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Research note

Farm-level economic impact of rice blast: a Bayesian approach

S Varadha Raj*, R S Saranya, D Suresh Kumar and M Chinnadurai

Tamil Nadu Agricultural University, Coimbatore-641003, Tamil Nadu, India

Abstract This paper assesses the farm-level impacts of rice blast on yield, cost and returns and resource use efficiency in paddy cultivation employing the Bayesian approach. The result shows about 27% less yield and 19% higher cost on the disease affected farms compared to that on unaffected farms, causing a difference of 80% in the net returns. The analysis of resource use efficiency shows a positive impact of plant protection measures on both disease affected as well as unaffected farms. In general, other inputs appear to be sub-optimally utilized.

Keywords Rice blast, Bayesian approach, Resource use efficiency, Profits

JEL classification Q1, Q10, Q12, Q19

1 Introduction

Rice production is constrained by a number of abiotic and biotic factors, such as droughts, floods, pests, and diseases. Several studies have shown that pests and diseases reduce crop yield significantly and may even result in complete crop loss at extremely high level of infestation (Heinrichs 1986; Thakur 1994; Jha 1998; Catling et al. 1978; Litsinger 1991; Sehgal et al. 2008; Singh 2014). Rice is vulnerable to a number of diseases, such as rice blast, brown spot, sheath blight, bacterial leaf blight and sheath rot. Amongst these, rice blast (*Magnaporthe grisea*) is considered as one of the most devastating. It occurs worldwide and may cause yield loss up to 85%. Evidence from several countries show that the diseases could result in yield loss of 40% in Nigeria (Ou 1985), 60-100% in Kenya (Kihoro et al. 2013), 70% in China (Chin 1975), 50-85% in the Philippines (Awodera & Esuruoso 1975) and 21-37% in Indonesia (Suprapta & Khalimi 2012). Kato (2001) reported a complete crop loss in Japan. Barman & Chattoo (2005) report that every year rice production is affected by blast resulting in production loss which, if averted, could feed 60 million people.

An ex-ante evaluation in India shows that if rice blast is epidemic, the yield loss would be more than 50% (Babujee & Gnanamanickam 2000). Rajarajeswari & Muralidharan (2006) reported yield loss in the range of 27% to 35% in Andhra Pradesh during 1995-97. Shanmugam et al. (2006) estimated a loss of 0.196 million tons in Tamil Nadu, equivalent to 34% of the total rice production in the state. In Tamil Nadu, about 80% farmers have reported blast as one of the major biotic constraints in rice production. The rice blast has been reported in almost all rice varieties, except CO47, BPT 5204 and IR 64 (Sundaram et al. 2014; Anonymous 2017). Farmers use several preventive and control measures to avoid crop loss due to blast, that lead to an increase in the variable cost. Variable cost accounts for nearly 70% of total cost, of which plant protection chemicals account for 11% (Chinnadurai & Varadha Raj 2011). The present paper aims to (i) compare the yield, cost and returns in rice cultivation between blast affected and unaffected farms, and (ii) estimate resource use efficiency in rice production.

2 Data and methodology

The study was conducted in Villupuram district of Tamil Nadu, where the area and yield of rice has witnessed severe fluctuations in recent years (figure

