable output in terms of the loss of desirable output (Färe et al., 2005).

As noted above, parameterizing the distance function plays a foundational role in judging efficient or inefficient and deriving shadow price. Much literature set the directional vector $g = (1, -1)$, see Färe et al. (2005), Wei et al. (2013), which implies an equal expansion in desirable outputs and undesirable outputs. We use the ratio of the means of the desirable output and undesirable input to set the directional vector (1, −1.06), which is based on empirical data. Please refer to Hou et al. (2015) for a detailed description of the estimation approach.

4. Results

Inefficiency is measured by $D(\boldsymbol{x}, \mathbf{y}, \mathbf{b}; g_y, g_b)$, which means a producer can reach the full efficiency if the desirable output is increased by $\frac{y \cdot g_y}{1-D} - y$ and the undesirable output is decreased by z −

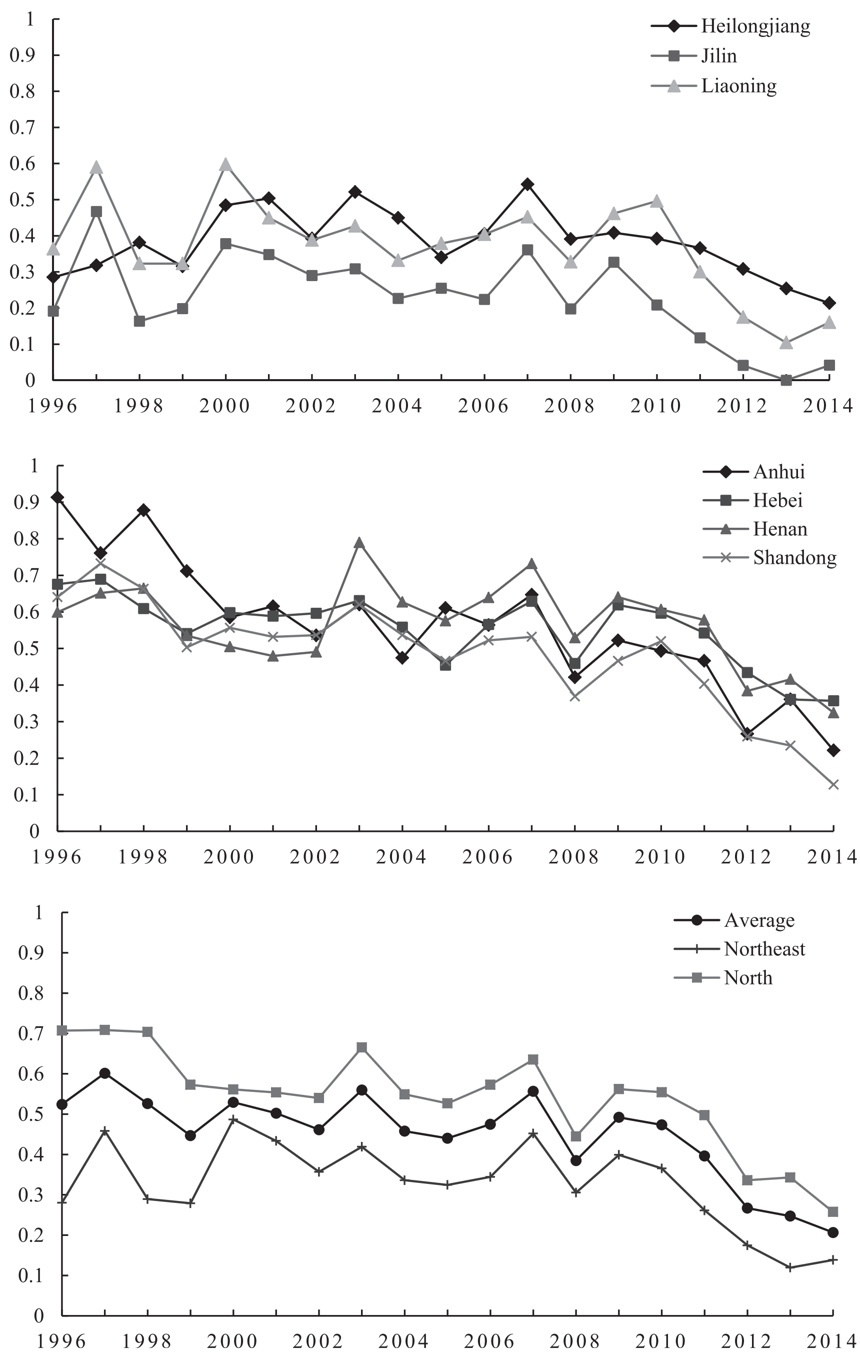

Fig. 5. Shadow price of CO_2 for the seven provinces over time.

$\frac{z\cdot g_b}{(1+D)}$, given a certain amount of inputs. For example, in Jilin, the directional distance function has a mean value of 0.126 and ranges from a low of 0 in 1998 to a high of 0.353 in 1997. The inefficiency score of Jilin in 1997 implies that Jilin can produce on the efficiency frontier in this year if its desirable output increases from 4047 kg/ha to 6297 kg/ha (4047/(1–0.353) = 6297), and its undesirable output decreases from 5530 kg/ha to 4087 kg/ha (5530*1.06/(1 + 0.353) = 4332).

The inefficiency scores decrease for all the provinces over time, yet some variation can be observed (Fig. 4). The downward trend of inefficiency score implies that the production efficiency improves over time. The inefficiency score of the North China Plain decreases from 0.161 in 1996 to 0.073 in 2014. For Northeast China, this number drops from 0. It implies that society will 118 in 1996 to 0.108 in 2014. The production efficiency improvement in the North China Plain is faster than that in Northeast China. Within Northeast China, the largest rate of decline in inefficiency score occurs in Jilin, followed by Heilongjiang. In contrast, Liaoning has a slightly increasing trend. The slopes of the trend lines imply that production efficiency in Jilin improves at a faster pace than it is the case Heilongjiang and Liaoning. Within the North China Plain, Henan and Hebei have the deeper downward slopes of inefficiency score than Anhui and Shandong. This implies that the production efficiency in Anhui and Shandong is relatively stable, while Henan and Hebei improve their production efficiency. In 2014, Shandong has an inefficiency score of 0, which implies that Shandong in 2014 reached full production efficiency with respect to the production frontier for the whole sample.

