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Full Length Research Paper

Total factor productivity growth and convergence in Northern Thai agriculture

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The paper estimates Total Factor Productivity (TFP) growth in six agro-economic zones of Northern Thailand covering a 23 year period (1977 to 1999) and tests convergence amongst regions using a stochastic production frontier approach. Results revealed that all the inputs excluding fertilizer significantly contribute to agricultural productivity. Increasing returns to scale prevail in these regions. Land, labor, irrigation and loan capital have substitution relationships but all are within the inelastic range. The mean technical efficiency level is low (0.88). The overall TFP declined slightly due to technical regress and modest improvement in technical efficiency change over time. However, convergence in productivity has been reached in all regions towards the end. The government's initiative to support investment through Bank of Agriculture and Agricultural Cooperative loan had a significant influence on technical efficiency improvements. Policy implications include provision of capital through loan, investments in irrigation, and proper functioning of land and labor markets to improve agricultural productivity.

Key words: Thailand, stochastic production frontiers, total factor productivity growth, convergence, technical efficiency change, technical change, agro-economic zone.

INTRODUCTION

Agricultural productivity and efficiency improvements have been the priority concern of the government in developing countries due to severe pressure imposed by declining agricultural prices as well as, prevailing highly competitive trade environment. Therefore, performance evaluation of the agricultural sector at the national, regional or provincial level is important for policy planning. Given the unprecedented food crisis in recent years, the importance of measuring performance of the agricultural sector became a topmost priority of many developing economies in order to ensure food security of its growing population base.

Traditionally, the rice industry has played an important role in the Thai economy by supplying main staple food, employing a large portion of the labor force, and contributing towards government revenue and foreign exchange earnings (Choeun et al., 2006). Thailand has experienced high rate of growth in agricultural sector over the past four decades mainly through expansion of areas (for example, by clearing forests) which however, cannot be continued from the 1990's onward (Krasachat, 2001). As a result, government promoted the use of modern inputs such as fertilizers and irrigation facilities to boost agricultural productivity. Nevertheless, the policy makers and economists have raised questions on the impact of modern input usage as well as, the availability of new lands on productivity growth of the Thai agricultural

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sector (Krasachat, 2001).

Studies on Total Factor Productivity (TFP) growth of Thai agriculture are highly limited. So far, only a few studies are available, perhaps largely due to data limitations but are characterized with similar overall conclusions. Luh et al. (2008) analyzed TFP growth using a DEA approach jointly for eight East Asian economies including Thailand using national level aggregate data for the period of 1961 to 2001. They concluded that the agricultural productivity in Thailand has deteriorated largely due to technical regress which in turn had a dominating effect on the improvement in technical efficiency. Although, this study provides a detailed examination of TFP growth in Thailand, the limitation in the study of Luh et al. (2008) is that the performance of Thailand is measured in relation to a multi-country production frontier. Therefore, intra-provincial or regional performance cannot be identified due to aggregate nature of the data. Suphannachart and Warr (2010) used national aggregate data for the period of 1970 to 2006 and measured agricultural TFP using the growth accounting method and concluded that TFP in crop sector grew at an annual rate of 0.68%. The obvious problem with this study is the limited number of observations (that is, only 36 observations) and the inability to provide information on TFP growth components as well as, results at a lower level of aggregation, that is, at the provincial or regional level. Krasachat (2001) estimated productivity growth for four agricultural regions of Thailand over a 22 year period of (1972 to 1994) using a cost function framework which implies perfect efficiency of production units, and therefore, inherently biased. This is because it is a common knowledge that developing country agriculture operates with considerable low level of technical efficiency ranging from 72.4 to 84.5% (Bravo-Ureta et al., 2007). Krasachat (2001) concluded that the TFP index declined at an annual rate of -0.4% partly explained by low level of technical progress, which in turn is biased towards saving labor, fertilizer and capital. Finally, Krasachat (2000) applied a DEA approach to measure technical efficiency change in Thai agriculture using the same dataset and concluded that technical efficiency has been very low in general, and there has been a decline in all types of efficiency (that is, overall technical efficiency, scale efficiency and pure technical efficiency) over time.

In this study, we select a panel-data of six Agro-economic Zones (AEZs) of Northern Thailand (covering 17 provinces) for a 23 year period (1977 to 1999) to: (a) measure agricultural TFP growth and its components: technical change and technical efficiency change; and (b) test for the existence of convergence in agricultural productivity amongst regions. We applied the stochastic production frontier approach in order to circumvent some of the inherent problems of DEA methodology used by Krashachat (2000) and Luh et al. (2008) as well as, to examine whether similar results hold for the Northern part of Thailand, which is essentially the most productive region of the country. The parameters of the stochastic frontier provide estimates of the changes in technical efficiency and technical progress as well as, TFP allowing policy implications to be inferred (Coelli et al., 2003).

METHODOLOGY

Stochastic production frontier

Since one of the objectives of this study is to estimate technical efficiency of these AEZs in Northern Thailand, we applied the stochastic production frontier method as proposed by Aigner et al. (1977). The stochastic frontier production function for panel data can be written as:

$$Yit = \exp(xit\beta + Vit - Uit) \qquad (1)$$

Where Yit is production in year t (t = 1, 2, …, 31) for region i (i = 1, 2, ….., 16);

β is the vector of parameters to be estimated;

Vits are the error component and are assumed to follow a normal distribution N (0, σ2v);

Uits are non-negative random variables, associated with technical inefficiency in production, which are assumed to arise from a normal distribution with mean, μ and variance, σ2u, which is truncated at zero.

