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Reduction potential, shadow prices, and pollution costs of agricultural pollutants in China

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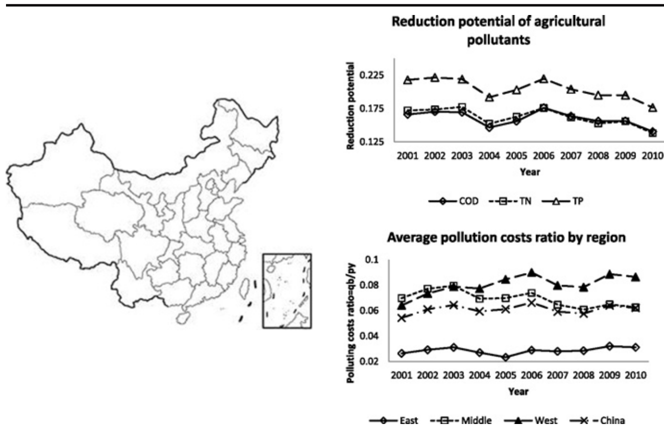
HIGHLIGHTS

- Reduction potential and shadow price of China's agricultural pollutants are assessed.
- A parameterized quadratic directional output distance function is used.
- There is scope for further pollution abatement for China's agriculture.
- The regional shadow prices and pollution costs of pollutants are heterogeneous.
- Overall the pollution costs are about 6% of the agricultural gross output value.

GRAPHICAL ABSTRACT



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ABSTRACT

This paper analyses the reduction potential, shadow prices, and pollution costs of agricultural pollutants in China based on provincial panel data for 2001–2010. Using a parameterized quadratic form for the directional output distance function, we find that if agricultural sectors in all provinces were to produce on the production frontier, China could potentially reduce agricultural emissions of chemical oxygen demand (COD), total nitrogen (TN), and total phosphorus (TP) by 16.0%, 16.2%, and 20.4%, respectively. Additionally, our results show that the shadow price of TN increased rapidly and continuously, while that of COD and TP fluctuated for the whole period. For the whole country, the average shadow price of COD, TN, and TP are 8266 Yuan/tonne, 25,560 Yuan/tonne, and 10,160 Yuan/tonne, respectively. The regional shadow prices of agricultural pollutants are unbalanced. Furthermore, we show that the pollution costs from emissions of COD, TN, and TP are 6.09% of the annual gross output value of the agricultural sector and are highest in the Western and lowest in the Eastern provinces. Our estimates suggest that there is scope for further pollution abatement and simultaneous output expansion for China's agriculture if farmers promote greater efficiency in their production process. Policymakers are required to dynamically adjust the pollution tax rates and ascertain the initial permit price in an emission trading system. Policymakers should also consider the different pollution costs for each province when making the reduction allocations within the agricultural sector.

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1. Introduction

The environmental cost of China's agricultural sector is enormous, although its food production has successfully fed more than 20% of the global population from only 7% of the world's arable area (Piao et al., 2010). China's agricultural production has caused some negative effects on the environment, such as water pollution (Ulén et al., 2007; Jarvie et al., 2013; Zheng et al., 2015). Excessive emissions of agricultural pollutants, including chemical oxygen demand (COD), total nitrogen (TN), and total phosphorus (TP), have become a critical cause of water pollution in China (Ma et al., 2011). It is estimated that the annual economic losses from water pollution in China are about 150 billion Yuan (World Bank, 2007).

Therefore, it is imperative to reduce agricultural pollutions in China. Since the late 1990s, China's government has attempted to reduce the emissions of agricultural pollutants. The first time that specific emission reduction targets were set was in 2012. These targets included reducing COD and TN emissions by 8% and 10% respectively by 2015, compared with 2010 levels[1]. While policymakers at the provincial level are required to adjust their local agricultural development policies according to the national reduction targets, this may not guarantee that local efforts to reduce agricultural pollutants are in line with the national goal.

Given the diversity in economic, social, and natural conditions in different regions and provinces, it is important to find a suitable way to measure the relevant parameters at the regional level. Such parameters may include reduction potential, marginal abatement costs (MAC), and pollution costs (shadow values). Estimating the MAC and reduction potential is essential to evaluate the cost-effectiveness of the allocation of agricultural abatement obligation among regions. In theory, the MAC of pollutant emissions should be equalized across regions to achieve the most efficient pollution reduction across the economy (Baumol and Oates, 1988). However, in reality this information may not be available because different regions usually exhibit different cost characteristics due to divergent production conditions. Therefore, in practice there are gains to be made from allowing lower cost regions with higher reduction potentials to contribute more to pollution reduction (Wei et al., 2013). Estimating the MAC can also assist the government to identify a benchmark price—the maximum amount to pay per tonne for pollutants reduced. In this case, only bids costing less than the benchmark price would be considered for selection in an auction-based or similar mechanism for the purchase of pollution credits. The pollution costs of agricultural pollutants (shadow values) reflect the opportunity costs for pollution abatement, which can be used for measuring the difficulty level of pollutant reductions (Färe et al., 2006). Regions with lower pollution costs can be identified as key pollution reduction regions in practice. Overall, reduction potential, MAC, and pollution costs are important information for policymakers to design more efficient domestic environmental policies, because they can be used to shape environmental tax and emissions trading systems across regions, etc. (Färe et al., 1993, 2006).

