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Spatial evaluation of the impact of a climate change participatory extension programme on the uptake of soil management practices*

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Participatory extension programmes (PEPs) are a popular policy tool to stimulate the uptake of climate change mitigation practices on a farm level. Given the public investment in PEPs, reliable evaluation is important. However, few studies evaluate climate change PEPs. Moreover, the evaluations conducted so far do not correctly account for potential spatial effects, such as the influence of neighbouring farms on PEP participation. Therefore, this paper estimates the impact of PEP participation on the uptake of a climate change mitigation practice and soil management, and identifies the importance of spatial effects on PEP participation. A spatial propensity score matching method is applied to a dataset from Scotland, consisting of 134 PEP and 184 control farmers. The results show that PEP participation facilitates the uptake of soil management practices and that spatial dependence exists in farmers' decision-making, indicating the need for the inclusion of spatial factors. This study contributes to the current literature by combining spatial econometric analysis and propensity score matching to conduct a quantitative evaluation of a climate change PEP. The evaluation methodology provides decision-makers with reliable insights into the potential contribution of PEPs towards climate change mitigation targets.

Key words: climate change, discussion groups, nutrient management, propensity score matching, spatial analysis.

1. Introduction

The agricultural sector is responsible for approximately 25 percent of global greenhouse gas emissions (IPCC, 2014; Le Quéré et al., 2016) and contributes to surface and groundwater pollution (Barnes et al., 2011; Cullen et al., 2006). These issues are partially caused by on-farm activities, such as fertiliser and soil management. Due to the impact on the environment, governments are increasingly interested in ways to reduce negative environmental effects of on-farm practices (Olander et al., 2014). Policies should account for

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heterogeneity in agricultural businesses, for example, differences in size, activities (Darnhofer et al., 2012) and overall decision-making factors (Knook et al., 2020a). The attempts to stimulate the adoption of emission reduction practices have, thus far, mainly been delivered through supporting voluntary uptake via participatory extension programmes (PEPs) (e.g. The Scottish Government, 2017).

PEPs are also known as 'farmer field schools', 'farmer participatory research', 'farmer advisory programmes' and 'farmer first' (Knook et al., 2018; Pretty & Chambers, 1993). They are a type of extension service, in which farmers, researchers and rural experts, collectively create knowledge by sharing information and experiences (Black, 2000). The popularity of participatory approaches has increased over the years, due to its association with high rates of practice adoption, its positive impact on productivity and income, and availability of peer support (Davis et al., 2012; van den Ban, 2000). Climate change PEPs can contribute to reducing emissions from agricultural activities via, for example, stimulating the adoption of soil management practices. According to a recent report from the UK's Committee on Climate Change, soil testing and management are highly important in reducing emissions while improving farm economic performance (Reid & Wainwright, 2018). The increase in the share of farmers carrying out soil tests will be one of the output indicators for policy outcomes of the Scottish Government's Climate Change Plan (The Scottish Government, 2017).

The public investment in PEPs and their importance in achieving emission reduction targets shows that reliable evaluation is important. So far, evaluation has been conducted on other types of PEPs, such as farmer field schools (Knook et al., 2018). These evaluations were mainly conducted in developing countries (e.g. Feder et al., 2004a; Pamuk et al., 2015), predominantly using financial and productivity indicators to identify the monetary return on PEP investment (Anderson & Feder, 2004). Furthermore, although there are evaluations correctly accounting for selection bias (e.g. Läpple & Hennessy, 2015a; Läpple et al., 2013), a recent literature review by Knook et al. (2018) shows that approximately 50 percent of the evaluations do not correctly account for endogeneity issues, which arise from incorrectly accounting for non-random selection of participants in the PEPs. This shows two gaps in literature: first, there is a lack of evaluations of pro-environmental PEPs in developed countries; and second, not all studies correctly apply econometric methods to account for endogeneity issues in PEP evaluation.

A third gap arises from the ignorance of spatial dependence between farmers: first, farmers located close to one another may influence PEP participation; second, farmers sitting in the PEP meetings may influence the choices of practice adoption. The existing PEP evaluations either did not account for these effects (e.g. Knook et al., 2020b), or modelled the spatial effects using exogenous variables to compare the intended outcomes between trained and neighbouring farmers (e.g. Feder et al., 2004b; Jørs et al., 2016). However, neglecting or inappropriately modelling spatial dependence between farmers may lead to inaccurate PEP evaluation.

The literature on farmer decision-making acknowledges the presence of spatial dependence arising from peers' involvement in the programmes: peers motivate one another to pursue environmental learning (Defrancesco et al., 2008; Oreszczyn et al., 2010; Sligo & Massey, 2007; Tamini, 2011). Furthermore, literature in agricultural economics highlights the importance of developing existing evaluation models that include spatial effects (Gonzales et al., 2018; Holloway et al., 2002). Empirical studies outside the field of PEP evaluations address the issue of spatial dependence effects on farmers' choice behaviours, mainly focusing on farmers' uptake of technology and adoption of good management practices. For example, a study from Ireland shows the existence of spatial dependence in farmers' adoption of organic farming (Läpple & Kelley, 2015). Similarly, Läpple et al. (2017) find that spatial dependence exists in the adoption of milk recording technology; they show that farmers consider their peers' decisions in their decision-making. While these two examples highlight the importance of accounting for spatial dependence in farmers' decisions, only one study considers the spatial effects in evaluating specific farming decisions on certain outcomes (Chagas et al., 2012). The study looks into the effects of sugarcane growing in Brazil on education, longevity and income by comparing a sugarcane producing region with a non-producing region. Considering that neighbouring growers influence a farmer's decision-making to grow sugarcane, spatial controls were used to allow a correct estimation. The study shows that spatial propensity score matching can address the bias which arises from comparing average indicators of producing regions with non-producing regions.