The model used here incorporates a simple exponential specification of the time-varying inefficiencies, following Battese and Coelli (1995). The technical efficiency of production for the ith region at the tth year can be predicted using Equation 2 (Coelli et al., 1998):

$$TEit = E[\exp(- Uit)|(Vit- Uit)] \qquad (2)$$

Measuring productivity change

Productivity change occurs when the rate of change in output differs from the rate of change in the use of an index of inputs (Kumbhakar and Lovell, 2000). TFP can be measured by constructing the Malmquist productivity index, a measure of TFP of a unit based on the ratio of total output quantity to an index of all input quantities. Unlike partial productivity measures (simple output/input ratios), TFP provides an overall measure of productivity (Helvoigt and Adams, 2009). Given the measure of TEit in Equation 2, technical efficiency change (ECit) is then calculated as:

$$ECit = TEit/TEis \qquad (3)$$

An index of technological change (TCit) between two adjacent period s and t for the ith region can be directly calculated from the estimated parameters of the stochastic production frontier. The partial derivatives of the production function are evaluated with respect to time at xit and xis. We then converted these into indices and calculated their geometric mean. Following Coelli et al. (1998, 2003), the calculation of the technical change index is given as:

$$TC_{it} = \left\{ \left[1 + \frac{\partial f(x_{is}, s, \beta)}{\partial s} \right] \times \left[1 + \frac{\partial f(x_{it}, t, \beta)}{\partial t} \right] \right\}^{0.5} \tag{4}$$

The indices of technical efficiency change and technological change obtained by using Equations 3 and 4 respectively can be multiplied to obtain a TFP index (Coelli et al., 2003) such as:

TFPit = ECit * TCit (5)

This is equivalent to the decomposition of the Malmquist index suggested by Fare et al. (1985).

Data issues and variables

A major drawback to conducting research on a long-term productivity performance of the agricultural sector is the lack of time-series panel data for most of the developing economies, and Thailand is no exception. Most often, data are available at a highly aggregated form which is of no use and as such unless a multi-country analysis is attempted (Luh et al., 2008), many relevant variables required for such assessment of performance disaggregated at the regional or provincial level over time are not available. Consequently, estimation of econometric models without relevant variables tends to be biased.

The Office of Agricultural Economics (OAE) of Thailand is responsible for providing agricultural statistics to facilitate planning. In general, output data is available at AEZ levels for some period and was discontinued in later years (for example, 2000 onward). Moreover, data on key production inputs such as labor and fertilizers, disaggregated at AEZ levels are even harder to come by. Farmers are hypothesized to incorporate natural environments in their response to economic factors (especially, price changes) which influence their decision on the use of modern inputs and adoption of technologies. Consequently, productivity and efficiency differ amongst regions. Hence, it is of utmost importance that performance evaluation of the agricultural sector of any economy needs to be examined at a disaggregated level so that policies can be directed to areas where it is most needed (Table 1).

Given these limitations, annual data of six AEZ were finally collated from the available OAE statistical yearbooks (various issues) for the period of 1977 to 1999. The series cannot be updated further due to a lack of disaggregated information on inputs. The 17 provinces included in these six AEZs of Northern Thailand are:

Zone 8 = Nakhon Sawan, Phetchabun
Zone 9 = Tak, Kamphang Phet, Sukothai
Zone 10 = Phrae, Nan, Uttaradit
Zone 11 = Phitsanulok, Phichit
Zone 12 = Chiang Rai, Lampang, Phayao
Zone 13 = Chiang Mai, Lamphun, Mae Hong Son.

The empirical model

To measure technical efficiency, TFP growth and its components from the stochastic production frontier, we have used the following fully flexible translog function:

$$\ln Y_{it} = \beta_0 + \sum_{k=1}^{5} \beta_k \ln X_{kit} + \beta_t t + \frac{1}{2} \sum_{k=1}^{5} \sum_{j=1}^{5} \beta_{kj} (\ln X_{kit})(\ln X_{jit}) + \frac{1}{2} \beta_{tt} t^2 + \sum_{k=1}^{5} \beta_{kt} \ln X_{kit} * t - u_{it} + v_{it} \tag{6}$$

Where;
t represents the year of the observation (1977=1);
yit is the agricultural gross domestic product at constant prices (million baht) in the ith region in year t;
xit is the land area (rai) of the ith region in year t;
x2it is the total labor used (persons) in the ith region in year t;
x3it is the amount of fertilizers used (ton) in the ith region in year t;
x4it is the share of irrigated area (percentage) in the ith region in year t;
x5it is the amount of loan capital disbursed (million baht) in the ith region in year t;
vit and uit are respectively, the symmetric and one-sided random error terms denned earlier.

The inefficiency effects model is specified as:

uit = δ0 + δ1time + δ2rainfall + δ3BAAC + ςit (7)

Where;
Rainfall = the amount of average rainfall per year (mm)
BAAC = the share of BAAC in total loan capital
ςit = the symmetric error.

RESULTS

The parameter estimates of the stochastic production frontier model (Equation 6) estimated jointly with the inefficiency effects model (Equation 7) using the Maximum Likelihood Estimation (MLE) procedure is presented in Table 3. Prior to discussing the results of the production frontier, we report the series of hypothesis tests conducted to select the functional form and to decide whether the frontier model is an appropriate choice rather than a standard mean-response or average production function as used by Krasachat (2001). The results are reported in Table 2. Sauer et al. (2006) raised the importance of checking theoretical consistency, flexibility and choice of the appropriate functional form when estimating stochastic production frontiers. However, given the purpose of our research, we concentrate on the choice of an appropriate functional form that is also flexible. The first test was conducted to

Table 1. Summary statistics of the variables.

