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SPECIAL ISSUE

Impact of farmer group participation on the adoption of sustainable farming practices—spatial analysis of New Zealand dairy farmers

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Abstract

This paper analyzes the impact of participation in farmer groups on dairy farmers' adoption of sustainable farming practices in New Zealand. A spatial propensity score matching method is used to consider the spatial dependence and social connections between farmers in the decision-making of farmer group participation and adoption of sustainable farming practices. The results show that farmers' decisions of farmer group participation are affected by their neighbors' choices, and participation in farmer groups has a positive effect on farmers' adoption of sustainable farming practices. The findings indicate the important role of social interactions in farmers' voluntary uptake of sustainable agricultural practices. Overall, the positive effect of farmer group participation on the adoption of sustainable agricultural practices highlights learning and knowledge spillover among farmers, which emerges as important to the formulation of sustainable farming policy.

KEYWORDS
farmer group participation, spatial propensity score matching, sustainable agricultural practices

JEL CLASSIFICATION
Q13, Q56, R12

1 INTRODUCTION

Policy responses to address water quality degradation have helped reduce the overall agricultural nutrient surpluses for countries in the Organisation for Economic Co-operation and Development (OECD), predominantly nitrogen and phosphorus. However, for a few countries such as New Zealand (NZ), there has been an upward trend in nutrient surpluses. According to a report from OECD, NZ's nitrogen balance (i.e., the difference between nutrients entering and leaving the system) increased more than in any other OECD country from 2000 to 2015 (OECD, 2017). The trend is not unexpected because NZ's dairy industry has increasingly intensified over the past few decades, represented by continued increases in land use, intensive inputs such as fertilizers, and stocking rates. Currently, the increasing nutrient pollution discharged from dairy farms is a threat to the water quality of NZ's lakes, streams, and rivers (Abell et al., 2011; McDowell et al., 2017); a third of NZ's lakes carry excessive nutrient loads, in particular, those surrounded by farmland fared worst (Verburg et al., 2010). To control nutrient pollution, the NZ government has launched a series of programs to support the sustainable development of the dairy farming sector (Pannell & Rogers, 2022). Those projects place greater responsibilities on dairy farmers that they are required to comply with good management practices (GMPs) to meet the new targets for sustainable growth as well as imminent regulations set by the government.

Therefore, farmers' decisions on the adoption of sustainable farming practices should be considered one of the most important determinants of the success of policy aiming at water quality protection. The literature on adoption analysis shows that farmers' adoption of sustainable agricultural practices is contingent on many factors that can be categorized into four broader groups namely, (1) farm and farmer-specific characteristics, (2) social and cultural norms, (3) availability of support and resources, and (4) perceived financial benefit (de Oca Munguia & Llewellyn, 2020; Pannell & Zilberman, 2020). However, extant studies on farmers' adoption behaviours in NZ are mainly qualitative studies based on interviews (Bewsell et al., 2007; Moon & Cocklin, 2011). Due to the small size of observations, results of the qualitative studies may lack generalisability. Also, there is not a lot of evidence on farmers' adoption of GMPs in NZ as only a handful of studies empirically investigate the above factors affecting farmers' adoption of GMPs (Rhodes et al., 2002; Fairweather et al., 2009; Small et al., 2016).

Another gap arises from the ignorance of social interactions among farmers in the empirical studies. Social interactions among farmers may influence their adoption of sustainable farming practices and environmental performance. Farmers' social networks, often established by farmer groups or discussion groups, provide a source of information about sustainable farming practices. Although nutrient management issues are often invisible and difficult to monitor, farmers often have a "fair idea" of what each other is doing (Burton, 2004; Thomas et al., 2019). Farmers may also exchange their farming experience with other farmers who participate in the same farmer groups (Läpple et al., 2013). More importantly, learning might occur during interaction activities in farmer groups (Oreszczyn et al., 2010; Šūmane et al., 2018): when a dairy farmer plans to adopt

GMPs, the farmer may refer to or learn from his/ her peers' experience or advice. It is expected that farmers interact with each other and construct their social networks in the farmer groups (Morfi et al., 2018), where their peers in the farmer groups could influence their decisions of farming practices across various aspects (i.e., peer effects), including the adoption of GMPs (Gest et al., 2001; Rustinsyah, 2019). Therefore, participation in farmer groups may stimulate voluntary uptake of GMPs to support sustainable farming. However, when exploring the impact of participation in farmer groups, the existing studies mainly focus on estimating the economic return on participating in farmer groups, such as production, productivity, and financial indicators (e.g., income and profitability) (Anderson & Feder, 2004; Grashuis & Su, 2019; Läpple et al., 2013;); and most of the studies are conducted in developing countries (e.g., Davis et al., 2012; Rustinsyah, 2019).