In light of the aforestated gaps in the literature, we evaluate a climate change PEP in Scotland, a developed country, by incorporating spatial dependence effects into the propensity score matching methods.

2. Methods

2.1 Conceptual framework

The propensity score matching (PSM) method has been used in a wide range of research fields, including medical, psychological, educational and social science research, in which studies focus on assessing the value of specific programmes or interventions on the intended outcomes (Rosenbaum & Rubin, 1983). PSM addresses selection bias of the treatment group by creating a propensity score for each participant in the treatment and control group based on relevant characteristics (e.g. age, education, size of farm). Subsequently, it matches scores between members of the treatment and control group to create groups that are as closely matched as possible (Stuart, 2010). One important assumption for typical PSM analyses is that the included covariates (the observed confounders) are sufficient to adjust for confounding the treatment–outcome relationship (Cuong, 2013). However, it is expected that the 'real' confounders are attributed to two parts: the observed and the unobserved confounders (Figure 1).

A schematic depiction of our conceptual analysis framework is included in Figure 1. Vector C denotes the confounders, including the observed covariates X and the unknown confounders U_n. The upper part of Figure 1 (in grey) shows the assessment of the causal treatment effect Z on the intended outcome Y, given the observed covariates X. This generates a 'balancing score', which adjusts for confounding the Z–Y relationship. PSM results in similar propensity score distributions of the treatment and control groups, yielding a matched dataset; this, in turn, is used to estimate the impact of PEP participation on the potential outcome. Although including as many covariates as possible may minimise the effect of unknown confounders (Cuong, 2013), they are seldom eliminated, and thus, influence the treatment–outcome relationship, shown in the lower part of Figure 1. For example, when spatial factors such as geographical locations affect observational units, the unknown confounders may show certain spatial patterns (e.g. spatial dependence) (Papadogeorgou et al., 2019). In the literature on practice adoption, the importance of spatial dependence effects is well understood—spatial dependence influences the decisions of spatial units (e.g. farmers) regarding technology adoption and uptake and calibration of best practices (Läpple et al., 2017; Yang & Sharp, 2017). This fact follows Tobler's First Law of Geography: close observations are more likely to be connected than distant observations (Tobler, 1970). In a geographic space, this means that an individual's decision-making is affected by other individuals located nearby, where the closeness of two individuals is measured by the inverse of the geographical distance. Therefore, if closer observational units are more similar (U_n), the typical PSM method may fail to adjust for confounding of the true treatment–outcome relationship. In this case, using spatial information of the observations is considered as an adjustment to control for the unknown confounding effect.

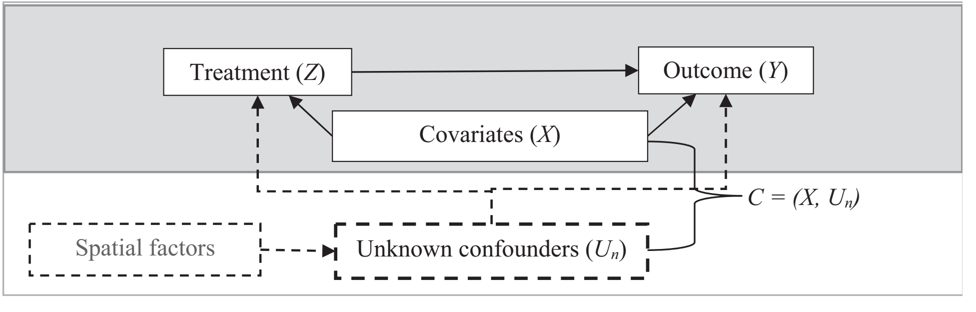

Figure 1 Conceptual framework of the study.

By developing a spatially indexed PSM method, it is possible to adjust for the effect of the unknown confounders (Papadogeorgou et al., 2019). This method addresses the effect of the unobserved confounders by including a distance calliper. By combining the typical propensity score estimates with the spatial proximity between the treated unit and control unit, a pure distance relationship is used to account for the unknown confounder depending on the contextual settings. Regression techniques adjust for the spatial confounders and identify the spatial dependence effects to pinpoint if spatial dependence exists in individuals' decision-making, contextual factors, or in the error terms (Akerlof, 1997). With the development of spatial econometric analysis, the regression techniques are used to improve the application of PSM analysis for PEP evaluation by using spatial propensity score matching (SPSM) to adjust the spatial confounding of the true treatment–outcome relationship and identify the existence of spatial dependence in farmers' decision-making (Chagas et al., 2012). Therefore, we apply the observations' spatial information as an addition to controlling for the unknown confounding effect.

2.2 Econometric modelling framework

2.2.1 Spatial propensity score matching

We assumed that, for the i^{th} farmer, the willingness to participate in PEPs according to the utility difference in the participation ($U_{1\text{i}}$) and non-participation ($U_{0\text{i}}$) decision-making was defined as a sample selection model:

$$Z_i^* = U_{1i} - U_{0i},\ z_i = \begin{cases} 1,\ \text{if } Z_i^* \geq 0 \\ 0,\ \text{if } Z_i^* < 0 \end{cases} \tag{1}$$

where Z_i^* is an $n \times 1$ latent variable which cannot be observed, with the treatment z_i denoting the binary outcomes (participation or non-participation). Thus, based on a typical choice model, Z_i^* is specified as a function of the determinants that may affect farmers' decision-making as $Z_i^* = X_i\beta + \varepsilon_i$, where the $n \times k$ matrix X_i denotes the covariates associated with the unknown parameter $\beta(n \times 1)$; and $\varepsilon_i \sim N(0, \sigma_\varepsilon^2)$ is the independent and identically distributed error term.