Variable	Measurement	Mean	Std. deviation
Deflated agricultural GDP	Million baht	7,783,022.00	1,632, 899.00
Land area	Rai	3,589,754.00	1,377,851.00
Labor	Thousand persons	63,315.60	144,863.40
Loan capital (commercial + BAAC)	Million baht	3,855.26	3,324.45
Fertilizer	Tons	3,283.76	1,814.66
Irrigation	Percent of land area	33.00	22.96
BAAC share	Percent of loan	47.61	14.50
Time	years	12	6.66
Number of regions		6	
Number of years		23	
Number of observations		138	

Table 2. Hypothesis tests.

Tests	Parameter restrictions	LR test statistic	Degree of freedom	χ^2 Critical value 5%	Outcome
Functional form test	H_0: all $\beta_{jk} = 0$	110.7	15	24.99	Reject H_0: CD is inadequate
Frontier test	H_0: M3T = 0 (that is, no inefficiency component)	z statistic = 40.12		p value of z = 0.000	Reject H_0: Frontier not OLS
No technical change	H_0: $\beta_t = \beta_{tt} = \beta_{kt} = 0$	719.90	7	14.07	Reject H_0
No inefficiency effects	H_0: $\delta_0 = \delta_1 = \delta_2 = 0$	23.45	3	7.82	Reject H_0
Constant returns to scale (CRTS)	H_0: $\Sigma\beta_k = 1$	17.67	1	3.84	Increasing RTS

Regularity conditions check	Monotonicity (dy/dx_i>0) for every input)		Diminishing marginal productivity (d^2y/dx^2_i<0) for every input)	
	Value	Outcome	Value	Outcome
Land	0.885	Fulfilled	-1.570	Fulfilled
Labor	10.927	Fulfilled	-1.423	Fulfilled
Fertilizer	31.451	Fulfilled	-31.222	Fulfilled
Irrigation	30.165	Fulfilled	-2.22	Fulfilled
Loan	1010.625	Fulfilled	-1.792	Fulfilled

determine the appropriate functional form, that is, the choice between Cobb-Douglas vs. translog functional form (H0: βjk = 0 for all jk). Generalized Likelihood Ratio (LR) tests confirmed that the choice of translog production function is a better representation of the production structure. Once the functional form is chosen, next we checked the sign of the third moment and the skewness of the OLS residuals of the data in order to justify use of the stochastic frontier framework (and hence, the MLE procedure)[1]. The computed value in the study of Coelli (1995) standard normal skewness statistic (M3T) based on the third moment of the OLS residuals is presented in the mid-panel of Table 3 which is tested against H0: M3T = 0. The null hypothesis of 'no inefficiency component' is strongly rejected in all cases and, therefore, the use of the stochastic frontier framework is justified. The coefficient of γ reported at the bottom of Table 3 also strongly suggests the presence of technical inefficiency.

Finally, in the last panel, we have provided checks for regularity conditions of the translog production frontier. The two checks are: (i) monotonicity, that is, positive marginal products, with respect to all inputs $\left(\frac{\partial y}{\partial x_i} > 0\right)$ and thus non-negative production elasticities;

[1]In the stochastic frontier framework, the third moment is also the third sample moment of the u_i. Therefore, if it is negative, it implies that the OLS residuals are negatively skewed and technical inefficiency is present (Rahman and Hasan, 2008).

Table 3. Parameter estimates of the stochastic production frontier and inefficiency effects model.

Production frontier function	Coefficient	t-ratio
Constant	15.7543	414.33***
ln land	0.3427	5.41***
ln labor	0.8719	16.84***
ln irrigation	0.0844	2.11**
ln fertilizer	0.0072	0.14
ln loan capital	0.1681	4.51***
0.5 * $(\ln \text{land})^2$	-1.5702	-2.21**
0.5 * $(\ln \text{labor})^2$	1.1642	5.27***
0.5 * $(\ln \text{fertilizer})^2$	0.1573	0.95
0.5 * $(\ln \text{irrigation})^2$	-0.5959	-3.01***
0.5 * $(\ln \text{loan capital})^2$	-0.1446	-1.06
ln land * ln labor	0.4354	1.38
ln land * ln fertilizer	0.8809	4.69***
ln land * ln irrigation	-1.8395	-3.73***
ln Land * ln loan capital	0.2632	0.75
ln Labor * ln Fertilizer	-0.6554	-5.10***
ln Labor * ln Irrigation	0.4618	1.74*
ln labor * ln loan capital	0.5470	2.71***
ln fertilizer * ln irrigation	0.6719	3.64***
ln fertilizer * ln loan capital	-0.3005	-2.62***
ln irrigation * ln loan capital	0.2687	1.03
Time	-0.0219	-4.42***
Time * ln land	-0.0291	-0.65
Time * ln labor	-0.1087	-3.82***
Time * ln fertilizer	-0.0050	-0.45
Time * ln Irrigation	-0.0341	-0.91
Time * ln loan capital	0.0491	2.53**
Time * time	-0.0050	-2.58***
Model diagnostics		
Log likelihood	166.677	
σ_u^2	0.0127	36.89***
σ_v^2	0.0017	15.58***
γ	0.99	
No inefficiency effects (H_0: $\delta_0 = \delta_1 = \delta_2 = 0$)	23.45***	
Inefficiency effects function		
Constant	-0.0742	-0.80
time	0.0274	3.52***
Rainfall	0.0001	0.79
BAAC loan share	-0.0001	-4.51***
Number of observations	138	

*** Significant at 1% level (p<0.01); ** significant at 5% level (p<0.05); * significant at 10% level (p<0.10).

diminishing marginal productivity $\left(\frac{\partial^2 y}{\partial x_i^2} < 0\right)$ with respect to all inputs (that is, the marginal products, apart from being positive should be decreasing in inputs) (Sauer et al. 2006). Results clearly demonstrate that both and (ii)

Table 4. Production elasticities and returns to scale.

