Research Article

A Bayesian Approach Estimation of Technical Efficiency in Paddy Farms of Canal Irrigated Systems in Tamil Nadu

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Abstract

The present study undertaken in Cauvery delta zone in Tamil Nadu has estimated the resource use efficiency in rice production and has assessed the effect of farm specific socio economic factors affecting the technical efficiency. The study also used the Bayesian approach which is considered superior to the conventional production function parameter estimates of maximum likelihood method. Stochastic frontier production functions using maximum likelihood and Bayesian approach were estimated to determine technical efficiency of individual farms and the parameters. The data collected for two years (2009-10 and 2010-11) under the Cost of Cultivation Scheme of Tamil Nadu Centre were used for the study. The Statistical Model Specification Test performed revealed the superiority of the Translog production frontier functional form over Cobb-Douglas model. Moreover, the Bayesian approach proved to be superior than the Maximum Likelihood Estimation. The results of Translog stochastic production function estimated using the Bayesian approach indicated that seed and fertilizer in canal irrigated conditions had positive impact on yield of paddy, while labour impacted negatively production of paddy. However, the marginal value product to input price ratios for seed at 1.875 and for fertilizer at 4.95, respectively indicated that it will be highly profitable to increase the use of seed and fertilizer in canal irrigated conditions. This ratio for labour happened to be negative and greater than one at -4.20 indicating the need for firm steps to reduce use of labour in canal irrigated conditions. The study has revealed that 99.08 per cent of farms were in the efficiency range of 70-100 per cent under canal irrigated conditions. Moreover, farms with efficiency range of 80 – 100 per cent accounted for 90.37 per cent. The mean efficiency happened to be 89.28 per cent. The return to scale at 0.564 indicated the operation of law of diminishing marginal returns in canal irrigated farms.

Keywords: Rice, Canal Irrigation, Technical Efficiency, Translog Production Function, Stochastic Frontier, Bayesian Estimation

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Introduction

Rice is the staple food of over half the world's population, (60 per cent) especially in East Asia, Southeast Asia, South Asia, the Middle East, and the West Indies. Rice crop suffers from various biotic and abiotic production constraints [1]. It is the predominant dietary energy source for 17 countries in Asia and the Pacific, nine countries in North and South America and eight countries in Africa. Rice provides 20 per cent of the world's dietary energy supply (FAO, 2004-05). According to the Food and Agriculture Organization, area and production of rice at the global level was 153.65 million hectare (mh) and 672 million tons (mt), respectively (FAO, 2010-11).

The present study was undertaken in Cauvery delta zone in the state of Tamil Nadu to estimate the resource use efficiency in rice production under canal irrigations, and to assess the effect of farm specific socioeconomic factors affecting the technical efficiency. Usually the Stochastic frontier production functions are estimated by using maximum likelihood estimation. But, Bayesian methods can make use of more available information and so typically produce stronger results than maximum likelihood estimates. Hence, in this study, Bayesian estimation method was used besides the maximum likelihood estimation procedure to estimate the stochastic frontier production functions to estimate the performance efficiency of paddy farms in canal irrigated conditions.

Objectives

The overall objective of the study is to explore the efficiency of paddy cultivation in Tamil Nadu under canal irrigated conditions. The specific objectives of the study were; to assess input use, output levels and to estimate the production frontiers using maximum likelihood estimation and Bayesian approach to compute the efficiency of rice production

Methodology

Sampling and Data Collection

The Cauvery delta zone is known as the *Rice Bowl of Tamil Nadu*. As such, the Cauvery delta zone was selected for canal irrigation purposively, for the present study. The data collected under the cost of cultivation scheme were used. Under the scheme a stratified random sampling method was adopted. Thanjavur and Thiruvarur districts in the Cauvery delta Zone were covered for canal irrigation under the above scheme during the two consecutive years from 2009-10 and 2010-11(these were normal years).

In Cauvery delta zone 109 farmers from seven taluks were selected for the present study. Ultimately, there were 218 sample points for two years (2009-10 and 2010-11).

Analytical framework

Stochastic frontier Analysis

In the present study, the stochastic frontier production function approach was used to measure Technical efficiency of rice cultivating farms [2-4]. The maximum likelihood estimates usually assume normal distribution of the data implying that these do not take into account the prior knowledge about parameters. Bayesian estimates are more reliable and accurate, because they take into account the prior knowledge about the distribution of the parameters and also the estimation gives rise to a posterior probability distribution of a parameter which accounts for uncertainties. This approach is of recent origin and useful in many decision making situations, because this approach gives consistent results when the underlying data are faced with uncertainty [5]. Complex statistical problems can be handled more easily by applying powerful computational techniques like Markov Chain Monte Carlo (MCMC) in Bayesian methods. The frequentist methods (OLS, MLE, etc.) on the other hand can only give approximate results or sometimes they fail completely.

