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Marginal revenue of land and total factor productivity in Chinese agriculture:
Evidence from spatial analysis

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Abstract: This paper attempts to explore the temporal and spatial nature of the marginal revenue of land, total factor productivity (TFP) change and its three components: technical change (TC), technical efficiency change (TEC) and scale efficiency change (SEC) as seen in Chinese agricultural production from 1995 to 1999. Based on county-level data, the study utilized both stochastic frontier and mapping analyses methods. The results show that growth in the marginal revenue of land was diverse across various regions, where most gain occurred in eastern coastal zone, while loss was in Northwest and North China. China has experienced moderate decreases in annual TFP change (–0.26%) with considerable regional variations. Specifically, the administrative intervention in grain production and the deterioration of the agricultural technology diffusion system led to a moderate drop in annual TFP change. County-level mapping analyses took into account interregional variances in TFP and its components. Regarding components of TFP, TEC differences explain the majority of regional dispersions in TFP. As developed areas in China, the Huang-Huai-Hai region and the Beijing-Tianjin-Tangshan economic zone face the challenges of land conversion and grain security amidst the process of urbanization.

Keywords: TFP change; grain production; technology efficiency change; Chinese agriculture

1 Introduction

Marginal revenue of land and total factor productivity (TFP) are widely cited as the indexes to investigate changes in agricultural production (Lin, 1992; Tian and Wang, 2000; Deng *et al*., 2010a; Jin *et al*., 2010). Marginal product of land, which measures contribution to agricultural output from land, can be treated as shadow value of land. Shadow value of land is

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highly correlated with output from agricultural production, and thus it can capture the aggregate impacts of urbanization and other factors on agriculture. The decomposition of TFP change is of policy implications targeted to improve technical and scale efficiency, as well as update technology. These, in turn, secure agricultural production and increase farmers' income. In areas with less developed economy and high population pressure, TFP plays a key role for development of agricultural production in China (Huang and Rozelle, 1995; Fan, 2002; Deng *et al*., 2010b). Liu and Wang (2005) found that technical progress accounted for 58% of total growth during 1991–1999.

The earlier studies documented that there exists substantial variation in the components of TFP by administration, location (the eastern, the central and the western regions), ecological zones or grain yield, respectively (Fan, 1991; Wu, 1995; Zhang and Carter, 1997; Liu *et al*., 1998). Using provincial level data, Lin (1991) provided the evidence that agricultural growth is achieved via labour-saving technology or land-saving technology. Some other researchers employed household panel data to explore the agricultural output growth in various locations (Huang and Kalirajan, 1997; Liu and Zhuang, 2000). Their results also found that agricultural productivity and its components followed the dissimilar growth pattern and spatial variations were observed across the selected provinces. Both sets of studies are subject to limitations. On the one hand, those based on the provincial level data potentially hid the spatial variation of output growth within the province. Therefore, the policy implications based on the provincial- or regional-level studies may not necessarily be appropriate at lower administrative level (Cho *et al*., 2007; Chen and Song, 2009). On the other hand, analyses based on household survey arouse the question of generalizing its findings and policy implication to a county or even provincial level. Furthermore, the household survey, which only presents the profile of the sampled households, can not explicitly capture the phenotype of the population within and across the obviously different economic and social location.

This paper aims to investigate the temporal and spatial nature of marginal revenue of land, TFP change and its three components in Chinese agriculture over 1995–1999 (Brümmer *et al*., 2006). The rest of the article proceeds as follows. Section 2 presents the econometric model used to estimate efficiency in agricultural production. Section 3 defines main variables and describes the dataset. After specifying Cobb-Douglas form of production function, we calculate marginal product of land and examine the spatial pattern of it in section 4.1. In section 4.2, we firstly explore the trend in TFP growth and its components. Then we explain why TFP change and its components declined in the late 1990s. We also implement mapping analysis of spatial features of TFP change and its components. The last section serves as conclusions.