Inputs	Value	t-ratio
Land	0.3427	5.41***
Labor	0.8719	16.84***
Irrigation	0.0844	2.11**
Fertilizer	0.0072	0.14
Loan	0.1681	4.51***
Returns to scale	1.4743	

*** Significant at 1% level ($p<0.01$); ** significant at 5% level ($p<0.05$).

Table 5. Elasticities of substitution among inputs.

Input combinations	Value	z-value
Land × labor	0.2160***	3.69
Land × irrigation	-0.9559	-0.70
Land × fertilizer	-0.0656	-0.11
Land × loan	0.2430**	1.96
Labor × irrigation	0.1207**	2.30
Labor × fertilizer	-0.0452	-0.16
Labor × loan	0.3911***	3.06
Irrigation × fertilizer	-0.02577	-0.03
Irrigation × loan	0.1233**	2.03
Fertilizer × loan	-0.0437	-0.16

*** Significant at 1% level ($p<0.01$); ** significant at 5% level ($p<0.05$).

these restrictions hold for all the inputs[2].

Other model diagnostics are presented in the mid-panel of Table 3. γ, σ2v and σ2u are measures related to the variance of the random variables vit and uit. γ is the percent of the composed error that is attributable to the one-sided inefficiency residual. In this case, almost 99% of the total "noise" in the estimation of the stochastic production function is attributable to inefficiency effects.

The inclusion of time and time^2 in the production function is intended to measure the rate of neutral technical change over time (Table 3). Likewise, the coefficients on the interaction terms between time and each of the inputs in the frontier production function are intended to measure the rate of biased technical change. Technical change was found to be both non-neutral and biased. The coefficients on time and time^2 are negative and statistically significant indicating that non-neutral technical change occurred over the period and that technical change declined at an increasing rate. The coefficient on the interaction term between loan capital and time is of the expected sign (positive) and is also statistically significant. Technical change in the agricultural sector has an average been capital using per unit of output, increasing at a rate of about 5.0% per year. Over this same time, technical change has also been largely labor saving, with labor use per unit of output decreasing by 11% per year, which is expected as labor cost is very high in Thailand. Helvoigt and Adams (2009) also noted similar result for sawmill industries in Northwest America over a 30 year period of (1968 to 2002). The coefficient estimates on the interaction between time and land area, time and fertilizers and time and irrigation inputs are not statistically significant.

Returns to scale, output elasticity, elasticities of substitution

Table 4 presents the aggregate returns to scale in agricultural sector of these six AEZs. All output elasticities has the expected positive signs. Four of the five outputs significantly increased productivity. Labor has the highest elasticity of 0.87 implying that a one percent increase in labor use will increase production by 0.87% followed by land area with an elasticity value of 0.34. It is encouraging to note that loan capital has a significant influence on increasing agricultural production with an elasticity value of 0.17. It is surprising to find no significant influence of fertilizers.

Increasing returns to scale prevails in agricultural sector (1.47) in these six AEZs implying that output will increase at a higher proportion (1.47 times) in response to increase in inputs which is very encouraging. The null hypothesis of constant returns to scale is strongly rejected in favor of increasing returns to scale (Table 2).

Table 5 presents the elasticities of substitution3 amongst inputs. Land has a substitution relationship with labor, irrigation and loan capital. Similarly, labor has a substitution relationship with irrigation and loan capital, and finally irrigation has a substitution relationship with loan capital. Although, all these aforementioned elasticities are significantly different from zero, the values are very small and are in the inelastic range. The results, however, differ substantially from Krasachat (2001) who reported that capital, hired labor and unpaid family labor are complements but are in inelastic range.

Region specific technical efficiency levels

The efficiency distribution shows a very high level of variation over time as well as, between regions in individual years. The overall range is from 0.63 to 1.00 with a mean of 0.88, implying considerable scope to increase productivity by eliminating technical inefficiency

[2]Both these restrictions should hold at least at the point of approximation (Sauer et al., 2006)

[3]Elasticities of substitution are computed using the formula presented by Boisvert (1982). In a scaled version of the translog function the elasticity of substitution becomes a function of the estimated coefficients only (Boisvert, 1982).

alone. The efficiency scores are particularly high for the years 1977, 1981, 1982, 1996, 1997 and 1999 (Figure 1). However, in the later period, from the 1990's, the variation between regions has reduced but overall technical efficiency level somewhat fluctuated and then rose to a maximum level during the last few years. The range commensurate with the average reported for developing economies (for example, Bravo-Ureta et al., 2007). Figure 2 presents regional distribution of technical efficiency scores over time. As evident from Figure 2, region 10 has the highest level of fluctuation in technical efficiency scores with the lowest average. It should be noted that observation of high efficiencies with wide variation across regions may also reflect the use of aggregated data with reduced variability and a potentially lower efficient frontier (Helvoigt and Adams, 2009).