To our knowledge, there is no study that has parametrically estimated the feasible reduction potential, the MAC, and pollution costs of agricultural pollutants in China. The novelty of this paper is that for the first time a parametric directional output distance function, which is differentiable and allows simultaneous expansion of good outputs and reduction of bad outputs (agricultural pollutants), is used to analyze China's agricultural pollution abatement. The differentiability promises the uniqueness of reduction potential, MAC, and pollution cost, while the simultaneous changes mean the potential 'double-dividend' pollution abatement and development in agricultural sector. Policymakers can use these results to design and optimise policies for agricultural pollution abatement.

The rest of the paper is organized as follows. In Section 2, we review the existing literature. We describe the parametric directional output distance function approach in Section 3. Then we present the data and variable specification in Section 4. In Section 5, we report and discuss the estimation results. Finally we conclude in Section 6.

2. Literature review

Recent development in distance functions of non-marketed products allows researchers to estimate the MAC of pollutants generated during production without market price and cost information (Hailu and Veeman, 2000, 2001; Färe et al., 1993, 2005, 2006). Generally, the estimation is performed by treating pollutants as bad (or undesirable) by-product outputs under a multi-input multi-output environmentally sensitive production. Then the distance function is used to derive the marginal abatement costs (shadow prices) of pollutants by using the duality between the distance function and the revenue or cost functions.

Existing studies generally use one of three distance functions. The radial output/input distance functions assume a proportional adjustment for all outputs/inputs (Färe et al., 1993; Hailu and Veeman, 2000). By contrast, the directional output distance function describes a simultaneous expansion of good (or desirable) outputs and reduction in bad outputs in a given direction (Chambers et al., 1998). The directional output distance function is thought to provide a more useful and flexible method to evaluate the performance of environmentally sensitive production in the presence of bad outputs (Färe et al., 2005; Du et al., 2015).

There are two ways to estimate the distance function. One is a nonparametric technique called Data Envelopment Analysis (DEA), and the other is a parametric technique. The DEA technique is a data-driven method which establishes the output set as a sectionalized linear combination of observed inputs and outputs. It has been widely used in productivity analysis due to its advantage that no functional form assumption is needed (Hailu and Veeman, 2001; Boyd et al., 2002; Färe et al., 2007). Nevertheless, the distance function using the DEA technique is not differentiable, so it is not well-suited to derive the shadow prices (Färe et al., 2005). In addition, the results estimated using DEA are sensitive to outliers, which may negatively affect the accuracy of results (Hailu and Chambers, 2012; Wei et al., 2013). With the parametric technique, a functional form is specified for the distance function and the parameters of this function are estimated using linear programing. Due to the ease with which theoretical restrictions can be imposed in estimation, this technique has been used in many applications (Coggins and Swinton, 1996; Hailu and Veeman, 2000; Färe et al., 2006; Murty et al., 2007; Hailu and Chambers, 2012; Wei et al., 2013; Du et al., 2015).

However, few existing studies estimate the MAC and reduction potentials of agricultural pollutants in China. Several studies attempt to estimate shadow prices, or equivalently as marginal abatement costs, and reduction potentials of pollutant emissions for the Chinese industrial sector (Aunan et al., 2004; Tu, 2009; Han et al., 2010; Yuan and Cheng, 2011; Yu, 2011). They find that there is considerable heterogeneity in the shadow prices and reduction potentials of industrial pollutants across different regions. However, studies of the Chinese agricultural sector are not present within this literature. To the best of our knowledge, only Li et al. (2013) estimate the reduction potential of agricultural pollutants in China, using a non-parametric approach. So far, no study has estimated the feasible reduction potential and MAC of agricultural pollutants in China using a parametric approach.

As mentioned above, the non-parametric DEA technique is less suited to the analysis of the environmentally sensitive production due to its non-differentiability. Furthermore, the parametric radial input/output distance functions are less flexible than the directional output distance function because of the proportional adjustment of outputs/inputs. Therefore, the directional output distance function estimated

[1] More details can be found in the National Energy-saving and Emission Reduction Project of the 12th Five-Year Plan (http://www.gov.cn/zwgk/2012-08/21/content_2207867.htm).

parametrically is an appropriate approach for analyzing agricultural pollution abatement in China.

This paper is the first study to estimate the provincial reduction potentials and shadow prices of agricultural pollutants in China using a directional output distance function which is estimated parametrically. Additionally, we analyze the provincial pollution cost and its determinants for China's agriculture. We hope these results can help design and optimize agricultural pollution abatement policies in China.

3. Method

In this section, we first introduce the directional output distance function and then derive shadow prices and pollution costs of bad outputs. The third subsection is the empirical specifications used in this study.

3.1. Directional output distance function

For a production process using a vector of inputs $x = (x_1,...,x_n) \in R_+^N$ to produce a vector of good outputs $y = (y_1,...,y_m) \in R_+^M$ and a vector of bad outputs $b = (b_1,...,b_j) \in R_+^J$, the production possibilities are defined by the set $T \subset R_+^N \times R_+^M \times R_+^J$ where:

$$T = \{(x, y, b) : x \text{ can produce } (y, b)\}. \quad (1)$$

In what follows, we first assume that T is a convex compact set. Standard properties are assumed on the outputs set based on Shephard (1970), including the axioms of possibility of inaction, no free lunch, free disposability of good outputs, and strong disposability of inputs (see also Grosskopf, 1986).

In addition, we assume that the technology is null-jointness, which means bad outputs are simultaneously produced with good outputs. Moreover, good and bad outputs are assumed to be weakly disposable. This means that proportional reduction of good and bad outputs is feasible, implying that it is costly to reduce any bad outputs.