2 Econometric model

2.1 Estimation of production function

A stochastic frontier model which has an error term with two components (one represents random errors and the other controls for technical inefficiency effects) can be expressed as follows to measure the agricultural production in China:

$$Y_{it} = f(X_{it}, t; \beta) \cdot e^{(v_{it} - u_{it})} \tag{1}$$

where Y_{it} denotes the output quantity for the i-th county at the t-th time period; X_{it} denotes a vector of input quantity for the i-th county at the t-th time period; β is an unknown parameter vector associated with the X-variables to be estimated; v_{it} s are a two-sided random-noise component assumed to be i.i.d. $N\left(0, \sigma_v^2\right)$ and u_{it} s are a non-negative technical inefficiency component. The v_{it} and u_{it} are distributed independently of each other, and of the regressors. The non-negative technical inefficiency component u_{it} is assumed to follow a half normal distribution $N^+\left(0, \sigma_u^2\right)$, and is defined by some appropriate inefficiency model (Battese and Coelli, 1992).

2.2 The Cobb-Douglas production function

To calculate marginal product of land, the function in equation (1) takes logarithmic Cobb-Douglas form:

$$\ln Y_{it} = \beta_0 + \sum_{n=1}^{N} \beta_n \ln X_{nit} + \beta_t t + v_{it} - u_{it} \tag{2}$$

$$TE_{it} = \exp\{-u_{it}\} \tag{3}$$

The appropriate models are estimated using Stata 10.0 program. Maximizing the log-likelihood function of the model by applying the Newton-Raphson method, the estimated results provide the direct information on σ_u, σ_v, $\lambda = \sigma_u / \sigma_v$ and $\sigma^2 = \sigma_u^2 + \sigma_v^2$. Hypothesis tests regarding the structure of production technology, such as the presence of technical inefficiency effects represented by u_{it}, are also reported via likelihood ratio (LR) test. If the null hypothesis of σ_u=0 can not be rejected at the traditionally statistical accepted level, which implies no technical inefficiency effects (u_{it}) are observed in the data, the model is equivalent to the average response function, in which the parameters can be efficiently estimated by ordinary least squares (Coelli *et al.*, 2005).

2.3 The Translog production function

Following Battese and Coelli (1992), the stochastic production frontier model takes the log-quadratic Translog functional form under a non-neutral TC assumption as follows:

$$\begin{aligned} \ln Y_{it} = {} & \beta_0 + \sum_{n=1}^{N} \beta_n \ln X_{nit} + \frac{1}{2} \sum_{n=1}^{N} \sum_{m=1}^{N} \beta_{nm} \ln X_{nit} \ln X_{mit} \\ & + \sum_{n=1}^{N} \beta_{nt} \ln X_{nit} \cdot t + \beta_t t + \frac{1}{2} \beta_{tt} t^2 + v_{it} - u_{it} \end{aligned} \tag{4}$$

$$TE_{it} = \exp\{-u_{it}\}\ . \tag{5}$$

where $m, n = 1, ..., N$ are index different inputs and u_{it} s are non-negative random variables which are assumed to account for technical inefficiency in production. Young's theorem requires that the symmetry restriction is imposed so that $\beta_{nm} = \beta_{mn}$ for all $m, n = 1, 2, 3, 4$.

Given functional and distribution assumptions, the values of the unknown estimators in equation (4), i.e., β s, η s, σ_u^2 and σ_v^2 can be obtained jointly using the maximum likelihood method (ML) (Battese and Coelli 1995). An estimated value of the output-orientated TE for the i-th producer at the t-th time period can then be calculated in expression as: $TE_{it} = \exp\{-u_{it}\}$.

TFP growth is theoretically defined as the growth rate of total output which cannot be explained by the growth rate of total inputs. To help understand the forces that affect the growth of TFP in a given economy, conceptually, TFP growth can be measured as the sum of three components—technical change (TC); changes in technical efficiency (TEC) and changes in scale economies (SEC) (Brümmer *et al.*, 2006; Wang and Rungsuriyawiboon 2010; Zhang and Brümmer 2011). The TC component means the expansion of output vector for a given input vector, given that all producers are producing along the frontier function; that is the frontier itself shifts. The TEC component (when it is positive) explains the "catching-up" part of the TFP growth with producer's getting closer to the frontier. In other words, given a specific production frontier, TEC occurs when output increases keeping inputs constant due to more efficient using of input. Finally, the SEC component represents the TFP growth due to the contribution of the scale of economy through choosing the optimal production scale. Better understanding which and to what extent the components driving or retarding TFP growth will help making the more feasible policy responses in achieving greater rates of TFP growth and then the production targets.