Spatial dependence between farmers is another factor that has often been neglected. Farmers may be easily influenced by their "neighboring" farmers' decisions, including participation in farmer groups and adoption of GMPs. It is especially evident in a small community, where farmers know and meet with each other frequently (Yang & Sharp, 2017). Then, farmers' decisions on the adoption of GMPs may be further influenced by those sitting in the farmer group meetings. Spatial dependence between farmers has been extensively studied in the literature on farmers' adoption of technology and sustainable agricultural practices (e.g., Engler et al., 2011; Läpple & Rensburg, 2011; Yang & Sharp, 2017; Zheng et al., 2021) . However, in the field of farmer group participation, most of the existing studies do not consider the spatial effects on farmer group participation; a few studies that consider the spatial effects simply use exogenous variables (i.e., dummy variables) to compare the impact of participation in farmer groups on the intended outcomes between neighboring farmers and those located far away (Jørs et al., 2016). One exception is from Yang & Knook (2021) who evaluate the effect of a participatory extension program (PEP) on farmers' adoption of soil management practices in Scotland. The results show that spatial dependence exists in farmers' participation in PEP and further influence their voluntary uptake of soil management practices.

In light of the above gaps in the literature, this study aims to explore the impact of participation in farmer groups on dairy farmers' adoption of GMPs in NZ, with the spatial dependence considered in their decisions on participating in farmer groups. Being the first attempt to address the social interaction effect through farmer group participation in NZ, we employ a spatial propensity score matching (PSM) method (Papadogeorgou et al., 2018; Yang & Knook, 2021) to account for selection bias in farmers' participation in farmer groups and allow for correcting estimation of the effect of farmer group participation in their adoption of sustainable farming practices. The contribution of the study is twofold. First, it demonstrates the mechanism of how neighours (via spatial connections) and peers (via farmer groups) affect farmers' decisions to adopt sustainable farming practices. Second, it illustrates the superiority of applying the spatial PSM method in the evaluation of the relationship between farmer group participation and their adoption of GMPs, with the spatial effects considered to correct selection bias.

The remainder of the study is structured as follows. Section 2 provides the econometric specifications and description of the sample data. Section 3 presents the results and discussion, followed by the last section to conclude the paper.

2 | METHODOLOGY

2.1 | Econometric specifications

We assumed that, for the i^{th} farmer, the willingness to participate in farmer groups is based on utility U_i maximization. z_i^* denotes the difference in the utility of participation and non-participation, that is $z_i^* = U_{1i} - U_{0i}$. z_i^* is an $n \times 1$ latent variable that cannot be observed, but we can use the treatment t_i to denote the binary outcomes of participation or non-participation in farmer groups. Hence, we can define a sample selection model:

$$t_i = \begin{cases} 1, & \text{if } z_i^* \geq 0 \\ 0, & \text{if } z_i^* < 0 \end{cases} \tag{1}$$

where z_i^* is specified as a function of the determinants $X_i(n \times k)$ that may affect farmers' decision-making in a typical choice model setting:

$$z_i^* = X_i\beta + \varepsilon_i \tag{2}$$

where $\beta(n \times 1)$ is an unknown parameter associated with X_i to be estimated and ε_i is the error term.

In a typical propensity score matching process, the observed covariates X_i are used to generate a "balancing score" to adjust for confounding the relationship between treatment t_i and the intended outcome Y (i.e., adoption of GMPs in our case). To consider the spatial dependence between farmers, we use a spatial propensity score method to include unknown spatial effects s_i^* in the matching process. Hence, z_i^* can be re-defined as:

$$z_i^* = U(X_i,\ s_i^*), \quad s_i^* = s(z_j(i),\ g_m) + u_i. \tag{3}$$

Note that, although the spatial effects s_i^* is unknown, it can be specified to capture the spatial dependence between the i^{th} farmer's decision and the decisions of neighboring farmers $z_j(i)$ $(i \neq j)$, and/or dependent on the contextual factors g_m, such as farm and farmer characteristics of the neighboring farmers. Here, the term "neighbor" is defined in a broad sense: people who live in the same or nearby community have more opportunities to interact with each other and are thus expected to have a greater impact on each other compared to others living in a community further away.

In this study, we use a spatial Durbin probit model (SDM probit model) to model the spatial effects:[1]

$$z_i^* = \lambda W z_i^* + X_i\beta + WX_i\theta + \varepsilon_i. \tag{4}$$

Here, the spatial effects are presented in two ways: $\lambda W z_i^*$ is a spatially lagged dependent variable that is used to model the spatial dependence in farmers' decision-making regarding the adoption of GMPs; $WX_i\theta$ represents the spatially lagged independent variables that are used to capture the contexture factors; λ and θ are two spatial parameters to be estimated.[2] W is an $n \times n$ spatial weight matrix, which is a distance-based weight matrix defined by the inversed distance

[1] As is discussed in LeSage (2014), the SDM model is most suited in practice to take into account potential spatial effects. Thus, we started from the SDM probit model and tested for other spatial models, such as spatial lagged probit and spatial error probit models. The spatial econometric regressions were conducted using packages of "sp", "spdep" and "spatialprobit" in R Studio 2022.02.0.

[2] To consider the spatial effect of the characteristics of neighboring farms and farmers, we included all the independent variables except for distance to nearest waterbodies (which has the spatial dependence in nature) in the spatially lagged independent variables.