*Corresponding author: varadharajs@rediffmail.com

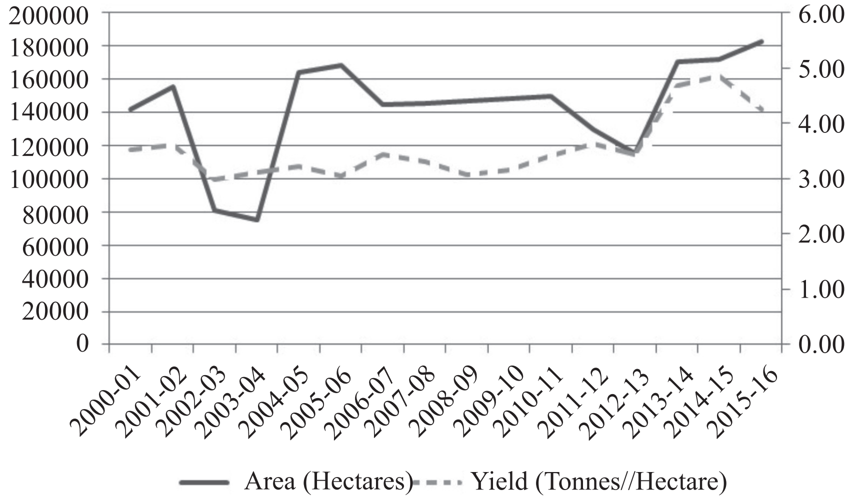

Figure 1. Trend in area and yield of paddy in Villupuram district

1). Although, erratic rainfall is the main reason for this, frequent incidence of rice blast is also reported as one of the main causes. For the purpose of this study, Gingee taluka has been purposively selected because of the high incidence of rice blast there. Two blocks from this taluka were purposively selected, and from each block five villages were selected randomly. From each village, based on Percentage Disease Index (PDI)[1] four farms affected by rice blast and four unaffected by rice blast were selected for implementing the survey. Thus, a total of 80 respondents were selected. The required data were collected by administering an interview schedule.

Following the approach of the Commission on Agricultural Cost and Price (CACP), economics of cultivation of rice on blast affected and unaffected farms was calculated. Resource use efficiency of the affected and unaffected farms was assessed using the Bayesian approach. In the Bayesian approach, uncertainty about unknown parameters is examined using probability. The Bayesian approach uses prior knowledge in addition to the survey data. The prior knowledge may be drawn from experts' opinion, experimental results, old data sets, and knowledge generally accepted in the fields. Several studies (Lyubov & Carriquiry 2002; Yuen & Hughes 2002; Yu & Babcock 2011; Brorsen 2013; Ouedraogo & Brorsen 2014) have employed this approach to estimate resource use efficiency. The data on rice yield and inputs like seed, fertilizers, plant protection chemicals, human labour, and machine labour were taken from the 'Cost of Cultivation of Principal Crops' for the period 2000-15 and were used as prior information in the Bayesian analysis.

The mean vector and covariance matrix of the multivariate normal prior distribution of regression coefficients and parameters (scale parameter and shape parameter) of gamma prior distribution of variance were estimated in SYSTAT 13. The task of each Bayesian analysis is to build a model for the relationship between parameters (θ) and observables (y), and then calculate probability distribution of parameters conditional on $\rho(\theta/y)$. In addition, the Bayesian analysis predicts the distribution of unobserved data.

[1]Percent disease index (PDI) was worked out using formula described by Wheeler (1969).

$$\text{PDI} = \frac{\left(n_1X1 + n_2X2 + n_3X3 + n_4X4 + n_5X5\right)}{\left(\text{Total number of leaves observed} \times \text{Maximum grade}\right)} \times 100$$

Where n_1 to n_5 represents the total number of leaves falling under 1-5 scales respectively. X1, X2… and X5 orderly represents 1-5 grades of disease infestation.

PDI for rice blast is above 20% of the leaf area damaged or above 20% of the neck infection to be considered as disease affected farm and if it is below 20% is considered as the unaffected farm.

Bayesian analysis begins with a model of the joint conditional probability distribution of θ and y, say $\rho(\theta,y)$. The θ may be a single parameter or a vector of parameters, and y may be a vector of observations of a single variable or a matrix of multiple observations of several variables. ρ is the probability distribution. Using the definition of conditional probability (Howson & Urbach, 1989), $\rho(\theta,y)$ can be decomposed into two components:

$$\rho(\theta, y) = \rho(\theta)\rho(y/\theta) \quad \ldots(1)$$

By convention, $\rho(\theta)$ is called the prior distribution of θ (i.e., the distribution prior to observing the data on y) and $\rho(\theta/y)$ is called the likelihood function, given a particular value of the parameter θ. Bayes' theorem provides the posterior probability distribution $\rho(\theta/y)$ (i.e., the distribution of θ obtained after observing and combining the information in the data with the information in the prior distribution):

$$\rho(\theta / y) = (\rho(\theta)\rho(y/\theta))/\rho(y) \quad \ldots(2)$$

Eq. (2) provides the probability distribution of θ given the observations on y. This distribution has three parameters, a vector of mean regression parameters, a matrix with variances along the main diagonal, covariance with the degrees of freedom. In this case, the mean vector contains k prior estimate of the mean regression parameters B_0 and the k × k parameter covariance matrix S_0, model variance S_{02} and degrees of freedom n_0. For secondary data, we have n_{1x1} response vector y_1 and n_{1xk} matrix of predictors X_1.