Following Orea (2002), a measure of TFP growth for each producer between any two time periods can be calculated by using the estimates of the coefficients of the stochastic frontier and the producer-level sample data. The logarithmic form of the TFP growth between period t and $t+1$ for the i-th producer is defined as

$$\begin{aligned}\ln\left(\frac{TFP_{it+1}}{TFP_{it}}\right) &= \ln\left(\frac{TE^*_{it+1}}{TE^*_{it}}\right) + \frac{1}{2}\left[\frac{\partial \ln f(X^*_{it+1},t;\beta^*)}{\partial t} + \frac{\partial \ln f(X^*_{it},t;\beta^*)}{\partial t}\right] \\ &+ \frac{1}{2}\sum_{n=1}^{N}\left[\left(SF^*_{it+1}\cdot E^*_{nit+1}\right)+\left(SF^*_{it}\cdot E^*_{nit}\right)\right]\left(\frac{\ln X^*_{nit+1}}{\ln X^*_{nit}}\right),\end{aligned} \tag{6}$$

where the three terms on the right-hand-side of equation (6) represent the output-oriented TEC, TC and SEC, respectively.

The output-orientated TE measure $\left(TE^*\right)$ in equation (6) is the output-orientated TE prediction of the i-th producer in the t-th time period, and is calculated from equation (4). The TC measure $\left(TC_{itt+1}\right)$ is the mean of the TC measures evaluated at the period t and period t+1 data points. The SEC measure $\left(SEC_{itt+1}\right)$ relates to the change in scale efficiency, which requires calculation of the scale factor (SF) and input elasticity (E_n) evaluated at the period t and period t+1 data points. The SF of the i-th producer in the t-th time period $\left(SF^*_{it}\right) = (E^*_{it}-1)\big/E^*_{it}$ where $E^*_{it} = \sum_{n=1}^{N} E^*_{nit}$ represents the scale elasticity and $E^*_{nit} = \partial \ln f(X^*_{it},t;\beta^*)\big/\partial \ln X^*_{nit}$ is production elasticity for the n-th input.

3 Data source

National Bureau of Statistics of China publicly reports the county-level social-economic statistics, covering 2177 counties in rural China (except those in Taiwan). This dataset also contains the measurement of agricultural production performance by including the aggregated value of agricultural output and various inputs with the years of 1995 and 1999. With carefully concerning administrative boundary changes over time and clarifying the missing data, 1924 counties within 4 municipalities, 4 autonomous regions and 22 provinces, remain in the analysis. The 253 counties are excluded from the study because one or more statistics are not recorded in either 1995 or 1999. In order to decompose TFP growth, the dataset should be kept as a two-year balanced panel data. By drawing the tempera map of the county, we find that agricultural production is likely not the main sector in the local economy of the missing counties or the excluded counties are mainly located in the very sparsely populated region in Tibetan Plateau, like Tibet and Qinghai provinces. Due to the altitude and the input factor endowment, agricultural production in Tibetan Plateau would follow the different production frontiers from those in other provinces (Chen and Song 2008).

The total population recorded for the 1924 counties reporting the relevant data was 949.801 million in 1999, representing 75.43% of the total population. The administrative areas of all the counties are around 7.097 million km^2, projecting to three quarters of areas in China. Table 1 presents descriptive statistics of dependent and independent variables in detail.

