doi: 10.17221/233/2014-AGRICECON

Efficiency change in North-East China agricultural sector: A DEA approach

Shiwei LIU, Pingyu ZHANG, Xiuli HE, Jing LI

Northeast Institute of Geography and Agroecology, Chinese Academy of Sciences, Changchun, Jinlin, China

Abstract: A non-parametric Data Envelopment Analysis (DEA) technique was applied to investigate the degree of efficiency and efficiency change of prefecture-level cities in the North-East China from 2000 to 2012. Mean pure technical efficiency in a DEA model with the number of agriculture was 0.79, indicating that there is a big potential for a more efficient input utilization in agricultural productivity. Decomposition results of the Malmquist index indicated that the average productivity (MALM) growth at 8.0 percent annually over the entire period in the North-East China and the major source of growth was the technical change. In order to stimulate the productivity growth, more attention should be paid to improving the production efficiency. Polices should be enacted to increase the technical investment in agriculture, to enhance the rural education and research in agriculture which may help farmers to improve the agricultural efficiency and productivity. Given the limitations of the Statistical Yearbook data, some field investigation may carry out in future studies.

Key words: agriculture, Data Envelopment Analysis, Malmquist productivity index, production efficiency

Food security is high on the global policy agenda. Demand for food is increasing as the populations grows and gains wealth to purchase more varied and resource-intensive diets (Garnett et al. 2013). The key to boosting the food security cannot be divorced from the agricultural productivity growth (Ogundari 2014). And the crucial role of efficiency in increasing the agricultural output has been widely recognized by researchers and policy makers. Thiam et al. (2001) highlighted the importance of efficiency as a means of fostering production which has led to the proliferation of studies in agriculture on the technical efficiency around the globe. The analysis of technical efficiency in agriculture has received a particular attention in developing countries because of the importance of the productivity growth in agriculture for the overall economic development (Kolawole 2009).

Efficiency refers to how well a system or unit of production performs in the use of resources to produce outputs, given the available technology relative to a standard production (Fried 2008). In order to increase agricultural output, the governments have advocated various policies on the efficiency growth, and the current research has also introduced various methodologies to assist in promoting efficiency. V. Ndlovu et al. (2014) compared the productivity and efficiency under the conservation and conventional agriculture, and found that the farmers produce 39% more in the conventional agriculture which may be a good choice for the land constrained farmers. Jaime and Salazar (2011) demonstrated that the farmers who participate in organizations have got higher efficiency levels and the governments should strengthen efforts to improve the existing participation space and to provide support for the existing productive organizations. Manjunatha et al. (2013) found that the land fragmentation has a reciprocal relationship with the farm efficiency, and some measures should be proposed to reducing the land fragmentation. Alston et al. (2009) reviewed the experience of agricultural development in developed countries and emphasized the revitalization of agricultural R&D investments will contribute to the global agricultural productivity.

The methods of measuring efficiency can be dated back to the works of Koopmas and Debreu (Ogundari et al. 2012). Inspired by the studies of Debreu and Koopmas, Farrell (1957) introduced a measure to decompose the economic efficiency into the technical and allocative efficiencies. Following Farrell's (1957) definition, the technical efficiency is the ability of a production unit to produce the maximum output given a set of inputs, the allocative efficiency is the

Supported by the National Natural Science Foundation of China (41571152, 41301111, and 41201159) and the Knowledge Innovation Program of the Chinese Academy of Sciences (KZCX2-YW-342, KZCX2-YW-321-04).

doi: 10.17221/233/2014-AGRICECON

ability of a production unit to produce a given level of output using optimal input proportions, while the economic efficiency is a measure of the overall performance and is the product of the technical and allocative efficiencies (Bravo-Ureta et al. 2001; Amor and Muller 2010). Broadly, methods of the efficiency analysis include the parametric (stochastic frontier production function) and non-parametric (DEA) approaches. In recent years, advanced technologies, such as the remote sensing, the nutrients balance approach, the EPIC model, and the energy method have been used to study the efficiency and productivity in agriculture(Liu and Chen 2007; Chavas et al. 2009; Tao et al. 2009; Hoang and Coell 2011; Gallego et al. 2014).

Since the implementation of the economic reform in 1978, Chinese agricultural productivity and efficiency have become a hot topic among scholars. Studies of agricultural efficiency in China concentrated on two aspects: one is the agricultural production efficiency analysis in sample periods (e.g., Mao and Koo 1997; Hu and McAleer 2005; Chen and Song 2008; Chen et al. 2008; Chen et al. 2009).The second means uncovering the factors which impact the production efficiency (Liu and Zhuang 2000; Monchuk et al. 2010; Tan et al. 2010; Ma and Feng 2013). Many of the above studies have used the provincial-level datasets. However, the provincial aggregates may not reflect the exact differences among regions and the prefecture-level data become necessary and possible (Herrmann-Pillath et al. 2002). Some studies (e.g., Chen and Song 2008; Chen et al. 2009; Monchuk et al. 2010) used the county-level datasets to evaluate the agricultural efficiencies in China. But sample periods in these studies are very short and cannot depict the change in efficiency. This paper estimates the production efficiency in the North-East China agricultural sector with a panel data set comprising 36 prefecture-level cities for the 13-year period 2000–2012. This study applies the data envelope analysis (DEA) approach to estimate the efficiency in the agricultural sector. The Malmquist productivity index is used to measure the productivity change over time and we decompose the TFP change in the North-East China into the technical change and efficiency change.

MATERIALS AND METHODS

Study area

The study area is located in the North-East of China, includes 36 prefecture-level cities, bordered to the North and West by Russia and Mongolia and to the South-East by the North Korea (Figure 1). With an area of 78.8 × 10^4 km^2 and a population of 109.73 million, the population density is about 139.3 persons per square km. This region is famous for its fertile soil and plentiful water resources. It is not only an important commodity grain base, but also a pivotal old industrial base in China. In 2012, grain output in the North-East China has reached 1.12 million tons, accounting for 18.95 % of the national grain production (Figure 2), and the most important crops in terms of areas produced were rice (15.72%), legumes (32.73%) and corn (33.51%). According to the China Statistical Yearbook 2013, arable land in the North-East China has reached 21.45 million hectare, and accounts for 17.62% of China arable land. Cultivated areas per

