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Research Paper

Bayesian Analysis of Spatial Probit Models in Wheat Waste Management Adoption

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Abstract

The purpose of this study was to identify factors influencing the adoption of wheat waste management by wheat farmers. The method used in this study using the spatial Probit models and Bayesian model was used to estimate the model. MATLAB software was used in this study. The data of 220 wheat farmers in Khouzestan Province based on random sampling were collected in winter 2016. To calculate Bayesian coefficients the Gibbs sampling and Metropolis–Hastings algorithm were used. A Lagrange Multiplier test for spatial error dependence [LM(err)] and a Lagrange Multiplier test for spatial lag dependence [LM(lag)] to extract the appropriate model were used.The results of both models were statistically significant with 99% probability. Thus, both models can be used in interpreting the results. Based on the results of the estimation of spatial models the variables of participation in extension courses, technical knowledge about management of waste, income, crop's yield, mechanization level and the spatial autoregressive coefficient had significant role on adoption of waste management.

Keywords:
Bayesian model, spatial models, wheat waste management

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INTRODUCTION

The increased amount of waste resulting from production and consumption processes is a great challenge for many developing countries particularly in Asia (Shams et al., 2017). Also, with global population increasing, the amount of waste generated by agriculture has also increased and this consequently leads to the environmental pollution (Gonzalez Sanchez et al., 2014; He et al., 2016; Isoda et al., 2014; Ommani, 2011). It is estimated that about 998 million tons of agricultural waste is produced yearly (Agamuthu, 2009). Crop residue burning is one among the many sources of air pollution. Burning of farm waste causes severe pollution of land and water on local as well as regional scale. This also adversely affects the nutrient budget in the soil. Straw carbon, nitrogen and sulphur are completely burnt and lost to the atmosphere in the process of burning (Kumar et al., 2015).

In the current situation, one of the main problems of agricultural sector in Iran is waste. According to the Ministry of Agriculture in 2010, 15 million tons of 85 million tons of agricultural products were waste (Mirtorabi et al., 2010). According to the Ministry of Agriculture waste reduction studies,wheat has the highest cost in terms of waste among all agricultural products (Mirmajdi et al., 2007; Ommani et al., 2009).

Agricultural waste management for sustainable agriculture and agricultural development has become a topic of concern for policy makers (Hai & Tuyet, 2010). It is essential to consider wastes as potential resources rather than undesirable to avoid contamination of air, water, and land resources, and to avoid transmission of hazardous materials (Obi et al., 2016). Asadi et al. (2010) revealed that it seems wheat wastes management is the best solution to reduce these wastes and to provide food security in Iran. Wheat wastes management includes components such as; education, policy making, establishing infrastructures and effective marketing system. In order to achieve self-sufficiency and food security we must pay attention to the components of wheat wastes management.

Malekmohammadi (2008) concluded that personal characteristics of the farmers were the major factors influencing wheat waste in his study. By applying the recommendations such as development extension education, Iran can manage its waste in wheat considerably and ensure self-sufficiency, save resources, reduce the unemployment rate, and most importantly, guarantee food safety, and security for the whole nation.

Omidi et al. (2014) revealed that, the variables of farmers' age, farmers' awareness of the causes of wheat losses, access to machinery, access to needed machines at harvesting time, and education level were significant at 5% levels.

METHODOLOGY

In this research, spatial probit models were used to evaluate binary data with the assumption of spatial correlation between observations. Spatial econometrics is a subfield of econometrics that deals with spatial autocorrelation and spatial heterogeneity in regression models for cross-sectional and panel data (Paelinck & Klaassen, 1979; Anselin, 1988). The Bayesian method was used to estimate parameters in spatial probit models (Wooldridge, 2002). LeSage (2000, 1998) is a good reference for spatial econometric models in general and for limited dependent variable spatial models in particular. Suppose we have the spatial autoregressive model:

$$\begin{gathered} z = \rho W_1 z + X\beta + \mu, \\ \mu = \lambda W_2 \mu + \epsilon, \\ \epsilon \sim N\left(0, \sigma_\epsilon^2 I_n\right) \end{gathered} \tag{1}$$