Table 1 Descriptive statistics of agricultural production at the county level

Variable	Symbol	Unit	Mean	Std. Dev.
Gross output value of agriculture	Value	Ten thousand yuan	62307	50923
Sown land	Land	Hectare	70625	50368
Agricultural laborers	Labor	Person	151021	111571
Machinery power	Capital	Kilowatt	188139	182789
Chemical fertilizer	Fertilizer	Ton	17918	17197

Dependent variable

The dependent variable used in this study is the *gross output value* normalized at 1995 constant price, which aggregated the output value of grain crops, cash crops, and fruits, the added value of forestry, animal husbandry and fishing production. It is constructed from the quantity of the physical output and the unit price of each output in each year. Since a large fraction of *gross output value* came from crop output (mainly grain crops and cash crops) in most counties, indicating high correlation between these two variables, *gross output value* is taken as proxy for crop output (Cho *et al*., 2007; Chen and Song, 2008).

Independent variables

Due to limitations of the data series in the original dataset, four kinds of physical input factors, which perfectly match the definition of the dependent variable, are included in this study. The independent variables are defined as follows:

Land refers to the sown land in hectare, which is the best measure of land under cultivation in China with considering the important farming pattern of multiple cropping. In China, especially in the Middle-Lower Yangtze River Valley, South and Southwest China, some of the cultivated area is cultivated more than once in a year whereas multiple cropping index (MPI) is greater than one (Lin, 1992). Thus, the sown land reflects the effective usage of the cultivated land in agricultural production.

Labor denotes the number of total rural labors who are directly engaged in farming, forestry, animal husbandry and fishery for each county at each year. Though several studies concludes that the surplus labor input is rooted in Chinese agricultural production (Xu, 1999), it is best thought of as a measure of the number of laborers in the agricultural sector.

Capital refers to the energy input, mainly mechanical power, applied in the annual agricultural production as the proxy of capital input in the unit of kw (Fan, 1991; Lin, 1992). The mechanical power also includes those used in forestry, animal husbandry and fishery.

Chemical fertilizer measures the pure-content quantity of chemical fertilizers, which is calculated to convert the gross weight of quantity used in annual agricultural production into weight containing 100% of effective components. The unit of chemical fertilizer is kg.

To investigate the spatial and temporal features of input and output factors and TFP growth in Chinese agricultural production, the key step is to match the SSB statistics with the county ID in the county GIS (Geographical Information System) boundary file. The merged datasets facilitate us to graphically illustrate the spatial analysis of agricultural production, especially marginal product of land, TFP and its components of TEC, TC and SEC.

4 Results and analysis

4.1 The equation of marginal product of land

Table 2 presents the maximum likelihood coefficients estimates under Cobb-Douglas and Translog specifications whereas the data variables used in the model estimation are each transformed by dividing by their respective geometric means. The null hypothesis of no technical inefficiency σ_u=0 is rejected in the two equations at the 1% significant level, and thus it points to the conclusion that technical inefficiency does exist in Chinese agricultural production. The results of Cobb-Douglas are presented here to compare with the other study that spatially analyzes input-output elasticity by only using Cobb-Douglas production (Cho *et al*., 2007).

The marginal revenue product can be derived from estimators from Table 2. The Cobb-Douglas specification of the production function produces the coefficients for inputs, which are elasticity for the coefficients. The marginal product of land for each county is calculated in two steps: first, the average output value per hectare of land is calculated by dividing the total output value of county production by the total land; secondly, marginal product of land is obtained from the product of the average revenue product of land times the coefficient in Table 2.

Figure 1a-c presents the difference in marginal product of land between 1995 and 1999, the marginal product of land in 1995 and 1999, respectively. It is obvious that most areas experience modest growth in marginal product of land except Xinjiang. Some areas in Inner Mogolia and Heilongjiang saw considerable drop in marginal product of land (Figure 1a). The beneficial regions are clustered in the eastern coastal zone.

