Spatial Analysis of Determinants of Dairy Farmers' Adoption of Best Management Practices for Water Protection

Wei Yang, Department of Economics, the University of Auckland, Auckland New Zealand
Email: wei.yang@auckland.ac.nz

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1. Introduction

1.1 Background

The clean-and-green image of NZ is well known internationally and is regarded as a marketing strategy attracting tourists all over the world (Abell, Hamilton & Paterson, 2011). The "green icon" is also connected with pure, safety and healthy food products, such as dairy and meat. Nevertheless, unsustainable dairy farming activities do not always complement this reputation (The Treasury, N. Z., 2009). It is undeniable that the NZ economy is heavily dependent on agriculture, especially dairy sector, but the increasing nutrient pollution discharged from dairy farms is a threat to the water quality of lakes, stream and rivers (Abell, Hamilton & Paterson, 2011). According to a report by NIWA, water quality in NZ's major rivers declined between 1989 and 2007. In particular, nutrient loadings (predominantly nitrogen and phosphorus) increased greatly at many monitor sites (NIWA, 2010a). Moreover, algal blooms in some NZ's iconic lakes, such as Lake Taupo and Lake Rotorua, have also become a concern of the public (Petch et al., 2002). Significantly, lakes surrounded by farmland fared worst. It is believed that more than a third of NZ's lakes carry excessive nutrient loads (NIWA, 2010b).

Therefore, the dairy industry is under increasing pressure to make a commitment to improving the environmental performance of farming practices to protect water quality in waterways. Among all the good practices, keeping stock out of waterways and riparian planting are regarded as the most direct and efficient practices for the NZ dairy farmers. The former avoids direct pollution of cow dung and urine to waterways, and the latter assists by filtering cow dung and slowing the flow of effluent and chemical fertilisers to waterways. In 2013, the dairy industry agreed to set a new voluntary project called "sustainable dairying: Water Accord" (the new Accord) to support the sustainable development of the NZ's economy (Dairy NZ, n.d.a)[1]. Compared to the old Accord, the new Accord continues to focus on protecting water quality in waterways but with broader and more stringent requirements. Previously, dairy farmers were required to have stock excluded from waterways that are "deeper than a red band gumboot (ankle deep), wider than a stride, and permanently flowing" (the Ministry for Primary Industries, 2013). It set a target that 90 percent exclusion of stock from waterways be met by 31st May 2012, but only 87 percent exclusion was achieved (the Ministry for Primary Industries, 2013). The new Accord, however, has clearly defined waterways as "rivers, streams, drains and springs over one metre wide and 30 centimetres deep that permanently contain water, all lakes, and wetlands". The new Accord target is set at 100 percent exclusion of stock from waterways by 31st May 2017. Moreover, farmers are expected to prepare riparian planting plans to adopt to protect water quality (Dairy NZ, n.d.a).

Under the new Accord, dairy farmers have greater responsibilities to comply with Best Management Practices (BMPs) to meet the new targets for sustainable growth. Hence, farmer's choice behaviour should be considered as one of the most important determinants of the success of policy aimed at water quality protection. In this way, farmers may face a significant challenge of balancing profitability and the cost of

[1] The new Accord is in accordance of the "the Dairying and Clean Streams Accord" (the Accord), which was launched in 2003 and expired in 2012. The old accord was agreed to by Fonterra Co-operative Group Ltd, the Ministry for the Environment, the Ministry of Agriculture and Forestry (Now the Ministry for Primary Industries), and regional councils.

adopting BMPs. However, the main focus of water quality protection has been on the public's opinion on the impacts of dairy farming on water quality. Studies have paid attentions to either the public's perception of environmental degradation due to unsustainable agricultural practices or the NZ residents' willingness to pay for water quality protection (e.g. Tait et al., 2011; Marsh, Mkwara & Scarpa, 2011; Hughey, Kerr & Cullen, 2013). However, it is equally important to explore the issues associated with water quality degradation from the perspective of dairy farmers and to understand what factors influence farmers' decisions as to their compliance with water protection requirements. Failing to understand this may make it difficult to reach the new Accord targets by the expected date.