Factors affecting technical efficiency

Whereas the time variable in the frontier production function captures technical change over time (that is, shifting of the production frontier), in the inefficiency equation the time variable is intended to capture inefficiency change (that is, changes in the distance of the average unit from the sector production frontier). The positive sign on the coefficient of the time variable in the inefficiency equation indicates that the distance of the typical production region from the technical frontier increased significantly over the study period. However, it is encouraging to see that the investment channeled through BAAC loan has a significantly positive impact on improving technical efficiency.

Productivity growth, technical change and technical efficiency change

Finally, Table 6 and Figure 3 present the average levels of technical change, technical efficiency change and overall TFP growth by year. It is clear from Figure 3 that TFP initially declined until 1987 and then picked up but dropped slightly in later years, a pattern also mirrored by technical efficiency change index. Specifically, overall TFP declined at an annual rate of -0.6% per annum due to technical regress at a rate of -2.1% while technical efficiency improved at a modest rate of 1.5%, respectively. The overall conclusion is remarkably similar to those of Krasachat (2001, 2000) and Luh et al. (2008).

Although, Figure 3 shows a clear and smooth pattern, it hides the level of fluctuation experienced by individual regions. Table 7 provides these measurements by region. Only Region 8 experienced positive growth in TFP, technical change and efficiency change, though, at a very modest rate. The highest level of technical regress is in Region 12. In fact, F-test confirmed that significant differences amongst region exist with respect to technical change (Table 7). Figure 4 shows the actual level of fluctuation in TFP index among regions which tend to be smoothened towards the end. The implication is that lagging regions are catching-up with the leading ones, that is, converging to a common level of productivity growth.

Testing convergence among regions

Convergence occurs when regions with poorer productivity level during the initial period grow more rapidly than regions with high initial level of productivity implying that the poorer regions are catching up. Table 7 and Figure 4 suggest that none of the regions are producing at a significantly higher level of productivity as evident from a narrow range of deviation between regions, hence, TFP growth is contributed by all of the regions. In other words, there is no evidence of significant divergence among the regions. However, more conclusive results can only be obtained by formally testing for convergence as discussed subsequently. We applied the cross-sectional method which examines the tendency of regions/countries with initial low levels of productivity to grow relatively faster in order to catch-up with those of high initial level productivity. Therefore, if the growth rates are regressed on the initial level of productivity and the coefficient is negative, there is said to be Beta convergence. The average growth rate of productivity for each region i between year 0 and T can be defined as:

gi,T = T-1 (yi,t – yi,0)

Then, a test of Beta convergence is conducted by a regression of growth rate as the dependent variable with the initial level of productivity as the regressor as follows:

$$g_{i,t} = \alpha + \beta y_{i,0} + \varepsilon_{i,T} \quad (8)$$

Where; α and β are parameters and εi,T is an error term with a zero mean and finite variance. Convergence exists if the value of β is negative and significant. The result of this exercise is presented in Table 8. The estimated parameter β, which is the coefficient of the initial level of productivity level is negative and significant at 1% confidence level. This provides strong evidence that agricultural productivity in Northern Thailand has converged. In other words, regions with initial poor level of productivity grew faster and are catching up with the high productivity regions.

Another simple cross-sectional test for convergence is the Sigma convergence, which holds if the cross-sectional standard deviations of the log of TFP decrease over time. In other words, it tests whether the productivity differences among regions are narrowing over time.

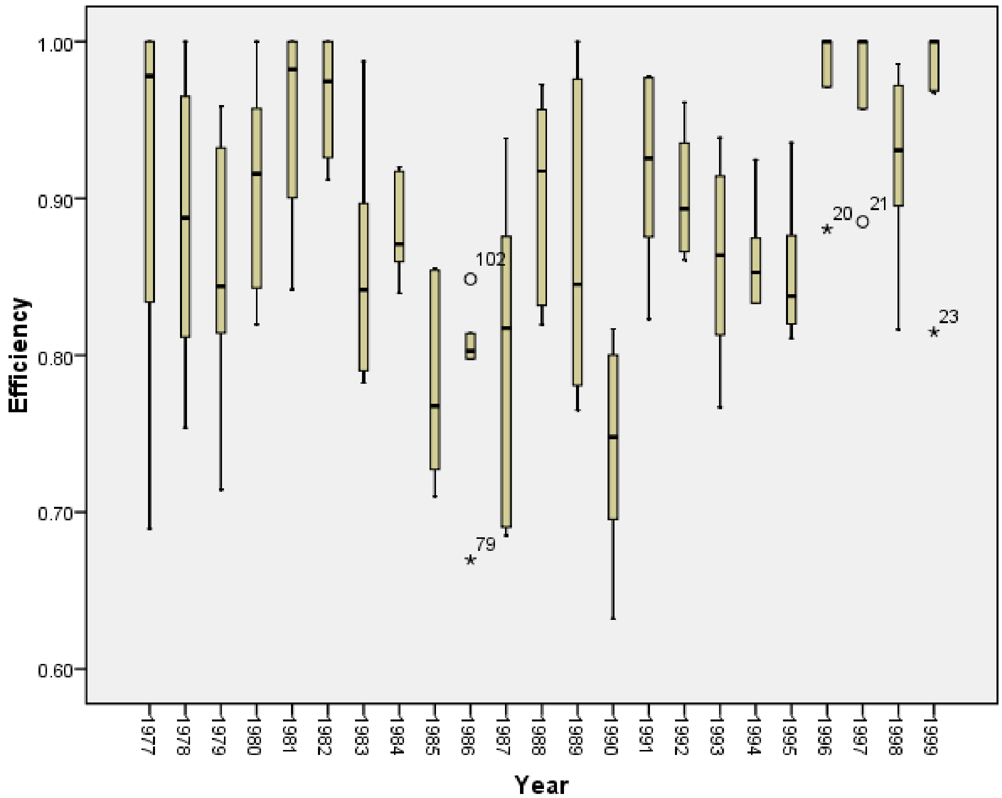

Figure 1. Distribution of technical efficiency by year (Box-plots).

