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Aquaculture Productivity Convergence in India: A Spatial Econometric Perspective*

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Abstract

This paper provides an illustration of evaluating productivity convergence using spatial econometric modelling framework for the aquaculture sector in India. Productivity has been measured using Total Factor Productivity (TFP). The β- and σ-convergence concepts that are used to test the convergence hypothesis have been extended to examine the possible presence of spatial autocorrelation and spatial heterogeneity. The results have confirmed the productivity convergence hypothesis, the presence of spillover effects on TFP growth and the presence of spatial regimes in the TFP convergence process which have policy implications. The paper concludes by providing recommendations for further research.

1. Introduction

Several studies on productivity evaluation of different crops, livestock and recently, on the fisheries as well as aquaculture sector have been conducted in India (see for example, Kumar and Mruthyunjaya, 1992; Sindhu and Byerlee, 1992; Dholakia and Dholakia, 1993; Kumar and Rosegrant, 1994; Rosegrant and Evenson, 1995; Kumar *et al*., 1998; Evenson *et al*.,1999; Fan *et al*., 1999; Kumar, 2001; Kumar and Mittal, 2003; Kumar *et al*., 2004; and 2004b). These studies have utilized the total factor productivity (TFP) framework to measure the productivity. Central to most of these

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studies are (i) evaluation of the performance of the production system and sustainability of the growth process, (ii) assessment of the quantitative effects over time of agricultural research, extension, irrigation, and other public and private investments on productivity, and (iii) examination of factors accounting to TFP growth and estimation of the marginal economic rates of return to public and private investments. These studies also differ in many aspects; while some studies have examined TFP at the national (i.e. all-India) level, some have analyzed TFP by administrative units (e.g. district or state) or agro-ecological regions. The district level analysis captures the differentials at micro level and allows a comparison of TFP growth across different regions.

This paper has dealt three additional issues in growth theory that need to be addressed in evaluating TFP at different administrative units and agro-ecological regions: (1) the phenomenon of productivity convergence (i.e. catching-up), (2) the presence of spatial autocorrelation implying that TFP growth rate in one state is affected by the growth in the neighbouring states (i.e. technological spillover effects), and (3) the possibility of spatial regimes in the convergence process. The intuition behind these issues is that spatially-adjacent regions can be characterized by regional production similarities which could be due to inherent common spatial influences such as weather and regional market influences. Endogenous growth theory and the new economic geography provide interesting arguments in this respect (e.g. spillover effects, technological diffusion, etc.).

In order to address these issues, an empirical investigation of TFP convergence on aquaculture sector in the country was conducted using a spatial econometric modelling framework. Following Kumar *et al*. (2004a and 2004b), TFP indices using Divisia-Tornqvist Index were computed for 31 states in the country for the period 1991-1998. With regards to the empirical question, we used two measures of convergence commonly used in the regional analysis, the β- and σ- convergences. A detailed discussion on these concepts has been provided in the subsequent section. Initially, our interest was devoted to the overall shape characteristics of the state-wise TFP productivity distribution and its evolution over time. Subsequently, we examined the possible presence of spatial autocorrelation and spatial heterogeneity[3] for which we applied different spatial econometric models. Our results have confirmed the productivity convergence hypothesis, the

[3] It must be noted that although single papers pointed to the spatial dimension of growth processes, the spatial effects have not explicitly been taken into account in the convergence studies. Rey and Montouri (1998) first addressed these questions while investigating US regional income convergence. Recent studies that have looked at spatial dimension of the economic processes include Lopez-Bazo *et al*. (1999) and Le Gallo *et al*. (2003).

presence of spillover effects on TFP growth and the presence of spatial regimes in the TFP convergence process.

The paper is structured as follows. In Section 2, we have provided a comprehensive discussion on methodology. Specifically, a brief discussion on the derivation of Divisia-Tornqvist Index as measures of TFP has been provided, followed by a discussion on the classical approach of convergence analysis and its limitations; and finally, the specification of spatial econometric models that extend the classical convergence analysis. Section 3 presents the results and the last section (Section 4) provides conclusions and recommendations for future research.