Specification of the Model

Maximum Likelihood Estimation

Assuming that each farm uses *m* inputs (vector *x*) and produces a single output *y*, the production technology of the i^{th} farm is specified by the stochastic frontier production function

$$y_i = f\left(x_i;\beta\right)\exp\left(\varepsilon_i\right) \tag{1}$$

where i=1,2,….n refers to farms, β is a vector of parameters and ε_i is an error term and the function $f\left(x;\beta\right)$ is called the 'deterministic kernel'. The frontier is also called as 'composed error' model because the error term ε_i is assumed to be the difference of two independent elements,

$$\varepsilon_i = v_i - u_i \tag{2}$$

where v_i is a two sided error term representing statistical noise such as weather, strikes, luck etc which are beyond the control of the farm and $u_i \geq 0$ is the difference between maximum possible stochastic output (frontier) $f\left(x_i;\beta\right)\exp\left(v_i\right)$ and actual output y_i. Thus u_i represents output oriented technical inefficiency. Thus, the error term ε_i has an asymmetric distribution. From (1) and (2), the farm-specific output-oriented technical efficiency can be shown as

$$TE_i^o = \exp\left(-u_i\right) = y_i \Big/ \left\{ f\left(x_i;\beta\right)\exp\left(v_i\right)\right\} \tag{3}$$

Since $u_i \geq 0$, $0 \leq \exp(-u_i) \leq 1$ and hence $0 \leq TE_i^o \leq 1$. When $u_i = 0$ the farm's output lies on the frontier and it is 100 per cent efficient. Thus, the output oriented technical efficiency tells how much maximum output is possible with the existing usage levels of inputs. The 'Cobb-Douglas' function in log form is given by

$$\ln(y_i) = X_i\beta + v_i - u_i, i = 1, 2, ...n \tag{4}$$

where X_i is a vector consisting of the logarithms of m inputs. Similarly the translog form which is more flexible is given by

$$lny_i = \beta_o + \sum_j \beta_j \, lnx_{ij} + \frac{1}{2}\sum_j \sum_k \beta_{jk} \, ln\, x_{ij} \, lnx_{ik} + v_i - u_i. \tag{5}$$

For panel data, Battesse and Coelli (1995), have modified the model which allows for firm-specific patterns of efficiency change over time. In this case, the Cobb-Douglas production frontier becomes

$$\ln(y_{it}) = X_{it}\beta + v_{it} - u_{it}, i = 1, 2, ...n \text{ and } t = 1, 2, ...T \tag{6}$$

which is used for the present study.

A similar model can be written for translog production frontier. Where y_{it} denotes the production of the i^{th} firm during the t^{th} period and T is the total number of periods. The firm-specific inefficiencies, u_{it} are specified by

$$u_{it} = z_{it}\delta + w_{it} \tag{7}$$

and are assumed to be non-negative and independently distributed random variables such that u_{it} is obtained by truncation at zero of the normal distribution with mean $z_{it}\delta$ and variance σ^2, where z_{it} is a vector of explanatory variables associated with technical inefficiency of production of firms over time and δ is a vector of unknown coefficients. In other words, w_{it} are defined by truncation of the normal distribution with zero mean and variance σ^2. The technical efficiency of production for the i^{th} firm at the t^{th} time period is given by

$$TE_{it} = \exp(-z_{it}\delta - w_{it}) \tag{8}$$

The generalized likelihood test was applied to test a number of hypotheses. The relevant test statistic was calculated using the formula

$$LR = -2\left\{ln\left[L(H_0)\right] - ln\left[L(H_1)\right]\right\} \tag{9}$$

Where; LR- Log likelihood ratio L(H_0) *and* $L(H_1)$: the values of the likelihood function under the null and alternative hypotheses respectively.

The computer programme FRONTIER 4.1 [6] was used to estimate simultaneously the parameters of the stochastic production frontier and the technical inefficiency effects.