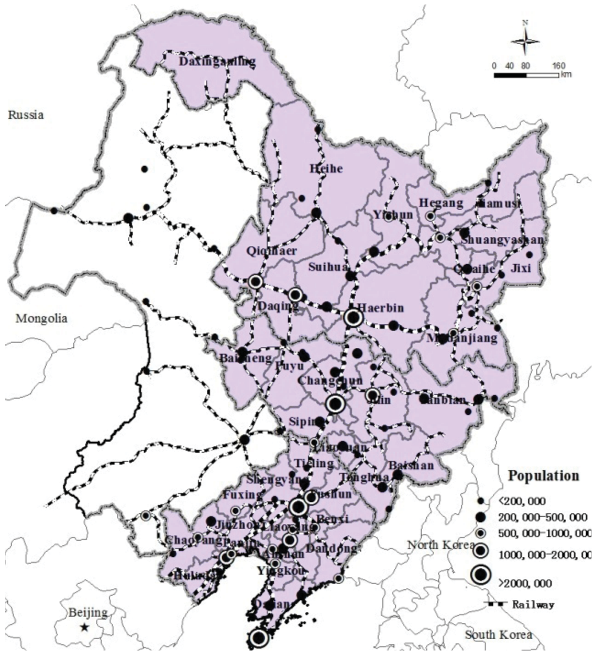

Figure 1. Study area of the North-East China

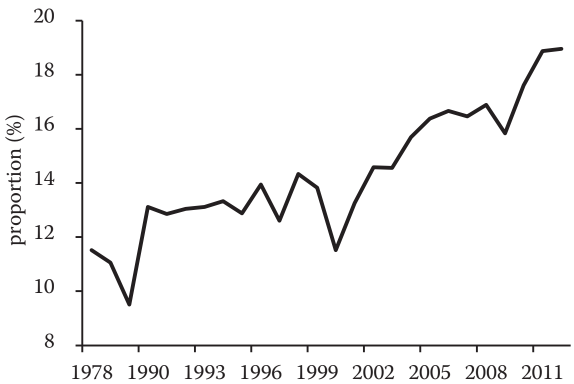

Figure 2. Proportion of grain output of the North-East relative to China (1978–2012)

doi: 10.17221/233/2014-AGRICECON

Table 1. Intensification management of agriculture in the North-East China

Country or province	The first industrial employment (10^4)	Proportion of first industry (%)	Cultivated areas per agriculture economic activity Population (hectares per capita)	Tractors used per thousand hectares cultivated areas (units/1000 hectares)	Consumption of chemical fertilizers per thousand hectares cultivated areas (tons/1000 hectare)
Liaoning	698.20	0.33	0.59	28.79	315.28
Jilin	510.96	0.45	1.08	36.37	295.95
Heilongjiang	775.60	0.46	1.53	40.74	152.75
China	30 654.00	0.40	0.40	24.61	430.43

agriculture economic activity population in the North-East China is higher than the national average, ranked in the provinces forefront (Table 1). Since 1978, the introduction of the household-responsibility system and technical progress has prompted the growth of the agricultural productivity. The level of agricultural intensification in the North-East China has gradually increased, the number of tractors used per thousand hectares cultivated areas has reached 37.34 now, the consumption of chemical fertilizers per thousand hectares cultivated areas is less than the national average (Table 1). This laid a good foundation and conditions for developing modern agriculture.

DEA model

Charnes et al. (1978) proposed a model which had an input orientation and assumed constant returns to scale (CRS). However, the CRS assumption is only appropriate when all DMU's are operating at the optimal scale. Banker et al. (1984) suggested an extension of the CRS DEA model to account for variable returns to scale (VRS) situations. This more accurately reflects operations and the management level of DMU. The DEA can be either input or output orientated. The former is to reduce the resource input to the greatest extent to improve efficiency under the condition that the output remains unchanged, while the latter is to increase the output efficiency evaluation under the condition that the input factors remain unchanged (Coelli 1996). As for the agricultural production efficiency evaluation, it is easy to control input. Hence, we choose to adopt the VRS input-orientated DEA in this paper.

For the given time period, there are n decision making units (DMU). x_i and y_r are input and output vectors for the representative DMU with m inputs and s outputs respectively.

$$X_j = (x_{1j}, x_{2j}, \cdots, x_{mj})T, Y_j = (y_{1j}, y_{2j}, \cdots, y_{mj})^T \quad j = 1, 2, \ldots, n$$

where X_{ij} (i =1, 2, ..., m) is the ith input variabe of the jth DMU; Y_{rj} (j = 1, 2, ..., s) is the rth output variable of the jth DMU. The VRS input-orientated DEA model is as follows (Wang et al. 2012):

$$\begin{cases} \min\theta = V_{D2} \\ \text{s.t.} \sum_{j=1}^{n} X_j \lambda_j \le \theta X_0 \\ \sum_{j=1}^{n} Y_j \lambda_j \ge Y_0 \\ \sum_{j=1}^{n} \lambda_1 = 1 \\ \lambda_j \ge 0, \quad j = 1,2,3,\cdots,n \end{cases}$$

θ in the above equation represents efficiency value of each DMU, and 0 ≤ θ ≤ 1, i.e., θ = 1 shows a technically efficient DMU; θ < 1shows a technically inefficient DMU.

Malmquist index

The Malmquist indexes were established by Caves et al. (1982) based on the distance functions (Mao and Koo 1997). It is quantity based, more suitable to the China's situation (Tong et al. 2009). Hence, in this paper we used the prefecture-level data for years 2000–2012 to construct the Malmquist productivity index. As specified by Caves et al. (1982) this index is:

$$M^t = D^t(x^{t+1}, y^{t+1}) / D^t(x^t, y^t)$$

M^t index measures the productivity changes from time period t to time period t + 1 under the technology in the time period t. D^t is the output distance function in the time period t, and x^t and y^t are inputs and outputs in the time period t. The technical efficiency changes at the time period t and time period t + 1 could also be calculated under the technology in time period t + 1. The Malmquist index is defined as:

$$M^{t+1} = D^{t+1}(x^{t+1}, y^{t+1}) / D^{t+1}(x^{t+1}, y^{t+1})$$

According to Färe et al. (1994), the output-oriented Malmquist index can be decomposed into two components, the efficiency change and the technical

doi: 10.17221/233/2014-AGRICECON

change based on the CRS. If we relax the CRS assumption and allow for variable returns to scales (VRS) technology, the efficiency change index can further be decomposed into the pure technical efficiency change index and the scale efficiency change index, as follows (Färe et al. 1994):