The directional output distance function is defined as:

$$\vec{D}_O(x, y, b; g) = \max\left\{\beta : \left(y + \beta g_y, b - \beta g_b\right) \in T, \beta \in R_+\right\} \quad (2)$$

where $g = (g_y, g_b) \in R_+^M \times R_+^J$ is a directional vector. The directional output distance function gives the simultaneous maximum expansion of good outputs and contraction of bad outputs that is technically feasible. That means, given the production technology T and $g > 0$, the directional output distance function expands y and contracts b along the g direction until it reaches the production frontier.

According to Färe et al. (2005), the directional output distance function has the following properties: First, $\vec{D}_O$ is concave and non-negative for feasible output vectors. Second, $\vec{D}_O$ is monotonic and freely disposable in good outputs and inputs. The third property implies that $\vec{D}_O$ is weakly disposable in bad outputs. Finally, $\vec{D}_O$ satisfies the translation property:

$$\vec{D}_O\left(x, y + \alpha g_y, b - \alpha g_b; g\right) = \vec{D}_O(x, y, b; g) - \alpha. \quad (3)$$

3.2. Deviation of shadow price and pollution cost

We derive the shadow price of bad output relying on the duality relationship between the revenue function and directional output distance function (Färe et al., 2005, 2006). The revenue function can be defined as

$$R(y, b, p, q) = \max_{y,b}\{py - qb : (y, b) \in T\}, \quad (4)$$

where $p = (p_1,...,p_M) \in R_+^M$ and $q = (q_1,...,q_J) \in R_+^J$ represent good output prices and bad output prices, respectively. The revenue function describes the maximum feasible total revenue represented as the sum of the positive revenue generated by good outputs and negative revenue caused by bad outputs.

Given a feasible directional vector $g = (g_y, g_b)$, Eq. (4) can be rewritten as:

$$R(x, p, q) \geq (py - qb) + p\vec{D}_O(x, y, b; g)g_y + q\vec{D}_O(x, y, b; g)g_b\}. \quad (5)$$

The left-hand side of Eq. (5) is the maximum feasible revenue while the right-hand side equals observed revenue $(py - qb)$ plus the revenue gained by technical efficiency improvement. Rearranging Eq. (5), we have

$$\vec{D}_O(x, y, b; g) \leq \frac{R(x, p, q) - (py - qb)}{pg_y + qg_b}. \quad (6)$$

Therefore, the directional output distance function in terms of the revenue function can be defined as

$$\vec{D}_O(x, y, b; g) \leq \min_{p,q}\left\{\frac{R(x, p, q) - (py - qb)}{pg_y + qg_b}\right\}, \quad (7)$$

which is an unconstrained minimization problem. Applying the envelop theorem twice to Eq. (7) yields two first-order conditions:

$$\nabla_b \vec{D}_O(x, y, b; g) = \frac{q}{pg_y + qg_b} \geq 0 \quad (8a)$$

$$\nabla_y \vec{D}_O(x, y, b; g) = \frac{-p}{pg_y + qg_b} \leq 0. \quad (8b)$$

Therefore, given the market price of the mth good output, the jth bad output's shadow price can be estimated as

$$q_j = -p_m\left(\frac{\partial\vec{D}_O(x, y, b; g)/\partial b_j}{\partial\vec{D}_O(x, y, b; g)/\partial y_m}\right), \quad j = 1, ..., J. \quad (9)$$

In the revenue function, $-qb$ denotes the negative revenue generated by bad outputs (for example, pollutants generated in the production). Moreover, qb can be treated as the pollution cost of pollutants (Färe et al., 2006). Both the shadow price and the associated pollution cost can be interpreted as opportunity costs.

3.3. Empirical specifications

The directional output distance function can be estimated either parametrically or non-parametrically. In this study, we choose the parametric method due to its differentiable property. We use a quadratic form to parameterize the directional output distance function (Chambers, 1998; Färe et al., 2006; Murty et al., 2007). The quadratic is the only form with the following theoretical properties: (1) linear in parameters, (2) includes first order and second order terms, and (3) provides second-order approximations to arbitrary functions that satisfy the translation property (Färe et al., 2010).

We choose the directional vector $g = (1, 1)$ where the first M components equal one and the next J components also equal one to make the parameterization parsimonious (Färe et al., 2006). Given $g = (1,1)$, the directional output distance function provides the unit expansion in good outputs and contraction in bad outputs. Assuming that $k = 1,...,K$ provinces producing in $t = 1,...,T$ periods, the quadratic directional output distance function for province K in period t is

$$\begin{aligned}\vec{D}_O^t\left(x_k^t, y_k^t, b_k^t; 1, 1\right) = {} & \alpha_0 + \sum_{n=1}^{N} \alpha_n x_{nk}^t + \sum_{m=1}^{M} \beta_m y_{mk}^t + \sum_{j=1}^{J} \gamma_j b_{jk}^t \\ & + \frac{1}{2}\sum_{n=1}^{N}\sum_{n'=1}^{N} \alpha_{nn'} x_{nk}^t x_{n'k}^t + \frac{1}{2}\sum_{m=1}^{M}\sum_{m'=1}^{M} \beta_{mm'} y_m y_{m'} \\ & + \frac{1}{2}\sum_{j=1}^{J}\sum_{j'=1}^{J} \gamma_{jj'} b_j b_{j'} + \sum_{n=1}^{N}\sum_{m=1}^{M} \delta_{nm} x_{nk}^t y_{mk}^t \\ & + \sum_{n=1}^{N}\sum_{j=1}^{J} \eta_{nj} x_{nk}^t b_{jk}^t + \sum_{m=1}^{M}\sum_{j=1}^{J} \mu_{mj} y_{mk}^t b_{jk}^t\end{aligned} \tag{10}$$

where $\alpha_{nn'} = \alpha_{n'n}, n \neq n', \beta_{mm'} = \beta_{m'm}, m \neq m'$, and $\gamma_{jj'} \neq \gamma_{j'j}, j \neq j'$.