Literature on the exploration of reasons for farmers' adoption of BMPs provides insights into a number of determinants (Knowler & Bradshaw, 2007). These determinants can be summarized in several categories, including farmers' perceptions of environmental practices, farm characteristics, household characteristics, and other contextual factors (e.g. Vanslembrouck, Van Huylenbroeck & Verbeke, 2002; Moon & Cocklin, 2011; Seo & Mendelsohn, 2008). Notably, recent studies have started to focus on location effects (or spatial effects) on individual's choice, as individuals who benefit from environment improvement are located across a geographical area (Jørgensen, 2013). For policy makers, therefore, the choice of an instrument to regulate nutrient pollution should be considered in a spatial context because of differences in the physical environment in a given region (Whittaker et al., 2003). The importance of spatial effects has also been addressed in the literature on distance decay effects on individual's recreation demand for non-market products, such as clean rivers and free-entry parks. For example, willingness to pay to improve water quality has been shown to decrease with the distance from residents' houses to rivers, as there are distance decay effects in their recreation demand for water quality (e.g. Sutherland & Walsh, 1985; Jørgensen, 2013). For the same reason, I assume that dairy farmers' willingness to adopt/ improve BMPs may also decrease with the distance from farm to the nearest water bodies as some farmers have hedonic demands for beautiful views or household water demands for clean groundwater quality. In other words, the distance from the dairy farm to water bodies will be considered as one of the determinants of dairy farmers' choices when considering the adoption of BMPs.

Besides, a few studies consider spatial effect as spatial spillover effects regarding neighbouring farmers' choices. Although the geographical location farms can be used to model the spatial dependence of choice between farmers, it is usually ignored (Kogler, 2015). Recently, some studies have begun to address spatial spillover effects in farmers' decision-making on participation in agri-environmental programs, farmers' adoption of clean technology and organic dairy farming (e.g. Lewis, Barham & Robinson, 2011; Läppl & Kelley, 2015). These studies imply that spatial spillover effects may reduce the fixed cost of learning about BMPs because farmers may economise by learning from their neighbours. Spatial spillover effects may also reduce farmers' uncertainty of the environmental performance of BMPs after talking to their neighbours. Thus, interdependence in farmers' decisions should be considered when exploring dairy farmers' adoption of BMPs.

This paper aims to explore determinants of dairy farmers' willingness to adopt BMPs for water quality protection. In addition, except for testing the commonly used determinants, such as farm characteristics, it will test the hypothesis that spatial effects influence farmers' choices. Bayesian spatial Durbin probit models are applied to sample survey data in the Waikato region of NZ.

1.2 Literature Review

Literature of empirical analysis of spatial dependence in farmers' adoption behaviours is quite thin. Spatial dependence means that farmers located nearby show similar choice preferences, which is also known as the neighbourhood effect (Manski, 1993). The dependence might be due to communication between farmers, which may raise awareness or reduce information costs, for example. Case (1992) was one of the first to apply a spatial probit model to explore the neighbourhood effect on Indonesian farmers' adoption of sickle. In addition to farmers' adoption of agricultural technology, spatial dependence has also been considered in adopting organic farming in some recent studies. Examples include Wollni & Andersson (2014) who uses survey data to analyse factors affecting farmers' decisions on organic conversion in Honduras. Lewis, Barham & Robinson (2011) examine the neighbourhood effect in organic conversions in southwestern Wisconsin of the U.S. La¨pple & Kelley (2015) applied Bayesian spatial Durbin probit models to account for spatial dependence in Irish drystock farmers' adoption of organic farming. The latter two articles show that farmers tend to get technical information from other organic farmers to reduce the uncertainty of organic conversion since organic farming is an information-intensive farming technique. Results of all these articles indicate that significant spatial dependence exists in farmer choice, and suggest that policy implications might be biased if spatial spillover effects are ignored.