Bayesian Estimation

The Bayesian approach to statistical inference is quite different from the classical approach, though both depend essentially upon the likelihood. In the classical approach the model parameters are regarded as fixed quantities that need to be estimated, and this is typically done by finding the values of the parameters that maximize the likelihood, considered as a function of the parameters. In the Bayesian approach, parameters are seen as variables and possessing a distribution. This approach follows from a simple application of Bayes Theorem.

The optimization of classical analysis has been replaced by integration for the Bayesian approach. The modern approach to Bayesian analysis is however, not to try to integrate the posterior joint distribution analytically, but instead to employ simulation procedures which result in samples from the posterior distribution. The simulated value from the posterior joint distribution means is the one naturally has simulated value from the posterior marginal distribution of the parameters of interest. This approach is called Markov Chain Monte Carlo (MCMC). [7] used this simulation procedure.

The Stochastic frontier production function is usually estimated by using MLE and this method is widely used. An alternative but advanced method is to use Bayesian estimation. [8] pointed out that the use of Bayesian approach to inference has the following characteristics:

- Estimators are chosen based on their ability to minimize the loss associated with an estimation error.
- Results are usually presented in terms of probability density functions. Thus, it is possible and convenient to make probability statements about unknown parameters, hypotheses and models.
- There is a formal mechanism for incorporating non-sample information into the estimation process.
- Exact finite-sample results can be obtained for most estimation problems.

Bayesian estimation of stochastic frontier model with normally distributed errors is described below:

Bayes Theorem

The unknown parameter in the classical linear regression model are $\beta=(\beta_1,\beta_2,....,\beta_k)'$ and σ. The Bayesian approach to inference, it summarizes pre sample information about these parameters in the form of prior pdf, denoted as $p(\beta,\sigma)$. Sample information (i.e., information contained in the data) is summarized in the form of the familiar likelihood function: $L(y/\beta,\sigma)$. These two types of information are then combined using Bayes theorem as follows

$$p(\beta,\sigma/y)\propto L(y/\beta,\sigma)\; p(\beta,\sigma)$$

where $p(\beta,\sigma/y)$ is the posterior probability distribution function (posterior pdf) and $\propto$ denotes "is proportional to". In other words, posterior probability distribution function (posterior pdf) is proportional to the likelihood function times the prior pdf. The posterior pdf underpins all types of Bayesian inference, including point and interval estimation, evaluation of hypothesis and prediction.

Specifying a Prior and Posterior Pdf

Prior pdfs are often classified as non-informative or informative. The non-informative prior conveys ignorance about the parameters. The prior pdf,

$$p(\beta,\sigma)\propto\frac{1}{\sigma} \tag{10}$$

which follows from the assumption that $\ln\sigma$ and the elements of β are all independently distributed and can take any value with equal probability. Now combining the above prior pdf with the likelihood function, yields a proper posterior pdf. According to Bayes' theorem, the joint posterior pdf for β and σ is proportional to the likelihood function times a prior pdf. If the likelihood function for the classical linear regression model with normal errors is given by

$$L(y/\beta,\sigma)=(2\pi\sigma^2)^{\frac{-1}{2}}\exp\left[-\frac{1}{2\sigma^2}\sum_{i=1}^{n}\left(y_i-x_i{}'\beta\right)^2\right] \tag{11}$$

combining equations (10) and (11) we get posterior pdf,

$$p(\beta,\sigma/y)\propto\frac{1}{\sigma^{n+1}}\exp\left[-\frac{1}{2\sigma^2}\sum_{i=1}^{n}\left(y_i-x_i{}'\beta\right)^2\right]$$

This joint posterior pdf summarizes all our post sample knowledge about β and σ^2.

The exponential stochastic frontier model can be written as

$$\ln q_i = x_i'\beta + v_i - u_i \tag{12}$$

$$p(v/h) = (2\pi)^{-\frac{I}{2}} h^{\frac{I}{2}} \exp\left[-\frac{h}{2}\sum_{i=1}^{I} v_i^2\right] \tag{13}$$

$$\text{and } p(u/h) = \prod_{i-1}^{I} \lambda^{-1} \exp(-u_i/\lambda) \tag{14}$$

where v = $(v_1, v_2, \ldots, v_I)^1$ and u=$(u_1, u_2, \ldots, u_I)^1$ are vectors of noise and inefficiency effects and $h \equiv \frac{1}{\sigma^2{}_v}$ is known as the precision.