We estimate the values of directional output distance function $\vec{D}_O$ basing on the estimation of a deterministic parametric production frontier using mathematical programming (MP). This estimation technique is popular in the literature partly because of the ease with which theoretical restrictions can be imposed as part of the estimation (Hailu and Chambers, 2012). See, for instance, Coggins and Swinton (1996); Hailu and Veeman (2000); Färe et al. (2006), and Du et al. (2015) for the application in using MP to estimate distance functions.

The sum of the distance between the individual producer observations and the production frontier in each period is minimized as

$$\min \sum_{t=1}^{T}\sum_{k=1}^{K}\left[\vec{D}_O^t\left(x_k^t, y_k^t, b_k^t; 1, 1\right) - 0\right] \tag{11}$$

subject to

$$\vec{D}_O^t\left(x_k^t, y_k^t, b_k^t; 1, 1\right) \geq 0, \qquad k = 1, \ldots, K, \quad t = 1, \ldots, T \tag{12a}$$

$$\partial \vec{D}_O^t\left(x_k^t, y_k^t, b_k^t; 1, 1\right)/\partial x_n \geq 0, \quad n = 1, \ldots, N \quad k = 1, \ldots, K, \quad t = 1, \ldots, T \tag{12b}$$

$$\partial \vec{D}_O^t\left(x_k^t, y_k^t, b_k^t; 1, 1\right)/\partial b_j \geq 0, \quad j = 1, \ldots, J, \quad k = 1, \ldots, K, \quad t = 1, \ldots, T \tag{12c}$$

$$\partial \vec{D}_O^t\left(x_k^t, y_k^t, b_k^t; 1, 1\right)/\partial y_m \leq 0, \quad m = 1, \ldots, M, \quad k = 1, \ldots, K, \quad t = 1, \ldots, T \tag{12d}$$

$$\begin{aligned}&\sum_{m=1}^{M}\beta_m - \sum_{j=1}^{J}\gamma_j = -1, \sum_{m'=1}^{M}\beta_{mm'} - \sum_{j=1}^{J}\mu_{mj} = 0, \quad m = 1, \ldots, M, \\ &\sum_{j'=1}^{J}\gamma_{jj'} - \sum_{m=1}^{M}\mu_{mj} = 0, \quad j = 1, \ldots, J, \quad \sum_{m=1}^{M}\delta_{nm} - \sum_{j=1}^{J}\eta_{nj} = 0, \quad n = 1, \ldots, N\end{aligned} \tag{12e}$$

$$\alpha_{nn'} = \alpha_{n'n}, n \neq n', \quad \beta_{mm'} = \beta_{m'm}, m \neq m', \quad \gamma_{jj'} \neq \gamma_{j'j}, j \neq j'. \tag{12f}$$

The restrictions in Eq. (12a) ensure the feasibility of all observations. Following Färe et al. (2006), the restrictions given in Eq. (12b) require the positive monotonicity on the inputs for the mean level of input usage, which implies that, at the mean level of inputs, an increase in input usage keeping the good and bad outputs unchanged causes the increase of directional output distance function, meaning a greater technical inefficiency. The restrictions in Eq. (12c) and Eq. (12d) impose the monotonicity requirement in bad and good outputs. The parameter restrictions in Eq. (12e) impose the translation property in Eq. (3). Moreover, symmetry conditions are ensured by (12f).

4. Data and variable specification

This section provides the definitions of inputs, good and bad outputs, and the dataset used in this study. We consider a case of four inputs: land, labor, capital, and material, one good output: gross agricultural output, and three bad outputs: COD, TN, and TP. Our data is aggregated at the provincial level and covers 26 provinces in mainland China[2]. The sample covers ten consecutive years, from 2001 to 2010.

Land is measured as the sown area. Labor is defined as the total number of rural workers at the end of each year. Material is measured as the intermediate consumption of the agricultural sector, which includes all purchases made by farmers for auxiliary and raw materials that are used as inputs for agricultural production and expenditure on agricultural services. The input land, labor, and material data are all obtained from the China Rural Statistical Yearbooks. The data of capital stock in China's agricultural sector are not directly reported from any of the statistical yearbooks. Therefore, we estimate it using the perpetual inventory method as suggested by Wu (2009).

The good output used in this study is the gross output value of the agricultural sector at 2001 constant prices. The data of good output is derived from the China Statistical Yearbooks. The provincial data for COD, TN, and TP emissions in the agricultural sector are not directly available. Following the inventory analysis method provided by Chen et al. (2006), we estimate the emissions of COD, TN, and TP by the following formula:

$$TE_j = \sum EL_{activity} = \sum\sum EL_{class} = \sum\sum\sum EC_{unit} * EUA \tag{13}$$

where TE_j is the total emissions of jth pollutant, $EL_{activity}$ is the of the emissions of jth pollutant from each class (EL_{class}).EL_{class} is evaluated by multiplying the element unit amount (EUA) from national statistics by scaled pollutant discharge by individual unit (EC_{unit}). The data of EC_{unit} is obtained from Lai et al. (2004). Other data used for estimation of emissions are derived from various versions of China Statistical Yearbooks and China Rural Statistical Yearbooks.

Table 1 provides the descriptive statistics for both inputs and outputs for China as a whole, and across three different regions.[3] We observe from this table that the average capital, material, and gross output value in the East region are considerably higher than those of the Middle and West regions.