$$M(x^t, y^t, x^{t+1}, y^{t+1}) = \left[\frac{D^t(x^{t+1}, y^{t+1})}{D^t(x^t, y^t)} \times \frac{D^{t+1}(x^{t+1}, y^{t+1})}{D^{t+1}(x^t, y^t)}\right]^{\frac{1}{2}}$$

$$= \left[\frac{D_c^t\ (x^{t+1}, y^{t+1})}{D_c^{t+1}(x^{t+1}, y^{t+1})} \times \frac{D_c^t\ (x^t, y^t)}{D_c^{t+1}(x^t, y^t)}\right]^{\frac{1}{2}} \times \frac{D_c^{t+1}(x^{t+1}, y^{t+1})}{D_c^t\ (x^t, y^t)}$$

$$= \mathrm{TC(CRS)} \times \mathrm{EC(CRS)}$$

$$= \mathrm{TC(CRS)} \times \mathrm{PTEC(VRS)} \times \mathrm{SEC(VRS, CRS)}$$

where

$$\mathrm{PTEC(VRS)} = \frac{D_v^t\ (x^{t+1}, y^{t+1})}{D_v^{t+1}(x^t, y^t)} \quad \text{and}$$

$$\mathrm{SEC(VRS, CRS)} = \frac{D_v^t\ (x^t, y^t)}{D_c^t\ (x^t, y^t)} \times \frac{D_c^{t+1}(x^{t+1}, y^{t+1})}{D_v^{t+1}(x^{t+1}, y^{t+1})}$$

The PTEC (VRS) is the pure technical efficiency change based on the VRS; SEC (CRS, VRS) is the scale efficiency change based on the CRS and VRS; Dc and Dv are the distance functions based on the CRS and VRS. EC > 1 indicates the increase of agricultural efficiency from the time period t to the time period $t + 1$; EC = 1 means the agricultural efficiency remains stable during the period t to the time period t + 1; EC < 1 shows the decrease of agricultural efficiency.

Data

The data used in this study are from various issues of the Liaoning Statistical Year Book 2001–2013, the Jilin Statistical Year Book 2001–2013, the Heilongjiang Statistical Year Book 2001–2013, and the China Statistical Year Book for the regional economy 2001–2013. The sample consists of all 36 Prefecture-level cities, autonomous regions in the North-East China over the period 2000–2012. The agricultural production output used in the study is the gross value of agricultural output (not including forestry, animal husbandry and fisheries). The agricultural production input includes capital and labour, land, machinery and fertilizer. Labour is measured as the number of workers employed in the primary industry. Land input is defined as the sown area which more accurately reflects the actual utilization of the cultivated land in the North-East China. Machinery input is measured by the total power of farm machinery. Chemical fertilizer refers to the sum of pure weights of potash, nitrogen, phosphate and the complex fertilizer.

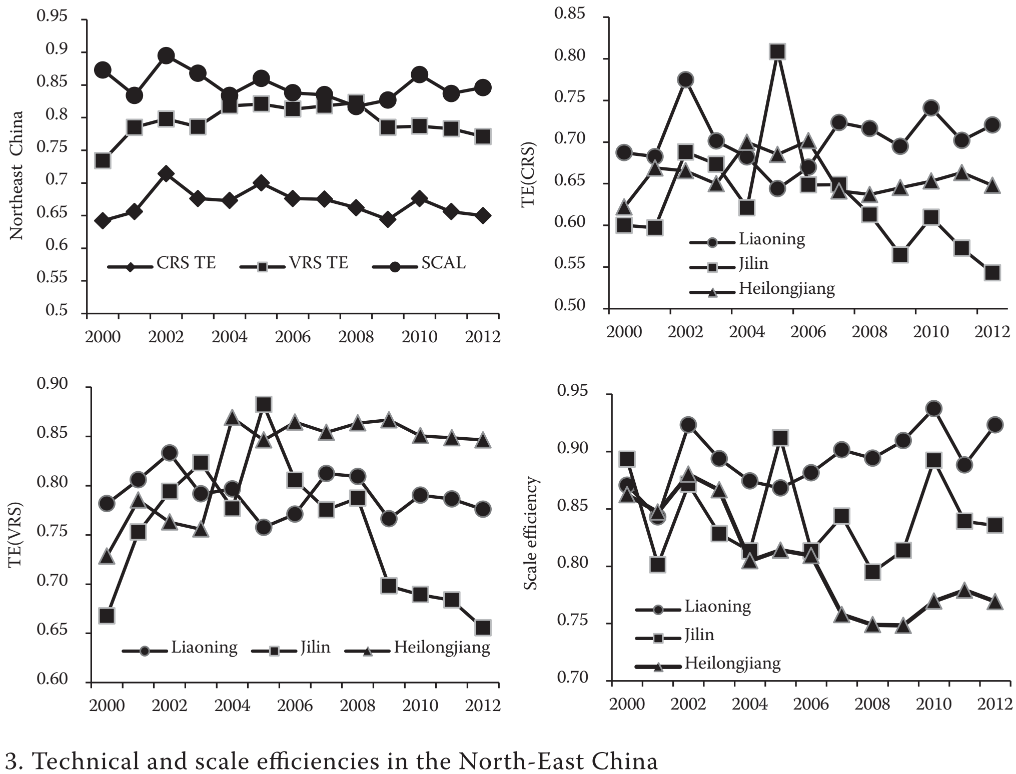

Figure 3. Technical and scale efficiencies in the North-East China

doi: 10.17221/233/2014-AGRICECON

RESULT AND DICUSSIONS

Technical and scale efficiency

Results obtained by the utilization of the input-orientated DEA are displayed in Figure 3. In 2000–2012, the mean radial technical efficiency of the North-East China is 0.669 and 0.794 under the CRS and VRS assumptions, respectively. This implies that the prefecture-level cities could reduce their inputs by 33.1% (20.6%) and still keep the same output level. Mean scale efficiency in the North-East China is 0.848, implying that the average size has not achieved the optimal size, although an additional 15.2% productivity gain would be practicable–postulating no other restricting factors – as long as they adjusted their arable land operation to the optimal scale. Figure 3 presents the North-East China and the provincial technical and scale efficiencies over the 13 year period. The regional and provincial technical and scale efficiency were obtained by averaging the prefecture-level cities' estimates. In 2000–2012, the mean technical and scale efficiency of the North-East China have not exhibited the same trend. There seemed to be a tendency of a downward TE movement over the period under the CRS assumption. While the TE movement under the VRS assumption was presenting an increase-falling trend, the scale