D_{ij}^{-1} between the i^{th} and the j^{th} farmer using the coordinates of the dairy farms:

$$w_{ij} = \begin{cases} D_{ij}^{-1}, & 0 \le D_{ij} \le D \\ 0, & D_{ij} > D. \end{cases} \tag{5}$$

Here, D denotes the threshold distance (0.288 km) beyond which there are no spatial effects. The threshold distance D calculated based on the minimum value of the maximum distance between farmers to ensure every farmer has a neighbor (Yang & Knook, 2021). We follow LeSage (2014) and Pace & LeSage (2009) to use the Bayesian Markov chain Monte Carlo estimation to estimate the SDM probit model.

The probabilities estimated with the SDM probit model are then used as matching estimators in the propensity score matching process to compare the adoption of GMPs of the treated group (i.e., farmers who participated in farmer groups) to the control group (i.e., farmers who did not participate in farmer groups). We then follow Papadogeorgou et al. (2018) to employ a distance-adjusted propensity score matching method to conduct the pairwise matching between the treated and control group, as shown in Equation (6). This matching method helps address the potential risk of bad matching in the typical nearest-neighbor (NN) matching method, in particular when the closest neighbor is too far away (Gonzales et al., 2018):

$$C_{dis} = C_{dis}(\hat{p},\, d_{ij}, \upsilon) = \min_j \left\| \upsilon * |\hat{p}_i - \hat{p}_j| + (1-\upsilon) * d_{ij} \right\|, \tag{6}$$

where $\hat{p}_i$ denotes the propensity score of the i^{th} treated group farmer and $\hat{p}_j$ for the j^{th} control group farmer. d_{ij} is the standardised Euclidean distance between farmer i and j, capturing the distance relationship between i and j, and υ ($\upsilon \in [0,1]$) is the distance calliper adjusting the tolerance level on the maximum propensity score distance. We test for the robustness of the score matching method by using the values of v from 0.1 to 0.9 with an interval of 0.1.[3] The efficiency of the spatial PSM process is evaluated by diagnostic analyses to identify any imbalance after matching and the variables to be included in the post-matching analyses (results shown in Section 3.1).

The spatial PSM stated above produces a matched data set that is used to analyze the impact of farmer group participation on the intended outcome Y (i.e., the adoption of GMPs), with $Y_i(1)$ and $Y_i(0)$ representing GMPs in states of participation and non-participation, respectively. Given Y has the characteristics of dummy variable ($=1$, adoption, and $=0$, non-adoption), we use a binary logit model to estimate the participation effect on the adoption of GMPs (McGuinness, 2008):

$$\log\left(\frac{\text{Prob}\,(Y_i = 1)}{\text{Prob}\,(Y_i = 0)}\right) = \alpha_i + \vartheta t_i + X_i\eta + \delta_i. \tag{7}$$

Here, the dummy t_i denotes the farmer's decision to participate in farmer groups; X_i, represented farm and farmer characteristics that were included in the spatial PSM as covariates; α_i is the constant; ϑ and η are unknown parameters to be estimated, and δ_i is the error term. After the logit model estimation, the average treatment effects (ATE) can be calculated (Heckman et al.,

[3] To avoid using extreme values 0 and 1 ($\upsilon = 1$ makes the matching to the typical NN matching, while $\upsilon = 0$ purely relies on distance). The analysis of spatial matching was conducted using packages of "MatchIt" and "geoMatch" in R Studio 2022.02.0.

1999):

$$ATE = E\left(Y^{*}{}_{1}X\right) - E\left(Y_{0}{}^{*}X\right), \tag{8}$$

with Y^* denoting the odds of adopting a specific GMP.

2.2 | Sample data

The Waikato region is regarded as the heart of NZ's dairy industry. The majority of dairy herds (71.1%) are in the North Island, with the greatest concentration (28.4%) situated in the Waikato Region (LIC & DairyNZ, 2021). Significantly, nutrient loss from dairy farms is a concern for the Waikato region. Currently, a variety of environmental protection practices have already been planned or operated in this region. Data used in the study is drawn from the Upper Waikato Sustainable Milk Project, the largest environmental good practice project ever undertaken by the NZ dairy industry. With NZD 685,000 co-funded by DairyNZ, the central government, and the Waikato River Authority, the project provides free, one-on-one advice and support to dairy farms in the Upper Waikato catchment over three years (2012–15), to control nutrient loss going into the Waikato River as well as to improve water use efficiency on farm (DairyNZ, 2015).[4] Farmers voluntarily made commitments to adopting sustainable farming practices at the start of the project. Follow-ups are made by face-to-face interviews and questionnaires (by experienced farm consultants) to see if farmers have completed their commitments to the plan. A total of more than 200 questionnaires were collected in 2015, which produces a final sample of 163 valid observations, with the incomplete or erroneous ones excluded. The outcome variable includes four GMPs, including nutrient management, land management, and waterways management. The data also includes information about farmer group participation (treatment variable), drivers and barriers to adopting GMPs, and farm and farmer characteristics (covariates). Details of the variables and statistical descriptions are presented in Table 1.