Urbanization is the main contributor to improvement in marginal product of land. The

Table 2 Estimated coefficients of stochastic frontier functions

	Cobb-Douglas function		Translog function	
Variables	Coefficients	Z-value	Coefficients	Z-value
Constant	0.2258**	(15.31)	0.1510**	(9.48)
Ln(Land)	0.1408**	(7.92)	0.1249**	(6.21)
Ln(Labor)	0.2437**	(17.84)	0.2472**	(15.50)
Ln(Capital)	0.2609**	(23.67)	0.1843**	(16.20)
Ln(Fertilizer)	0.2377**	(20.21)	0.3714**	(25.85)
t	0.0019	(0.13)	0.0027	(0.19)
0.5Ln(Land)× Ln(Land)			0.1591**	(3.67)
Ln(Land)×Ln(Labor)			–0.1682**	(–5.95)
Ln(Land)×Ln(Capital)			–0.1027**	(–4.01)
Ln(Land)×Ln(Fertilizer)			0.0852**	(3.75)
0.5Ln(Labor)×Ln(Labor)			0.1432**	(5.40)
Ln(Labor)×Ln(Capital)			0.0849**	(3.98)
Ln(Labor)×Ln(Fertilizer)			–0.0416*	(–2.03)
0.5Ln(Capital)×Ln(Capital)			0.0314	(1.71)
Ln(Capital)×Ln(Fertilizer)			–0.0390*	(–2.29)
0.5Ln(Fertilizer)×Ln(Fertilizer)			0.0673**	(4.35)
Ln(Land)×t			0.0115	(0.33)
Ln(Labor)×t			0.0286	(1.08)
Ln(Capital)×t			–0.0714**	(–3.32)
Ln(Fertilizer)×t			0.0177	(0.77)
0.5t×t			0.0000	(.)
σ_v			0.3810**	(55.22)
σ_u			0.1958**	(15.25)
σ^2	0.2058**	(41.89)	0.1835**	(41.38)
λ	0.4743**	(25.33)	0.5141**	(28.53)
Wald χ^2	12883.38(5)		14726.38(19)	
Log likelihood	–2419.9468		–2193.4286	
Observation	3848		3848	

Note: Z-statistics are given in parentheses. ** and * denote statistically different from zero at 1% and 5% significant level, respectively.

villages close to urban areas have advantage of proximity to market. Farmers who have the use right of these lands can plant high value-added varieties, for example, vegetables to supply urban residents. Thus, urbanization enhances marginal product of land. Our results reveal this pattern, in which lands with higher marginal product are located across eastern developed zone (Figure 1a-c).

Systematic drop in marginal product of land in Northwest China, especially in Xinjiang, might reflect variation in down-stream product market. It is notable that textile sector shrank a lot in the late 1990s. Consequently, the demand for cotton declined and price of cotton decreased accordingly. Since cotton is the most popular crop in this area, farmers' revenue decreased due to the shock in textile sector.