To evaluate the impact of farmers' participation in PEPs, we included the spatial effects in the matching process. Thus, we re-defined Z_i^* as:

$$Z_i^* = U(X_i,\ S_i^*), \quad S_i^* = S(l_m,\ Z_j(i)) + \eta_i \tag{2}$$

where S_i^* represents the unknown spatial effects used to capture the unobserved confounders U_n (shown in Figure 1). Although S_i^* is unknown, it was specified and tested to see whether the spatial dependence effects exist between the i^{th} farmer's decision and the decisions of farmers located in close

proximity $Z_j(i)$ $(i \neq j)$, and/or depended on contextual factors l_m, such as the farm characteristics of the neighbouring farmers. Here, the term 'neighbour' was defined in a broad sense: people who live in the same or nearby community have more chance to interact with each other and are thus expected to have greater impact on each other compared with others living in a community further away. Notably, in our sample, the minimum distance between farmers is 0.26 km and the average was 156 km, which provided adequate variation to 'categorise' the farmers into 'neighbours' and 'not neighbours'. Hence, the i^{th} farmer's willingness to participate depended on utility maximisation when $\Pr(Z_i = 1) = \Pr(U_{1i} - U_{0i} \geq 0) = \Pr(Z_i^* \geq 0)$.
In this study, we used a spatial Durbin probit model (SDM probit model) to model the spatial effects in farmers' participation in PEPs, and the effects took the form shown in the following equation[1]:

$$Z_i^* = \lambda W Z_i^* + X_i \beta + W X_i \theta + \varepsilon_i \tag{3}$$

where the two spatial terms $\lambda W Z_i^*$ and $W X_i \theta$ were included to represent the spatially lagged dependent variable (i.e. spatial dependence in farmer's decision-making) and the spatially lagged independent variables (contexture factors). λ and θ were the unknown spatial parameters. To consider the spatial effect of the characteristics of neighbouring farms and farmers, we included all the independent variables except for distance to nearest demonstration farm (which has the spatial dependence in nature) in the spatially lagged independent variables. W represents an $n \times n$ spatial weight matrix defined by the inversed distance d_{ij}^{-1} between the i^{th} and the j^{th} farmer using the postal codes[2] of the farms included in the study:

$$w_{ij} = \begin{cases} d_{ij}^{-1}, & 0 \leq d_{ij} \leq d \\ 0, & d_{ij} > d \end{cases} \tag{4}$$

Here, d refers to the threshold distance of 39 km beyond which spatial effects are zero.[3] Following LeSage (2014), the SDM probit model was regressed using the Bayesian Markov Chain Monte Carlo estimation (Pace & LeSage, 2009).

[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.

[2] Postal codes, also known as ZIP codes, postcodes or unit postal codes, can be used to identify the location of a specific farm in the rural areas of Scotland. They provide the smallest level of postal geography in Scotland and typically contain approximately 15 address points in urban areas and often only one address point in rural areas.

[3] We set the threshold distance d as 39 km to ensure every farmer has a neighbour. A similar example can be found in Läpple et al., (2017) and Läpple and Kelly (2015). In our case, given the threshold distance of 39 km, five farms were identified as least connected but having at least one link with others, and the most connected farm had 54 links (the density plot of W is shown in Figure A1 of the Appendix 1).

Based on the probabilities estimated with the SDM probit model, matching estimators were used in the PSM to compare the intended outcomes of the treated farmer (in this case a farmer who participated in the PEP) with the control group farmers (farmers who did not participate in the PEP). Subsequently, we used the nearest-neighbour (NN) matching method to conduct the pairwise matching between treated and control group:

$$C_{nn} = \min_{j} \| \hat{p}_i - \hat{p}_j \|, \quad j \in n_c \tag{5}$$

Here, $\hat{p}_i$ denotes the propensity score of the i^{th} treated farmer and $\hat{p}_j$ for the j^{th} control group farmer, and n_c represents the set of control group members.

Because the typical NN matching method is believed to have the potential risk of bad matching when the closest neighbour is too far away (Gonzales et al., 2018), we used a distance calliper to test for the robustness of the typical NN matching when the spatial effects are controlled in the sample selection equation (Equation 3) (Papadogeorgou et al., 2019). By applying a distance calliper, the tolerance level on the maximum propensity score distance was captured through the distance relationship:

$$C_{dis} = C_{dis}(\hat{p}, D_{ij}, v) = \min_{j} \| v * |\hat{p}_i - \hat{p}_j| + (1 - v) * D_{ij} \| \tag{6}$$

Here, the distance relationship between i and j was captured by the standardised Euclidean distance D_{ij} between unit i and j, and the tolerance level was adjusted with $v\,(v \in [0, 1])$. To avoid using extreme values 0 and 1 ($v = 1$ reduces the matching to the typical NN matching, while $v = 0$ makes the matching rely on pure distance), we chose the values for distance calliper v from 0.1 to 0.9 with a 0.1 interval. This showed whether the typical NN matching method provided appropriate matching when the spatial effects were considered in the sample selection model.

It is possible that the PSM was not able to balance the included covariates in the matching process and therefore created a difference between the efficiency of the PSM and SPSM. To assess and compare the efficiency of the matching processes, we adopted post-matching analyses: (i) the two-sample t-test; and (ii) the standardised mean differences. These diagnostic analyses identified any imbalance after matching and the inclusion of variables in the post-matching regressions (result shown in section 4.1).