5. Results and discussion

To to avoid the convergence problem, we normalize the data by dividing each input and output by their average values as suggested by Färe et al. (2006). This normalization implies that $(x, y, b) = (1, 1, 1)$ for a hypothetical province that uses average input to produce average output.

5.1. Reduction potential of agricultural pollutants

We estimate the parameters for the quadratic directional output distance function (10) by solving the MP (11) using R. The directional output distance function measures the level of technical inefficiency since it provides the maximum unit expansion of the good outputs and contraction of the bad outputs. If the value of the directional output distance function is zero, then the production is fully efficient. A positive value implies the existence of technical inefficiency. A higher value of

[2] Tibet and Ningxia are not included due to the problem of data availability. Beijing, Tianjin, and Shanghai are excluded because of the tiny proportion of the agricultural sector within the whole economy.

[3] The East region includes Hebei, Liaoning, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, and Hainan. Middle region includes Shanxi, Jilin, Heilongjiang, Anhui, Jiangxi, Henan, Hubei, and Hunan. The West region includes Inner Mongolia, Guangxi, Chongqing, Sichuan, Guizhou, Yunnan, Shaanxi, Gansu, Qinghai, and Xinjiang.

Table 1
Mean and standard deviations of inputs/outputs variables, 2001–2010.

Region	Inputs				Good input	Bad outputs		
	Land (10^3 ha)	Labor (10^4 persons)	Capital (10^8 Yuan)	Material (10^8 Yuan)	Gross output value (10^8 Yuan)	COD (10^4 tonnes)	TN (10^4 tonnes)	TP (10^4 tonnes)
China	5873	1132	2844	516	1254	55.6	10.3	1.9
	(3188)	(704)	(2179)	(373)	(839)	(42.8)	(8.4)	(1.7)
East	5203	1076	3953	750	1753	68.6	13.5	2.6
	(3297)	(596)	(2484)	(428)	(916)	(49.8)	(10.3)	(2.1)
Middle	7855	1324	3073	557	1357	65.6	12.5	2.1
	(3201)	(834)	(2339)	(312)	(741)	(40.7)	(7.7)	(1.4)
West	4823	1022	1774	295	773	37.1	6.0	1.1
	(2256)	(644)	(971)	(212)	(541)	(30.6)	(4.6)	(1.1)

Note: Parentheses indicate standard deviations.

the directional distance function means a higher level of technical inefficiency.

We can further estimate the feasible reduction potential of agricultural pollutants using the derived values of the directional output distance function:

$$\Delta b_{jkt} = b_{jkt} - \left(b_{jkt} - \beta_{kt} g_{b_j}\right) = \beta_{kt} g_{b_j} \tag{14}$$

where b_{jkt} and β_{kt} are the amount of jth pollutant emissions of province k in year t, and the estimated value of the directional distance output function of province k in year t, and g_{b_j} is the directional vector of jth bad output. Δb_{jkt} describes the maximum attainable amount of jth pollutant emissions for province k in year t when production is fully efficient. Since the scales of pollution for the different provinces are considerably heterogeneous (Table 1), it is difficult to directly compare each province's relative ability to mitigate pollution based on its production size. So we divide the scale of estimated potential reduction emissions by the emissions for each province. This gives us a ratio which can be used to compare across provinces and years.

Fig. 1 plots the annual average abatement potential ratios of three agricultural pollutants for the whole of China during the study period. From Fig. 1, we observe that the mean reduction potential ratios of COD, TN, and TP for China fluctuate during the sample period. At the country level, the mean reduction potential ratios of COD, TN, and TP are 0.160, 0.162, and 0.204, respectively (Table 2). This indicates that if all provinces produce at the efficient level, China could potentially reduce emissions of COD, TN, and TP by 16.0%, 16.2%, and 20.4%, respectively. From Table 2, we further find that there is a considerable disparity between the average reduction potentials of agricultural pollutant emissions for three different regions. The reduction potential of agricultural pollutant emissions of the East region is considerably lower than that of the Middle and West regions. This also indicates that inland provinces have more potential to reduce pollution.

It is helpful to discuss the determinants of the regional heterogeneity in reduction potential of agricultural pollutants. The agricultural sector of the East region is more developed than that of the Middle and West regions. Agricultural production in the East region is leading the transformation from traditional unsustainable ways to modern sustainable patterns that balances agricultural production and environmental protection (Chen and Song, 2008). In the Middle and West regions, agricultural production is still expanding using traditional practices, and is oriented more toward output growth than environment improvement. A more developed economy means that the East region has the capacity to invest more in the application of advanced and clean agricultural production technology, while the Middle and West regions have to use their limited capital to ensure adequate food production rather than mitigate pollution (Long et al., 2010). Therefore, the Middle and West regions have larger potentials to mitigate agricultural pollution than the East region.

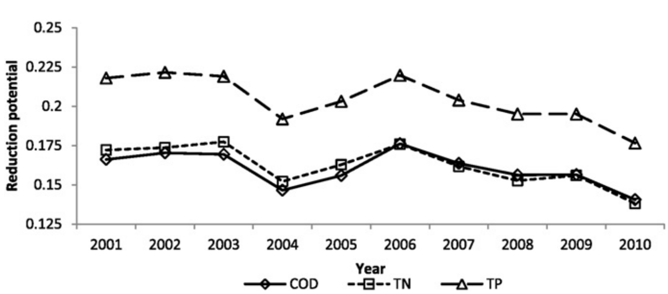

Fig. 1. The annual reduction potential of agricultural pollutants in China from 2001 to 2010.