A few studies focus on the NZ farmers' attitudes on sustainable agriculture or farmers' willingness to adopt BMPs. Earlier studies used qualitative methods based on interviews and some recent studies attempted to use simple linear regressions to analyse factors affecting farmers' choices. For example, Parminter, Tarbotton & Kokich (1998) interviewed 60 farmers to identify their attitudes to riparian management practices, and how different criteria influence their choice of riparian management practices. Their results show that farmers' adoption of riparian management practices would happen only if the practices were regarded to be feasible and not to increase the difficulty of implementation in management. Similarly, Bewsell, Monaghan & Kaine (2007) used qualitative methods to collect data from 30 dairy farmers in four NZ catchments to analyse the factors affecting dairy farmers' willingness to adopt stream fencing practices. Results of this study indicated that farm contextual factors, resulting from local government guidelines, influenced farmer's decision-making on the adoption of stream fencing. Notably, there are only two papers investigating determinants of farmers' adoption of BMPs using econometric methods. Rhodes, Leland & Niven (2002) applied simple linear regression to assess the effectiveness of environmental information on farmers' choices of riparian management practices in the Otago region and Southland region of NZ. They also examined the relationships between financial assistance for riparian planting and willingness to adopt the practice. The results showed positive but weak associations between information and the three response variables (attitude, knowledge, and adoption intention). A positive correlation was observed between the access to information and money and the adoption of riparian management. Significantly, financial issues were the most influential factor that hindered farmers from adopting permanent fencing. Fairweather et al. (2009) employed a two-way analysis of variance (ANOVA) and cluster analysis to examine conventional farmers in their evaluation of farm practices and environmental orientation for NZ's sheep and beef, dairy, and horticulture sectors. Their results showed that the development of environmental orientation is found in farmers' exposure to best-practice audits and policy regulation.

The above studies in NZ provide insights into the factors that should be considered in the analysis of farmers' adoption of BMPs. Notably, except for commonly considered factors, such as farm and household characteristics, financial and information issues are highlighted in some of the studies (Rhodes, Leland & Niven, 2002; Bewsell, Monaghan & Kaine, 2007; Fairweather et al., 2009). Nonetheless, the qualitative studies based on interviews only have limited number of observations, and results derived from the studies may lack generalizability. Moreover, although some studies attempted to quantify environmental orientation according to farmers' environmental practices, these studies used either simple linear regressions or ANOVA method, which cannot accurately measure to what degree the factors influence farmer's willingness to adopt BMPs.

This paper contributes to the literature in the following aspects. First, it contributes to the empirical literature on the determinants of farmer's adoption of BMPs in NZ by using spatial econometric analysis methods, which considers various determinants, including drivers and barriers for farmers to adopt BMPs, farm and household characteristics as well as spatial issues[2]. Significantly, dairy farms are geographically located. Thus, spatial effects are presented as the distance from the farm to the nearest water bodies and neighbourhood effect, which is measured according to spatial relationships among dairy farms. Secondly, direct impacts (from own characteristics) and indirect impacts (from neighbours' characteristics) will be captured because I examine the determinants of adoption by using a spatial Durbin probit model that allows for the inclusion of direct and indirect effects of each independent variable on the probability of adoption.

This paper is structured as follows. Section 2 details the econometric models, including a basic probit model of farmer choice and a spatial Durbin probit model of farmer choice with spatial spillover effects considered. Section 3 describes empirical models and data. Section 4 presents results and discussions. Conclusions are presented in section 5.

2. Econometric Models

2.1 Modelling Framework

I assume that dairy farmers make decisions on the adoption BMPs according to the difference in utility derived from the adoption and non-adoption of BMPs. Thus, for the i^{th} farmer, the difference in utility is constructed by $y_i^* = U_{1i} - U_{0i}$, where U_{1i} and U_{0i} is the utility associated with observed 1 (to adopt BMPs) and 0 (not to adopt BMPs) indicators. y_i^* is an $n \times 1$ latent variable that cannot be observed, and $y_i(0,1)$ denotes the binary outcome variable that can be observed and expressed in the following equation.

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[2] The BMPs in this paper refer to fencing off stocks from water and riparian practices.