The shadow prices of CO_2 also decreases over time with some variation (Fig. 5). The shadow price represents the marginal abatement cost, which is the cost of abating the marginal unit of pollutant by reducing the corresponding desirable output. The downward trend of shadow price of CO_2 indicates that it has been becoming less expensive to reduce CO_2 given the production technology. The downward trend in Northeast of China is less steep than that in the North China Plain, which means that the shadow prices of CO_2 is more stable across time in Northeast China but decreases significantly in the North China Plain. The trend line for shadow prices of CO_2 in the North China Plain has always been above that for Northeast of China, which means it is always more expensive to reduce CO_2 marginally in the North China Plain than in Northeast China.

Comparing the magnitude of shadow price renders significant policy implications. The average shadow price of CO_2 in Northeast China is 0.328 yuan/kg (50.5 US$/t, 1US$ = 6.5 yuan), which is lower than that in the North China Plain (0.541 yuan/kg, equivalent to 83.2 US$/t) (Table 2). The shadow prices mean that it cost 50.5 US$ to abate one ton of CO_2 marginally by reducing the associated crop production in Northeast China, while it costs 83.2 US$ in the North China Plain. It implies that society will benefit from abating CO_2 emissions in the regions with lower shadow prices. Furthermore, policy makers should abate CO_2 emissions from Northeast China until the shadow prices of CO_2 are equal to that in the North China Plain.

The marginal abatement cost (MAC) curve can be derived by plotting shadow price versus the amount of CO_2 emissions. The resulting MAC curve has a downward slope (Fig. 6). It shows that as the emissions of CO_2 increase, the marginal abatement cost goes down. The downward trend reflects the fact that given a certain level of crop yield, the higher emissions will render a lower level of opportunity cost to reduce one marginal unit of emission. It implies the rationality that abatement activities should start from the most polluted areas. Modelling a log linear regression model can give us that the shadow price elasticity at the mean value of CO_2 emissions is −3.37. It means a 1% increase of CO_2 emissions can lead to a 3.37% decrease of shadow price.