5.2. Shadow prices of agricultural pollutants

We use Eq. (9) to calculate the shadow prices of the agricultural pollutants reported below. We inflate the formula by multiplying the ratio of the average value of agricultural output by the average amount of pollutants because we have normalized the inputs and outputs. The price of good output, agricultural gross output, is set at 1.

Table 3 reports the shadow prices of three agricultural pollutants for the three different regions and the whole country. From the table, we find that the dynamic trends of the mean shadow prices of three agricultural pollutants show great disparity. The shadow price of TN increased rapidly and continuously, while that of COD and TP fluctuated for the whole period. For the whole country, the average shadow price of COD, TN, and TP are 8266 Yuan/tonne, 25,560 Yuan/tonne, and 10,160 Yuan/tonne, respectively. The regional shadow prices of agricultural pollutants are unbalanced. The mean shadow prices of the East region are lower than that of the Middle and West regions, which indicates that it is cheaper for the East region to control agricultural pollution compared with the Middle and West regions.

We offer two possible explanations for the regional heterogeneity in shadow prices. First, the shadow prices are best interpreted as opportunity costs (Färe et al., 2006). They reflect the trade-off between good output and bad output — the producer needs to pay for mitigating one more unit of bad output by foregoing units of good output. Since agriculture in the Eastern provinces is more developed and local producers have more opportunities to apply more advanced and cleaner

Table 2
Average reduction potential ratio by region.

Region	Average reduction potential ratio		
	COD	TN	TP
East	0.097	0.110	0.100
Middle	0.185	0.166	0.237
West	0.190	0.201	0.262
China	0.160	0.162	0.204

Table 3
Estimates of average shadow prices of agricultural pollutants by region, 2001–2010 (Yuan/tonne).

Year	Shadow price for COD				Shadow price for TN				Shadow price for TP			
	East	Middle	West	China	East	Middle	West	China	East	Middle	West	China
2001	5017	8951	9350	7894	8227	14,479	13,748	12,274	5237	11,275	10,605	9159
2002	5109	8925	9821	8096	10,568	18,265	17,882	15,749	6061	11,845	10,903	9703
2003	5086	9359	10,093	8327	12,675	19,597	21,468	18,187	6876	12,762	11,438	10,442
2004	4657	8683	10,229	8039	13,355	21,528	24,317	20,086	7962	13,166	12,273	11,222
2005	3937	8363	10,277	7737	14,107	23,323	26,857	21,846	8441	14,032	13,277	12,022
2006	4215	8798	10,818	8165	20,772	31,305	31,480	28,131	6692	11,016	12,309	10,183
2007	4334	8830	11,002	8282	23,624	33,752	35,469	31,296	6133	10,861	11,825	9777
2008	4788	8756	11,328	8524	23,943	35,054	38,290	32,880	7045	11,550	12,557	10,551
2009	5027	8730	11,667	8720	27,505	38,198	42,391	36,520	7555	12,237	13,196	11,165
2010	5274	8566	12,011	8878	29,020	40,114	45,051	38,600	8221	12,842	13,913	11,832

production technology, farmers in the East region potentially need to pay less units of good output for reducing one more unit of bad output compared with the Middle and West regions. Thus, the shadow prices of the East region are lower. Second, the West and Middle regions have less favorable natural conditions for agricultural production. The interior regions are mountainous and lack arable land. They usually have more volatile precipitation levels and poorer soil quality compared with the East region (Verburg and Chen, 2000). It is much more difficult to reduce agricultural pollutions in the West and Middle regions, and therefore the opportunity cost of agricultural pollutions abatement in these regions is much higher than in the East region. Consequently, the West and Middle regions have higher shadow prices than the East.

Readers need to be cautious about interpreting the shadow prices in this study. The shadow prices, in fact, reflect the opportunity cost of the most efficient observations which are located on the production frontier. The observations located within the production frontier may have lower shadow prices (Murty et al., 2007). Therefore, the shadow prices derived in this study give the upper-bound for agricultural production in those provinces. Additionally, the shadow price is a short-run partial equilibrium. It may be overestimated as the possible adoption of new technology is ignored (Wei et al., 2013).

5.3. Polluting costs of agricultural pollutants

We estimate the polluting costs (qb) (the shadow values) of agricultural pollutants for all sample provinces using the derived shadow prices and the estimated pollutant emissions. It is difficult to directly compare each province's relative pollution costs based on its production size due to the considerable heterogeneity in the scale of agricultural gross output for different provinces. Thus, we divide the scale of estimated pollution costs by the agricultural gross output for each province. This gives us a pollution cost ratio which allows for spatial and temporal comparison.

Fig. 2 shows the average annual pollution cost ratio of agricultural pollutants for the whole of China from 2001 to 2010. From the figure, we observe that the average pollution cost ratio for China has fluctuated from 5.42% (in 2001) to 6.62% (in 2006) during the period 2001 to 2010.

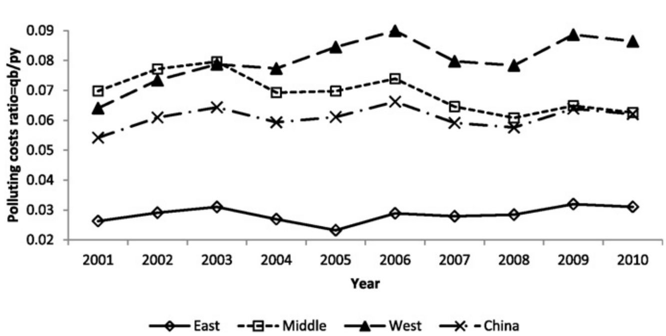

Fig. 2. Annual average pollution cost ratio by region, 2001–2010.