3 | RESULTS AND DISCUSSION

3.1 | Spatial effects in participation in farmer groups

Table 2 presents the regression results of the non-spatial PSM and spatial PSM model estimated via a probit model and SDM probit model, respectively, with the coefficient estimates for the probit model and effects estimates of the covariates for the SDM probit model (considering direct and indirect effects) (LeSage & Pace, 2009; Lacombe & LeSage, 2015). Overall, the results indicate spatial effects should be considered in the analysis of factors influencing farmers' participation in farmer groups. The coefficient of the spatially dependent lag term (λ) is estimated to be significantly positive, indicating the spatial dependence between farmers: a farmer's decision-making on GMP adoption is affected by neighboring farmers (Läpple & Kelley, 2015; Läpple et al., 2016; Yang & Sharp, 2017). We employed the Lagrange multiplier (LM) test and LM robust test to test

[4] Although there are recent surveys on farmers' GMP adoptions (e.g., Survey of Rural Decision Makers by Manaaki Whenua, Landcare Research), these surveys have not collected any spatial-based data to capture the geographical information about farmers.

TABLE 1 Variables descriptions and descriptive statistics

Variable	Descriptions	Mean (S.D.) $N = 163$
Outcome variables	Good management practices (GMPs)	
Nutrient management (*NM*)	Dummy, = 1, if the farm has an up-to-date nutrient budget or a nutrient plan.	0.76 (0.43)
Winter off cows (*WIFF*)	Dummy, = 1, if the farm has cows wintered off.	0.5 (0.5)
Soil test (*ST*)	Dummy, = 1, if soil test frequency is less than two years.	0.8 (0.4)
Riparian plantation (*RP*)	Dummy, = 1, if the farm has had riparian plantations or a plantation plan.	0.35 (0.48)
Treatment	Dummy, = 1, if the farmer participates in farmer groups.	0.43 (0.49)
Covariates	Variables used in propensity score matching and outcome models	
Drivers for adopting GMPs (*DR*)	Categorical variables	
DR1	Self-initiated, coded as 1.	0.24 (0.34)
DR2	Access to industry information, coded as 2.	0.39 (0.49)
DR3	Others, coded as 3 (baseline).	0.37 (0.48)
Barriers to adopting GMPs (*BA*)	Categorical variables	
BA1	Financial problems, coded as 1.	0.51 (0.39)
BA2	Lack of information, coded as 2.	0.28 (0.45)
BA3	Personal and other reasons, coded as 3 (baseline).	0.21 (0.41)
Production systems (*PS*)[a]	Categorical variables	
PS1	Low input system, coded as 1 (baseline).	0.44 (0.5)
PS2	Medium input system, coded as 2.	0.35 (0.47)
PS3	High input system, coded as 3.	0.21 (0.39)
Stocking rate	Peak cow numbers/ effective areas.	2.80 (0.51)
Farm size	Areas of dairy farms in hectare.	171.9 (133.78)
Farm contour	Percentage of flat areas over total farm areas.	38.22 (31.89)
Distance[b]	Distance from farm to the nearest water bodies (km).	3.93 (2.44)
Income	Household income of the farmer (in 1000 NZ dollar).	82.83 (18.62)
Age	Age of the farmer.	36.1 (7.81)
Education	Dummy, = 1, if the farmer is educated at and over level 5 (including certificate, diploma level 5 and above).	0.24 (0.12)

Notes:
[a]DairyNZ has provided descriptions of the production systems used by the NZ dairy farms, please find the details at: https://www.dairynz.co.nz/farm/the-5-production-systems/.
[b]to control for the non-linear relationship between distance and the farmer's adoption of GMPs, the distance is natural log-transformed in the analysis.

for the existence of two types of spatial effects in the non-spatial probit models—that is, the spatial lag term and the spatial error term. Results of the tests indicate the existence of the spatially lagged dependent term and the spatial auto-correlated error term in the non-spatial probit models. In addition, the Wald test results confirm that the SDM probit model is preferred and must not be reduced to only including one spatial effect—that is, the spatial lagged (SAR) probit model or spatial error (SEM) probit model.

TABLE 2 Regression results of spatial propensity score models

Variable	Non-spatial probit model Coefficients (std. error)	Spatial probit model Direct effects	Indirect effects	Total effects
DR1	0.345 (0.11)**	0.123**	0.081**	0.204**
DR2	0.231 (0.09)**	0.223**	0.041**	0.264**
BA1	−0.421(0.12)***	−0.367***	−0.089***	−0.456***
BA2	−0.123 (0.4)	−0.049	−0.017	−0.066
PS2	0.016 (0.02)	0.062	0.003	0.065
PS3	0.012 (0.009**)	0.014**	0.002**	0.016**
Stocking rate	0.313 (0.102) *	0.313*	0.021*	0.334*
Farm size	0.0001 (0.00002)***	0.0001***	0.0001***	0.0002***
Farm contour	−0.004 (0.01)	−0.014	−0.007	−0.021
Distance	−4.41 (1.45)***	−3.326***	−1.004**	−4.33**
Income	0.004 (0.02)	0.004	0.002	0.006
Age	−0.038 (0.002)***	−0.03***	−0.011***	−0.041***
Education	0.173 (0.04)***	0.117***	0.061***	0.178***
Wy (λ)	-		0.415***(0.04)	
LogLik	−123.48		−156.190	
McFadden R^2	0.230		0.361	
LM spatial lag	23.680 ($p < 0.0001$)			
Robust LM spatial lag	19.210 ($p < 0.0001$)			
LM spatial error	34.904 ($p < 0.0001$)			
Robust LM spatial error	21.450 ($p < 0.0001$)			
Wald test spatial lag			15.230 ($p < 0.0001$)	
Wald test spatial error			8.690 ($p < 0.0001$)	