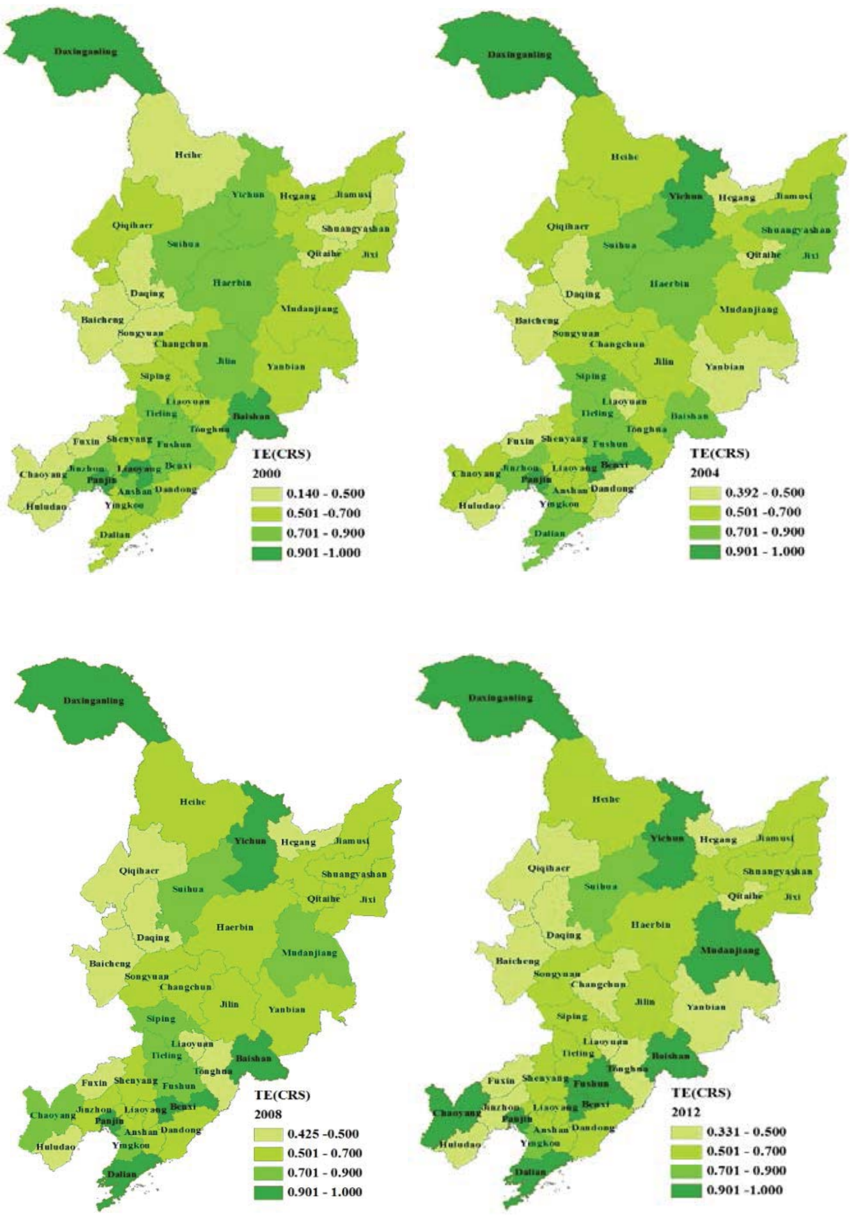

Figure 4. Spatial-temporal variation of technical efficiencies (CRS) in the North–East China (2000–2012)

doi: 10.17221/233/2014-AGRICECON

efficiency was presenting a falling- increase trend by 2008.

Efficiencies in the three provinces were exhibiting a different trend (Figure 3). The technical efficiency under the CRS assumption (TE (CRS)) in the Liaoning province clearly leads the other two provinces. TE (CRS) in the Liaoning province rose from 0.687 in 2000 to 0.721 in 2012. The Liaoning and Heilongjiang provinces had the upward TE (CRS) trends, but the Jilin province experienced a downward trend from 0.600 in 2000 to 0.543 in 2012. The Heilongjiang province clearly leads the other two provinces in the TE (VRS) and rose from 0.728 in 2000 to 0.846 in 2012. The Liaoning province had the upward TE (CRS) trends, while the Jilin province exhibited an increase- falling trend by 2005. The scale efficiency in Liaoning province is higher than in the Heilongjiang and Jilin province and exhibited smooth and generally upward changes in scale efficiency. However, the Heilongjiang seemed to show a tendency of a downward scale efficiency movement over the period. Scale efficiency in the Heilongjiang province decreased from 0.862 in 2000 to 0.769 in 2012.

The technical efficiency indexes under the CRS and VRS of 36 prefecture-level cities in 2000, 2004, 2008, and 2012 are presented in Figure 4 and Figure 5. In 2000, four cities, Panjin, Baishan, Daxinganling and Liaoyang are showing the best practice or close to the best practice under the CRS and twelve cities under the VRS. In 2004, the city number of those scored very well are increased to 19 under VRS. The number of the cities scoring well under the CRS are not changed