4.2 Decomposition of TFP change

Table 3 shows the average annual change in TFP, TC, TEC and SEC over the period

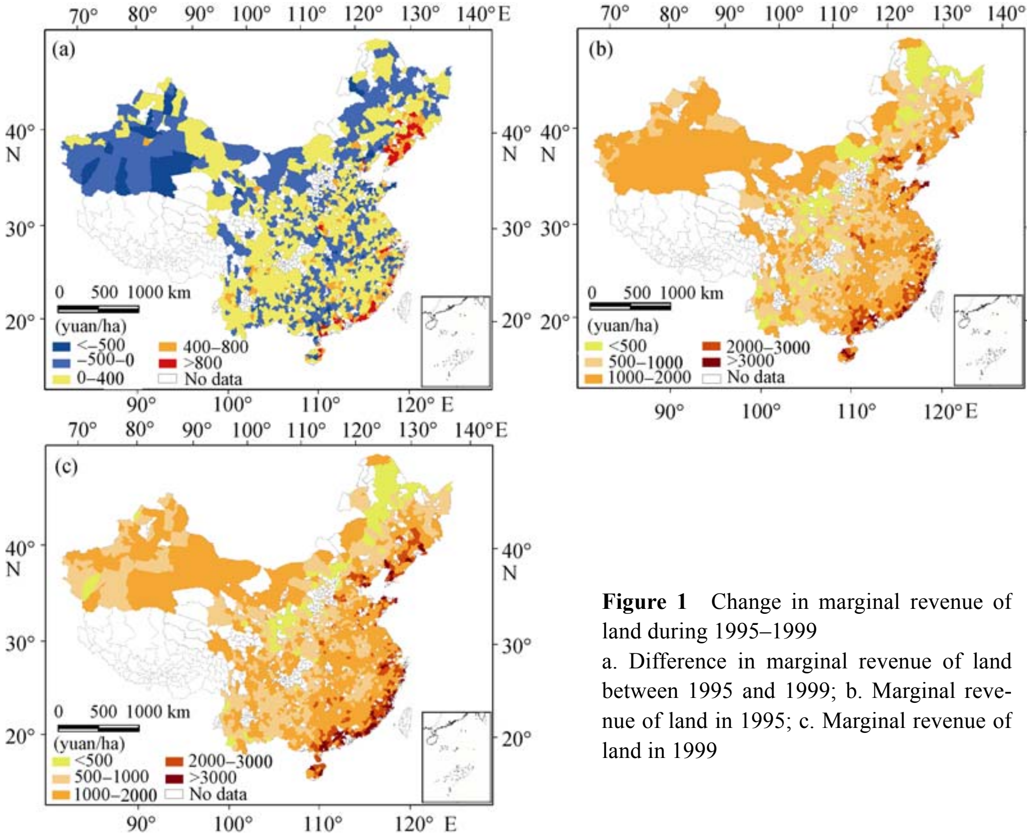

Figure 1 Change in marginal revenue of land during 1995–1999
a. Difference in marginal revenue of land between 1995 and 1999; b. Marginal revenue of land in 1995; c. Marginal revenue of land in 1999

Table 3 Averagely annual growth of TFP change and its decomposition by regions

Region	TFP change (%)	TC (%)	TEC (%)	SEC (%)
North	–1.68	–0.04	–1.13	–0.51
Northeast	–0.50	0.08	–0.31	–0.27
East	–0.29	–0.10	–0.13	–0.06
South	0.17	0.07	0.26	–0.17
Southwest	0.89	0.08	1.14	–0.34
Northwest	–0.84	–0.33	0.11	–0.62
Total	–0.26	–0.04	0.07	–0.29

Note: Results are calculated by authors.

1995–1999 by regions. China, as a whole, witnessed a slight TFP decline (–0.26%) mainly due to SEC drop (–0.29% per year). This estimate is consistent with Chen *et al*. (2008), who found that the pure efficiency deteriorated prior to 1999. At regional level, Table 3 shows that Southwest China gained 0.89% annually average growth of TFP, and the growth of TFP is mainly driven by the growth of TC (1.14%). North China experienced the largest decrease in TFP (–1.68%) (mainly due to the drop of TC at 1.13% per year).

The change in TFP and its components during the period can be attributed to institutional reform at national or provincial level. In 1995, the liberalization of agriculture was impeded. The central government restored to administrative intervention in grain production and sales because of grain prices spike, which was caused by a large shortage in grain supply (Lin, 1997). This rigorous administration was relaxed until 1999. Another reason behind the change of TFP might be agricultural technology extension system. As Jin (2010) argued, fall in efficiency during the 1990s was partly induced by the deterioration of the extension system. These institutional changes jointly accounted for large TFP loss during 1995–1999.

SEC, TC and TEC played different roles in TFP changes in different regions over the study period. SEC decreased in all of the regions during 1995–1999 (Table 3). Overuse of input and low growth in output led to moderate SEC decline over 1995–1999. Rapid input increase, especially fertilizer, has been recorded by researchers (Huang *et al*., 2003). TC across all the regions appeared to be fairly stable over the period. However, TEC varied largely in North (–1.13%) and Southwest China (1.14%); which implies that farmers are different in exploitation of the available agricultural technology across regions. It should be noted that TEC has the same sign as TFP change except for Northwest China. The ratio of TEC over TFP, which is calculated by dividing TEC (Table 3, column 4) over TFP (Table 3, column 2), ranges from 0.45 to 1.53 in all regions with the exception of Northwest China. This suggests that TEC difference is the dominant source of regional differentiation in TFP.