The posterior can be computed by treating the prior as additional data points, and then weighting their contributions to the posterior (Gelman et al. 1995). To perform the computations, we construct a new vector of observations y, predictor matrix X, and weight matrix Σ as follows:

$$y = [y_1' B_0']' \quad \ldots(3)$$

$$X = [X_1' I_k']' \quad \ldots(4)$$

$$\sum = [I_n 0 : 0 S_0] \quad \ldots(5)$$

I_k and I_n stand for identity matrices of dimension k and n, respectively. θ denotes zero element necessary to fill out the square matrix Σ, which has I_n as the upper left elements and S_0 as the lower right elements. The posterior estimate of the parameters follows a multivariate Student-t distribution. The mean vector β_E is as follow:

$$\beta_E = (X' \Sigma^{-1} X)^{-1} X' \Sigma^{-1} y \quad \ldots(6)$$

The scale matrix is s_2V with n-k degrees of freedom, where n is the number of observations, k is the number of parameters to be estimated as:

$$V = (X' \Sigma^{-1} X)^{-1} \quad \ldots(7)$$

Variance s_2 with $n_0 + n_{1-k}$, k degrees of freedom is calculated as:

$$s_2 = (n_0 s_{02} + n_1 s_{12})/(n_0 + n_1) \quad \ldots(8)$$

Variance s_{12} is calculated as:

$$s_{12} = (y - X\beta_E)'(y - X\beta_E)/(n_{1-k}) \quad \ldots(9)$$

Predictions for new data X_p using regression for both data sets also follow a multivariate Student t distribution:

$$\rho(y_p / y) \sim \text{Multivariate Student 't'} \; [n_0 + n_{1-k,} X_p \beta_{E,} (1 + X_p' V X_p') s_2) \quad \ldots(10)$$

In this distribution, X_n is the new set of predictors, β_E is computed using Eq. (6), V is computed using Eq. (7) and s_2 is computed using Eq. (8) and (9). The t-test is used to determine whether the Bayesian regression coefficient is significantly different from zero.

3 Results and discussion

3.1 Costs and returns

Costs and returns on the disease affected and unaffected farms are given in Table 1. Total cost (C2) on the disease affected farms is ₹ 42724 / ha, which is 10.22% higher than on the unaffected farms. The contribution of plant protection chemicals to the total input cost is 7.65% and 2.11% in disease-affected and unaffected farms, respectively.

The difference in the total input cost between disease affected and unaffected farms is 18.75%, which is largely on account of higher cost of plant protection chemicals (Table 2). Average yield of paddy is 3.1 tons/ha on disease-affected farms, almost 27% less than on unaffected farms. These result in about 80% less returns on the diseases-affected farms. The lower returns on disease-affected farms are mainly due to (i)

Table 1. Cost and returns of rice cultivation in the sample farms

(₹/ha)

Particulars	Description of costs	Unaffected	Disease-affected	Percentage difference
Cost A1	All variable inputs cost + interest on working capital	28122	33394	18.75***
Cost A2	Cost A1 plus rent paid for leased in the land	29022	33994	17.13***
Cost B1	Cost A2 plus interest on fixed capital (excluding land)	31362	37244	18.76***
Cost B2	Cost B1 plus a rental value of owned land	36462	42644	16.95***
Cost C1	Cost B1 plus an imputed value of family labour	33662	37324	10.88***
Cost C2	Cost B2 plus an imputed value of family labour	38762	42724	10.22***
Cost C3	Cost C2 + 10% of cost C2 as a managerial input of the farmer	42638	46996	10.22***
Average yield (kg/ha)		4314	3149	-27.01***
Gross returns		66174	48304	-27.01***
Net income (Gross income returns-Cost C2)		27412	5580	-79.65***

Source: Authors' calculations.
***significant at 1%, **significant at 5%.

Table 2. Input-wise expenditure on unaffected and disease-affected rice farms

(₹/ha)

Inputs	Unaffected	Disease-affected	Percentage difference
Seeds	1409 (5.18)	1409 (4.36)	0.00
Fertilizers	6615 (24.31)	7767 (24.03)	17.41**
Plant protection chemicals	574 (2.11)	2471 (7.65)	330.49***
Human labour	10132 (37.23)	12228 (37.84)	20.69***
Machine power	8484 (31.18)	8442 (26.12)	-0.50
Total input cost	27214 (100)	32317 (100)	18.75***

Source: Authors' calculations.
Figures in parentheses indicate a percentage of total cost of cultivation. *** significant at 1%, ** significant at 5%.

misallocation of resources, i.e. over-use of chemical fertilizers and delayed planting season and (ii) insufficient knowledge about rice diseases and their control measures.