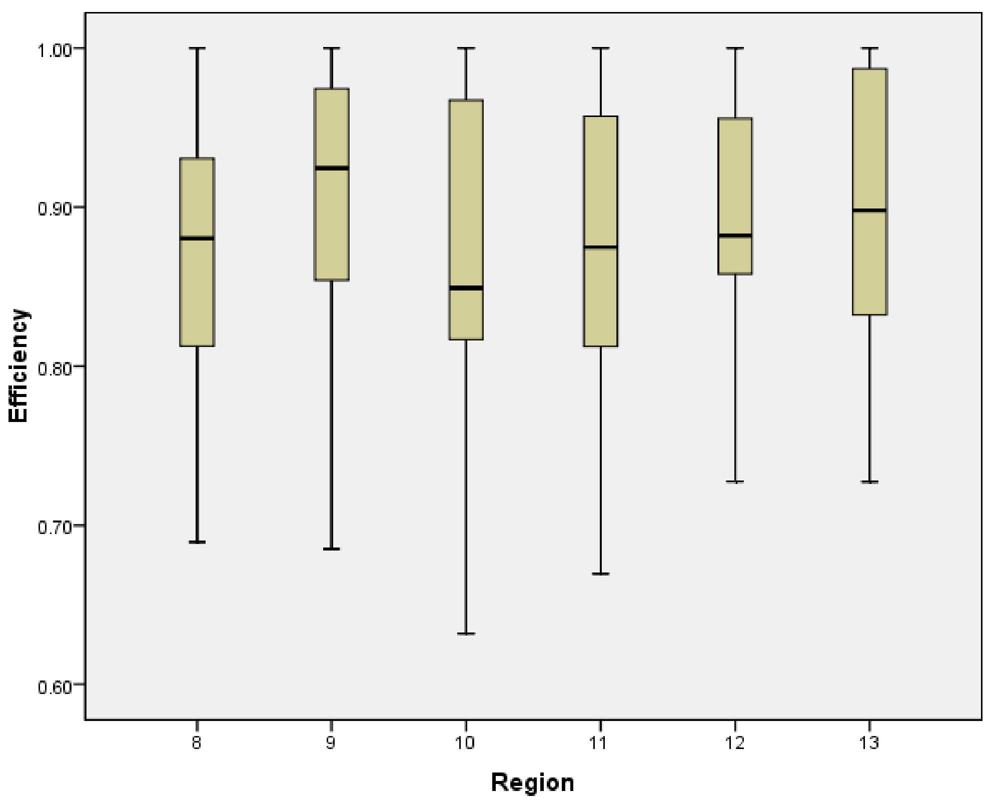

Figure 2. Distribution of technical efficiency by region (Box-plots).

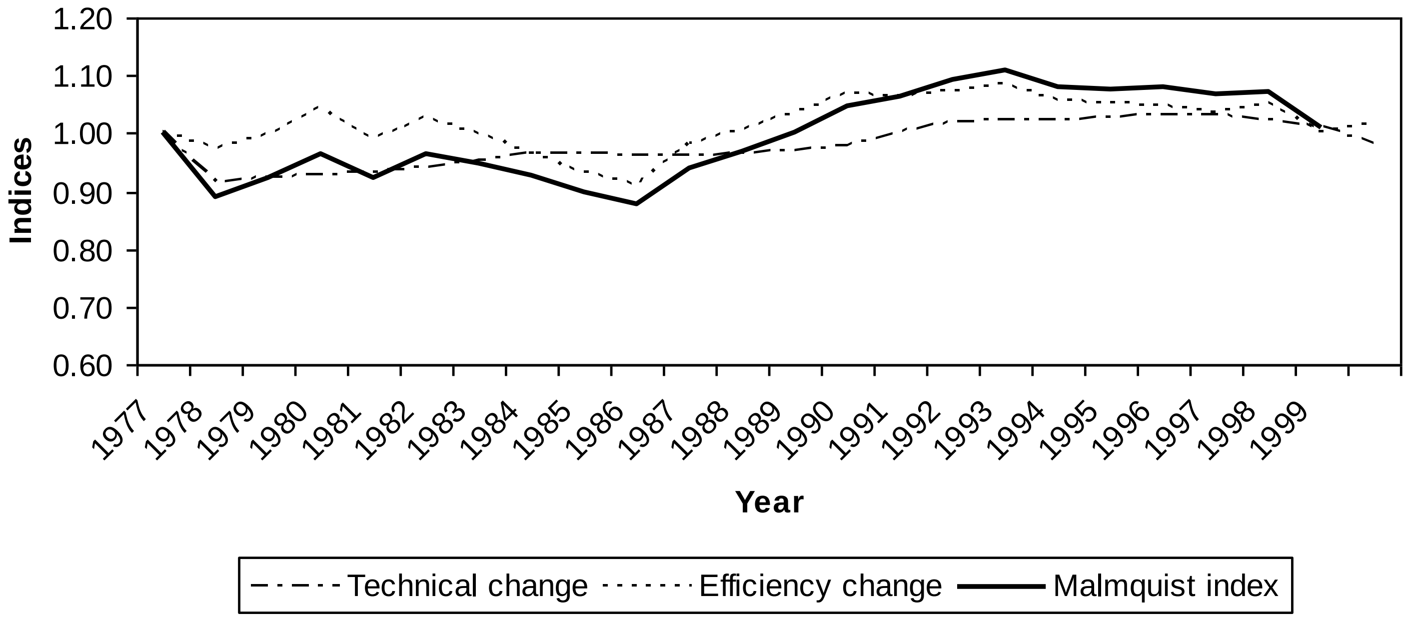

Figure 3. Technical change, efficiency change and productivity growth in Northern Thai agriculture, 1977 to 1999.

