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Energy efficiency and production technology heterogeneity in China's agricultural sector: A meta-frontier approach

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ABSTRACT

Following agricultural technological heterogeneity, we employ the meta-frontier DEA method to measure agricultural energy efficiency in China's agricultural sector, and then use Malmquist index approach to explore the energy productivity change. The results show that agricultural energy efficiency is quite low and has the characteristics of regional differences. The energy efficiency of eastern coastal regions is significantly higher than that of the western interior. The energy efficiency loss comes mainly from managerial inefficiency rather than technology gap on the whole. The Malmquist index reveals that agricultural energy productivity has improved in general, mainly due to technological advancements while the deterioration in agricultural energy productivity is due to reduction in technical efficiency. We suggest that technological innovation and managerial efficiency should be promoted to increase energy efficiency and more attention should be paid to the western region to balance the regional difference. The findings are of great significance to energy conservation and sustainable development in China's agricultural sector.

1. Introduction

Since the reform and opening up, the Chinese government has implemented various economic policies to emancipate and develop the productive forces of different departments and industries; and the economy has experienced unprecedented growth for >30 years. As one of the most important sectors, China's agriculture has also achieved great success. It has provided food for more than one fifth of the world's population with less than a tenth of global arable land (Xiao, 2012; Wang et al., 2015). Meanwhile, China's agricultural economy output has maintained an average growth rate of nearly 5% over the past years (2000 − 2012) as the population continues to increase while the cultivated land decreased (*China Statistical Yearbooks*). In recent years, with the development of agricultural mechanization and agricultural intensification, fertilizer, pesticides and plastic film are widely used in agricultural production, resulting in an annual increase in the energy consumption of the agricultural sector. Energy consumption increased from 43.45 million tons in 2001 to 74.44 million tons in 2012 (*China Statistical Yearbooks*). In 2013, China's energy consumption accounted for 22.4% of the world's total energy consumption and the dependence on foreign oil exceeded 60%. China's CO_2 and energy intensity targets are rather stringent (Luukkanen et al., 2015). It is becoming more evident that energy constrains economic and social development and influences ecological environment across industries (Jiang and Lin, 2013), which is the same for agriculture sector.

Theoretically, the growth of agricultural output comes from two aspects: increase in input factors and progress of agricultural technology (Lin and Fei, 2015). In recent years, China's agricultural labor force continues to decline and cultivated land and water resources also become relatively scarce. Consequently, it seems impossible to raise agricultural output by only relying on the increase in natural resources and agricultural factor inputs. In 2007, China began to enter the middle stage of agriculture mechanization (Guo et al., 2011). It can be expected that energy consumption in the agricultural sector will increase faster with the constant employment of agricultural mechanization and advancement in modern agricultural technology. Therefore, studying of energy efficiency in the agricultural sector is of great significance for agricultural sustainable development.

In the previous literatures, energy efficiency indicators generally can be classified into two types: partial-factor energy efficiency and total factor energy efficiency. For partial-factor energy efficiency indicators, a general definition is “the specific value of energy output and energy input” (Choi et al., 1995; Patterson, 1996; Ang and Liu, 2001; Lin and Moubarak, 2014), such as energy intensity which is measured as the ratio of energy input to economic output (Zhang, 2003; Liddle, 2010) and energy productivity which is the ratio of economic output to energy consumption (Ghali and El-Sakka, 2004). These indicators identify a linear correlation between economic growth and energy consumption,

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and thus reducing energy intensity may have negative impact on economic growth (Shi et al., 2010). Because these indicators do not take the complement effect and substitution effect of other factor inputs in the production process into consideration, they may exaggerate energy contribution to the economy when they are employed to measure energy efficiency.

However, as industrial and academic scholars investigated this issue further, they found that the partial-factor energy efficiency indicators were not applicable and might be misleading (Wilson et al., 1994; Hu and Wang, 2006; Boyd, 2008; Stern, 2012). Wilson et al. (1994) clearly pointed out that the traditional definition of energy efficiency was difficult to measure potential technical efficiency in energy utilization. Thereafter, Hu and Wang (2006) proposed the total factor indicators in the multi-factor input framework, which were defined as the ratio of the optimal energy input to actual energy input. This method has been employed to evaluate China's regional energy efficiency. Wei et al. (2009) used 1997–2006 panel data for 29 provinces with DEA method to examine China's energy efficiency. They found that there is a large gap in energy efficiency among the eastern, central and western regions. They found that the energy efficiency level of the eastern region is significantly higher than that of the central and western regions. Shi et al. (2010) also used DEA method for the 28 administrative regions during 2000–2006 to investigate China's industrial energy efficiency and further estimated the maximum energy-saving potential. They found that industries in the eastern region usually have the best average energy efficiency, followed by the central region. Wu et al. (2012) estimated industrial energy efficiency in both static and dynamic indices for China's provinces for the period 1997–2008 using several environmental DEA models which consider CO_2 emissions. Wang et al. (2013) investigated provincial energy efficiency and productivity in China for the period 2006–2010 using the non-radial directional distance function. Energy efficiency in China is negatively associated with the proportions of government expenditure, state-owned enterprises, and secondary industry in GDP, but is positively related with the share of non-coal energy in energy consumption and technical level. Besides, Lin and Du (2015) employed the non-radial directional distance function DEA model to investigate regional energy and CO_2 emission performance in China during 1997–2009. They found that provinces in the eastern region usually performed better than those in the central and western areas and provinces in the western region are generally have the lowest efficiency. This method is also used to measure carbon emission performance (Guo et al., 2011; Choi et al., 2012; Zhang and Choi, 2013; Zhang et al., 2014).