2.2.2 Outcome models

A matched data set was used to explore the effect of participation on outcome Y, where $Y_i(0)$ and $Y_i(1)$ denote the good environmental practices in states of participation and non-participation, respectively. Given the outcome variable Y represented levels of soil management practices, which have the characteristics of ordered categories, an ordinal logit model was used (McGuinness, 2008). Y was the ordinal outcome with M categories, and $P(Y \leq m)$ the cumulative probability of Y less than or equal to category $m = 1, ..., M - 1$. The odds of being less than or equal to a particular category was estimated through an ordinal logistic regression model:

$$\log \frac{P(Y \le m)}{1 - P(Y \le m)} = \text{logit}(P(Y \le m)) = \zeta Z_i + X_i \gamma + X_i' \theta + \delta_i \tag{7}$$

Here, the dummy Z_i specified the farmer's decision to participate in the PEP; X_i, represented farm and farmer characteristics that were included in the PSM as covariates; X_i' denoted other variables associated with soil management practices (e.g. soil pH and soil types) in determining the farmer's soil management practices; ζ, γ, and θ were unknown parameters; and δ_i was the error term.

Subsequently, the average treatment effects (ATE) were calculated, with Y^* denoting the odds of being a specific level of soil management practices (Heckman et al., 1999):

$$ATE = E(Y_1^* | X, X') - E(Y_0^* | X, X') \tag{8}$$

We also explored the effect of meeting attendance frequency on the uptake of soil management practices within the PEP group:

$$Y_i^*(1) = \xi' P + X_i \gamma' + X_i' \theta' + \delta_i' \tag{9}$$

Here, in addition to including the covariates X_i and X_i' considered in Equation 8, we used P, the frequency of discussion group attendance on the individual farmer's choice of soil management practices. This is based on the assumption that the more frequent a farmer attends discussion group meetings, the more likely practice adoption occurs.

3. Data and descriptive statistics

3.1 The PEP

We evaluate the PEP 'Farming for a Better Climate' (Scotland's Rural College, 2020), which was initiated in 2010 by the Scottish Government to increase farmers' uptake of voluntary emission reduction practices by 50 percent (The Scottish Government, 2010; The Scottish Government, 2013). Discussion group meetings comprising presentations and demonstrations were pivotal to the PEP, as well as discussions between farmers, experts and facilitators. More than 800 farmers attended the discussion group meetings throughout the programme. The PEP focused on five topic areas: using electricity and fuel efficiently; developing renewable energy; locking carbon into the soil; making the best use of nutrients; and optimising livestock management. Because soil management practices were of relevance to all farmers included in the programme, this evaluation focuses on the uptake of soil management practices.

3.2 The survey

No baseline data were collected for the PEP farmers at the initiation of the programme in 2010, and therefore, only cross-sectional data were obtained. Data were collected via 20-minute phone surveys, which were conducted by a professional data collection team in December 2017 and January 2018. The survey[4] included questions on socio-demographic data (including postal code information for the identification of the geographical location of the farms) and soil management.

Three hundred and fifty farmers[5] participated in the survey, of which 150 participated in the PEP discussion groups (the treatment group), and 200 did not (the control group). We obtained the contact details for the treatment group from the recorded attendance list of meetings, while the control group was recruited via a stratified randomised sample from the Scottish Government national database of agricultural producers. The stratification improved the chances of obtaining suitable matches by (i) excluding the regions of Orkney, Shetland and Eileanan and Iar, because these areas were not targeted in the PEP and showed differences to farming in the PEP areas; and (ii) excluding farmers of categories not targeted by the PEP: ‘specialist horticulture & permanent crops’, ‘specialist pigs’, ‘specialist poultry’ and ‘unclassified’. Although the survey included 350 respondents, only 318 farmers provided information on their geographical location, and therefore, the final sample of this study included 134 farmers in the treatment group and 184 farmers in the control group.

3.3 Matching data and outcome variables

The farmers were matched on observable variables, such as age, agricultural training, farm type and distance to the nearest focus farm. A list of explanatory variables was included in both the PSM and the outcome models (Table 1).

The selection of outcome variables was guided by (i) the focus areas of change for the PEP; (ii) the measurability of the variables amongst all of the different types of farmers participating in the study; and (iii) the obtainability of information via a phone survey. This resulted in two outcome variables: (i) the frequency of soil testing, which represents the interval between soil tests, where a higher score is ‘better’, for example, ‘4’ represents yearly soil testing,

[4] The survey questions are available from the authors upon request.

[5] A number of farms were located within the nitrate vulnerable zones, which are areas that are at high risk of agricultural nitrate pollution (https://www.gov.uk/government/collections/nitrate-vulnerable-zones). Although farmers within these zones are obliged to adopt soil management practices, such as limiting fertiliser use, none of these obligations includes regulation on soil testing frequency or proportion. Hence, it is unlikely to influence the outcome variables of this study.