Simulation methods

Bayesian approach involves evaluation of complex integrals. Recent advances in computer technology and the theory of simulation allows evaluating these integrals numerically. The procedure is as follows;

Let θ be a vector of unknown model parameters. Then almost anything a Bayesian would want to calculate can be written in the form,

$$E[h(\theta)/y] = \int_{-\infty}^{\infty} h(\theta)\, p(\theta/y)\, d\theta \tag{15}$$

where $h(\theta)$ is some function of θ and p(θ / y) is the pdf of θ given y.

Unfortunately, integrals of the above form are often analytically intractable. However suppose $\theta^1, \theta^2, \ldots, \theta^S$ is a random sample drawn from p(θ / y), then, provided S is large, the integral (15) can be estimated using the sample mean $\hat{h}(\theta) = \frac{1}{S}\sum_{s=1}^{S} h(\theta^s)$

To obtain a point estimate of σ^2 simply average sample observations on σ^2.

Markov Chain Monte Carlo Methods

The technique for drawing random sample or simulating from a pdf involved random sampling and is known as Monte Carlo methods. The simplest method yields samples of independent observations. More sophisticated methods yield chains of correlated observations that satisfy the properties of Markov processes. These methods are known as Markov Chain Monte Carlo (MCMC) algorithms. Implementing Bayesian approach often requires the use of an iterative MCMC algorithm. The two most popular algorithms are the Metropolis-Hastings algorithm and the Gibbs Sampler.

Gibbs Sampling Algorithm

The Gibbs sampling algorithm is one of the simplest Markov Chain Monte Carlo algorithms. It was introduced by [9] in the context of image processing and then discussed in the context of missing data problems by [10]. The paper by [11] helped to demonstrate the value of the Gibbs algorithm for a range of problems in Bayesian analysis. The Gibbs Sampler is particularly useful for problems involving latent variables as stochastic frontier models. It relies on our ability to partition θ as $\theta = (\theta_1, \theta_2, \ldots, \theta_P)$, where, θ_P's may be multidimensional and where it is possible to simulate from the conditional densities,

$$p(\theta_p / \theta_1, \ldots, \theta_{p-1}, \theta_{p+1}, \ldots, \theta_P, y) \text{ for p = 1,2,3,…, P.}$$

one can then draw observations on θ using the following steps;

1. Choose a starting value θ^{0} that is in the support of θ and set s =0
2. Draw θ_1^{s+1} *from* $p(\theta_1 / \theta^{s}{}_2, \theta^{s}{}_3, ..., \theta^{s}{}_p, y)$
3. Draw θ_2^{s+1} *from* $p(\theta_2 / \theta^{s+1}{}_1, \theta^{s}{}_3, ..., \theta^{s}{}_p, y)$ and so on.
4. Draw θ_p^{s+1} *from* $p(\theta_p / \theta^{s+1}{}_1, \theta^{s+1}{}_2, ..., \theta^{s+1}{}_{p-1}, y)$
5. Set s = s+1 and repeat from step 2.

Quickly the algorithm draws a sample depending on the methods used to sample from the conditional densities in each step.

The large number of priors and likelihoods in econometrics makes it difficult to build a computer package that can be widely used for MCMC simulation. These type of Stochastic frontier models can be estimated using packages such as BUGS-Bayesian Inference using Gibbs Sampling.

Win BUGS

Win BUGS is the MS Windows operating system version of Bayesian Analysis using Gibbs Sampling. It is a versatile package that has been designed to carry out Markov chain Monte Carlo computations for a wide variety of Bayesian models. It is the statistical package and is specifically designed for Bayesian analysis and is based on Markov Chain Monte Carlo (MCMC) techniques for simulating samples from the posterior distribution of the parameters of the statistical model.

Results and Discussion

Empirical model

In the present study, both Cobb-Douglas and Translog type of production functions were initially considered to study the technical efficiency among rice farms.

$$\ln y_i = \beta_0 + \sum_j \beta_j \ln x_j \quad \text{, j = 1,2,3,...6 (Cobb- Douglas type)}$$

$$\ln y_i = \ln \beta_0 + \sum_j \beta_j \ln x_j + \frac{1}{2} \sum_j \sum_k \beta_{jk} \ln x_j x_k + v_i - u_i \text{, j,k = 1,2,3,…6 (Translog type)}$$