2. Data and Methodology

2.1. Productivity Index

We started with the construction of state-wise productivity index using the TFP approach. Following Kumar *et al*. (2004a and 2004b), we applied the Divisia-Tornqvist index. This procedure allowed us to define growth in TFP as factor share-weighted growth in output (TOI) over the factor share-weighted growth in input (TII) (the subscript for state was omitted for simplicity).

$$TFP_t = \frac{TFP_t^o}{TFP_t^i} \quad \ldots(1)$$

where,

$$TOI_t^o = \Pi_j \left(\frac{Q_{jt}}{Q_{jt-1}} \right)^{(R_{jt}+R_{jt-1})^{1/2}} \quad \ldots(2)$$

$$TII_t^i = \Pi_k \left(\frac{X_{kt}}{x_{kt-1}} \right)^{(S_{kt}+S_{kt-1})^{1/2}} \quad \ldots(3)$$

Q_{jt} = Fish production of the j^{th} fish group in the year t

R_{jt} = Share of the j^{th} fish group in total revenue,

X_{kt} = Quantity of the k^{th} fish input, and

R_{jt} = Share of the k^{th} fish input in total input cost.

The model identified three species groups consisting of the Indian major carps, namely Rohu, Catla and Mrigal, and six inputs, namely, seed, feed, fertilizer, fuel and labour. The natural logarithm of Equations (1), (2) and (3) are the productivity growth rates between two succeeding periods. The average annual growth rate for the entire period can be computed by either fitting an exponential (or semi-log) trend or computing the compound growth rate. As shown in the subsequent section, the β-convergence is based on the natural logarithm of the compound growth rate.

2.2. β- and σ-Convergence

The two most popular approaches in the quantitative measurement of convergence are based on the concepts of β- and σ- convergence[4]. The σ-convergence approach, which is a more restrictive concept of convergence, consists of computing measures of dispersion (e.g., standard deviation, coefficient of variation) of productivity and analyzing its long-term trend. A σ-convergence is seen when the cross-sectional dispersion of the regional productivity diminishes over time. Thus, σ-convergence only looks at the temporal dynamic behaviour of productivity.

In contrast to σ-convergence, the β-convergence occurs when states with lower initial levels of productivity tend to grow, on average, faster than those with higher initial levels and eventually catch-up with them. So far, the β-convergence approach has been considered as one of the most convincing approaches from the economic theory point of view. It also appears very appealing from the policymaking point of view, since it quantifies the important concept of the speed of convergence.

The β-convergence is usually tested following Baumol's (1986) specification:

$$\begin{aligned} &\frac{1}{T}\ln\left(\frac{TFP_t}{TFP_0}\right) = R = \alpha + \beta \ln\left(TFP_0\right) + u \\ &u \sim N\left(0, \sigma^2 I\right) \end{aligned} \qquad \ldots(4)$$

where, T is the number of periods (years) under study, ln refers to natural logarithm, TFP_t is the productivity at the year t (i.e. ending period, in our case 1998), and TFP_0 is the productivity of a district at the initial year (1993)[5].

[4] Most of the empirical studies on territorial convergence take per capita GDP as the variable of reference; less frequently, productivity is used. It is important to remember, however, that from a theoretical point of view, economic growth models — particularly those with neoclassical roots, on which the hypothesis of β-convergence is based — refer exclusively to productivity. Readers are referred to Durlauf and Quah (1999) for a comprehensive review.

[5] The initial year is supposed to be 1992. However, since this is the base year, the TFP index will be a constant of 100% for all states making it impossible to estimate Equation (4) (i.e. perfect multicollinearity).

[6] Note that for data with only T= 6 period, the rate of convergence (b) is only feasible for $\beta > 0.17$

There is absolute β- convergence if the coefficient β is negative and statistically significant.