(1) $$\begin{cases} y_i = 1, \ if \ y_i^* \geq 0 \\ y_i = 0, \ if \ y_i^* < 0 \end{cases}$$

According to a traditional choice model, y_i^* is assumed as a function of the observed decision-making characteristics and farm characteristics. These characteristics are denoted by an $n \times k$ matrix X_i. The interpretation of the relationships between y_i^*, y_i and X_i depend on utility maximization that the i^{th} farmer chooses to adopt BMPs when:

(2) $$\Pr(y_i = 1) = \Pr(U_{1i} - U_{0i} \geq 0) = \Pr(y_i^* \geq 0)$$

Therefore, the relationships can be regressed on the basis of Equation 3, in a non-spatial choice model:

(3) $$y_i^* = X_i\beta + \varepsilon_i$$

where $\beta(k \times 1)$ are the unknown regression coefficients to be estimated, $\varepsilon_i \sim N(0, \sigma_\varepsilon^2)$ is an error term (i.i.d.) with zero mean and variance σ_ε^2. Then, when $\Phi(.)$ denotes the cumulative density function of the normal distribution, the probability of the i^{th} farmer's adoption of BMPs can be expressed as $\Pr(y_i = 1) = \Phi(X_i\beta)$.

When farmers' choice are considered in a spatial context, the choice model should consider contextual factors (also known as contextual effects in the sociological literature), i.e. characteristics of neighbouring farms, and spatial spillover effects from neighbouring farmers' decisions. In other words, y_i^* depends on the own farm and household characteristics as well as on the spatial dependence between the farmer and his/ her neighbours. Then, y_i^* can be constructed as:

(4) $$y_i^* = U(X_i, S_i^*) + \eta_i$$

Here, S_i^* represents the unobservable impacts of spatial dependence, which exists between farmer *i* and farmers located in close proximity, on farmer *i*'s decision. Although it is unobserved, it may depend on contextual factors, for example, the extent of farming intensification in the neighbourhood, and on the adoption/ non-adoption decisions of farmer *i's* neighbouring farmers. Therefore, S_i^* can be expressed as:

(5) $$S_i^* = S\left(Z_k, \, y_j(i)\right) \; + \; \zeta_i$$

Here, Z_k denotes the vector of the exogenous characteristics of the group *k* or in the area *k* to which farm *i* belongs, and $y_j(i)$ denotes the vector of decisions of his/ her neighbours ($i \neq j$). Notably, when the spatial dependence is included, the decisions of farmer *i's* neighbours influence his/ her decision that, in return, affects the decisions of the neighbours.

2.2 Spatial Durbin Probit Model

This paper uses a spatial Durbin probit model (SDM probit model) to analyse how interdependence in farmers' decisions contributes to their adoption of BMPs. it follows the design LeSage and Pace (2009), and the model includes spatial dependence that takes the form shown in the following equation:

$$y_i^* = \lambda W y_i^* + X_i \beta + W X_i \gamma + \varepsilon_i \quad (6)$$

In the above Equation, except for farmer *i's* own characteristics $X_i\beta$ that have been introduced in the previous section, two spatial terms, $\lambda W y_i^*$ and $WX_i\gamma$, are also considered. In particular, Wy_i^* is the spatially lagged dependent variable with an $n \times n$ spatial weights matrix W defined on the basis of the inverse distance between farmer *i* and farmer *j* ($i \neq j$):

$$w_{ij} = \begin{cases} d_{ij}^{-1}, 0 \le d_{ij} \le d \\ 0, \quad d_{ij} > d \end{cases} \quad (7)$$

d denotes a threshold distance beyond which spatial spillover effects are assumed to be zero. Considering the data size of this study, the threshold distance is set such that each farmer in the data set has at least one neighbour. According to this definition, therefore, the impacts of farmer *j* on farmer *i* decay with the distance between them. Thus, Wy_i^* represents the weighted average neighbouring farmers' utility that captures the spatial dependence of adoption choice among farmers. The scalar spatial parameter λ measures the strength of the spatial dependence, which is to be estimated. Similarly, WX_i is the spatially lagged independent variables, which captures the weighted average characteristics of neighbouring farms, with $\gamma(k \times 1)$ as the unknown regression coefficients to be estimated.