An earlier study shows that conservation tillage can lead to reduction of CO_2 emissions, while in the short term it may also cause reduction of crop yield (Su et al., 2007). We assume 50% reduction in CO_2 emission and 10% reduction in crop yield as an example to compare the profit with and without considering CO_2 emissions (Fig. 7). The profit without considering CO_2 emissions is calculated by subtracting total cost from total revenue, while the profit with considering CO_2 emissions is calculated as subtracting both total cost and total abatement cost from the total revenue. Total abatement cost is calculated by multiplying the shadow price of CO_2 by the volume of CO_2 emissions. If not considering CO_2 emissions, the profit from traditional tillage is biasedly higher than that from conservation tillage in all the seven provinces. However, if taking CO_2 emissions into account, the profit from traditional tillage is lower than that from conservation tillage in all the seven provinces.

More specifically, in this example (50% reduction in CO_2 and 10% reduction in yield for conservation tillage, compared to traditional tillage), under traditional tillage, the total abatement cost of reducing CO_2 emissions from 6605 ton/ha to 3302.5 ton/ha (50% off) is 1486 yuan/ha (0.450 yuan/kg*3302.5 ton/ha, 228.6 US$/ha). However, if adopting conservation tillage, the CO_2 emissions will be 3302.5 ton/ha, but the revenue generated from maize will decrease by 2 yuan/kg * 10% * 5757 kg/ha = 1151 yuan/ha (177.1 US$/ha). This implies adopting conservation tillage can achieve the abatement goal (i.e. 3302.5 ton/ha CO_2 emission), but at a sacrifice of crop yield loss of 1151 yuan/ha. If the government spends less than 335 yuan/ha (1486 yuan/ha - 1151yuan/ha) on promoting implementation of conservation tillage (say 200 yuan/ha for example), society will

Table 2
Summary of descriptive statistics for the shadow price of CO_2 by province, 1996–2014 (yuan/kg).

	Mean	Std. Dev.	Min	Max
All seven provinces	0.450	0.174	0.000	0.913
Northeast China	0.328	0.134	0.000	0.598
Heilongjiang	0.383	0.090	0.214	0.542
Jilin	0.229	0.123	0.000	0.467
Liaoning	0.371	0.131	0.104	0.598
North China Plain	0.541	0.141	0.128	0.913
Anhui	0.562	0.181	0.221	0.913
Hebei	0.553	0.097	0.357	0.689
Henan	0.567	0.117	0.324	0.790
Shandong	0.485	0.152	0.128	0.733

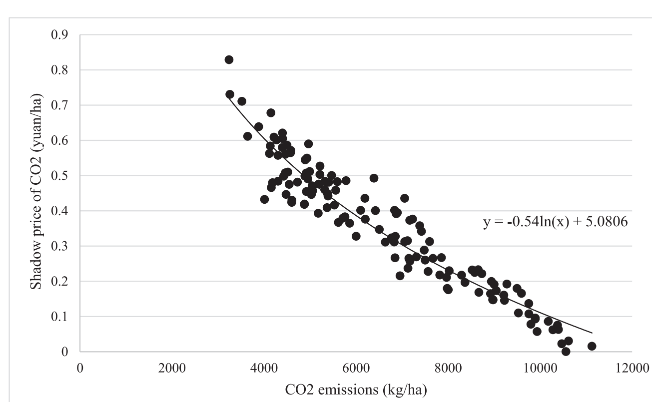

Fig. 6. Marginal abatement cost.

benefit from this promotion policy (135 yuan/ha in this case). Society will further benefit from the added value of the reduced emissions as well.