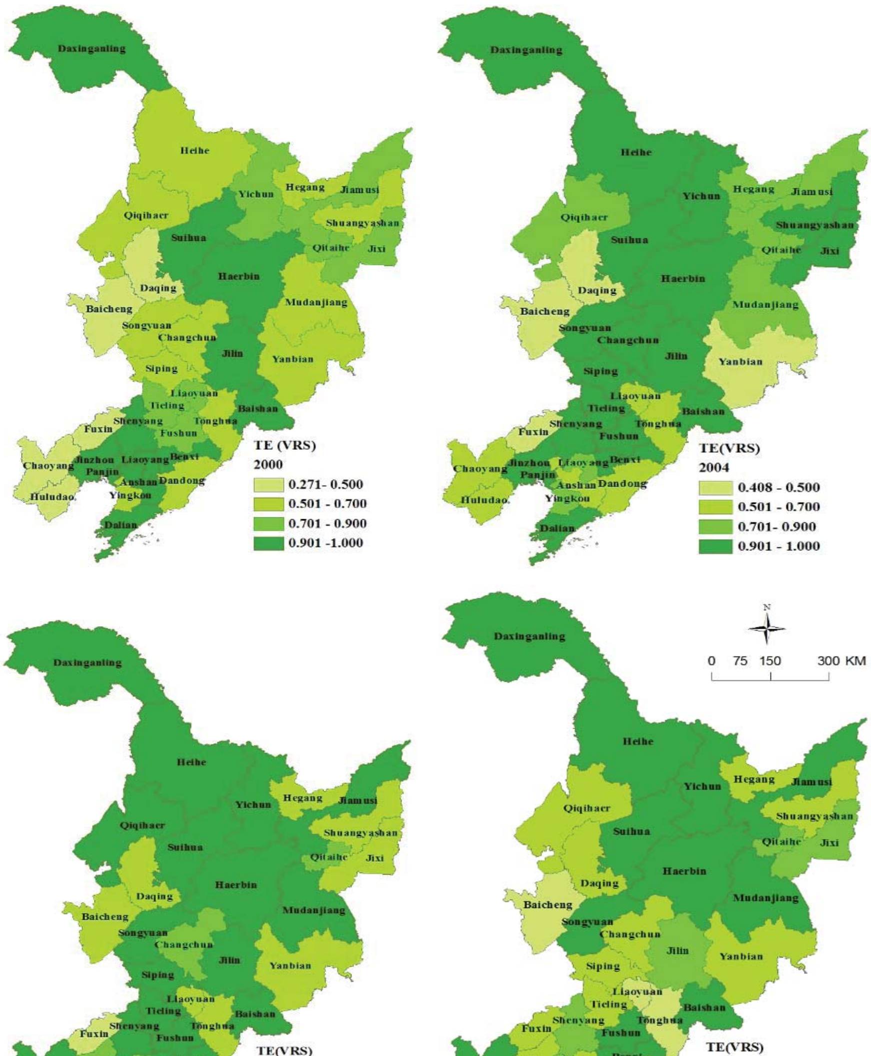

Figure 5. Spatial-temporal variation of technical efficiencies (VRS) in the North–East China (2000–2012)

doi: 10.17221/233/2014-AGRICECON

in 2004. But in 2008 and 2012, it increased to 6 and 9. However, the number of the cities scoring well under the VRS exhibited decreasing trends in 2012. Among the 36 cities, six of them (Dalian, Benxi, Panjin, Baishan, Haerbin and Daxinganlin) were persistently efficient and show the best practice in the four time periods under the VRS. Only two cities (Panjin and Daxinganlin) persistently lie on the best production frontier in the four time periods. From the spatial distribution of the technical efficiency under the CRS, most cities exhibited technical inefficiencies. This implies that cities could increase their inputs for improving the output level. Scale efficiencies were exhibiting a different trend in the 36 prefecture-level cities. In 2000, 18 cities achieved or were close to the optimal size. However, the number of cities achieving or close to the optimal size decreased in 2004 (decrease to 13) and 2008 (decrease to 14). The situation in 2012 was changed and the number of cities achieving or close to the optimal size increased to 20. Most scale-inefficient cities are operating under the increasing returns to scale in 2008–2012.

Decomposition results of the Malmquist index

In this study, we decomposed the Malmquist productivity index into the efficiency change (EFFI) index and the technical change (TECH) index. To identify the change in the scale efficiency, the EFFI was further decomposed into the PUREFF and SCAL. To obtain the Malmquist productivity (MALM) indexes and other indexes for each prefecture-level city and each pair of years, we use the DEAP2.1 to calculate the output distance functions. The results show that the average productivity growth (MALM) in the agricultural production averaged at 7.7, 6.9, 9.4 and 8.0 percent for Liaoning, Jilin, Heilongjiang and North-East China (Table 2). A higher productivity growth rate reflects a higher growth rate in output and lower growth rates in the use of all four inputs. In average, the technical change (TECH) index also rose by 7.9 percent for the entire region. Meanwhile, the efficiency change (EFFI) index rose in the Liaoning and Heilongjiang provinces. The efficiency change (EFFI) index in the Jilin province declined by 0.9 percent. The growth in technical change and technical efficiency suggest that the increased total factor productivity in the North-East China agricultural production arose from the innovation in technology and the improvement in the technical efficiency. However, the growth rate of the technical efficiency is small. This was partially due to the decline in the scale efficiency.

Among the total 36 prefecture-level cities, seventeen cities had positive average growth rates in the EFFI and TECH during the 2000–2012 periods (Table 3 and Table 4). Only seven cities, Fushun, Dandong, Yingkou, Fuxin, Shuangyashan, Yichun and Mudanjiang had an improvement in all five indexes. On the whole, all 36 cities had a positive average growth rate in the TECH and sixteen cities had a decline in the EFFI, indicating that the agricultural productivity growth in the North-East China was mostly attributed to the technology progress. From the results of the index value rank, the Fuxin experienced the highest growth in both the total productivity and technical

Table 2. Comparison of the agriculture production efficiency variation trend in provinces (2000–2012)

Time period	Provinces/region	EFFI	TECH	PUREFF	SCAL	MALM
2000–2004	Liaoning	1.017	0.993	1.012	1.004	1.010
	Jilin	1.013	1.024	1.038	0.976	1.038
	Heilongjiang	1.034	1.019	1.053	0.984	1.054
	Northeast China	1.019	1.010	1.031	0.989	1.029
2004–2008	Liaoning	1.012	1.099	1.006	1.005	1.112
	Jilin	0.999	1.078	1.006	0.993	1.077
	Heilongjiang	0.976	1.121	0.998	0.979	1.094
	Northeast China	0.995	1.101	1.002	0.992	1.096
2008–2012	Liaoning	1.001	1.115	0.991	1.011	1.115
	Jilin	0.964	1.139	0.952	1.014	1.098
	Heilongjiang	1.002	1.136	0.996	1.007	1.138
	Northeast China	0.991	1.128	0.982	1.009	1.118
2000–2012	Liaoning	1.009	1.068	1.002	1.006	1.077
	Jilin	0.991	1.079	0.997	0.994	1.069
	Heilongjiang	1.003	1.090	1.014	0.989	1.094
	Northeast China	1.002	1.079	1.005	0.997	1.08

doi: 10.17221/233/2014-AGRICECON

efficiency change, followed by the Heihe and Yichun. The Daxinganling had the largest improvement in the technical change (TECH). The Chaoyang showed the greatest improvement in the pure efficiency during the 2000–2012 period, but it also showed a large decline in the scale efficiency. The Fuxin had the most gain in scale efficiency. The Jinzhou, Liaoyuan and Jiamusi, three old industry cities in the North-East China, experienced the largest falls in the technical efficiency, the pure efficiency and the scale efficiency.