In this paper, the SDM probit model is regressed by using the Bayesian Markov Chain Monte Carlo (MCMC) estimation, and a detailed description of the estimation procedure for the model is provided in LeSage and Pace (2009) and LeSage et al. (2014). Regarding the choice of the most appropriate spatial weights matrix, several models with different thresholds *d* are run and compared using posterior model probability (LeSage and Pace, 2009). The range of the threshold values is from 1.5 km to 4 km (in intervals of 0.5 km), which is chosen on the basis of the distance band calculation in Arc GIS 10.2. The model with the highest posterior probability with a threshold value of 1.5 km is the preferred model fitting the data best.

3. Data

The data used in this paper is based on a cross-sectional survey of data in the Waikato region of NZ to empirically test and verify the hypothesis that spatial dependence exists in farmers' decision-making by using an SDM probit model presented in the previous section. The data are collected as a part of the study of the Upper Waikato Sustainable Milk Project held by DairyNZ. In this project, dairy farmers voluntarily committed to adopting BMPs at the beginning, and the reasons for adoption or non-adoption of the BMPs were collected by the means of face to face interview at the end of the project. Over 200 questionnaires were collected in 2013 by DairyNZ and 171 questionnaires were considered usable. The dependent variable is a binary variable, indicating farmer choice on the adoption or non-adoption of BMPs: coded as 1 representing the farmer has adopted BMPs as committed, and coded as 0 indicating the farmer has not adopted BMPs (set as the base category).

In addition to farmers' adoption and non-adoption choices, dairy farmers also gave answers on what motivates them to adopt BMPs and what prevents them from implementing BMPs. Hence, drivers and barriers associated with the adoption choices are grouped to form categorical variables considered as explanatory variables in this paper. The survey data on farm characteristics included farm size, farm contour and participation in dairy-related social activities. Meshblock data from the NZ 2013 census are used for the purpose of capturing household characteristics. Although the meshblock data cannot completely describe the variance of the individual (farm-level) data, 141 counts are collected from the meshblock data[3]. The 171 farms are located in rural areas instead of city blocks in the Waikato region. Thus, it is not a perfect but acceptable alternative to represent household characteristics. Three types of spatial variables are also included as explanatory variables: the lagged dependent variable Wy_i^*, the lagged explanatory variables WX_i (shown in Equation 6), and the distance from the farm to the nearest water bodies, which are calculated in Arc GIS 10.2 using the coordinates of the 171 dairy farms[4]. A detailed description of all the explanatory variables is shown in Table 1. Accordingly, the expected signs of the coefficients associated with the variables are also given in the third column of Table 1. Where it is a priori difficult to set the expected sign of coefficients, "+ or –" and "– or +" are used. However, the preference for the signs is offered given the orders. Statistics descriptions of the dependent and explanatory variables are presented in Table 2.

[3] A Meshblock is defined as the smallest geographic unit for which statistical data is collected by Statistics NZ. Meshblocks vary in size from part of a city block to large areas of rural land.

[4] Here, different from the definition of waterways in the Accord, water bodies used to calculate the distance from the farm to water bodies in refer to observable streams, rivers, and lakes in Google map with the scale of 1:8000 that is seen as an appropriate scale to see small road (http://wiki.openstreetmap.org/wiki/Zoom_levels).

Table 1 Descriptions of Variables

Explanatory variables	Descriptions	Expected signs
Drivers for adopting BMPs (DR)	Categorical variables: DR1: self-initiated, coded as 1. DR2: industry information, coded as 2. DR3: others, coded as 3 (set as the base).	 + or - + or -
Barriers to adopting BMPs (BA)	Categorical variables: BA1: financial problems, coded as 1. BA2: lack of information, coded as 2. BA3: personal reasons and others, coded as 3 (set as the base).	 - or + - or +
Farm size	Effective areas of dairy farms (hectares).	+
Farm contour	Percentage of flat areas over total farm areas.	-
Social activities	The number of dairy-related activities, such as discussion group and field days that farmers participated in the past year (2012).	+
Distance	The distance from the dairy farm to the nearest water bodies (metres). To control for the non-linear relationship between distance and the farmer's adoption of BMPs, the distance is natural log transformed in the empirical analysis.	-
Staff training	Binary variable=1, if there are staffs (the farmer himself/ herself is also counted as a staff) who have been trained or are being trained toward BMPs.	+
Income (Proximity)	The median income of people, who are greater than 16, in meshblocks.	+
Age (Proximity)	The average age of people, who are greater than 16, in meshblocks.	-
Education level (Proximity)	Education level, which is the proportion of people (who are greater than 16) educated at and over level 5, in meshblocks.	+