Based on the estimated β-coefficient, the convergence process is then characterized by two additional parameters. First, the rate of convergence is calculated using the expression (5)[6] :

$$b = -\frac{\ln(1+T\beta)}{T} \qquad \ldots(5)$$

Second, the half-life is the time required to close half the gap separating the productivity of the state from its corresponding steady state, and is defined as:

$$\tau = -\frac{\ln(2)}{\ln(1+\beta)} \qquad \ldots(6)$$

2.3. Spatial Econometric Specifications

To account for the geographical location of the states in the analysis and to examine spillover effects of the convergence process, the β-convergence equation defined in Equation (4) was extended to spatial econometric specifications. Specifically, the spatial econometric model accounts for the possible spatial effects such as spatial dependence (or autocorrelation) in either the dependent variable or the error-terms. Following Anselin (1988), we referred to the model that incorporated spatial dependence in the dependent variable as spatial lag model or spatial autoregressive model (SAR) and the model that incorporated spatial dependence in the error-term was labelled as the spatial error model (SEM). A SAR model is appropriate when the productivity in one location both affects and is affected by the productivity in the neighbouring locations, or when there is a spatial contagion of productivity or a trend over space (and through time). The SEM models are often employed when data on important variables involving the spatial structure of convergence process are unobserved. Spatial dependence may therefore act as a proxy to all these omitted variables and catch their effects. This is particularly useful in the case of Indian aquaculture data, where explanatory variables are scarce. Mathematically, the SAR and SEM specifications of β-convergence can be expressed as follows:

$$\begin{aligned} R &= \alpha + \rho WR + \beta \ln\left(TFP_0^i\right) + u \\ u &\sim N\left(0, \sigma^2 I\right) \end{aligned} \qquad \ldots(7)$$

and

$$\begin{aligned} R &= \alpha + \beta \ln\left(TFP_0^i\right) + u \\ u &= \lambda Wu + e \\ e &\sim N\left(0, \sigma^2 I\right) \end{aligned} , \qquad \ldots(8)$$

where, W is a spatial weight matrix that defines the neighbouring structure of states and is defined using the rook contiguity relation (i.e. the elements take the value of 1 if two states share a common boundary, 0 otherwise)[7]. It is row-standardized (i.e. row-sum is equal to 1) so that WR represents the average productivity growth (R) of neighbouring states. The spatial lag parameter, ρ, measures the strength of the spatial dependence, which is constrained to be less than one. More meaningfully, ρ can be considered as a measure of spillover. As noted by Anselin (1988), failure to estimate a spatial lag or SAR model (when called for) will lead to biased estimates and all inferences based on the standard regression will be incorrect, while failure to estimate a spatial error model (when called for) will lead to unbiased but inefficient estimates.

In order to decide which model is more appropriate, the statistical significance of the ρ and λ parameters is compared. If both spatial coefficients are significant in their respective models, the preferred model is the one with the highest value (Anselin and Rey, 1991). The SAR and SEM models are estimated using the ML approach, as outlined in Anselin (1988)[8]. Specifically, the spatial regression models are assessed using the GeoDa software (Anselin *et al*., 2004).

The β-convergence process defined in Equations (3) and (4) assumed that convergence process was the same across the country, that is, the convergence rate was spatially stationary. However, relationships between the initial productivity and productivity growth may vary across space since regions with an initial lower productivity than a certain threshold level converge to one steady state level while regions above the threshold converge to a different level. This implies spatial heterogeneity of convergence process, suggesting the presence of spatial regimes.

The geographically weighted regression (GWR, Fotheringham *et al*., 2002) provides a method to assess the degree to which process varies across space[9]. It allows estimation of the location-specific β-convergence process that takes into account spatial dependence in the data. The GWR β-convergence model takes the form:

[7] Kelejian and Robinson (1995) have provided a comprehensive review and a comparison of different spatial matrices.

[8] As Anselin (1988) noted, the OLS estimators will be biased as well as inconsistent when there is spatial dependence in the spatial models. The literature provides several alternative approaches that include the instrumental variable estimation (Anselin and Bera, 1998), Maximum Likelihood (ML) approach and method of moments.