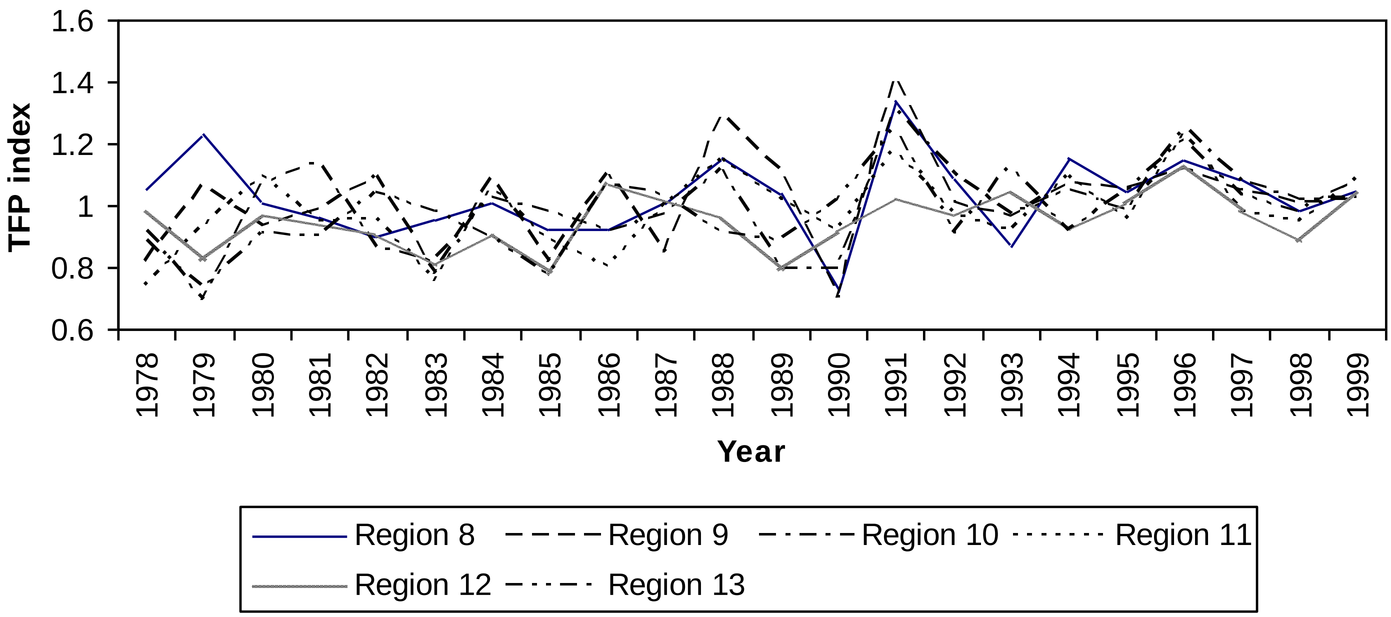

Figure 4. Total factor productivity growth by region, 1978 to 1999.

Technically, a necessary condition for Sigma convergence is the existence of Beta convergence although Beta convergence does not guarantee a reduction in the distribution of dispersion among TFP growth rates (Thirtle et al., 2003). Figure 5 shows that the cross-sectional standard deviations for the log of TFP over time are in fact fluctuating within a narrow range, which further corroborate the result obtained from Beta convergence test.

Evidence of productivity convergence in Thailand should not be treated as exceptional. There are evidences of convergence in agricultural productivity and its components in Asia. Wu (2000) found that overall TFP growth in China has shown signs of convergence since