Table 2 Statistics Descriptions of Variables

Variable name	Min.	Max.	Mean	SD.
Dependent variable	0	1	0.41	0.49
DR1	0	1	0.24	0.35
DR2	0	1	0.39	0.49
DR3	0	1	0.37	0.48
BA1	0	1	0.51	0.39
BA2	0	1	0.28	0.45
BA3	0	1	0.21	0.41
Farm Size	25	874	169.63	122.88
Farm Contour	0	100	38.94	33.25
Social event	0	33	4.83	7.10
Distance	55.11	11100	3934.81	2435.82
Staff training	0	1	0.46	0.34
Income	36700	125000	82833.13	18678.13
Age	17.5	57.2	36.10	7.84
Education	0	0.46	0.24	0.12

4. Results and Discussions

4.1 Model Comparison and Coefficient Estimation

An SDM probit model with a 1.5 km threshold *d* is chosen as the preferred model due to the highest posterior model probability. For comparison purposes, I have calculated the posterior model probabilities comparing alternative SDM probit models with threshold values ranging from 1 km to 4 km (in intervals of 0.5 km). The results indicate that spatial spillover effects are assumed to be zero beyond the 1.5 km threshold distance. Similarly, I have compared posterior model probabilities of spatial model specifications, including the spatial autoregressive (SAR) probit model, spatial error (SEM) probit model, the spatial lag of X (SLX) probit model and the SDM probit are compared, with a threshold value of 1.5 km. Results show that the SDM probit model has the biggest posterior model probability.

Table 3 presents the coefficient estimates for the parameters β, λ, and γ in the preferred SDM probit model. It is noted that λ is statistically significant at the 1 percent level indicating the existence of spatial dependence in the adoption of BMPs among dairy farmers. Moreover, the positive sign of λ implies that a dairy farmer is more likely to adopt if his/ her neighbours are also BMPs adopters. Furthermore, most of the explanatory variables are statistically significant at different statistically significant levels. Although the statistical inference of magnitudes of the explanatory variables cannot be made according to the coefficient estimates shown in Table 3, expectations on the signs of the coefficients, which is made in Table 1 in the previous section, can be verified.

Table 3 Coefficient Estimates of the SDM Probit Model

Variable	Coefficient	Std. dev.	P value
Constant	1.161	0.401	0.003
Drivers and barriers			
DR1: self-initiated	0.345	0.421	0.002
DR2: industry information	0.231	0.378	0.005
BA1: financial problems	-0.421	1.231	0.012
BA2: lack of information	-0.123	0.987	0.048
Own farm characteristics			
Farm size	0.056	0.024	0.065
Farm contour	-0.004	0.042	0.026
Social activities	0.312	0.876	0.035
Log Distance	-4.42	0.029	0.085
Staff training	0.765	1.345	0.007
Income (Proximity)	0.004	0.005	0.102
Age (Proximity)	-0.038	0.021	0.098
Education level (Proximity)	0.173	0.324	0.078
the Spatially lagged independent terms (Neighbours' characteristics)			
W-DR1: self-initiated	0.125	0.214	0.052
W-DR2: industry information	0.013	0.178	0.015
W-BA1: financial problems	-0.182	0.965	0.056
W-BA2: lack of information	-0.076	0.047	0.038
W-Farm size	0.066	0.004	0.123
W-Farm contour	-0.002	0.003	0.216
W-Social activities	0.112	0.679	0.095
W-Log Distance	-1.26	0.004	0.078
W-Staff training	0.378	1.032	0.023
W-Income	0.002	0.003	0.241
W-Age	-0.014	0.002	0.145
W-Education level	0.084	0.152	0.098
the Spatially lagged dependent term λ	0.412	0.021	0.001

Source: authors' elaboration based on Matlab software.