3.2 Comparison of resource use efficiency

The Bayesian approach involves selection of a dependent variable (yield) and five explanatory variables viz., seed, fertilizer, plant protection chemicals, human labour and machine labour along with prior information on the parameters of the model in terms of the mean vector and covariance matrix of a multivariate normal distribution of the regression coefficients, and the scale and shape parameters of the inverse gamma distribution of the error variance. The mean vector (b_0) and covariance matrix (V_0) of the multivariate normal prior distribution of the regression coefficients are given below.

b_0= (yield, seed, fertilizer, plant protection chemicals, human labour, and machine labour)

b_0 = (2.355, 0.278, -0.018, -0.186, 0.564, 0.225)

and

$$v_0 = \begin{pmatrix} 2503.326 & -47.918 & -35.578 & 17.539 & -255.875 & -73.022 \\ -47.918 & 3.998 & -1.482 & -4.087 & 4.137 & 1.862 \\ -35.578 & -1.482 & 3.992 & 2.215 & 1.865 & 0.504 \\ 17.539 & -4.087 & 2.215 & 6.500 & -0.490 & -2.514 \\ -255.875 & 4.137 & 1.865 & -0.490 & 29.079 & 7.390 \\ -73.022 & 1.862 & 0.504 & -2.514 & 7.390 & 3.656 \end{pmatrix}$$

The diagonal line of covariance matrix represents variance of chosen parameters. The yield has the largest variance (2503.33) and the smallest variance is estimated for machine labour (3.66). The positive covariance coefficient is found only between yield and plant protection chemicals. The covariance between fertilizer and machine labour is the least. It tends to be a less predictable relationship between the movement

Table 3. Resource use efficiency using OLS and Bayesian approaches

Explanatory variables	OLS		Bayesian	
	Unaffected Coefficient	Disease-affected Coefficient	Unaffected Coefficient	Disease-affected Coefficient
Constant	2.089 (3.189)	1.169 (4.023)	6.999 (0.656)	3.951 (0.833)
Seed (kg/ha)	0.326***(0.088)	0.424 (0.245)	0.043 (0.077)	-0.153 (0.095)
Fertilizer (kg/ha)	0.274***(0.069)	0.063 (0.097)	0.347 (0.078)	0.058 (0.100)
Plant protection chemicals (litre/ha)	0.061(0.061)	0.474***(0.110)	-0.048 (0.070)	0.539***(0.050)
Human labour (Man-days/ha)	0.616 (0.717)	0.775 (0.912)	-0.291 (0.166)	0.727 ^{NS}(0.235)
Machine labour (hrs/ha)	0.176 ^{NS}(0.128)	0.067 ^{NS}(0.149)	0.198 ^{NS}(0.110)	0.075 ^{NS}(0.124)
Error variance estimate			0.021	0.030

Source: Authors' calculations.
Note: Figures in parentheses are standard errors. ** and *** respectively denote significance at 5 and 1% level.

of fertilizer and machine labour. The parameters of the gamma prior distribution for variance for shape parameter and scale parameter are 4.5 and 0.021, respectively. The shape parameter indicates the width of Probability Density Function (PDF), and the scale parameter denotes the height of PDF. The ideal result should have that posterior coefficient of parameters with a low standard error. This may not always be the case and the posterior may have a larger standard error. Irrespective of how much the variance has changed, it is desirable that the coefficients in the posterior model be statistically significant.

We compare results of the Bayesian approach with those estimated using OLS, regressing log yield on log of inputs used (table 3). In the case of OLS, the estimated regression coefficients of seed and fertilizer are positively significant at 1% level on unaffected farms, whereas on disease-affected farms, it is only plant protection chemical that is positive and significant at 1% level. As in the case of the Bayesian approach, the regression coefficients of the variables from OLS estimates are not significant except plant protection chemicals on the disease-affected farms where it is positively significant at 1% level. The coefficient of plant protection chemicals is 0.474 in OLS as compared to 0.539 from Bayesian approach. The result reveals that the Bayesian approach improves efficiency by reducing standard error of the parameters. The Bayesian approach also captures additional uncertainty associated with parameters estimation.

It is evident from figure 2 that the spreads of yield density with respect to plant protection chemicals of prior distribution are larger than the posterior distribution, on both affected and unaffected farms.