$$\mu = \delta_0 + \sum_{i=1}^{6} \delta_i z_i \quad \text{(Linear type)}$$

Where,

y	=	Yield of paddy (quintal /ha)
Seed (x_1)	=	Quantity of seeds (kg. /ha.)
Fer (x_2)	=	Quantity of NPK nutrients (kg. /ha.)
Lab (x_3)	=	Human labour (hrs. /ha.)
Mach (x_4)	=	Machine hours (hrs. /ha.)
Pes (x_5)	=	Cost of plant protection (Rs. /ha.)
x_6	=	Trend (‘1’for year 2009-10 and ‘2’ for year 2010-11)
Age (z_1)	=	Age of the farmer in years
Farm Size (z_2)	=	Area in hectares
Edn (z_3)	=	Education of the farmer (illiterate(1), upto primary(2), upto secondary(3), upto collegiate(4) and post graduate(5)),
Household size (z_4)	=	Size of the farmer’s household (number of family members)
Sea 1 (z_5)	=	Season dummy variable indicating season 1 (June-Sept.); 0 otherwise.
Sea 2 (z_6)	=	Season dummy variable indicating season 2 (Oct.-Jan.); 0 otherwise. Season 3 is taken as base.

Mean yield and Input use levels in Sample farms

The descriptive statistics are presented in **Table 1**

Table 1.Mean yield and input use levels in the canal irrigated paddy farms

Year	**2009-10**		**2010-2011**		**2009-10 & 2010-11**	
Measures	Mean	SD	Mean	SD	Mean	SD
Yield (quintal/ha)	47.4	9.0	48.6	9.8	47.99	9.4
Inputs used in paddy cultivation						
Seed (kg)	92.1	18.7	91.4	16.6	91.75	17.6
N,P,K nutrients (kg)	200.3	41	210.1	36.1	205.2	38.8
Labour (Hrs)	500.4	195.7	573.6	431.4	536.9	336.2
Machine (Hrs)	6.4	3.6	6	2.3	6.21	3.1
Pesticide (Rs)	847.2	597.2	972.5	603.2	909.8	602.1
Socio Economic variables of Sample Farms						
Age	58.9	11.7	58.7	12.1	58	11.8
House hold Size	5.6	2.9	5.6	2.9	5.5	2.9
Area of the farm (ha)	1.5	1.4	1.48	1.47	1.5	1.45

The average yield of rice in the sample farms under canal irrigation worked out to 47.99 quintal per hectare. The quantity and type of seed planted by rice farmers depend on the production system, size of the farm, availability of the seed varieties, price, and the technology available to the farmer, ability of the farmer to take risks and the suitability of the variety to a particular environment [12]. The recommended seed rate per hectare in paddy production happens to be 65kg (crop protection guide, TNAU and Department of Agriculture). In the present study the paddy farmers used an average of 91.75kg/ha and which is exceeded the recommended one.

Fertilizer is known to be one of the most critical inputs in paddy production because of the high response of the crop to fertilizer application. On the average 205.2kg of fertilizer nutrients was applied per hectare by the canal irrigated paddy farmers. In the face of scarcity and increasing wage rate of farm labour, the use of herbicides has been observed as a major labour saving device as the labour requirement for weeding always accounts for a high proportion of the total farm labour cost in rice production. Besides rice like other grains, requires prompt application of agrochemicals such as insecticides and fungicides to check the menace of pest and disease infestation. Results presented in the table shows that a sum Rs. 909.80 was spent per hectare on pesticide. The labour use was found to be 536.9 hrs/ha and in the case of machine hours on an average 6.21 hrs/ha was used.

Model results

Frontier estimation

To analyze the efficiency of paddy farmers in canal irrigated farms, the stochastic frontier production function was employed. Among different forms of production function, the model specification test was performed to find a suitable (Cobb-Douglas or Translog) type of production function that would give the best fit.

Two types of model specification tests were considered;

1. to select the functional form (Cobb-Douglas production function or Translog production function)
2. to test whether the production function is Stochastic in nature
3. To perform the above model specification tests the null hypotheses considered are as follows;
   I. Null Hypothesis H_0 such that the production function is Cobb-Douglas.
   II. Null Hypothesis H_0: $\gamma = 0$, *i.e.* no technical inefficiency exists in paddy production

The generalized likelihood test was applied to test the above hypotheses. The relevant test statistic was calculated using the formula

$$LR = -2\left\{ln\left[L\left(H_0\right)\right] - ln\left[L\left(H_1\right)\right]\right\}$$

where, $L(H_0)$ is likelihood value of the Cobb-Douglas stochastic frontier production function. $L(H_1)$ is likelihood value of the Translog stochastic frontier production function.

The model specification tests were performed accordingly using LR test (λ) statistic and the test results are given in **Table 2**.