5. Discussion and conclusions

In this paper, we estimated the shadow prices and abatement costs of CO_2 emissions from burning maize straw, using the data

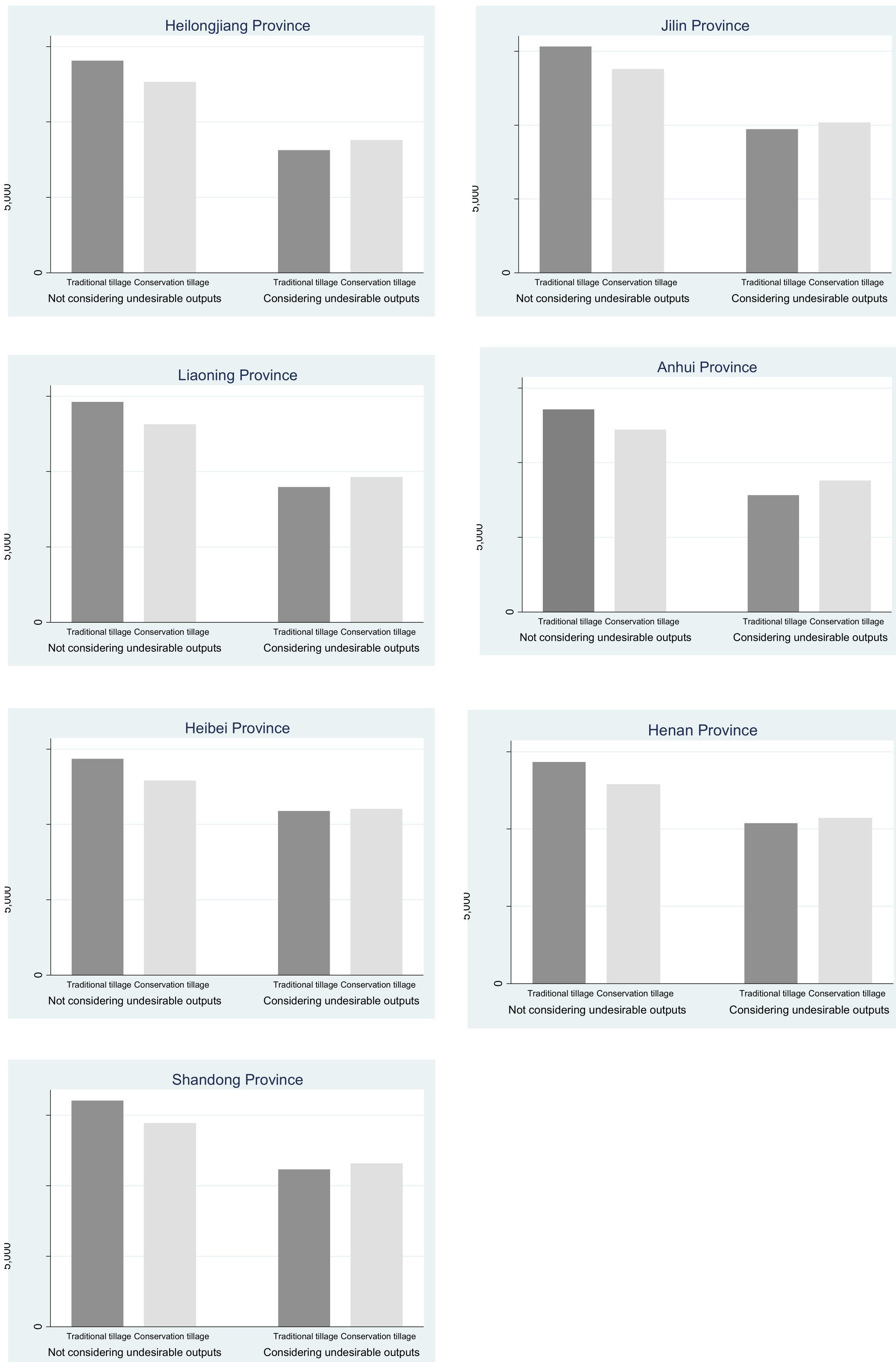

Fig. 7. Profit with (light shaded bar) and without (dark shaded bar) considering the environmental damage for traditional tillage and conservation tillage.

Table 3
Comparison with previous studies [a].