4.2 Effects Estimation

The SDM probit model accounts for both direct and indirect effects. The direct effects represent the impact of a change in the explanatory variables of farmer *i* on the adoption probability of farmer *i*, and the indirect effects (spatial spillovers) express the cumulative effect of a change in the explanatory variables of neighbouring farms on the adoption probability of farmer *i*. The indirect effects come from the interdependence in decision-making among farmers, i.e., a change in the independent variable has an effect on farmer *j's* probability to adopt BMPs and thereby also on farmer *i's* probability to adopt. To what extent changes in the neighbourhood influence the adoption probability of farmer *i* depends on the spatial proximity defined by the spatial weights matrix. The total effect of an explanatory variable is thus the sum of its direct effect and its indirect effect (LeSage and Pace, 2009).

Table 4 shows the marginal effect estimates, including direct, indirect and total effects as well as Bayesian 95 percent credible intervals for total effect estimates. The results show that for all explanatory variables, direct effects are about 1.5 times larger than the indirect effects, on average. According to magnitudes of the total effects, the most influential determinants are access to industry information (in the category of drivers), financial problems (in the category of barriers), participation in dairy related social activities, and staff training.

Table 4 Direct, Indirect and Total Effects Estimates of the SDM Probit Model

Variable	Direct effects	Indirect effects	Total effects
DR1: self-initiated	0.123	0.082	0.205 [0.005, 0.405]
DR2: industry information	0.223	0.041	0.264 [0.236, 0.702]
BA1: financial problems	-0.367	-0.098	-0.465 [-0.585, -0.345]
BA2: lack of information	-0.049	-0.017	-0.066 [-0.089, -0.043]
Farm size	0.062	0.031	0.093 [0.001, 0.185]
Farm contour	-0.014	-0.009	-0.023 [-0.053, 0.007]
Social activities	0.313	0.021	0.334 [0.114, 0.554]
Log Distance	-4.42	-1.95	-6.37 [-8.18, -4.16]
Staff training	0.173	0.115	0.288 [0.101, 0.475]
Income	0.004	0.002	0.006 [-0.002, 0.014]
Age	-0.041	-0.019	-0.06 [-0.08, -0.04]
Education level	0.156	0.104	0.27 [0.145, 0.395]

Source: authors' elaboration based on Matlab software.

5. Conclusion

This paper employes a spatial Durbin probit model to empirically analyse spatial dependence and determinants of dairy farmers' adoption of BMPs. It used a set of survey data of 171 farms in the Waikato region of New Zealand, and socioeconomic data were drawn from the 2013 Census. The advantage of the SDM probit model is that it allows for the inclusion of both the spatially lagged dependent variable and spatially lagged independent variables, which takes account of impacts of the neighbouring farmers' decisions as well as neighbouring farmers' characteristics. The statistically significant and positive parameter λ indicates that spatial spillover effects exist, and farmers are more likely to adopt BMPs if their neighbours are also adopters. Spatial spillover effects are also observed through impacts of the neighbouring farmers' characteristics. In addition, a farmer's willingness to adopt BMPs decay with the increase in the distance from the farm to the nearest water bodies.

This paper also highlights the importance of information acquisition for dairy farmers to adopt BMPs. Firstly, the existence of spatial dependence in decision-making between farmers indicates the information exchange among farmers. Secondly, the results show that access to industry information, as a driver, has the greatest impact on farmers' adoption of BMPs. Thirdly, participation in different (dairy-related) social activities also promotes farmers' adoption of BMPs, as it is another way of obtaining relative knowledge and exchanging information with others.

Policy implications can be made based on the findings of the paper as follows. Firstly, an understanding of dairy farmers' drivers and barriers to adopting BMPs could assist policy makers to focus on specific strategies and deliver support to solve problems that are badly in the need of help. Also, the importance of information availability in the neighbourhood network and social activities suggests that policies and strategies that address the whole community may be more efficient than targeting individual farmers to induce behavioural changes in adopting BMPs. Lastly, the existence of a distance decay effect in dairy farmers' adoption of BMPs provides a different point of view of education as a vehicle for regional governments to use in the promotion of

BMPs. That is, during the education and promotion process, instead of treating dairy farmers as polluters, they could also be seen as individuals who also demand good water quality for recreation purposes.

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