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Most of the variables are found to be statistically significant in the SDM probit model, with the significant indirect effects indicating the existence of spatial effects from neighboring farmers. In particular, dairy farmers are more likely to participate in farmer groups if they are self-initiated or have access to information, whilst financial issues may prevent them from participating in farmer groups; farmers have the most intensified production system, a higher stocking rate, larger farm size, and higher education level are more likely to participate in farmer groups; older farmers and those living further from waterways are less likely to participate in farmer groups. Note that, to various degrees, the magnitudes of the total effects estimated through the SDM probit model are found to be different from the coefficient estimates of the probit model. That is, the inaccuracy of ignoring spatial effects may cause a biased estimation of the treatment effect (Lippert & Chatzopoulos, 2015; Gonzales et al., 2017).

The above findings indicate that the non-spatial model could not adjust the observed confounders in the matching process. Ignoring spatial effects leads to an inaccurate estimation of the "true" propensity score and could not estimate the effect of farmer group participation on GMP adoption.

TABLE 3 Comparison of mean differences of the covariates between control and treatment group before and after matching

Variable	Unmatched sample ($n_T = 70$, $n_C = 93$) Mean differences	SMD	Matched sample-non spatial ($n_T = 70$, $n_C = 70$) Mean differences	SMD	Matched sample - spatial ($n_T = 70$, $n_C = 70$) Mean differences	SMD
DR1	−0.045*	0.27	−0.391**	0.19	−0.382*	0.18
DR2	0.044*	0.07	0.039	0.03	98.72	0.04
DR3	0.001	0.1	0.001	0.1	0.001	0.1
BA1	−0.049*	0.02	−0.038	0.01	−0.036	0.007
BA2	0.021	0.08	0.021	0.08	0.021	0.06
BA3	0.030	0.09	0.030	0.08	0.03	0.08
PS1	0.163**	0.17	0.134	0.16	0.128	0.16
PS2	−0.031	0.02	0.025***	0.36	0.024**	0.35
PS3	−0.153**	0.17	−0.146*	0.12	−0.138	0.12
Stocking rate	−0.041**	0.62	−0.028***	0.39	−0.026	0.38
Farm size	−30.150	0.35	−29.672**	0.33	−26.189**	0.23
Farm contour	0.187	0.1	0.187	0.09	0.187	0.06
Distance	−0.532**	0.17	−0.467**	0.13	−0.442	0.12
Income	−2608.530	0.06	−2538.815	0.06	−2512.321	0.06
Age	−0.240*	0.23	0.211*	0.22	0.209*	0.18
Education	0.017**	0.57	0.014***	0.34	0.012***	0.32
NU	0.056**	0.41	0.054**	0.40	0.051**	0.40
WIFF	−0.030**	0.39	−0.026**	0.36	−0.023**	0.33
ST	−0.079***	0.54	−0.075***	0.51	−0.073***	0.49
RP	0.012*	0.26	0.010*	0.20	0.009*	0.20

Note: Reports are mean differences and absolute value of SMD, and n_T and n_C represents the sample size of treatment and control group; *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$ for Welch two sample t-test of mean differences in control and treatment group.

3.2 | Diagnosis analysis results

We conducted three different diagnostic analyses to compare the spatial matching and non-spatial matching process. Results of the three tests show the spatial matched sample is less imbalanced than that of the non-spatial matched one, indicating the spatial matching process outperforms the non-spatial matching. First, according to the t-tests shown in Table 3, the values of the mean differences of the covariates between the treatment and control group become smaller after the non-spatial and spatial matching process, when compared to those of the unmatched sample; the values of the differences are the smallest for all variables after the spatial PSM. Second, the values of standardized mean differences (SMD) that indicate the level of imbalance (greater than 0.1 indicating imbalance) are consistent with the changes in mean differences. Although imbalance exists in the same variables across all three samples, the values of SMD are the smallest after the spatial PSM. Lastly, as shown in Figure 1, the distribution of propensity scores of the PSM and spatial PSM shows that the propensity scores of the treatment and control groups are more balanced after the spatial PSM than after the PSM.