Table 1 Variable description and descriptive statistics of the sample

Variable	Description	Total (n = 318)	Control (n = 184)	Treatment (n = 134)	Sig.
Outcome variables					
Soil test frequency	Frequency of soil testing (scales), = 1, do not know/refuse to answer, = 2, every 6 years or less often, = 3, every 2 to 5 years, = 4 yearly.	2.51 (0.88)	2.16 (0.88)	2.85 (0.88)	***
Soil test proportion	Proportion of farm being soil tested, =1 don't know/refuse to answer, = 2, less than 25%, = 3, 25 to 75%, = 4, more than 75%	2.06 (0.85)	1.86 (0.85)	2.32 (0.85)	***
Covariates in propensity score matching and outcome models					
Age of the farmer	Years of age (scales), where 1 = < 25 years, 2 = 25 to 34 years, 3 = 35 to 39 years, 4 = 40 to 44 years, 5 = 45 to 54 years, 6 = 55 to 64 years and 7 = >65 years	5.5 (1.47)	5.73 (1.4)	5.18 (1.51)	***
Farm size	Area of farm land (ha)	358.68 (1586.37)	293.12 (1863.75)	448.71 (1097.54)	
Farming experience	Years of experience as farmer (scales), where = 0, 0 years, = , 1 to 10 years, = 2, 11 to 20 years, = 3, 21 to 30 years, = 4, 31 or more	3.28 (1)	3.29 (0.99)	3.27 (1.01)	
Presence of successor	Dummy, = 1 if farmer has a successor	0.43 (0.5)	0.4 (0.5)	0.45 (0.49)	
Agricultural training	Levels of agricultural training, 1 = practical agricultural experience only; 2 = obtained basic agricultural training course, 3 = obtained full agricultural training course	1.99 (0.93)	1.75 (0.9)	2.33 (0.86)	***
Rented land	Dummy, = 1, if farmer has land rented from others	0.59 (0.49)	0.63 (0.48)	0.53 (0.5)	*
Distance to focus farm	Euclidian distance to the nearest focus farm	30.2 (24.52)	38.25 (27.27)	19.14 (14.01)	***
Farm types	Categorical variables: =1 dairy farm (set as base)	0.22 (0.41)	0.14 (0.45)	0.28 (0.35)	***
	= 2 sheep and beef farm	0.18 (0.47)	0.2 (0.4)	0.16 (0.37)	

Table 1 (*Continued*)

Variable	Description	Total (n = 318)	Control (n = 184)	Treatment (n = 134)	Sig.
	=3 arable & forage farm	0.22 (0.41)	0.23 (0.42)	0.2 (0.4)	
	=4 mixed livestock farm	0.14 (0.39)	0.1 (0.31)	0.19 (0.4)	**
	=5 mixed farm	0.22 (0.41)	0.2 (0.4)	0.3 (0.46)	
Other independent variables in the outcome models					
Soil type	Quality of soil types (scales), =1 very limited for agriculture, for example mountain areas, =2 Somewhat limited for agriculture, for example by poor drainage or altitude, =3 suitable for a wide range of agricultural uses	1.73 (0.57)	1.76 (0.72)	1.71 (0.57)	
Soil pH	Dummy, =1 soil pH is seen as a relevant factor in calculating fertiliser needs	0.92 (0.35)	0.89 (0.32)	0.96 (0.19)	**
Manure or slurry	Dummy, =1 if manure or slurry is applied on farm	0.73 (0.43)	0.61 (0.49)	0.9 (0.31)	***
PEP meeting frequency	Frequency of discussion group meeting attendance (only for treatment group)	–	–	1.65 (0.79)	

***$P < 0.01$, **$P < 0.05$, *$P < 0.1$ for Welch two-sample t-test of mean differences in control and treatment. †Reports are mean and standard deviation in parentheses.

Table 2 Regression results of propensity score-matching model and spatial propensity score model

Variable	Non-spatial probit model	Spatial Durbin probit model		
	Coefficient (Std. error)	Direct effect	Indirect effect	Total effect
Intercept	−0.06 (0.8)	–	–	–
Age of the farmer	−0.18 (0.12)	−0.03***	−0.01	−0.04
Farm size	−0.00001(0.00007)	−0.0001***	−0.0001	−0.0002
Farming experience	0.1 (0.18)	0.011*	0.006*	0.017
Presence of successor	0.08 (0.29)	0.011***	0.006	0.017
Agricultural training	0.54(0.16)***	0.11***	0.06***	0.17
Rented land	0.11 (0.29)	0.02**	0.01**	0.03
Distance to focus farm	−0.03 (0.008)***	−0.006***	−0.004**	−0.01
Sheep and beef farm	0.53 (0.39)	0.11	0.07	0.18
Arable and forage farm	0.37 (0.4)	0.07	0.04	0.11
Mixed livestock	0.76 (0.4)**	0.15***	0.09**	0.24
Mixed farm	−2.07 (0.86)**	−0.36***	−0.2**	−0.56
W*Age of the farmer	–	−0.06***	−0.002	−0.062
W*Farm size	–	0.0001***	0.00008	0.00018
W*Farming experience	–	0.02**	0.0008**	0.0208
W*Presence of successor	–	−1.58	−1.62	−3.20
W*Agricultural training	–	0.09***	0.0003	0.0903
W*Rented land	–	0.07**	0.01	0.08
W*Distance to focus farm	–	−0.015**	−0.012	−0.027
W*Sheep and beef farm	–	−0.35	0.02	−0.33
W*Arable and forage farm	–	0.46	0.32	0.78
W*Mixed livestock farm	–	1.44	1.01	2.45
W*Mixed farm	–	−0.27**	−0.08	−0.35
Wy (λ)	–	0.12***(0.04)		
LogLik	−159.19	−165.54		
McFadden R^2	0.24	0.35		
LM spatial lag	23.68 ($P < 0.0001$)			
Robust LM spatial lag	19.21 ($P < 0.0001$)			
LM spatial error	34.9 ($P < 0.0001$)			
Robust LM spatial error	21.45 ($P < 0.0001$)			
Wald test spatial lag		10.86 ($P < 0.0001$)		
Wald test spatial error		7.69 ($P < 0.0001$)		

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

and '3' represents every 4–6 years; and (ii) the proportion of soil tested, where a higher number indicates a higher proportion of the land tested, and thus in which a higher score is 'better'. According to the *t*-test results in Table 1, pre-matching the treatment, treatment group farmers test soil more frequently and have larger farm areas soil tested compared with the control group.