for $z = (z_1, \ldots, z_n)$ with some fixed matrix of covariates X ($n \times k$) associated with the parameter vector β ($k \times 1$). The matrix W_1 and W_2 ($n \times n$) are called the spatial weight matrix and captures the dependence structure between neighboring observations such as friends or nearby locations. The term W_z is a linear combination of neighboring observations. The scalar ρ is the dependence parameter and will be assumed abs (ρ) < 1. The k + 1 model parameters to be estimated are the parameter vector β and the scalar ρ.In a spatial probit model, z is regarded as a latent variable, which cannot be observed. Instead, the observables are only binary variables yi (0, 1) as (Loomis &Mueller, 2013):

$$y_i = \begin{cases} 1\ if z_i \geq 0, \\ 0\ if z_i < 0 \end{cases} \quad (2)$$

y_i can reflect any binary outcome such as survival, a buy/don't buy decision or a class variable in binary classification problems. For identification, σ^2_e is often set to σ^2_e =1 (Anselin,1988).
The data generating process for z is:

$$z = (I_n - \rho W)^{-1} X\beta + (I_n - \rho W)^{-1}\epsilon \quad (3)$$
$$\epsilon \sim N(0, I_n)$$

Note that if ρ =0 or W =I_n, the model reduces to an ordinary probit model (Wilhelm & Godinho de Matos, 2013). Another popular spatial model is the Spatial Error Model (SEM) which takes the form:

$$z = (I_n - \rho W)^{-1} X\beta + (I_n - \rho W)^{-1}\epsilon \quad (4)$$
$$\epsilon \sim N(0, I_n)$$

By placing X = 0 and W_2=0, the first-order spatial autoregressive model is obtained

$$Z=\rho w_1 y+\varepsilon \quad (5)$$
$$\varepsilon \sim N(0, \sigma^2 I_n)$$

By putting W_2=0, the spatial autoregressive model is a mixed regression. This model is similar to the dependent latent variable model in the time series. In this model, there are additional explanatory variables in the matrix X that are used to explain the variations in Z over the spatial sample of observations.

$$Z=\rho w_1 y+X\beta+ \varepsilon \quad (6)$$
$$\varepsilon \sim N(0, \sigma^2 I_n)$$

The Bayesian paradigm is named after Rev Thomas Bayes for its use of his theorem. Take the rule for conditional probability for two events A and B (Johnson, 2012):

$$P\left(A/_B\right) = \frac{P(A\cap B)}{P(B)} = \frac{P\left(B/_A\right)P(A)}{\int P\left(B/_A\right)P(A)dA} \quad (7)$$

The mathematician Pierre-Simon Laplace popularized the idea that instead of just defining probability on variables, we could also define probability on parameters too. And by using Bayes' Rule we can make inference on parameters. We can effectively treat parameters as random variables. He laid the groundwork for the Bayesian paradigm of statistics (Johnson, 2012).

In our regression example, let θ = {β, σ2} and D = the data. Using Bayes' Rule we get (Johnson, 2012):

$$P\left(\theta/_D\right) = \frac{P\left(D/_\theta\right)P(\theta)}{P(D)} \quad (8)$$

P(θ|D) is called the posterior distribution. It is what we will use to make inference about the parameters θ = {β, σ2}.

P(D|θ) is the likelihood we discussed previously. It contains all the information about θ we can learn from the data.

P (θ) is called the prior distribution for θ. It contains the information we know about θ before we observe the data.

If the posterior distribution is unclear, by using the Markov Chain Monte Carlo Simulation (MCMC) methods for the desired sample volume, we obtain a precise deduction of the parameters (Tierney, 1994). The two most popular MCMC algorithms for producing these samples are the Gibbs sampler and the Metropolis-Hastings sampler (MH) (Johnson, 2012). In Bayesian statistics, the recent development of MCMC methods has been a key step in making it possible to compute large hierarchical models that require integrations over hundreds or even thousands of unknown parameters (Banerjee et al., 2014).