Table 2 Results of Model Specification Tests

Hypothesis	$\lambda-Statistic$ (Log Likelihood Ratio)	Critical value $(\alpha=0.01)$	Conclusion
	Canal irrigated farms		
H_0: Cobb Douglas H_1: Translog	47.67	$\chi_{15}^2 = 30.57^{***}$	H_0 *is rejected*
$H_0:\gamma=0$	46.66	$\chi_1^2 = 5.412^{***}$	H_0 *is rejected*

***= significant at 1% level

Hypotheses test regarding model specification test results would indicate that the null hypotheses $H_0:\gamma_i=0$ *for all* i are both rejected at 1% level of significance. According to the results presented in Table 2, the null hypothesis that the production function being Cobb - Douglas had been rejected and the Translog frontier production function adequately represents the data had been accepted, under canal irrigated conditions.

The yield of rice (quintal per hectare) was taken as dependent variable and it was regressed on per hectare use of seeds, fertilizer nutrients, human labour in hours, machine power in hours, and plant protection cost, using a software package FRONTIER 4.1.The parameters were estimated by Maximum Likelihood Estimation (MLE) method. The estimated results are presented in **Table 3**.

Model Results of Maximum Likelihood Estimation

It could be inferred from the results of the frontier Translog production function analysis that inputs such as; seeds, fertilizers, human labour remained critical in paddy production. The interpretations are however, made for the elasticities derived.

The results would show that the MLE of γ happened to be 0.885 is highly significant, consistent with the theory that true γ-value should be greater than zero. The value of γ-estimate while significantly different from one, still indicates that random error is playing limited role explaining the variation in paddy production. From the results, it could also be inferred that the farm level inefficiency accounted for 88 per cent of the error and 12 per cent due to stochastic random noise in canal irrigated farms.

In order to investigate the determinants of inefficiency, the technical inefficiency model was estimated using Frontier 4.1. The coefficient of education turned out to be highly significant and it turned out to be negative implying that investments on human capital take away their participation from agriculture in canal irrigated conditions. It is also debatable whether this would be an added cause for relatively lower yield in canal irrigated paddy farms.

Bayesian Estimation

For the present study two types of stochastic frontier model namely, Bayesian estimation of stochastic frontier model with normally distributed errors and exponentially distributed errors were estimated. However the standard deviation of the error term (sigma) for exponential distribution was relatively low compared to that with normal distribution, estimated for canal irrigated farms. This would show that the error component of stochastic frontier translog production function remained exponentially distributed and thus chosen for interpretation. Thus, the results for the Bayesian estimates following the exponential distribution alone are discussed.

The Win BUGS software was used for Bayesian Analysis, as the exponentially distributed inefficiencies, could be generated showing posterior mean, median and standard deviation with a 95% posterior credible interval. The results are presented in **Table 4**.

Table 3 Estimated results of Stochastic Frontier Translog Production Function using MLE for Sample Paddy Farms

Variables	**Canal irrigated farms**		
	Coefficient	**SE**	**t-ratio**
Constant	8.291	7.456	1.112
Seed(kg/ha)	**-5.010****	2.474	-2.025
Fer(kg/ha)	**6.774*****	1.966	3.445
Lab(hrs/ha)	**-3.249****	1.422	-2.286
Mach(hrs/ha)	-1.451	1.348	-1.076
Pes (Rs./ha)	0.110	0.836	0.132
$(\text{Seed})^2$	**0.312****	0.181	1.721
$(\text{Fer})^2$	**-0.857*****	0.264	-3.249
$(\text{Lab})^2$	0.045	0.040	1.126
$(\text{Mach})^2$	-0.060	0.067	-0.891
$(\text{Pes})^2$	**-0.027*****	0.008	-3.205
Seed*Fer	0.221	0.330	0.671
Seed*Lab	0.176	0.196	0.900
Seed*Mach	-0.118	0.230	-0.513
Seed*Pes	0.062	0.091	0.682
Fer*Lab	0.259	0.225	1.152
Fer*Mach	-0.108	0.182	-0.593
Fer*Pes	-0.008	0.104	-0.075
Lab*Mach	**0.348*****	0.121	2.865
Lab*Pes	-0.039	0.063	-0.617
Mach*Pes	0.098	0.058	1.678
Trend	0.035	0.024	1.425
Constant	0.402	0.227	1.776
Age(Z_1)	-0.003	0.003	-0.831
Area of the farm(Z_2)	0.008	0.023	0.337
Edn(Z_3)	**-0.179****	0.082	-2.177
Household Size(Z_4)	-0.001	0.012	-0.091
Sea 1 (Z_5)	**-2.176***	1.190	-1.828
Sea 2 (Z_6)	-0.575	0.229	-2.517**
sigma-squared	**0.115*****	0.043	2.657
Gamma (γ) $\frac{\sigma^2_u}{\sigma^2_v}$	**0.885*****	0.047	18.735