4. Results and discussion

4.1 Spatial effects in farmers' participation in PEP

Table 2 shows the regression results of the non-spatial PSM model and SPSM model. In the non-spatial model, a standard probit model was used and for the spatial model a Spatial Durbin (SDM) probit model. According to the key statistical indicators, such as McFadden R^2 and *LogLik* values, the SDM probit model outperforms the standard probit model. We employed the Lagrange Multiplier (LM) test and LM robust test to examine the appropriateness of including two types of spatial effects in the non-spatial probit model. Results of the two tests indicate the existence of the spatially lagged dependent term and the spatial auto-correlated error term. In addition, a Wald test confirmed that the SDM probit model should not be reduced to the model that includes one spatial effect, that is the spatial autoregression (SAR) or spatial error (SEM) probit model (Pace & LeSage, 2009).

The results of the two models show a difference in the magnitude and significance level of the coefficients. The interpretation of the SDM probit model is based on effects estimates[6] combining average direct effects and indirect effects (Lacombe & Lesage, 2015; Pace & LeSage, 2009).[7] The 'age of the farmer', 'farm size', 'farming experience' and 'presence of successors' are not significant in the non-spatial probit model, but all are significant at different levels in the SDM probit model. 'Distance to focus farm' indicates the existence of spatial effects, with a negative and significant associated coefficient. This indicates farmers close to focus farms are more likely to participate in the PEP (Asfawa et al., 2016; Ogutu et al., 2018; Yang & Sharp, 2017).

The results show a positive and significant difference in the coefficient estimate of lambda (λ) in the spatial model. This indicates neighbouring effects, where a farmer's decision-making is influenced by neighbouring farmers (Läpple et al., 2017; Läpple & Kelley, 2015; Tamini, 2011). In addition, due to the significance of most coefficient estimates of lagged independent variables, characteristics of neighbouring farmers play a role in a farmer's PEP participation. For example, 'Agricultural training' (i.e. the average agricultural training years of neighbouring farmers) positively affects an individual farmer's decision to participate in the PEP.

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. This results in a failure to further estimate the PEP effect on the uptake of mitigation practices.

Three different diagnostic analyses show the spatial matching process outperforms the non-spatial matching as it further reduces the imbalance of the unmatched sample: first, the changes of means (t-tests) (Table 3); second, the standardised mean differences (SMD) (Table 3) (Austin, 2011); and third, visualisation of the distribution of the propensity scores (Figure 2).

[6] The Effects estimates of the SDM probit model are included in Table A2 of the Appendix 1.

[7] We also ran regressions using spatially lagged X, SAR, SEM and SDEM probit models and tested the associated spatial effects for these models. The results show that the SDM probit model outperformed all the other models. Regression results of the other spatial models are included in Table A2 of the Appendix 1.

Table 3 Comparison of mean differences of the covariates before and after matching

Variable	Unmatched sample (n_T=134, n_C=184)		Matched sample – non-spatial (n_T=134, n_C=134)		Matched sample – spatial (n_T=134, n_C=134)	
	Mean differences	SMD	Mean differences	SMD	Mean differences	SMD
Age of the farmer	−0.55***	0.27	**−0.39****	0.19	**−0.38***	0.18
Farm size	155.59	0.07	**79.93**	0.03	**98.72**	0.04
Years of experience	−0.02	0.01	−0.08	0.01	**−0.01**	0.007
Presence of Successor	0.05	0.1	0.05	0.08	**0.04**	0.06
Agricultural training	0.58***	0.47	**0.45*****	0.36	**0.44****	0.35
Rented land	−0.1*	0.2	**−0.06***	0.12	**−0.08**	0.1
Distance to focus farm	−19.11***	0.62	**−8.07*****	0.39	**−6.55**	0.1
Dairy farm	0.14***	0.35	**0.08****	0.33	**0.09****	0.23
Sheep and beef farm	−0.04	0.1	**−0.02**	0.03	**−0.01**	0.03
Arable and forage farm	−0.03	0.07	−0.04	0.02	**−0.01**	0.03
Mixed livestock	0.09**	0.26	**0.05****	0.16	**0.07****	0.19
Mixed farm	0.1	0.23	0.11	0.25	**0.07**	0.13
Soil test frequency	0.69***	0.57	0.41***	0.34	0.42***	0.36
Soil test proportion	0.46***	0.37	0.35***	0.29	0.36***	0.3

*** $P < 0.01$, **$P < 0.05$, *$P < 0.1$ for Welch two-sample t-test of mean differences in control and treatment group. Reports are mean differences and absolute value of SMD, and n_T and n_C represents the sample size of treatment and control group. The decrease in mean differences between the treatment and control group are highlighted in bold. The variables associated with SMD values greater than 0.1 are shaded in grey.