4.3 Mapping analysis of spatial pattern in TFP and its components

Previous studies on spatial analysis usually compared mean of TFP and its components at provincial or larger regional level. These kinds of comparison neglected within-region variance of TFP and its components (Fan and Zhang, 2002; Chen and Song, 2009; Ito, 2010). Figure 2a-d provides county-level TFP, TC, TEC and SEC growth respectively. The maps of these changes in TFP, TC, TEC and SEC allow us to investigate details in within-region spatial characteristics, as well as between-region patterns. In line with pattern revealed by regional mean (Table 3), the annual TFP growth and its components, TC and SEC, follow a pattern of spatial contagion, in which zones with higher growth or lower growth are clustered together (Figure 2a-d). Furthermore, between-region disparity in these indexes is less than within-region disparity. These correlations within regions reveal that common driving force at provincial or regional levels determines agricultural production.

The TFP change (Figure 2a) shows considerable heterogeneity across regions, relatively consistent with regional mean (Table 3). The highest TFP progress lies in Southwest, Northeast China (Jilin) and part of South China (Jiangxi), where TFP growth in adjacent counties kept nearly at the same level. Notably, the Huang-Huai-Hai Plain suffered a large drop in TFP growth over 1995–1999. In line with Yan *et al*. (2009), they found that cropland shrank widely in the 1990s in the Huang-Huai-Hai Plain. The findings that increase in TFP growth was coupled with increase in marginal revenue of land, verified our judgment that growth in output originated from addition of input, not efficiency gain. Since this region has been traditional “bread basket” for China, the implicit meaning of TFP loss to food security needs to be taken into account by policy maker.

The largest TC drop happened in the Huang-Huai-Hai Plain and Beijing-Tianjin-Tangshan economic zone while other area only saw a slight change (Figure 2b), indicating that TC is not a big contributor to change in TFP. As the developed area in China, agriculture faced various problems rendered by industrialization in these two areas. For example, manufacture and service sector competed for labor from rural area, causing labor shortage in agriculture. Most importantly, land transition induced by urbanization took much cropland from farmers (Yan *et al*., 2009).