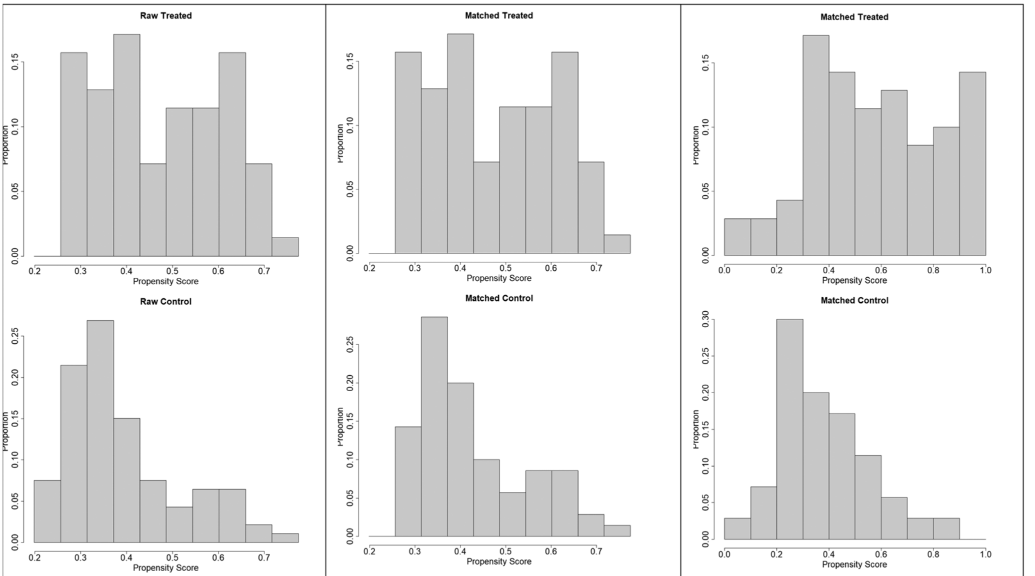

FIGURE 1 Distribution of propensity scores of the unmatched sample, non-spatial PSM sample, and spatial PSM sample

In addition to looking at the covariates, we explored the treatment effect on the outcome variables of the GMPs by examining the mean difference and SMD of the four GMPs between the treatment and control group. Based on the two-sample t-test results and SMD values, we find that the mean differences of GMPs are significant and the SMD values are greater than 0.1 in the matched samples (for both non-spatial and spatial). This indicates the positive effect of farmer group participation on the adoption of sustainable farming practices. Note that, although the sample is much more balanced after the spatial PSM, not all the included covariates are balanced after matching. Thus, we need to use post-matching regressions to address the imbalance.

3.3 | Factors influencing the adoption of GMPs

After matching, the data were used in the post-matching analysis to examine the factors that affect farmers' adoption of GMPs. All the covariates included in the matching process were included in the outcome models. Table 4 shows the odds ratios of binary logit estimates for all four types of GMPs after the spatial PSM (results of the PSM model are included in the Appendix). The odds ratio estimates differ in magnitude and significance levels between the spatial PSM and PSM model across all four GMPs, indicating ignoring spatial effects may lead to an inaccurate estimation of the treatment effect (Lippert & Chatzopoulos, 2015; Gonzales et al., 2018).

Based on Table 4, seven factors are found to affect farmers' adoption of GMPs. First, participation in farmer groups has a positive effect on the adoption of all four GMPs. For example, farmers who took part in farmer groups are 1.88 times more likely to adopt nutrient management practices. This finding confirms that, in addition to bringing in economic benefits (e.g., increased profits and productivity), participating in farmer groups has a positive effect on the adoption of sustainable farming practices (Anderson & Feder, 2004; Läpple & Hennessy, 2015; Yang & Knook, 2021).

TABLE 4 Post-matching regression results for the adoption of GMPs using the spatial PSM sample

	GMPs			
	NM	WIFF	ST	RP
Variable	**Odds ratio**	**Odds ratio**	**Odds ratio**	**Odds ratio**
Treatment	1.88 (0.12)***	1.51 (0.12)***	1.76 (0.11)***	1.89 (0.11)***
DR1	1.01 (0.09)	1.08 (0.09)**	1.13 (0.08)**	1.12 (0.08)**
DR2	1.23 (0.08)**	1.041 (0.07)**	1.34 (0.07)**	1.22 (0.08)**
BA1	0.64 (0.02)***	0.889 (0.03)***	0.90 (0.02)***	0.77 (0.03)***
BA2	0.85 (0.56)	0.71 (0.51)	0.72 (0.54)	0.35 (0.62)
PS2	0.76 (0.71)	0.933 (0.79)	0.93 (0.76)	0.96 (0.66)
PS3	1.61 (0.05)**	1.76 (0.04)**	1.46 (0.06)**	1.31 (0.05)**
Stocking rate	1.31 (0.29)	1.221 (0.31)	1.22 (0.30)	1.30 (0.41)
Farm size	1.09 (0.0001)***	1.06 (0.0001)***	1.11 (0.0001)***	1.08 (0.0001)***
Farm contour	0.91 (0.21)	0.97 (0.22)	0.97 (0.26)	0.92 (0.41)
Distance	0.77 (0.31))	0.56 (0.22)	0.74 (0.33)	0.636 (0.02)***
Income	1.23 (0.22)	1.01 (0.13)	1.12 (0.23)	1.00 (0.33)
Age	0.45 (0.03)***	0.61 (0.02)***	0.51 (0.03)***	0.49 (0.02)***
Education	1.12 (0.02)***	1.06 (0.01)***	1.65 (0.02)***	1.19 (0.02)***
LogLik	−119.05	−126.81	−134.24	−167.89
McFadden R^2	0.13	0.13	0.14	0.16
LR test	21.36 (P<0.0001)	28.13 (P<0.0001)	37.22 (P<0.0001)	42.68 (P<0.0001)

Note: Robust standard errors in paratheses; $*p < 0.1$; $**p < 0.05$; $***p < 0.01$.