The MCMC is based on simulation, instead of obtaining point estimates, it runs for many repetitions, and an estimate for each unknown parameter is obtained for each repetition. Estimates from previous replication are used for future estimates. The purpose of this method is to obtain a sample of the posterior distribution values of unknown parameters (Browne, 2012).

The wheat farmers in Khuzestan Province were considered as the statistical population of 12450 people. According to the Cochran formula, the sample size was 220. The required data were collected through a questionnaire. The factors influencing acceptance of wheat waste management were identified.

The spatial probit model was used to evaluate the acceptance of wheat waste management in the following two situations:

Spatial Autoregressive Model - Mixed Regression or Spatial Lag Model: This model is similar to the dependent variable model of the latent time series. In this model, there are additional explanatory variables in the X matrix that are used to explain the variations in y over the spatial sample of observations (Table 1).

$$y=\rho w1y+X\beta+\varepsilon$$

$$y=\beta 0+\rho wy+\beta_1 EXT+\beta_2 KNO+\beta_3 INCO+\beta_4 CRO+\beta_5 EDU+\beta_6 COOP+\beta_7 SIZE+\beta_8 MECH+\varepsilon$$

$$\varepsilon\sim N(0,\sigma^2 I_n)$$

Spatial Error Model: Results are presented in a regression model with spatial autocorrelation in disorders.

$$y=\beta X+\mu$$

$$y=\beta_0+\beta_1 EXT+\beta_2 KNO+\beta_3 INCO+\beta_4 CRO+\beta_5 EDU+\beta_6 COOP+\beta_7 SIZE+\beta_8 MECH+\mu$$

$$\mu=\lambda Wu+\varepsilon$$

$$\varepsilon\sim N(0,\sigma^2 I_n)$$

y = in this research, acceptance of wheat waste management is a dependent variable. If the farmer is accepted, the number 1 and if it is not accepted, then the number is zero.

ρ = includes spatial autoregressive-mixed regression coefficient in the spatial lag model that shows the intensity of the proximity effect in this study.

λ =autoregressive coefficient in spatial error model.

ε =error

W=spatial weight matrix, that in this study, 220 in 220 dimensions.

EXT=the participation of farmers in extension courses about waste management. If the farmer has participated, the number 1 and if not participant, the zero number is allocated to it.

KNO=in order to assess the technical knowledge, specialized questions about waste management were asked, and a grade was obtained for each farmer. The desired degree was used in the functions.

INCO=the revenues from wheat cultivation in the previous year were considered in terms of million IR Rials in the model.

CRO=crop yield was observed in the previous year, which was considered as a kilogram per hectare.

EDU=the level of education of the farmer was considered as the number of years of education.

COOP=the membership in the rural production cooperative is that if the farmer is a member, the number is 1, and if it is not a member, a zero is assigned to it.

SIZE=represents the amount of arable land is owned in terms of hectares taken into account.

MECH=Indicates the mechanization level of the farm, which is calculated based on the degree of mechanization.

RESULTS AND ESTIMATION OF THE MODEL

In this research to calculate the Bayesian coefficients the Gibbs sampling method and the Metropolis-Hastings algorithm was used. The Lagrange coefficient was also used to extract the appropriate model based on the lag or spatial error. According to the results of both models, they were probably 99% significant. Therefore, both models can be used to interpret the results.