Since it is expected that the regional efficiency would have been improved with the economic reform and its components over the entire 2000–2012 sample period and the average of three sub-periods, i.e. 2000–2004, 2004–2008, and 2008–2012, are presented in Table 3 and Table 4. It is clear that the annual MALM growth rate in average increased from 2.9 percent in 2000–2004 to percent in 2004–2008, and went up to 11.8 percent. Over the study period, it grew at the rate of 0.6 percent per annum and resulted in the 8 percent overall increase. Observing two components of the MALM index, the annual TECH change is found to be 1.0, 10.1 and 12.8 percent for the three sub-periods, respectively. While the average growth rates of efficiency

Table 3. Annual and cumulative productivity growth and decompositions, 2000–2012

Prefecture level cities	MALM				TECH				EFFI			
	2000–2004	2004–2008	2008–2012	2000–2012	2000–2004	2004–2008	2008–2012	2000–2012	2000–2004	2004–2008	2008–2012	2000–2012
Shenyang	1.000	1.070	1.130	1.066	0.995	1.093	1.098	1.061	1.005	0.979	1.029	1.004
Dalian	1.024	1.177	1.137	1.111	0.998	1.097	1.157	1.082	1.027	1.072	0.983	1.027
Anshan	0.881	1.108	1.138	1.036	0.994	1.090	1.096	1.059	0.886	1.016	1.038	0.978
Fushun	0.928	1.101	1.144	1.053	0.935	1.096	1.086	1.036	0.993	1.004	1.054	1.017
Benxi	0.920	1.210	1.145	1.084	0.898	1.187	1.145	1.069	1.024	1.020	1.000	1.014
Dandong	0.937	1.148	1.146	1.072	0.941	1.122	1.130	1.061	0.996	1.023	1.015	1.011
Jinzhou	0.981	1.058	1.079	1.039	1.021	1.114	1.125	1.086	0.962	0.950	0.959	0.957
Yinkou	1.083	1.120	1.146	1.116	1.014	1.092	1.167	1.089	1.068	1.026	0.982	1.025
Fuxin	1.301	1.158	1.137	1.197	0.999	1.124	1.155	1.091	1.303	1.030	0.984	1.097
Liaoyang	0.899	1.044	1.100	1.011	1.033	1.047	1.076	1.052	0.870	0.998	1.023	0.961
Panjing	0.998	1.093	1.069	1.052	0.998	1.093	1.078	1.055	1.000	1.000	0.992	0.997
Tieling	1.045	1.035	1.026	1.036	1.036	1.072	1.094	1.067	1.009	0.965	0.938	0.970
Chaoyang	1.118	1.152	1.125	1.131	1.038	1.064	1.099	1.067	1.076	1.083	1.024	1.061
Huludao	1.026	1.095	1.091	1.070	1.008	1.100	1.105	1.070	1.018	0.995	0.988	1.000
Changchun	1.082	0.989	1.038	1.035	1.053	1.037	1.083	1.057	1.027	0.954	0.959	0.979
Jilin	1.000	1.041	1.106	1.048	1.051	1.048	1.126	1.075	0.951	0.993	0.982	0.975
Siping	1.180	1.015	1.065	1.085	1.033	1.062	1.094	1.063	1.141	0.956	0.974	1.021
Lioayuan	0.997	1.071	1.070	1.046	1.040	1.059	1.157	1.084	0.959	1.012	0.925	0.965
Tonghua	1.000	1.048	1.058	1.035	1.043	1.060	1.097	1.066	0.959	0.989	0.965	0.971
Baishan	0.903	1.123	1.180	1.062	0.932	1.089	1.180	1.062	0.969	1.031	1.000	1.000
Songyuan	1.163	1.111	1.145	1.140	1.032	1.116	1.176	1.106	1.127	0.996	0.974	1.030
Baicheng	1.060	1.179	1.085	1.107	1.053	1.127	1.176	1.118	1.006	1.046	0.922	0.990
Yanbian	0.956	1.120	1.134	1.067	0.981	1.106	1.161	1.080	0.975	1.013	0.977	0.988
Haerbin	0.990	1.022	1.145	1.051	1.000	1.115	1.143	1.084	0.990	0.917	1.002	0.969
Qiqihaer	0.998	1.063	1.077	1.045	0.994	1.119	1.116	1.074	1.004	0.950	0.965	0.973
Jixin	1.015	1.073	1.162	1.081	0.981	1.134	1.131	1.079	1.035	0.946	1.027	1.002
Hegang	1.001	1.091	1.178	1.087	1.052	1.132	1.176	1.119	0.951	0.964	1.002	0.972
Shuangyashan	1.160	1.017	1.154	1.108	1.017	1.135	1.156	1.101	1.141	0.897	0.998	1.007
Daqing	1.052	1.136	1.171	1.118	0.988	1.130	1.139	1.083	1.065	1.006	1.028	1.033
Yichun	1.152	1.141	1.143	1.145	1.079	1.141	1.143	1.121	1.067	1.000	1.000	1.022
Jiamusi	1.048	1.074	1.055	1.059	1.017	1.084	1.107	1.069	1.030	0.991	0.953	0.991
Qitaihe	1.016	1.118	1.064	1.065	0.977	1.089	1.121	1.060	1.040	1.027	0.949	1.004
Mudanjiang	1.052	1.169	1.153	1.123	0.982	1.110	1.105	1.064	1.071	1.052	1.044	1.056
Heihe	1.144	1.125	1.171	1.146	1.066	1.179	1.128	1.123	1.073	0.954	1.039	1.021
Suihua	1.008	1.045	1.108	1.053	1.030	1.061	1.090	1.060	0.978	0.984	1.017	0.993
Daxinganling	1.066	1.150	1.217	1.143	1.066	1.150	1.217	1.143	1.000	1.000	1.000	1.000

doi: 10.17221/233/2014-AGRICECON

increased by 1.9 percent in 2000–2004, however, it decreased by 2.4 and 0.9 percent in 2004–2008 and 2008–2012. Among the total 36 cities, twelve cities, seven in the Liaoning province, three in the Jilin province and two in the Heilongjiang province, had a negative average growth rate in the MALM during 2000–2004, while in 2004–2008, the Changchun was the only city with the negative growth in the MALM change and in 2008–2012 all cites had positive growth. The TECH index has the same change trend with the MALM index. However, the efficiency change (EFFI) index had a reverse tendency. In 2000–2004, twenty one cities had positive average growth rates, while in 2008–2012 only thirteen cities had positive average growth rates.