*=significant at 10% level,**=significant at 5% level,***= significant at 1% level

Model Results of Bayesian Estimation

Even while, the value of coefficient varied, the variable affecting production significantly and their sign remained the same under the both Maximum Likelihood Estimation and Bayesian methods of estimation.

Production Elasticities

Estimates of production elasticities, marginal value product to input price ratio and returns to scale for maximum likelihood estimation and Bayesian estimation of canal farms are presented in **Table 5**.

As regards the maximum likelihood estimates, the MVPy/P_x ratios for those input variables that turned out to be significant, reveal the potential to invest more only in seed in respect of canal irrigated sample paddy farms. However, the Bayesian estimates produced the MVP_y/P_x ratios that turned out to be positive and greater than one for seed as well as fertilizers. This ratio for labour happened to be negative and greater than one indicating the need for firm steps to reduce use of labour. The returns to scale at 0.5144 for maximum likelihood estimates and 0.5641 for Bayesian estimates would indicate the operation of decreasing returns to scale at the present level of technology and the need for breakthrough in technology by way of new varieties or management methods and research extension farmer linkage.

Table 4 Estimated results of Stochastic Frontier Translog Production Function using Bayesian Estimation for canal irrigated sample paddy Farms

Variable	Mean	SD	MC error	2.5%	Median	97.5%
constant	22	13.64	0.13440	-4.514	22.02	48.71
Seed(kg/ha)	**-8.612**	3.139	0.03088	**-14.79**	**-8.61**	**-2.409**
Fer(kg/ha)	**6.973**	2.982	0.03646	**1.099**	**6.999**	**12.76**
Lab(hrs/ha)	**-5.196**	1.789	0.01697	**-8.706**	**-5.196**	**-1.661**
Mach(hrs/ha)	-2.049	1.769	0.01831	-5.514	-2.061	1.468
Pes (Rs./ha)	0.2178	0.8168	0.00876	-1.387	0.2231	1.814
$(Seed)^2$	**0.5602**	0.2097	0.00239	**0.1468**	**0.5612**	**0.9696**
$(Fer)^2$	**-0.9758**	0.2707	0.00302	**-1.504**	**-0.9783**	**-0.452**
$(Lab)^2$	0.04405	0.0418	0.00033	-0.03753	0.044	0.1274
$(Mach)^2$	**-0.1553**	0.06382	0.00069	**-0.2795**	**-0.1554**	**-0.02958**
$(Pes)^2$	**-0.02658**	0.00845	0.00009	**-0.04297**	**-0.02662**	**-0.00985**
Seed*Fer	0.1482	0.3467	0.00349	-0.5363	0.1514	0.8263
Seed*Lab	0.4059	0.2465	0.00262	-0.08578	0.4055	0.8863
Seed*Mach	0.06743	0.2698	0.00378	-0.4688	0.07064	0.5911
Seed*Pes	0.04657	0.1058	0.00151	-0.1585	0.04648	0.257
Fer*Lab	0.4615	0.2358	0.00227	-0.00287	0.4631	0.9268
Fer*Mach	0.007846	0.1746	0.00151	-0.3379	0.009942	0.3453
Fer*Pes	-0.00409	0.1078	0.00104	-0.2151	-0.00458	0.2083
Lab*Mach	**0.2884**	0.1332	0.00140	**0.02726**	**0.2885**	**0.5485**
Lab*Pes	-0.04636	0.06257	0.00056	-0.1699	-0.0458	0.07403
Mach*Pes	0.08863	0.06657	0.00088	-0.04296	0.08854	0.2188
Trend	0.03408	0.02174	0.00017	-0.00887	0.034	0.07701
constant	0.86200	0.02147	0.00015	0.82010	0.86190	0.90370
Age(Z_1)	0.00003	0.00029	0.00000	-0.00054	0.00003	0.00060
Area of the farm(Z_2)	-0.00068	0.00225	0.00002	-0.00514	-0.00066	0.00373
Edn(Z_3)	**-0.00456**	0.00270	0.00002	**-0.00072**	**-0.00455**	**-0.00988**
Household Size(Z_4)	0.00044	0.00112	0.00001	-0.00173	0.00044	0.00264
Sea 1 (Z_5)	**-0.06873**	0.01401	0.00009	**-0.04164**	**-0.06870**	**-0.09626**
Sea 2 (Z_6)	**-0.01611**	0.00897	0.00006	**-0.00165**	**-0.01621**	**-0.03358**
Sigma	0.04659	0.00228	0.00002	0.04235	0.04651	0.05129