Table 1
Identify the Appropriate Model of Spatial Lag or Spatial Error

Model	Test	Coefficient	*P*-value
$y=\rho w_1 y+X\beta+\varepsilon$	[LM(lag)]	103.762**	0.000
$y = \beta X + \mu$	[LM(err)]	56.648**	0.000

** $P<0.01$

Table 2
Estimated Parameters for Model of Spatial Lag or Spatial Error

Variables	Parameters	Model of spatial lag			Model of spatial error		
		Coefficients	S.E.[a]	*P*-value	Coefficients	S.E.[a]	*P*-value
EXT	β_0	2.653	0.876	0.014	1.696	0.834	0.019
KNO	β_1	0.637	0.345	0.005	0.743	0.309	0.001
INCO	β_2	0.239	0.109	0.043	0.290	0.176	0.035
CRO	β_3	0.459	0.224	0.015	0.398	0.221	0.019
EDU	β_4	0.359	0.198	0.012	0.413	0.208	0.013
COOP	β_5	0.014	0.067	0.087	0.018	0.159	0.075
SIZE	β_6	0.008	0.17	0.138	0.011	0.138	0.122
MECH	β_7	0.006	0.15	0.165	0.014	0.156	0.134
	β_8	0.378	0.195	0.014	0.432	0.234	0.011
	ρ	0.712	0.154	0.001			
	λ				0.782	0.128	0.000

[a] Standard error

Based on the results of the estimation of spatial models, it was found that in both models, the role of the variables of the participation of farmers in extension courses about waste management, the technical knowledge of waste management, the income, crop yield, the mechanization level and the spatial autoregressive coefficients on the adoption of waste product management were significant. The role of each one is expressed in terms of (Table 2):

The variable of the participation of farmers in extension courses about waste management with coefficients of 0.673 in the spatial lag model and 0.743 in the spatial error model has a significant role in adoption of waste management at 1% level. This suggests that the logarithm of the adoption of wheat waste management by farmers who participated in the extension classes was 67% in the first model and 74% in the second model, respectively, rather than of farmers who did not participate in the extension class.

The variable of technical knowledge about waste management with coefficients of 0.239 in the spatial lag model and 0.290 in the spatial error model has a significant role in adoption of waste management at 5% level. This suggests that the logarithm of the adoption of wheat waste management by farmers with high technical knowledge was 23.9% in the first model and 29% in the second model, respectively, rather than other farmers.

The variable of income with coefficients of 0.456 in the spatial lag model and 0.398 in the spatial error model has a significant role in adoption of waste management at 5% level. This suggests that the logarithm of the adoption of wheat waste management by farmers with high income was 45.6% in the first model and 39.8% in the second model, respectively, rather than other farmers.

The variable of crop yield with coefficients of 0.359 in the spatial lag model and 0.413 in the spatial error model has a significant role in adoption of waste management at 5% level. This suggests that the logarithm of the adoption of wheat waste management by farmers with high crop yield was 35.9% in the first model and 41.3% in the second model, respectively, rather than other farmers.

The variable of mechanization level with coefficients of 0.378 in the spatial lag model and 0.432 in the spatial error model has a significant role in adoption of waste management at 5% level. This suggests that the logarithm of the adoption of wheat waste management by farmers with high mechanization level was 37.8% in the first model and 43.2% in the second model, respectively, rather than other farmers.

The spatial autoregressive coefficients ρand λ in level of 1% were significant. This reflects spatial autocorrelation.

The prior distribution was no informative. Analyses were based on a single Gibbs chain with 5000 burn-in cycles and a length of 650000 cycles. The effective number of estimates retained greater than 200 for all parameters

CONCLUSION AND RECOMMENDATION

Due to the significant role of the participation in the extension classes in the adoption of wheat waste management and considering about 60 percent of the farmers that have not participated in any of the extension classes, it is essential that planners of farmers' educational programs, while assessing the educational needs of wheat farmers, should take a coherent course of these classes and encourage the participation of the farmers to attend the extension classes.

Due to the significant role of the technical knowledge about waste management in the adoption of wheat waste management and considering about 73 percent of the farmers that had a moderate and low level of knowledge, it is essential that take necessary measures in particular to increase the technical knowledge of wheat farmers.

Due to the significant role of income and crop yield variables in adoption of wheat waste management, it is necessary to increase the income and crop yield of wheat farmers; through training programs on the optimal use of resources, reducing production costs and application of the scientific principles of wheat production.

Due to the significant role of mechanization level in adoption of wheat waste management, it is necessary to develop the mechanisms for the development of mechanization level in the study area.

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