[9] GWR has been applied in agricultural and environmental analyses (Nelson and Leclerc, 2001), spatial structural instability of consumption behaviour (Paraguas *et al*., 2006a), and of aquaculture adoption (Paraguas *et al*., 2006b).

$$R_i = \alpha_i + \beta_i W_i \ln\left(TFP_{0i}\right) + u_i \qquad \ldots(9)$$

where, the subscript *i* indicates the state. Equation (9) is estimated for each state. Unlike the spatial regression models specified earlier, the *W* is expressed as the relative weight of locations that is assumed to decay at an empirically-determined rate as their distance from the focal location *i* increases. Simply stated, the spatial heterogeneity is operationalized by this weighting scheme (*W*) in such a manner that locations closer to the focal location have higher weights. In the current paper, the weighting scheme has been defined by an exponential distance-based decay function (10):

$$w_{ij} = e^{\left(-d_{ij}^2/\theta\right)} \qquad \ldots(10)$$

where, d_{if} is the Euclidean distance between locations *i* and *j* that are derived from the longitude-latitude coordinates of the centroid for each state. The optimal bandwidth, θ, is the distance decay parameter and is determined using the least-squares cross-validation procedure, suggested by Cleveland (1979). The GWR β-convergence model [Equation (9)] was estimated using the GWR software (Charlton *et al.*, 2003).

3. Results

Using the compound annual growth rate formulation, it was revealed that the aquaculture TFP of an average state in India grew at an annual rate of 6.97 per cent during 1992-1998. This growth can be partly attributed to the output growth (4.15 % /annum) and decelerating input growth (-2.82% / annum). The average TFP across states over the years has been presented in Appendix I. The state-wise TFP growth during this period has been depicted in Figure 1. Among the sates, only the state of Punjab experienced the decreasing TFP growth. This state was also characterized by a decelerating productivity in output and input. Interestingly, the neighbouring state of Rajasthan also experienced the decelerating productivity growth in output and input. However, unlike Punjab, Rajasthan posted a positive overall TFP growth. In general, a spatial clustering of TFP growth levels can be observed. For example, a relatively higher TFP growth is observed in the neighbourhood of West Bengal states (i.e. states that surround Bangladesh).

Figure 2 depicts the results of σ-convergence, calculated as the coefficient of variation (CV) of the logarithm of productivity. The dispersion in the state-wise distribution of TFP has increased during the period 1993-1995, but diminished during the later years — an indication of productivity convergence. Productivity convergence is more pronounce in the input and output productivity. Appendix II also provides the listing of σ.

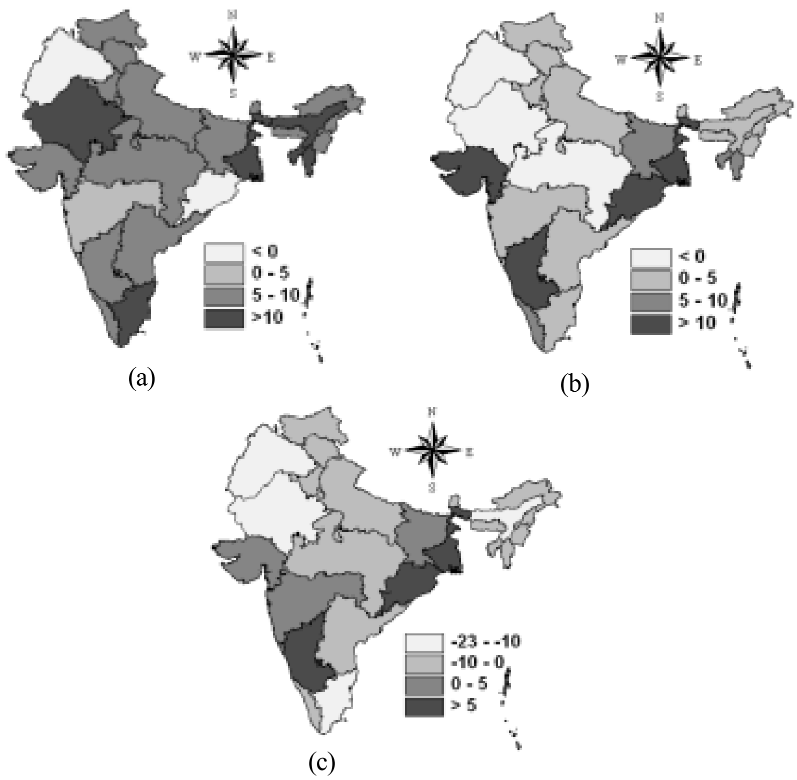

Figure 1. Spatial distribution of compound annual growth in (a) TFP, (b) output, and (c) input