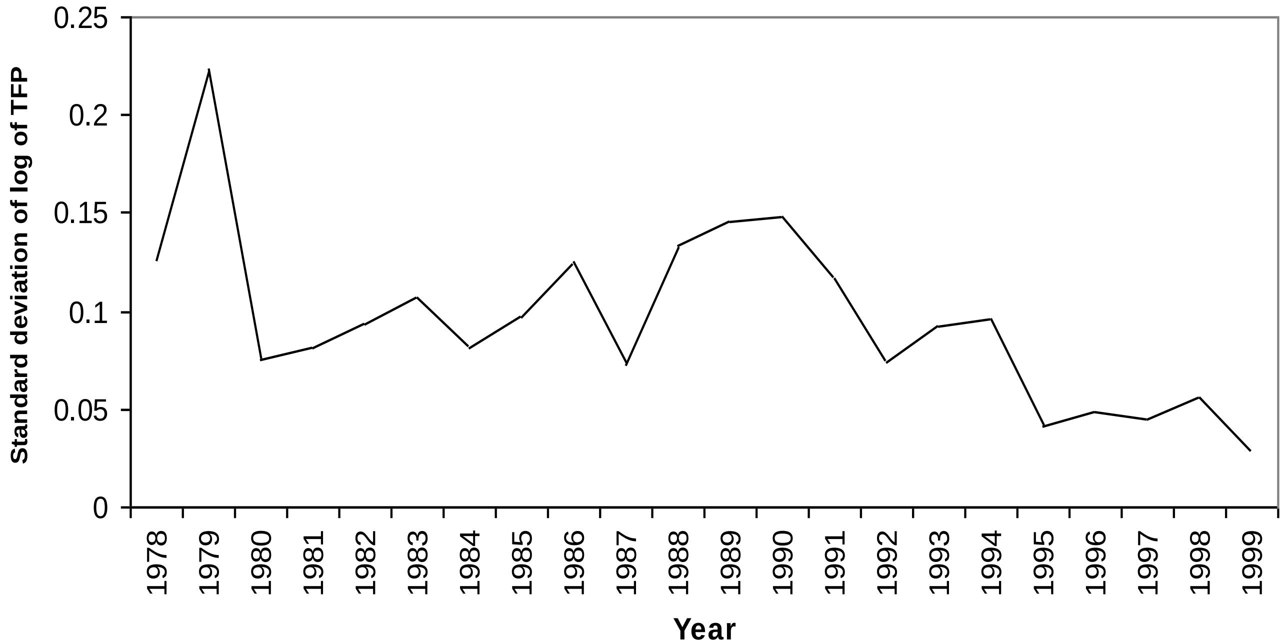

Figure 5. Sigma convergence: standard deviations of the logarithm of TFP index.

Table 6. TFP growth and its components by year.

Year	Technical change	Efficiency change	TFP change (Malmquist index)
1977	1.0000	1.0000	1.0000
1978	0.9156	0.9722	0.8901
1979	0.9240	0.9970	0.9213
1980	0.9260	1.0411	0.9640
1981	0.9301	0.9909	0.9216
1982	0.9394	1.0265	0.9643
1983	0.9511	0.9958	0.9471
1984	0.9621	0.9630	0.9265
1985	0.9648	0.9317	0.8989
1986	0.9614	0.9105	0.8753
1987	0.9601	0.9795	0.9404
1988	0.9630	1.0057	0.9686
1989	0.9683	1.0337	1.0009
1990	0.9784	1.0696	1.0465
1991	1.0007	1.0621	1.0628
1992	1.0190	1.0714	1.0918
1993	1.0236	1.0824	1.1080
1994	1.0231	1.0566	1.0810
1995	1.0247	1.0505	1.0764
1996	1.0304	1.0473	1.0791
1997	1.0322	1.0339	1.0672
1998	1.0216	1.0506	1.0733
1999	1.0088	1.0009	1.0096
Mean	0.9788	1.0152	0.9937

the 1990's with technical efficiency across regions having converged as early as the 1980's. Rahman (2007) showed that productivity growth in Bangladeshi regions has converged during the mature stage of Green

Table 7. TFP growth and its components by region.

Region	Technical change	Efficiency change	TFP change (Malmquist index)
8	1.0125	1.0076	1.0203
9	1.0027	0.9985	1.0011
10	0.9805	1.0014	0.9819
11	0.9734	0.9986	0.9721
12	0.9292	1.0083	0.9369
13	0.9707	1.0006	0.9713
Mean	0.9788	1.0152	0.9937
Difference among regions			
F-value $_{(5,126)}$	11.35***	0.02	1.14

*** Significant at 1% level (p<0.01).

Table 8. Testing for Beta convergence.

Period	Variable	Coefficient	SE	t-statistics	R^2
1978 – 1999	α	12.26	0.088	12.26***	0.54
	β	-12.35	0.088	-12.35***	

*** = significant at 1% level (p<0.01).

Revolution technology diffusion. Mukherjee and Kuroda (2003) noted that there is evidence of conditional long-run convergence in agricultural productivity among states of India towards an all-India average TFP estimate.

Conclusion and policy implications

The present study provides an assessment of the performance of the agricultural sector of six AEZs of Northern Thailand by examining technical change, efficiency change, and productivity growth over a 23 year period from 1977 to 1999. Results revealed that labor, land, irrigation and loan capital significantly contributed to the growth of agricultural productivity. All inputs have substitution relationships except fertilizers and all are in the inelastic range. Increasing returns to scale prevails in these regions implying that output will increase proportionately at a higher rate with corresponding increase in inputs. The mean technical efficiency level is 0.88 thereby, implying considerable scope to improve productivity by eliminating technical inefficiency alone. The distribution of technical efficiency scores reveals larger variation across regions with higher levels of mean technical efficiency during the earlier period. However, the variation across regions reduced with a corresponding decline in the mean level of technical efficiency during the mid-1980's to 1990's and then rose sharply to a very high level during the last four years under study. Overall TFP index has declined slightly due to technical regress which offset any gains from technical efficiency improvements over time. There were significant variations with respect to technical change amongst the AEZs although, no significant difference was observed in TFP growth. The convergence tests confirmed that agricultural productivity has converged to a common level in Northern Thailand. The government's initiative to support investment through BAAC loan capital has a significant influence on technical efficiency improvements.

The policy implications of this study are clear. Agricultural credit disbursed by the BAAC played its expected role in increasing productivity and efficiency improvements. Therefore, policies directed towards increasing access to credit to raise capital will positively contribute towards agricultural productivity in these regions. Also, Thailand needs to focus on promoting new technologies rather than relying on the existing technology. Furthermore, evidence suggests that investments in irrigation and facilitation of the labour and land markets will increase productivity.

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