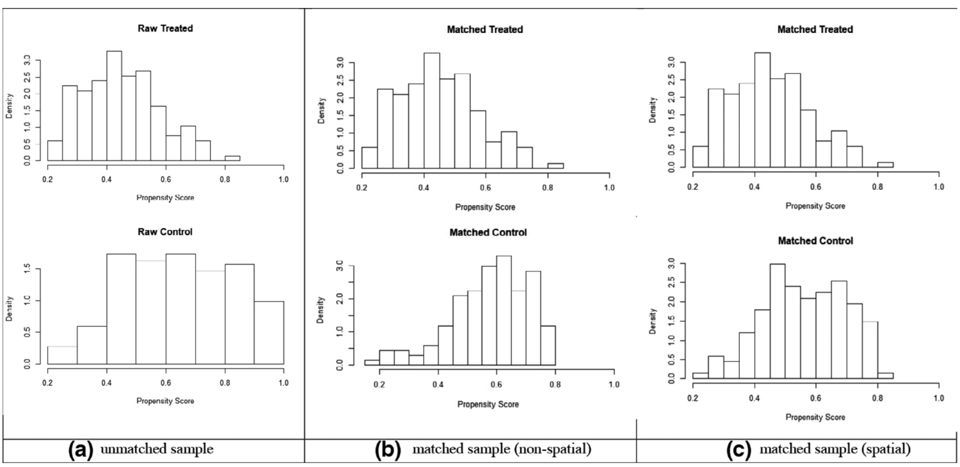

Figure 2 Distribution of propensity scores of the unmatched sample and matched sample of both non-spatial and spatial PSM. (a) unmatched sample. (b) matched sample (non-spatial). (c) matched sample (spatial).

The values of the mean differences change before and after matching: for most variables, mean differences between the treatment and control group become smaller (highlighted in bold) after the non-spatial PSM, while after the SPSM, the mean differences are smaller for all variables. The values of SMD are consistent with the changes in mean differences, with the variables associated with SMD values greater than 0.1 (indicating imbalance) shaded in grey. The visualisation of the distribution of propensity scores of the PSM and SPSM (Figure 2) shows that the propensity scores of the treatment and control groups are balanced after the SPSM.

We also explored the treatment effect on the outcome variables of the soil management practices by examining the mean difference and SMD of soil test frequency and soil test proportion between the treatment and control group. Based on the two-sample t-test results and SMD values, we find that soil management practices' mean differences are significant (SMD values greater than 0.1 are shown in parentheses) in the matched samples (non-spatial and spatial). This indicates the positive effect of focus group participation on the adoption of good soil management. However, as shown in the balance diagnosis analysis in Table 3, not all the included covariates are balanced after matching. Hence, post-matching regression was adopted to address the imbalance.

4.2 Factors influencing the uptake of soil management practices

After matching, the data were used to examine the potential factors determining the uptake of soil management practices. All the covariates included in matching, and three other variables that are directly related to soil management, were included in the outcome models. Table 4 shows the odds ratios of ordered logit estimates for both soil test frequency and soil test proportion. The odds ratio estimates differ in magnitude and significance levels between the PSM and SPSM model. Hence, interpretations based on the estimation results of PSM lead to inaccurate measurement of the uptake of soil management practices. Different spatial models (SAR, SEM and SDM) show a similar result.[8] The inaccuracy of ignoring spatial effects can lead to either an over- or underestimation of the treatment effect (Chatzopoulos & Lippert, 2016; Gonzales et al., 2018).

Six factors are important for the uptake of soil management practices. First, the variable 'PEP participation' facilitates the uptake of better soil management practices: the odds of adopting more frequent soil test increases by 19 percent and the odds of the proportion of land tested increases by 13 percent. Second, the variable 'farmer's age' shows that older farmers are less likely to have a higher soil test frequency. Third, farmers who have a successor are more likely to frequently conduct soil testing compared with farmers who do not have a successor, which is supported by findings from Ahnström et al. (2009). Fourth, the more agricultural training farmers have, the higher the likelihood of frequent soil testing, and the larger the tested area (Llewellyn, 2011). Fifth, a higher likelihood of soil testing and soil tested area

[8] Results of the spatial regression results are available upon request to the authors.

Table 4 Regression results of determinants of good soil management practices

Variable	Non-spatial matching						Spatial matching					
	Soil test frequency			Soil test proportion			Soil test frequency			Soil test proportion		
	Odds Ratio	Std. error	Sig.	Odds Ratio	Std. error	Sig.	Odds Ratio	Std. error	Sig.	Odds Ratio	Std. error	Sig.
PEP participation	1.32	0.03	***	1.25	0.02	**	1.19	0.03	***	1.13	0.03	**
Age of the farmer	0.1	0.11	***	0.98	0.04		0.91	0.02	**	0.97	0.05	
Farm size	1.00005	0.00002		1.00	0.001		1.00007	0.00003		1.00	0.001	
Years of experience	1.03	0.06		0.99	0.06		1.06	0.06		0.96	0.07	
Presence of Successor	1.16	0.03	*	0.93	0.11		1.2	0.03	**	0.94	0.11	
Agricultural training	1.11	0.02	**	1.28	0.03	***	1.01	0.002	**	1.25	0.03	***
Rented land	1.11	0.09		1.1	0.09		1.15	0.09		1.10	0.11	
Distance to focus farm	0.996	0.002		0.995	0.003		0.991	0.003		0.992	0.00	
Sheep and beef farm	0.82	0.16		0.86	0.18		0.81	0.15		0.91	0.18	
Arable and forage farm	1.003	0.15		1.01	0.17		1.002	0.15		1.07	0.17	
Mixed livestock	0.71	0.15		0.79	0.17		0.86	0.15		0.83	0.18	
Mixed farm	0.95	0.13		0.99	0.15		0.98	0.13		0.93	0.15	
Soil type	0.92	0.07		0.87	0.08		0.94	0.009	**	0.89	0.02	*
Soil pH	1.17	0.18		1.06	0.20		1.21	0.17		1.02	0.21	
Manure or slurry	1.51	0.06	***	1.17	0.14		1.5	0.05	***	1.31	0.05	**
Pseudo R^2	0.11			0.12			0.13			0.16		
LogLik	−271			−306.06			−264.85			−308.13		
LR test	31.56 ($P < 0.0001$)			38.13 ($P < 0.0001$)			57.22 ($P < 0.0001$)			68.39 ($P < 0.0001$)		