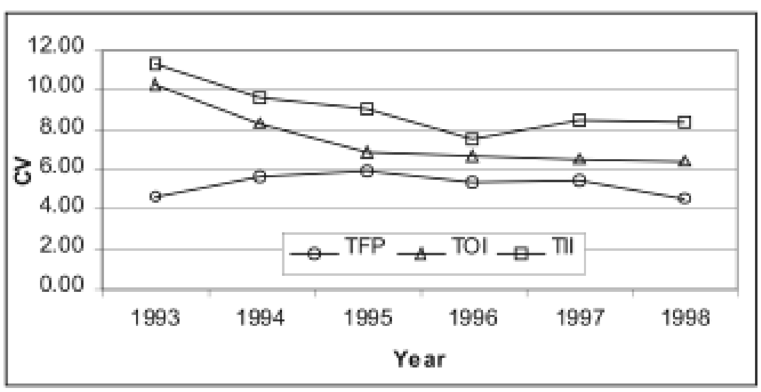

Figure 2. The σ-convergence in (log) productivity indices

For comparison purposes, the results of the β-convergence analysis estimated using the Ordinary Least Square [OLS, Equation (4)], SAR [Equation (7)] and SEM [Equation (8)] models, have been presented in Table 1. The negative and significant β confirmed that there was a process

Table 1. A comparison of the TFP convergence parameters, India

	Ordinary least squares (OLS)		Spatial autoregressive (SAR)		Spatial error model (SEM)	
	Estimate	S.E.	Estimate	S.E..	Estimate	S.E.
Constant	0.67***	0.15	0.58***	0.14	0.55***	0.15
β (ln TFP_{93})	-0.13***	0.03	-0.10***	0.03	-0.10***	0.03
ρ (spatial lag parameter)			0.51***	0.19		
λ (spatial error parameter)					0.64***	0.22
R^2	0.35		0.42		0.39	
β (rate of convergence)	24.22		16.0		15.98	
τ (half-life)	5.07		6.37		6.39	

*** statistically significant at $a = 0.01$
S.E. = Standard error

of β-convergence in the TFP growth between the Indian states during 1992-1998. However, the absolute value of β estimates were quite high with the OLS posting the highest estimate of 0.13, indicating an upward bias which illustrated the misleading effect that spatial autocorrelation might have on inference using OLS estimates. In contrast, the SAR and SEM models revealed a 10 per cent β-convergence which occurred at a rate of 16 per cent per year and implying a 6-year period for the states to close half of the productivity gap between their initial values and steady states. The SAR model was able to explain approximately 42 per cent of the variability in the TFP growth compared to 35 and 39 per cent by the OLS and the SEM models, respectively. The spatial lag parameter (ρ) was estimated at a sizeable 0.51, which was statistically positive at a 99 per cent level of significance. The estimated ρ can be interpreted to suggest that a 10 per cent increase in the TFP growth of the surrounding states will result in a 5.1 per cent increase in the TFP growth of the focal state, *ceteris paribus*. Moreover, a state whose neighbours' aquaculture TFP growth is increasing is in a better position to enjoy the growth spillovers and externalities generated by the surrounding states than which are isolated.

Figure 3 presents the distribution of (a) local β estimates, (b) local R^2, and (c) implied τ. The estimated local R^2 ranges from 0.30 to 0.89 with an average of 0.62, providing a significant improvement over the SAR model (0.42) and the OLS model (0.35). In general, a spatial clustering of states with similar convergence behaviour can be observed. It will take a longer period for Uttar Pradesh and other states in the northern and northeast