At the country level, the mean pollution costs ratio of agricultural pollutants is 6.09% for the study period. We also observe that the annual average pollution cost ratio of the East region is much lower than that of the Middle and West regions throughout the study period. For the whole period, the mean pollution cost ratio of the East region is 2.85%, while that of the Middle and West regions are 6.92% and 8.01%, respectively (Table 4). The dynamic trends of the average pollution cost ratio for the three regions also show great disparity. The curve for the East and Middle regions fluctuated, while that of the West region increased for the whole study period. The highest pollution cost ratio was observed in Sichuan (13.07%) in the West, while the lowest appeared in Shandong in the East. The six provinces that have an average pollution cost ratio larger than 10% (Yunnan, Guangxi, Hunan, Henan, Qinghai, and Sichuan) are all located in the West and Middle regions, while the six provinces with an average pollution cost ratio smaller than 3% (Hebei, Jiangsu, Zhejiang, Fujian, Hainan, and Shandong) are all located in the East region (Table 4).

How do our results for pollution costs compare with those of other studies? Färe et al. (2006) examine pollution costs from the leaching and runoff of pesticides in U.S. agriculture from 1960 to 1996. They estimate that the average annual pollution cost ratio of pesticide use is about 6% of crop and animal revenues. According to Muller et al. (2011), the pollution costs of the U.S. agricultural sector are about \$20.4 billion per annum, representing approximately 10% of the gross output value of U.S. agriculture. In the United Kingdom, water pollution costs from the agricultural sector are about £300 million per annum, representing 2% of the gross output value of U.K. agriculture (Pretty et al., 2000). In Germany, a pesticide ban in the agricultural sector would cause a net welfare loss of around 5% of net domestic agricultural product (Waibel and Fleischer, 1998). Therefore, our estimates of the pollution costs from agricultural pollutants are generally consistent with those of other studies.

What factors do impact on the pollution cost ratio of agricultural pollutants? Identifying the determinants of the pollution cost ratio is fundamentally important for understanding whether anything can be done to promote the transition of China's agriculture toward sustainable and low-pollution production patterns in the future. Specifically, we run the following panel regression model:

$$pcs_{kt} = \alpha + \beta X_{kt} + \varepsilon_{it} \tag{15}$$

where pcs_{kt} is the pollution cost ratio of province k in year t, X_{kt} is a vector of variables that could influence pollution cost ratio, and ε_{it} is the error term. More specifically, we consider the following potential drivers:

Per hectare output (*per_output*). Intensive modern agricultural production could bring higher per hectare output and less pollution compared with extensive traditional agricultural production (Tilman et al., 2002; Pimentel et al., 2005). Thus we include per hectare output and its quadratic term in the regression.

Table 4
Estimates of average polluting costs ratio by province, 2001–2010, per cent.

Provinces	Average polluting cost ratio	Provinces	Average polluting cost ratio
Anhui	8.12	Jiangxi	7.18
Chongqing	6.38	Jilin	5.28
Fujian	2.20	Liaoning	3.78
Gansu	6.35	Qinghai	12.52
Guangdong	5.23	Shaanxi	4.83
Guangxi	10.43	Shandong	1.96
Guizhou	8.90	Shanxi	4.54
Hainan	2.15	Sichuan	13.07
Hebei	2.70	Xinjiang	3.23
Heilongjiang	3.44	Yunnan	10.27
Henan	11.01	Zhejiang	2.21
Hubei	4.81	East region	2.85
Hunan	11.00	Middle region	6.92
Inner Mongolia	4.13	West region	8.01
Jiangsu	2.56	China	6.09

Agricultural proportion (*ratio_ag*). In China, there is a linear relationship between the shadow price of industrial pollution and the proportion of industrial output in the provincial GDP (Du et al., 2015), which may in turn moderate the relationship between the pollution cost ratio and industrial proportion. Therefore, we speculate that a similar relationship exist in the agricultural sector. To test this hypothesis, we derive a measure to represent the proportion of agriculture in each province by calculating the agricultural gross output scaled by provincial GDP. The data of provincial GDP are derived from the China Statistical Yearbooks. GDP is deflated using 2001 as a base year.

Capital-labor intensity (*inten_cl*). In China, the level of capital–labor intensity affects the shadow prices of pollutants (Du et al., 2015; Cao and Qu, 2014), which may moderate the relationship between capital–labor intensity and pollution cost ratio. We employ the ratio of capital to labor in the agricultural sector to represent the capital–labor intensity.

Material–labor intensity (*inten_ml*). The intensity of material–labor denotes the resource allocation within a production. In the agricultural sector of developing countries like China, a higher intensity of material–labor usually means more advanced production technology, which may further influence the pollution cost ratio. We use the ratio of material to labor in the agricultural sector to measure the material–labor intensity.

Labor–land intensity (*inten_lbld*). In rural China, labor surplus and cultivated land shortage usually lead to massive emissions of pollutants and consequent deterioration of the environment (Qin, 2010). Thus we include the labor–land intensity in the regression. This is measured as the ratio of labor input to land input.

Market price of agricultural output (*price*). As mentioned above, the shadow price of pollutant derived in this study is best treated as an opportunity cost and reflects the tradeoff between the agricultural output and pollutant. The growth in market price of output will increase the value of agricultural output foregone for reducing an extra unit of pollutant, therefore lifting the opportunity cost of pollution abatement. Therefore, we consider the market price of agricultural output in our regression. This is measured by the general province-special price index for farm products using 2001 as the base year. The data are derived from the China Statistical Yearbooks.