Second, regarding drivers and barriers to GMPs adoption, access to information (driver) and financial issues (barrier) are found to be the potential factors that affect farmers' uptake of GMPs. This finding is consistent with the previous studies, such as Yang & Sharp (2017) and Yang et al. (2021) that the availability of information and financial support are indicated as the most important factors determining farmers' choices in the adoption of sustainable agricultural practices. Third, as for farm characteristics, farmers having a high-input farming system and larger farm size are more likely to adopt GMPs, compared to those operating a small farm with a low-input farming system (Llewellyn & Brown, 2020). Fourth, it is more likely for younger farmers with higher education levels to adopt GMPs. Lastly, distance to the nearest water bodies is found to only affect farmers' adoption of riparian plantation, indicating that the characteristics of a specific GMP affect farmers' adoption choices—riparian plantation is closely related to waterways management (Rhodes et al., 2002; Thomas et al., 2019). This finding is also aligned with the results of hedonic studies that people's willingness to pay for water quality protection decline with the increase in distance to the waterways (e.g., lakes, rivers, and wetlands) (Van Houtven et al., 2007; Yang & Sharp, 2017).

3.4 | Average treatment effects of farmer group participation

Table 5 shows the ATEs across pre- and post-matching regressions. The results show that participation in farmer groups increases the probability of adopting GMPs, which is in line with existing studies (Läpple & Hennessy, 2015; Knook et al., 2020; Yang & Knook, 2021). Note that differences exist in the odds of adoption across the estimation specifications: the regression results based

TABLE 5 ATE of participation in farmer groups on the adoption of GMPs across different estimation settings

	Regression Unmatched sample	Post PSM with regression: Regression Non-spatial matched sample	Post PSM with regression: Regression Spatial matched sample
NM	1.93 (0.1)***	1.86 (0.04)***	1.81 (0.06)***
WIFF	1.73 (0.1)***	1.68 (0.04)***	1.43 (0.05)***
ST	1.86 (0.09)***	1.79 (0.04)***	1.73 (0.05)***
RP	1.95 (0.15)***	1.88 (0.03)***	1.83 (0.03)***

Note: standard errors reported in parentheses; *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

TABLE 6 ATEs of participation in farmer groups on GMPs across a range of distance calipers

Caliper	NM	WIFF	ST	RP
$\upsilon = 0.1$	1.826 (0.06)***	1.449 (0.08)***	1.745 (0.06)***	1.846 (0.03)***
$\upsilon = 0.2$	1.824 (0.08)***	1.441 (0.05)***	1.742 (0.05)***	1.846 (0.04)***
$\upsilon = 0.3$	1.819 (0.07)***	1.435 (0.07)***	1.735 (0.04)***	1.835 (0.04)***
$\upsilon = 0.4$	1.816 (0.06)***	1.437 (0.06)***	1.738 (0.06)***	1.836 (0.03)***
$\upsilon = 0.5$	1.812 (0.07)***	1.435 (0.07)***	1.735 (0.05)***	1.837 (0.04)***
$\upsilon = 0.6$	1.806 (0.07)***	1.433 (0.07)***	1.734 (0.06)***	1.835 (0.05)***
$\upsilon = 0.7$	1.805 (0.07)***	1.434 (0.05)***	1.733 (0.04)***	1.832 (0.04)***
$\upsilon = 0.8$	1.803 (0.06)***	1.431 (0.05)***	1.731 (0.05)***	1.831 (0.03)***
$\upsilon = 0.9$	1.798 (0.06)***	1.431 (0.06)***	1.732 (0.05)***	1.829 (0.04)***

Note: standard errors reported in parentheses. *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

on the unmatched sample produce the largest ATE estimates for the adoption of all four GMPs; the values of ATEs decrease after matching, with the smallest ATE estimates obtained from the regression based on the spatial matched sample. For example, participating in farmer group activities increases the odds of adopting nutrient management practices by 1.93, 1.86 and 1.81 times on the unmatched, PSM, and spatial PSM sample, respectively. Although the results from the three samples show the positive effect of farmer group participation, the estimated likelihood of adoption (1.93) based on the unmatched sample is the largest whilst it is the smallest (1.81) based on the spatial PSM estimation. The findings indicate the potential overestimation of farmer group participation when sample selection bias and spatial effects are not controlled (Gonzales et al., 2017; Papadogeorgou et al., 2018; Yang & Knook, 2021). In addition, we used different values of the distance calipers (υ) in the spatial PSM to check the robustness of the ATE estimates (shown in Table 6). The results show that changing the values of υ does not change the values of ATEs significantly, and all ATEs are statistically significant. For example, the values of ATEs for the adoption of nutrient management practices are estimated to be between 1.798 and 1.826, with the larger value of υ producing a smaller ATE. Here, however, the ATE estimate based on different values of υ are close to the ATE estimate (1.81) based on the typical NN matching method shown in Table 5. We thus conclude that the ATE estimates are robust and consistent as the spatial effects were captured in the spatial estimation of the matching probabilities.