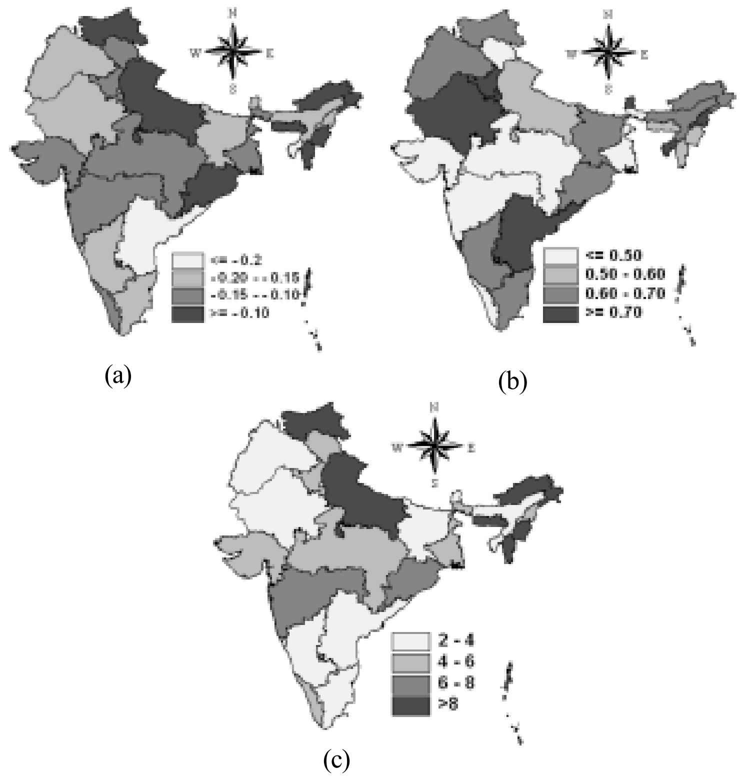

Figure 3. GWR outputs (a) local β estimates, (b) local R^2, and (c) implied local τ

region to close half of the productivity gap between their initial values and their steady states.

4. Summary and Conclusions

This paper has provided an illustration of evaluating the productivity convergence using spatial econometric modelling framework for the aquaculture sector in India. Productivity has been measured using TFP. The β- and σ-convergence concepts that are used to test the convergence hypothesis have been extended to spatial framework. The spatial approach provides, in this sense, various techniques of analysis that attempt to evaluate the impact of geography on the aforementioned processes. Initially, a spatial perspective of the pattern of state-wise growth in productivity has been conducted and subsequently, extended the model of β-convergence to include possible spatial effects.

An understanding of the spatial dimension of convergence process can help the policymakers in designing the programs to expand the fish production potential of the country. Also, from an econometric point of view, the inclusion of spatial factors allows modelling of regional interdependence and spillovers — a region experiencing growth propagates positive effects onto the neighbouring regions. Secondly, as has been evidenced from the results, the spatial models are capable of explaining a high proportion of the variance of productivity convergence. The results obtained from the SAR and SEM models which are better than those of the classical one, have confirmed the existence of β-convergence but at a slightly lower rate than that of the classical model. Finally, the results have also provided a strong evidence of the spatial heterogeneity of productivity convergence and spatial clustering of states with similar convergence behaviour which has policy implications specific to different regions.

Three related areas have been recommended for further research. Firstly, the provisional hypotheses set out in this paper can be validated in the crops and livestock where data are available for longer period and smaller administrative units. Secondly, these sectors which are subjected to several productivity evaluations and are rich with variables that can be hypothesized to affect productivity growth, provide an avenue for the extension of the spatial models to include such variables as independent variables. Lastly, spatial dimensions can also be incorporated in the previous studies that decomposed the productivity growth into several factors.

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Appendix I

Average productivity index of aquaculture across states in India

Year	Total factor productivity index (TFP)	Total output index (TOI)	Total Input index (TII)
1992	100.0	100.0	100.0
1993	113.2	140.7	129.2
1994	103.9	149.3	151.2
1995	124.4	147.6	127.9
1996	168.9	154.0	94.0
1997	149.5	154.1	108.4
1998	172.5	160.8	97.3

Source: Kumar *et al*. (2004a)

Appendix II

σ- convergence computed as the coefficient of variation of the natural logarithm of aquaculture productivity indices across states in India

Year	Coefficient of variation (CV)		
	TFP	TOI	TII
1993	4.65	10.33	11.30
1994	5.65	8.30	9.62
1995	5.94	6.92	9.02
1996	5.36	6.74	7.57
1997	5.49	6.56	8.49
1998	4.61	6.44	8.44

Note: The coefficient of variation is defined as the ratio of the standard deviation σ to the mean μ