Education (*edu*). A number of previous studies find that education contributes significantly to the growth of agricultural productivity in China (Fan et al., 2004; Chen et al., 2008, etc.). Farmers with a higher level of education are potentially more capable of adopting advanced production technology and it is easier for them to master the adopted technology, which may further reduce the pollution cost ratio. We derive a measure to represent the average level of education in each province. It is measured as the proportion of farmers who have finished senior high school education. The data are derived from the China Rural Statistical Yearbooks.

Table 5 reports the summary statistics of the dependent and independent variables. From the table, we can see that there is considerable variation between regions and over years. The East region has the highest per hectare output, capital–labor intensity, material–labor intensity, labor–land intensity, and education level, and the lowest agricultural ratio and price of the three regions.

We first estimate the regression model using the OLS method. We test for heteroskedasticity using the Breusch–Pagan Test (Koenker, 1981) and for serial correlation using the Breusch–Godfrey Test (Godfrey, 1978). The test results imply that significant heteroskedasticity and serial correlation problems exist.

To retain the provincial characteristics that do not vary over time, we choose to focus on the random effects models. These models are estimated by General Feasible Generalised Least Squares (General FGLS) (Wooldridge, 2002) to overcome heteroskedasticity and serial correlation problems. Given the panel nature of the data, it is helpful to test for time and individual effects separately. The results of time and individual effects models are reported in Table 6.

From Table 6, we can see that the parameters of per hectare output are negative and significant in both models, a result which is consistent with our expectation. Since the average per hectare agricultural output of China has been increasing since 2000 (Department of Foreign Affairs and Trade, 2012), we expect that the pollution cost ratio will decrease with the increase of per hectare output. The effect of labor–land intensity and education are also significant. A province with higher labor–land intensity in agricultural production has a higher pollution costs ratio. A higher education level of famers is associated with a lower pollution costs ratio. Moreover, we find that the estimated coefficients of market price of agricultural output are significantly positive in both models. This indicates that a province with a higher market price of agricultural output has more to lose because of agricultural pollution. The effects of agricultural structure and material–labor intensity are significant in the time effect model, but not significant in the individual effect model. The effect of capital–labor intensity is not significant in both models.

6. Conclusions

In this study, we use the parametric directional output distance function approach to estimate the reduction potential, shadow prices, and pollution costs of agricultural pollutants in China, based on a

Table 5
Summary statistics of dependent and independent variables.

Variable	Unit	China		East region		Middle region		West region	
		Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.
Pcs	–	0.061	0.037	0.028	0.014	0.069	0.032	0.080	0.036
Per_output	10^5 Yuan/ha	0.232	0.132	0.388	0.123	0.171	0.059	0.156	0.047
ratio_ag	–	0.319	0.101	0.280	0.127	0.336	0.090	0.335	0.075
inten_cl	10^4 Yuan/person	2.822	1.665	3.615	1.365	2.432	1.196	2.499	1.973
inten_ml	10^4 Yuan/person	0.495	0.267	0.728	0.224	0.467	0.196	0.331	0.210
inten_lbld	10 persons/ha	0.203	0.069	0.228	0.064	0.166	0.059	0.213	0.069
Price	–	1.288	0.278	1.262	0.254	1.315	0.300	1.287	0.279
Education	–	0.136	0.042	0.173	0.030	0.132	0.026	0.110	0.038

Table 6
Regression results for pollution cost ratio.

	Time effect model		Individual effect model	
	Value	Std. error	Value	Std. error
Intercept	−0.111***	0.009	−0.084**	0.028
ln(per_output)	−0.126***	0.005	−0.096***	0.015
ln(per_output)2	−0.031***	0.001	−0.021***	0.004
ratio_ag	0.055***	0.003	0.019	0.014
inten_cl	−0.000	0.000	−0.001	0.001
inten_ml	−0.011**	0.004	−0.007	0.010
inten_lbld	0.292***	0.012	0.286***	0.043
ln(price)	0.058***	0.002	0.044***	0.006
Education	−0.200***	0.011	−0.104***	0.031

Multiple R^2: time effect model 0.656, individual effect model 0.603.
*** Significant at 0.1% level.
** Significant at 1% level.

provincial panel dataset covering the years 2001–2010. Our results indicate that there is scope for further pollution abatement in Chinese agriculture if the agricultural sectors in all provinces were to produce on the production frontier. The regional shadow prices and pollution costs of agricultural pollutants are unbalanced. Overall the pollution costs of China's agriculture are significant, averaging about 6% of the annual gross output value of the agricultural sector.

Some important policy implications can be drawn from our estimates. First, our estimates indicate that there is scope for further pollution abatement and simultaneous output expansion for Chinese agriculture if the agricultural sectors in all provinces were to produce on the production frontier. Opportunities for win–win agricultural production and pollution reduction do exist. This can be achieved if China's farmers promote greater efficiency in their production process. Policymakers are also advised to provide more incentives to help farmers reduce the technical inefficiency of agricultural production. Second, the Chinese government is proposing domestic emission trading systems for various pollutants including some relevant to agriculture. Our estimated shadow prices provide a yardstick by which the government can identify an initial benchmark price for the trading system. Third, the fluctuating trends in the shadow prices and pollution costs suggest that abatement pricing policies need to be dynamic. This requires the government to dynamically adjust pollution tax rates and ascertain the initial permit price in an emission trading system. Finally, considering the identified determinants of pollution costs discussed above, an agricultural pollution abatement policy should take into account the heterogeneity in agricultural characteristics between provinces. To minimize the social abatement cost, policymakers should consider the different pollution costs for each province when setting reduction allocations within agricultural sector. Provinces' abatement burdens should be set in accordance with their differing pollution costs.

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