4 | CONCLUSION

Water quality degradation calls for designing and implementing policies to reduce nutrient pollution due to unsustainable agricultural activities. However, for countries such as NZ, the effectiveness of nutrient-reducing policies is highly dependent on the voluntary actions of farmers. Hence, exploring the determinants of farmers' adoption of GMPs may benefit the understanding of the effect of policies that rely on the voluntary efforts of farmers. Although there has been an extension of studies on the factors affecting farmers' adoption of sustainable agricultural practices, the empirical evaluations often ignore the impact of social interactions among farmers on GMP adoption. Being one of the first studies to address this issue, this study uses a spatial propensity score matching method to empirically analyze the effect of farmer group participation on the adoption of sustainable agricultural practices for dairy farmers in NZ, with the spatial dependence between farmers considered. Our results show that the spatial PSM process addresses the selection bias in farmers' participation in farmer groups and controls for the spatial effects of farmer group participation in their adoption of GMPs. In particular, spatial dependence exists in farmers' participation in farmer groups which further motivates their adoption of GMPs; farmers' decision-making on GMP adoption is affected by the characteristics of their neighours.

Our results and findings have important policy implications. Social interactions among farmers should be considered in designing policies to promote the voluntary adoption of sustainable agricultural practices. Specifically, policymakers should consider providing support for farmer group activities: farmers can share information and farming experience with other farmers who participate in the same farmer groups; the interaction activities in farmer groups may motivate learning and knowledge spillover. Until now, most of the existing farmer groups in NZ have been formed and supported either by the industry, such as Fonterra and DairyNZ, or by farmers themselves; the government (e.g., Ministry for Primary Industries) tends to support extension services programs for farmers, such as farm environmental plans at catchment level. In fact, the central and regional governments can integrate their support for extension services programs on GMPs into farmer group activities, where farmers can make use of the fund to work together, share, and discuss their experiences of GMPs. In addition, policymakers should consider ways of facilitating social interactions amongst farmers living in the same community (i.e., geographically close by). Peer effects among farmers may stimulate their neighours and neighours' neighours to participate in farmer groups and further affect their uptake of sustainable agricultural activities. For example, the farmers identified as good environmental performers (e.g., through the young farmer leader program) can be introduced as leaders to local farmer groups. These leaders can help lead activities and discussions about the adoption of GMPs.

Note that we use the geographical connections based on the distance between farmers to measure farmers' social interactions and evaluate the impact of the spatial effects on their participation in farmer groups. Future research may consider gathering information about social network connections between farmers to model the social network effects on farmer group participation. The comparison between spatial and social network effects may benefit the understanding of the effect of social interactions on farmer group participation and the adoption of sustainable agricultural practices. In addition, due to data unavailability, results and findings of the empirical analysis are based on limited information about farmer characteristics, such as gender and farm household composition. We suggest future studies include these characteristics as control variables in the empirical analysis to test for the associated impacts on GMPs and the robustness of the econometric analysis methods proposed in the study.

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AUTHOR CONTRIBUTIONS

WEI YANG: Methodology, Conceptualization, Data Analysis, Investigation, Writing, Review & Editing. LE WANG: Data Analysis, Writing.

CONFLICT OF INTERESTS

The authors declare that there are no conflict of interests. The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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A1

APPENDIX

TABLE A1 Post-matching regression results for the adoption of GMPs using the non-spatial PSM sample

	GMPs			
	NM	WIFF	ST	RP
Variable	Odds ratio	Odds ratio	Odds ratio	Odds ratio
Treatment	1.89 (0.11)***	1.71 (0.12)***	1.81 (0.09)***	1.92 (0.12)***
DR1	1.05 (0.05)*	1.12 (0.09)**	1.16 (0.06)**	1.21 (0.09)**
DR2	1.63 (0.06)**	1.15 (0.07)**	1.42 (0.06)**	1.78 (0.11)**
BA1	0.45 (0.02)***	0.76 (0.03)***	0.95 (0.04)***	0.41 (0.06)***
BA2	0.96 (0.68)	0.93 (0.87)	0.81 (0.62)	0.44 (0.69)
PS2	0.84 (0.71)	0.63 (0.79)	0.35 (0.76)	0.76 (0.88)
PS3	1.23 (0.03)**	1.11 (0.11)	1.89 (0.89)	1.67 (0.09)*
Stocking rate	1.56 (0.89)	1.95 (0.65)	1.09 (0.55)	1.67 (0.81)
Farm size	1.08 (0.0001)***	1.07 (0.0001)***	1.05 (0.0001)***	1.11 (0.0002)***
Farm contour	0.96 (0.87)	0.97 (0.34)	0.99 (0.82)	0.94 (0.51)
Distance	0.23 (0.46))	0.11 (0.21)	0.56 (0.77)	0.69 (0.01)***
Income	1.89 (0.82)	1.12 (0.13)	1.43 (0.76)	0.99 (0.53)
Age	0.59 (0.02)***	0.78 (0.03)***	0.78 (0.02)***	0.56 (0.03)***
Education	1.27 (0.02)***	1.16 (0.02)***	1.89 (0.02)***	1.32 (0.03)***
LogLik	−89.23	−102.10	−104.29	−127.17
McFadden R^2	0.12	0.12	0.12	0.13
LR test	11.28 ($p < 0.0001$)	23.76 ($p < 0.0001$)	17.20 ($p < 0.0001$)	35.11 ($p < 0.0001$)

*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.