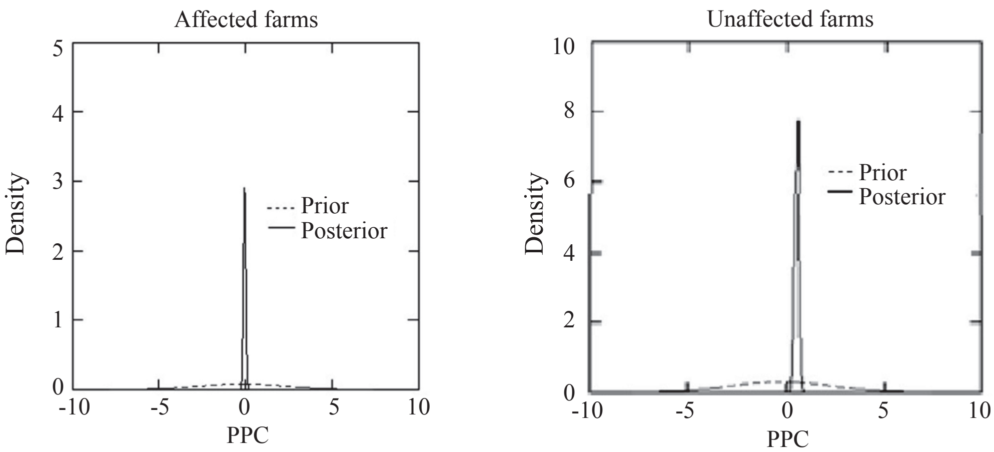

Figure 2. PDF plot for plant protection chemicals of both affected & unaffected farms

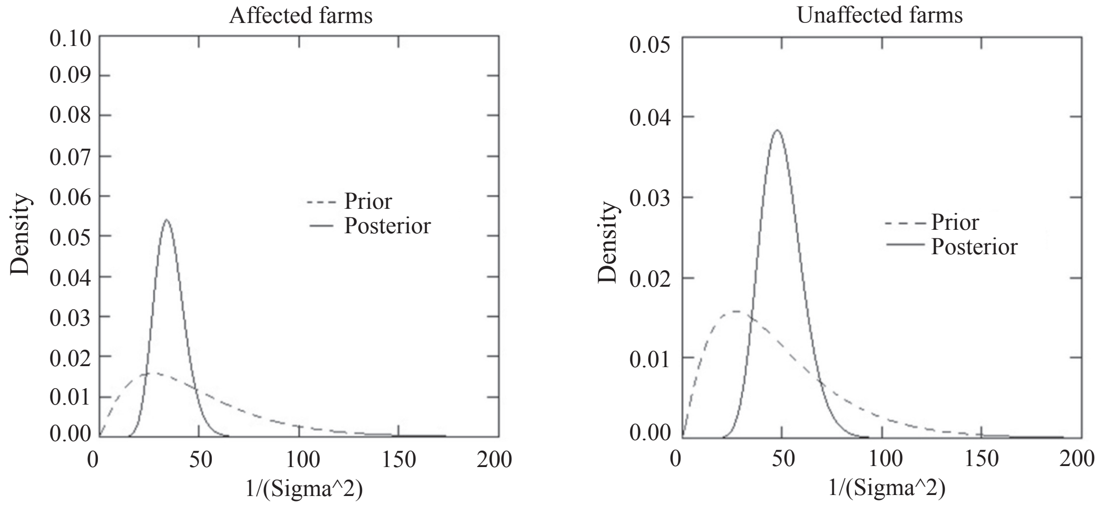

Figure 3. PDF plot for plant protection chemicals of both affected and unaffected farms

Large spreads of yield density represent low accuracy in the estimate of the plant protection chemicals. Figures 3 indicates the reciprocal of variance representing the precision of coefficient of the plant protection chemicals. The posterior distribution of the estimate of plant protection chemicals has lower spread than the prior distribution. The probability density function of yield on the affected farms has a higher value (peak) than on the unaffected farms which means that the è value is higher. In brief, lower spread and higher peak indicate the accuracy of an estimate of the selected parameters of the prior and posterior distribution.

Conclusions

The findings indicate that there is a lower yield and higher costs on rice blast affected than on unaffected farms resulting in less net returns. In the analysis of resource use efficiency, the seeds, inorganic fertilizers, and machine labour are positive and significant on unaffected farms, whereas on affected farms it is only the plant protection chemicals that appear significant on the disease affected farms. The Bayesian approach improves efficiency of the results. This suggests incorporation of prior distribution/knowledge in decision-making process so as to improve farm profits.

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