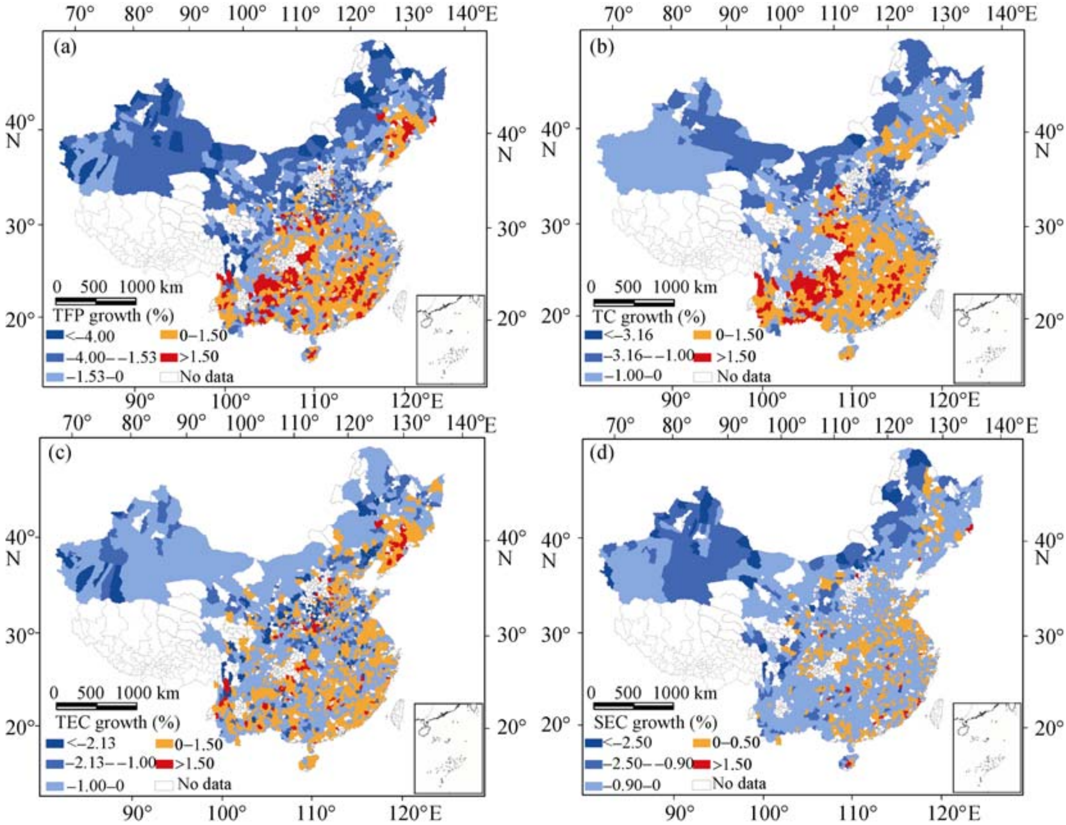

Figure 2 Spatial distribution of annual TFP (Total factor productivity) growth and its components, annual TC, TEC and SEC during 1995–1999
a. Annual TFP growth; b. Annual TC growth; c. Annual TEC growth; d. Annual SEC growth

Conflicted with pattern reflected by regional mean (Table 2), TEC in Northeast China followed the spatial pattern of large dispersion, in which tracts of land with high growth rate were separated by counties with drop in TEC (Figure 2c). This verifies our concern that researchers prior to us might reach weak conclusion of regional pattern without consideration of within-region variance. Limited by data, it is hard to find reasonable interpretation to this strange pattern in this study. But Deng *et al*., (2006) reported that large tracts of unused wetland and unused barren land were converted to cultivated land in Northeast China over 1986–2000. Difference in area of converted land might lead to dispersion in TEC in Northeast China.

In concordance with the pattern in Table 3, the negative effects of SEC were evenly distributed nationally during this period (Figure 2d). The deterioration in annual SEC during the 1995–1999 period signals that many counties moved to a less optimal input–output point due to over-use of input.

5 Conclusions

This paper explores the temporal and spatial nature of marginal revenue of land, TFP growth and its three components in Chinese agriculture over the period 1995–1999 using stochastic frontier analysis (SFA) method and mapping analysis. Marginal revenue of land took on spatial diversity, in which eastern coastal zone gained but Northwest China, especially Xinjiang, witnessed considerable loss. Nationally, average annual growth of TFP, TC and SEC saw moderate drop during the study duration. From regional perspective, Southwest China, as the region with maximum TFP changes, experienced 0.89% of annually average gain in TFP. Meanwhile, North China emerged as a region with largest decrease in TFP (–1.68%). County-level mapping analysis of TFP and its components shows that researches prior to ours might be misleading in regional pattern without consideration of within-region variance. Especially, annual growth of TEC in Northeast China followed the spatial pattern of large dispersion within region.

Specifically, administrative intervention in grain production, as well as deterioration of agricultural technology diffusion system, accounted for moderately annual drop in TFP over 1995–1999 at national level. As Figure 2a-d shows, the spatial homogeneity in TFP growth within region indicates that some common factors, for example, urbanization or land conversion, played vital role in evolution of agricultural production. Among components of TFP, difference in TEC explained majority of regional variation in TFP. The negative sign of SEC across all regions signals that overuse of input, for instance, fertilizer, caused scale inefficiency in agricultural production.

The annual TFP growth and its components, TC and SEC, follow a pattern of spatial contagion. In addition, worsening of TFP and TC in the Huang-Huai-Hai Plain and Beijing-Tianjin-Tangshan economic zone, coupled with increase of marginal revenue of land, indicates that output in these areas are attributed to input expansion, not efficiency gain. A caveat we want to address is that, how to balance urbanization, land conversion and grain security issues in these areas calls for further investigation.

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