Study	Period	Sector	Sample	Model[b]	Mean value (\$/t) [c]
Wang et al. (2011)	2007	Economy	30 Provinces in China	DEA	62.5
Wei et al. (2012)	1995–2007	Economy	30 Provinces in China	DEA	13.9
Du et al. (2015a)	2001–2010	Economy	30 Provinces in China	DDF + LP	120–310
Wei et al. (2013)	2004	Energy	124 Power plants in China	DDF + LP, DDF + ML	248.2, 73.8
Tang et al. (2016)	1998–2005	Agriculture	29 farms in Australia	DF + LP	29.3
Thamo et al. (2013)	Simulation data	Agriculture	Farms in Western Australia	MIDAS[d]	50
Flugge and Abadi (2006)	Simulation data	Agriculture	Two regions in Western Australia	MIDAS	55
This study	1996–2013	Agriculture	7 provinces in China	DDF + LP	75[e]

[a] Adapted from Du et al. (2015b).
[b] SDF, DDF, LP, ML, DEA denote Shephard Distance Function, Directional Distance Function, Linear Pro-ta Envelopment Analysis, respectively.
[c] All the shadow prices are transformed into US dollars according to the corresponding exchange rate for the convenience of comparison.
[d] A steady-state optimization farm model.
[e] US\$ 1 = 6 yuan.

from the seven major maize provinces in China during 1996–2014. The estimated shadow price of CO_2 from burning maize straw ranges within 0–0.913 yuan/ha (or US\$152/t) with an average of 0.450 yuan/kg (or US\$75/t). Turning to the earlier studies, there is a wide range of shadow prices of CO_2 depending on the study period, sector, sample and model (Table 3). Our estimation results fall in the range in the literature.

More importantly, our results provide a reference value for policy makers to decide the spending on conservation practices program. Given the policy goal of 50% reduction of CO_2 from burning maize straw, the abatement cost will be 1486 yuan/ha by reducing maize production, while it will be 1151 yuan/ha by adopting conservation practices. If the transaction cost of promoting conservation practices is less than 335 yuan/ha (1486 minus 1151), the social welfare will be improved.

There are several practical policy implications arising from this study. One area that merits additional exploration is the trade-off between reduced yields and practices that substantially decrease CO_2 emissions. Decreasing CO_2 emissions provides marginal social benefits that may conflict with societal food security goals and individual farmer production. Clearly, the results from this model show that there are not incentives for farmers to implement production practices that decrease yield and presumably, profits. Thus, it would be paramount for the government's willingness to compensate farmers to implement conservation practices that will reduce CO_2 emissions. However, the implications of reduced agricultural yields may be juxtaposed with other dietary and nutritional goals that otherwise enhance food security. Furthermore, there may be differences between the regions that warrant additional consideration, and as a result, the regions might not be managed uniformly. In summary, this preliminary analysis provides guidance about environmental and agricultural targets that require more extensive research, and that may have implications at many tiers, extending from the level of the farm to the international scale.

The study features certain limitation. Indeed, this paper only focuses on maize, one major crop in China. The results of this paper cannot be applied to other major crops such as wheat and rice. Policy makers should pay attention to crop-specific shadow prices and call for the corresponding research aimed at different crops. What is more, the province-level input-output data may overlook the spatial variation within province. However, county level input-output data are unavailable in our case. Therefore, creation of a more detailed database remains a task for the future research. Farmers' utilization of crop residue also affects the shadow prices of CO_2 through affecting the total emissions. Due to unavailability of the county- or province-level statistical data of crop residue utilization, we, therefore, used surveyed village sampling data.

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Appendix A

Please refer to Appendix A in Hou et al. (2015) for the detailed specification of the shadow pricing model.

The estimated coefficients in the quadratic distance function is shown in Table A1.

Table A1
Estimated Coefficients in the Quadratic Distance Function.

Coefficient	Variable	Estimate
α_0	Intercept	−0.021
α_1	x	0.468
β_1	y	−0.373
γ_1	z	0.592
α_{11}	$\frac{1}{2}x^2$	−0.019
β_{11}	$\frac{1}{2}y^2$	−0.123
γ_{11}	$\frac{1}{2}z^2$	−0.110
δ	xy	−0.145
η	xz	−0.137
μ	yz	−0.116

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