Table 5 Estimated Elasticities for Variables Influencing Production Significantly in Canal Irrigated Condition

S.No.	Variable	Maximum likelihood Estimation(Frontier)		Bayesian(Exponential)	
		Elasticity	MVP_y/P_x	Elasticity	MVP_y/P_x
1.	Seed (kg)	0.3997	2.369	0.2718	1.875
2.	Fertilizer (kg)	0.224	0.849	0.44006	4.95
3.	Labour (hrs)	-0.1093	-3.96	-0.1479	-4.20
Returns to scale		0.5144		0.5641	

The actual use of NPK nutrients is 205.2 kg, are lower compared to the recommended dose of fertilizer nutrients at 150, 50 and 50 of N, P and K respectively (total 250 kg), for most seasons in rice cultivation. Therefore, the results indicating the scope to increase the use of fertilizer nutrients is in consonance with the status of nutrient use in the sample farms.

The mean Technical efficiency computed based on Maximum Likelihood and Bayesian estimates are presented in **Table 6** in the form of frequency distribution within a deciles range. The estimated mean output oriented technical efficiency was found to be 82.97 per cent. Most farms (35.78 per cent) were in the efficiency range of 80-90 per cent followed by 28.44 per cent of farms in the range of 90-100 per cent. Farms in efficiency range of 70-80 per cent accounted for 27.06 per cent and the rest of farms have been in the range below 70 per cent. The estimated mean output oriented technical efficiency was found to be 89.28 per cent. Most farms (58.72 per cent) were in the efficiency range of 80-90 per cent followed by 90-100 per cent (31.65 per cent and the mean technical efficiency is higher based on Bayesian estimates.

Table 6 Technical Efficiency Distribution of Paddy Farmers derived from Maximum Likelihood and Bayesian Estimates

Range	Maximum Likelihood Estimates			Bayesian Estimates		
	2009-10	2010-11	Total	2009-10	2010-11	Total
<60	6 (5.50)	1 (0.91)	7 (3.21)	1 (0.91)	0	1 (0.46)
60-70	3 (2.75)	9 (8.26)	12 (5.51)	1 (0.91)	0	1 (0.46)
70-80	19 (17.43)	40 (36.70)	59 (27.06)	10 (9.17)	9(8.26)	19 (8.72)
80-90	43 (39.45)	35 (32.11)	78 (35.78)	33 (30.28)	95(87.16)	128 (58.72)
90-100	38 (34.86)	24 (22.02)	62 (28.44)	64 (58.72)	5 (4.59)	69 (31.65)
Number of farmers	109 (100.00)		218 (100.00)		109 (100.00)	218 (100.00)
Mean Technical Efficiency(%)	83.89	82.09	82.97	89.29	88.42	89.28
Numbers in parentheses indicate percentage to total						

Conclusion and Policy implications

According to the theoretical back ground of Bayesian analysis, the Bayesian estimates are more reliable and accurate, because they take into account the prior knowledge about the distribution of the parameters and also the estimation gives rise to a posterior probability distribution of a parameter to account for uncertainties. The higher mean yields associated with higher mean efficiency levels implying consistency in the case of values derived from Bayesian estimates indicate that Bayesian estimates are more reliable than maximum likelihood estimates. The study results call for the promotion of use of quality seeds and fertilizer nutrients to harness the yield potential of the rice varieties grown in the Cauvery delta zone of Tamil Nadu as signified by the MVP_y/P_x ratio and The returns to scale at 0.5144 for maximum likelihood estimates and 0.5641 for Bayesian estimates would indicate the operation of decreasing returns to scale at the present level of technology and the need for breakthrough in technology by way of new varieties or management methods and research extension farmer linkage. The results also call for greater efficiency and strategic use of the human labour in view of negative returns. The results also call for the extension system to be better prepared in stocking and supply of the inputs namely, seeds and fertilizers.

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