CONCLUSIONS

The DEA approach has been applied in order to investigate the degree of efficiency and efficiency change of the prefecture-level cities in the North-East China. This procedure allows the determination of the best practice cities and can also provide helpful insights for the agricultural management. By using these cities as benchmarks, the inefficient cities can

Table 4. Annual and cumulative decomposition of the technical efficiency change, 2000–2012

Prefecture level cities	PUREFF				SCAL			
	2000–2004	2004–2008	2008–2012	2000–2012	2000–2004	2004–2008	2008–2012	2000–2012
Shenyang	1.026	0.983	0.984	0.997	0.980	0.996	1.046	1.007
Dalian	1.000	1.000	1.000	1.000	1.027	1.072	0.983	1.027
Anshan	0.858	1.016	1.064	0.975	1.033	1.000	0.975	1.003
Fushun	1.017	1.004	1.007	1.010	0.977	1.000	1.046	1.007
Benxi	1.000	1.000	1.000	1.000	1.024	1.020	1.000	1.014
Dandong	0.964	1.020	1.033	1.005	1.033	1.002	0.982	1.006
Jinzhou	1.026	0.934	0.934	0.964	0.937	1.016	1.026	0.992
Yinkou	1.064	1.014	0.987	1.021	1.004	1.012	0.995	1.003
Fuxin	1.108	1.040	1.012	1.053	1.176	0.991	0.972	1.042
Liaoyang	0.931	0.999	0.968	0.966	0.935	0.998	1.056	0.995
Panjing	1.000	1.000	0.999	1.000	1.000	1.000	0.992	0.997
Tieling	1.037	1.000	0.886	0.972	0.973	0.965	1.059	0.998
Chaoyang	1.097	1.103	1.000	1.065	0.982	0.982	1.024	0.996
Huludao	1.038	0.976	0.997	1.003	0.980	1.020	0.991	0.997
Changchun	1.077	0.987	0.920	0.993	0.954	0.967	1.042	0.987
Jilin	1.021	0.988	0.951	0.986	0.932	1.005	1.033	0.989
Siping	1.171	1.000	0.912	1.022	0.975	0.956	1.068	0.998
Lioayuan	0.975	1.002	0.900	0.958	0.984	1.009	1.028	1.007
Tonghua	0.962	0.989	0.966	0.972	0.996	1.000	0.999	0.998
Baishan	1.000	1.000	1.000	1.000	0.969	1.031	1.000	1.000
Songyuan	1.154	1.015	1.000	1.054	0.976	0.981	0.974	0.977
Baicheng	1.039	1.054	0.925	1.004	0.968	0.992	0.997	0.986
Yanbian	0.947	1.015	0.994	0.985	1.030	0.997	0.982	1.003
Haerbin	1.000	1.000	1.000	1.000	0.990	0.917	1.002	0.969
Qiqihaer	1.041	1.067	0.915	1.006	0.965	0.890	1.055	0.968
Jixin	1.061	0.914	1.016	0.995	0.975	1.035	1.011	1.007
Hegang	1.011	0.994	0.994	1.000	0.941	0.970	1.008	0.972
Shuangyashan	1.162	0.882	0.994	1.006	0.981	1.017	1.004	1.001
Daqing	1.080	1.031	1.013	1.041	0.986	0.976	1.015	0.992
Yichun	1.044	1.000	1.000	1.014	1.023	1.000	1.000	1.007
Jiamusi	1.044	1.043	1.000	1.029	0.986	0.950	0.953	0.963
Qitaihe	0.993	0.977	1.010	0.993	1.047	1.051	0.940	1.011
Mudanjiang	1.062	1.049	1.000	1.037	1.009	1.003	1.044	1.018
Heihe	1.186	1.000	1.000	1.058	0.905	0.954	1.039	0.964
Suihua	0.999	1.019	1.000	1.006	0.980	0.966	1.017	0.987
Daxinganling	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000

doi: 10.17221/233/2014-AGRICECON

determine which changes in the input are necessary in order to increase the agricultural overall performance and profitability. The results displayed that, in average, a potential 20.6% reduction in the input use could be achieved provided that all cities operated efficiently. In general, the scale efficiency appears to be performing better than the technically efficient. The distribution of efficiency scores across the three study provinces showed that the cities located in the Heilongjiang province are the most technically efficient units now, and the cities located in the Liaoning province are the most scale efficient. Decomposition results of the Malmquist index indicated that the average productivity (MALM) growth at 8.0 percent annually over the entire period in the North-East China and the major source of growth was the technical change. In order to stimulate the productivity growth, more attention should be paid to improving the production efficiency. It was also found that the scale efficiency did not recover until in 2008–2012. It seems that the scale operation of agricultural land in recent years has promoted the growth of the scale efficiency. The rapid deterioration in the pure efficiency during the three sub-periods implies that polices should be enacted to increase the technical investment in agriculture, to strengthen the technical training for farmers, enhancing the rural research in agriculture. Regional disparity of the efficiency value indicated that the technical cooperation among cities should be developed and strengthened.

The DEA and Malmquist model are two popular methods to the calculation of the efficiency change. However, there are some shortcomings in this study. The Malmquist and DEA model have high requirements for the consistency and comprehensiveness of the data. Owing to objective factors, data sources of this study are from the Statistical Yearbook. Some indicators such as the agricultural labour time and other indicators are not included in the model. In the subsequent study, more attention should be paid to improving the data consistency and comprehensiveness of the indicators.

Acknowledgments

This work was supported by the National Natural Science Foundation of China (41571152, 41301111, and 41201159) and the Knowledge Innovation Program of the Chinese Academy of Sciences (KZCX2-YW-342, KZCX2-YW-321-04). We are grateful to Pujia Yu for his valuable comments on this manuscript.

REFERENCES

Alston J.M., Beddow J.M., Pardey P.G. (2009): Agricultural Research, Productivity, and Food Prices in the Long Run. Science, 325: 1209–1210.

Amor T.B., Muller C. (2010): Application of stochastic production frontier in the estimation of technical efficiency of irrigated agriculture in Tubisia. Agricultural Journal, 5: 50–56.

Banker R.D., Charnes A., Cooper W.W. (1984): Some models for estimating technical and scale inefficiencies in Data Envelopment Analysis. Management Science, 30: 1078–1092.

Bravo-Ureta B.E., Rivas T.E., Thiam A. (2001): A meta-analysis of technical efficiency in farming: a multi-country perspective. Available at http://www.ifmaonline.org/pdf/congress/Bravo-Ureta.pdf

Caves D.W., Christensen L.R., Diewert W.E. (1982): Multilateral comparisons of output, input, and productivity using superlative index numbers. Economic Journal, 92: 73–86.