With respect to agriculture, Mousavi-Avval et al. (2011) used the non-parametric DEA technique to study the energy use pattern of canola production in Iran and they found that the mean efficiency was 0.74 and 0.88 under constant and variable returns to scale assumptions respectively. Falavigna et al. (2013) used DEA model to estimate environmental efficiency of the Italian agricultural industry, and found that there is a significant difference in environmental performances among Italian regions and that the productivity estimates differ when emissions are taken into consideration. Khoshnevisan et al. (2013) also used this method to study energy efficiency of greenhouse cucumber production and further determined technical efficiency (TE), pure technical efficiency (PTE) and scale efficiency (SE). Vlontzos et al. (2014) employed a non-radical DEA model to estimate the energy and environmental efficiency of the agricultural sectors of EU member states for the period 2001–2008. They found that countries with strong environmental protection standards always have lower energy and environmental efficiency.

On the whole, these efficiency measurements are mainly from the technical point of view. However, most previous studies are based on the assumption that all the decision-making units (DMUs) which are required to be measured share a common production technology. Nevertheless, due to the different climatic conditions and regional endowments, it is very obvious that there are differences in natural resources, agricultural industrial structure and technology levels in the agriculture sector in different regions in China. Hence, the assumption of homogeneous technology may inevitably lead to a biased result. For example, in vast western regions with large population, mountainous terrain, and small arable farmland, technology spreads slowly. As a result, the provinces in this region share a similar backward production technology. In contrast, provinces in the eastern region have good production conditions including resource endowment and climatic conditions and benefit much better from preferential policies. As a result, the eastern region spreads and enjoys advanced technology. Given this, we intend to estimate and analyze China's agricultural energy efficiency with heterogeneous technology hypothesis under the meta-frontier framework. We will further explore the temporal and spatial characteristics of the different regions.

So far, research on China's energy efficiency is mainly focused on the national macro level or on the industrial and service sectors. Within existing literatures, there are few studies that specifically examine the energy efficiency problem in China's agricultural sector, but they seldom consider technological heterogeneity on the industry development. This therefore motivates us to carry out further research on an area that seems to be a large oversight in the existing studies.

2. Methodology

2.1. Total factor energy efficiency based on meta-frontier

Based on the existing literatures, the main idea of total factor energy efficiency indicator is to analyze the relationship between each DMU and the frontier production boundary by defining the production possibility set and constructing the frontier production boundary. If the production decision unit deviates from the frontier production boundary, it means production factors have not been fully utilized and there exists the possibility of Pareto improvement. In this paper, we introduce energy distance function to measure energy efficiency in the process of agricultural production under the meta-frontier theoretical framework. It is established on the assumption that each province has potential approach to the same level of agricultural technology. In order to explore the energy efficiency of China's agricultural sector with technology heterogeneity, we take China's 30 provinces (DMUs) as samples. From the perspective of the development of provincial economies and their geographical distribution, the 30 provinces are divided into 3 groups. They are the eastern region (Beijing, Tianjin, Hebei, Liaoning, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, Hainan), central region (Shanxi, Mongolia, Jilin, Heilongjiang, Anhui, Jiangxi, Henan, Hubei, Hunan, Guangxi) and western region (Chongqing, Sichuan, Guizhou, Yunnan, Shaanxi, Gansu, Qinghai, Ningxia, Xinjiang). This is a traditional classification system for China and is used in a large number of studies (Wang et al., 2013; Lin and Du, 2013, 2014; Zhang et al., 2015). Input factors are capital (CAP), labor force (LAB) and energy (ENE) and economic output is agricultural GDP (Y). This kind of production framework has been employed in macroeconomic analysis across countries and areas (Zhou et al., 2012 Lin and Du, 2013). Following the framework of neoclassical production economy and assuming constant returns to scale technology, we can describe it as:

$$T = \{(\mathrm{LAB}, \mathrm{KAP}, \mathrm{ENE}, \mathrm{Y}) | (\mathrm{LAB}, \mathrm{KAP}, \mathrm{ENE}) \text{can produce } \mathbf{Y} \text{ with technology} \mathbf{T}\} \tag{1}$$

Generally speaking, the collection T is a bounded and closed set, and the inputs and output satisfy the property of strong disposability.

Given agricultural labor **LAB**, agricultural capital **KAP**, and agricultural output Y, the energy input requirement is defined as:

$$\mathrm{EI} = \{E : (\mathrm{ENE}, \mathrm{LAB}, \mathrm{KAP}, \mathrm{Y}) \in \mathrm{T}\} \tag{2}$$