Charnes A., Cooper W.W., Rhodes E. (1978): Measuring the efficiency of decision making units. European Journal of Operations Research, 2: 429–444.

Chavas D.R., Izaurralde R.C., Thomson A.M., Gao X.G. (2009): Long-term climate change impacts on agricultural productivity in eastern China. Agricultural and Forest Meteorology, 149: 1118–1128.

Chen P.C., Yu M.M., Chang C.C., Hsu S.H. (2008): Total factor productivity growth in China's agricultural sector. China Economic Review, 19: 580–593.

Chen Z., Huffman W.E., Rozelle S. (2009): Farm technology and technical efficiency: Evidence from four regions in China. China Economic Review, 20: 153–161.

Chen Z., Song S.F. (2008): Efficiency and technology gap in China's agriculture: A regional meta-frontier analysis. China Economic Review, 19: 287–296.

Coelli T. (1996): A Guide to DEAP Version 2.1: A Data Envelopment Analysis (Computer) Program. Available at http://www.une.edu.au/econometrics/cepawp.htm.

Färe R., Grosskopf S., Norris M., Zhang Z. (1994): Productivity growth, technical progress, and efficiency change in industrialized countries. American Economic Review, 84: 66–83.

Farrell J.M. (1957): The measurement of productive efficiency. Journal of the Royal Statistical Society, 120: 253–290.

Fried H.O. (2008): Effciency and production. In: Fried H.O., Lovell C.A.K., Schmidt S.S. (eds): Measurement of Productive Effciency and Productivity Growth. Oxford University Press, New York.

doi: 10.17221/233/2014-AGRICECON

Gallego F.J., Kussul N., Skakun S., Kravchenko O., Shelestov A., Kussul O. (2014): Efficiency assessment of using satellite data for crop area estimation in Ukraine. International Journal of Applied Earth Observation and Geoinformation, 29: 22–30.

Garnett T., Appleby M.C., Balmford A., Bateman, Benton I.J., Bloomer T.G.P., Burlingame B., Dawkins M., Dolan L., Fraser D., Herrero M., Hoffmann I., Smith P., Thornton P.K., Toulmin C., Vermeulen S.J., Godfray H.C.J. (2013): Sustainable intensification in Agriculture: Premises and Policies. Science, 341: 33–34.

Herrmann-Pillath C., Kirchert D., Pan J. (2002): Prefecture-level statistics as a source of data for research into China's regional development. The China Quarterly, 172: 956–985.

Hoang V.N., Coelli T. (2011): Measurement of agricultural total factor productivity growth incorporating environmental factors: A nutrients balance approach. Journal of Environmental Economics and Management, 62: 462–474.

Hu B.D., McAleer M. (2005): Estimation of Chinese agricultural production efficiencies with panel data. Mathematics and Computers in Simulation, 68: 475–484.

Jaime M.M., Salazar C.A. (2011): Participation in organizations, technical efficiency and territorial differences: a study of small wheat farmers in Chile. Chilean Journal of Agriculture Research, 71: 104–113.

Kolawole O. (2009): A meta-analysis of technical efficiency in Nigerian agriculture. In: International Association of Agricultural Economists 2009 Conference, August, 16–22, Beijing: 1–24.

Liu X.W., Chen B.M. (2007): Efficiency and sustainability analysis of grain production in Jiangsu and Shaanxi Provinces of China. Journal of Cleaner Production, 15: 313–322.

Liu Z.N., Zhuang J.Z. (2000): Determinants of technical efficiency in post-collective Chinese agriculture: Evidence from farm-level data1. Journal of Comparative Economics, 28: 545–564.

Ma S.Z., Feng H. (2013): Will the decline of efficiency in China's agriculture come to an end? An analysis based on opening and convergence. China Economic Review, 27: 179–190.

Manjunatha A.V., Anik A.R., Speelman S., Nuppenau E.A. (2013): Impact of land fragmentation, farm size, land ownership and crop diversity on profit and efficiency of irrigated farms in India. Land Use Policy, 31: 397–405.

Mao W.N., Koo W.W. (1997): Productivity growth, technological progress, and efficiency change in Chinese agriculture: A DEA approach. China Economic Review, 8: 157–174.

Monchuk D.C., Chen Z., Bonaparte Y. (2010): Explaining production inefficiency in China's agriculture using data envelopment analysis and semi-parametric bootstrapping. China Economic Review, 21: 346–354.

Ogundari K. (2014): The paradigm of agricultural efficiency and its implication on food security in Africa: What does meta-analysis reveal? World Development, 64: 690–702.

Ogundari K., Amos T.T., Okoruwa V.O. (2012): A Review of Nigerian agricultural efficiency literature, 1999–2011: What does one learn from frontier studies? African Development Review, 24: 93–106.

Tan S., Heerink N., Kuyvenhoven A., Qu F. (2010): Impact of land fragmentation on rice producers technical efficiency in South-East China. Wageningen Journal of Life Sciences, 57: 117–123.

Tao F.L., Yokozawa M., Zhang Z., Xu Y.L., Hayashi Y. (2009): Remote sensing of crop production in China by production efficiency models: models comparisons, estimates and uncertainties. Ecological Modelling, 183: 385–396.

Thiam A., Bravo-Ureta B.E., Rivas T. (2001): Technical efficiency in developing country agriculture: a meta-analysis. Agricultural Economics, 25: 235–243.

Tong H.Z., Fulginiti L.E., Sesmero J.P. (2009): Chinese Regional Agricultural Productivity: 1994–2005. Available at http://digitalcommons.unl.edu/cgi/viewcontent.cgi?article=1009&context=ageconfulginiti

V. Ndlovu P., Mazvimavi K., An H., Murendo C. (2014): Productivity and efficiency analysis of maize under conservation agriculture in Zimbabwe. Agricultural Systems, 124: 21–31.

Wang W.G., Li R.Z., Song Y.X., Wang F. (2012): The various components of agricultural land production efficiency in Jilin Province, China. Scientia Geographica Sinica, 32: 25–231.

Received: 15th December 2014
Accepted: 20th January 2015

Contact address:

Pingyu Zhang, Northeast Institute of Geography and Agroecology, Chinese Academy of Sciences, 4888 Shengbei Street, Changchun 130102, Jilin, China
e-mail: liushiwei@iga.ac.cn, zhangpy@iga.ac.cn