***$P < 0.01$, **$P < 0.05$, *$P < 0.1$. The errors in the table are robust standard errors.

is observed amongst farmers who apply manure or slurry. Lastly, better soil or landscape conditions lower the odds of adopting good soil management practices. With a one unit increase in soil condition, the odds of conducting more frequent soil testing increases by 6 percent, and odds of testing larger farm areas decreases by 11 percent. This might be caused by better soil or landscape conditions providing high soil fertility and irrigation efficiencies, which decreases the adoption of good soil management practices (Green & Sunding, 1997).

4.3 Average treatment effects of PEP participation

The ATEs across different estimation settings (pre- or post-matching, and with or without regression, shown in Table 5) show that participation in the PEP increases the odds of more frequent soil testing and larger soil test areas, which is in line with other studies conducted in developed countries (Goodhue et al., 2010; Knook et al., 2020b; Läpple & Hennessy, 2015b; Läpple et al., 2013; Tamini, 2011). The results based on post-PSM regression models are presented in Table 5 (columns 5 and 6), along with the estimates from the regression without matching (column 2), and post-PSM without regression (columns 3 and 4).

Using the unmatched sample, the regression models produce the largest ATE estimates for both soil test frequency and soil test proportion. After PSM, the magnitudes of ATEs show a decrease. When comparing the non-spatial and spatial PSM process, the ATEs are larger in the non-spatial matched sample than in the spatial matched sample. In the non-spatial model, PEP participation increases the odds of frequent soil testing by 38 percent, which is higher than the effect estimated by the SPSM model (33 percent). A similar difference is observed in the ATEs of soil test proportion, where the non-spatial PSM model shows an increase in odds by 28 percent,

Table 5 ATE of participation in the PEP on soil management practices across different estimation settings

	Regression Unmatched sample	Post-PSM without regression		Post-PSM with regression	
		Non-spatial matched sample	Spatial matched sample	Regression on-spatial matched sample	Regression Spatial matched sample
Soil test frequency	1.53 (0.1)***	1.42	1.35	1.38 (0.04)***	1.33 (0.06)***
Soil test proportion	1.5 (0.15)***	1.35	1.31	1.28 (0.03)***	1.23 (0.03)***

***$P < 0.01$, **$P < 0.05$, *$P < 0.1$. ATE estimates of PSM without regression are odds ratio of being in better soil management practices (i.e. soil test frequency =3 and =4, and soil test proportion =3 and =4) in the treatment versus control group. Standard errors reported in parentheses.

Table 6 Effects of participation in the PEP across a range of distance callipers

Calliper	Soil test frequency ATE	Soil test proportion ATE
$v = 0.1$	1.332 (0.078)***	1.231 (0.086)***
$v = 0.2$	1.334 (0.079)***	1.231 (0.09)***
$v = 0.3$	1.338 (0.078)***	1.234 (0.09)***
$v = 0.4$	1.337 (0.079)***	1.233 (0.089)***
$v = 0.5$	1.336 (0.078)***	1.235 (0.088)***
$v = 0.6$	1.336 (0.077)***	1.237 (0.088)***
$v = 0.7$	1.341 (0.075***	1.235 (0.087)***
$v = 0.8$	1.343 (0.083)***	1.241 (0.082)***
$v = 0.09$	1.348 (0.08)***	1.249 (0.088)***

***$P < 0.01$, **$P < 0.05$, *$P < 0.1$. Standard errors reported in parentheses.

while the SPSM model shows an increase of 23 percent. The overestimated ATEs in the unmatched and non-spatial model indicate the potential overestimation of PEP participation without controlling for sample selection bias and spatial effects.

The robustness of the ATE estimates is assessed by using callipers (Table 6). Changing the values of the distance callipers does not make a

Table 7 Frequency of PEP meeting attendance effects on practice adoption

Variable	Soil test frequency			Soil test proportion		
	Odds ratio	Std. error	Sig.	Odds ratio	Std. error	Sig.
Frequency of PEP participation	1.38	0.06	***	1.44	0.04	***
Age of the farmer	0.89	0.44		0.78	0.35	
Farm size	1.00001	0.23		1.0003	0.21	
Years of experience	1.08	0.26		1.06	0.17	
Presence of Successor	1.12	0.02	**	1.11	0.02	*
Agricultural training	1.07	0.01	**	1.18	0.02	***
Rented land	1.24	0.09		1.19	0.11	
Distance to focus farm	0.9991	0.003		0.9992	0.001	
Sheep and beef farm	0.91	0.15		0.87	0.18	
Arable and forage farm	1.02	0.15		1.06	0.17	
Mixed livestock	1.12	0.15		1.01	0.18	
Mixed farm	0.98	0.13		0.93	0.15	
Soil type	0.86	0.02	**	0.89	0.03	*
Soil pH	1.41	0.14		1.08	0.23	
Manure or slurry	1.32	0.05	***	1.28	0.05	**
Pseudo R^2	0.09			0.07		
LogLik	−164.23			−279.32		
LR test	37.61 ($P < 0.0001$)			32.25 ($P < 0.0001$)		
LM spatial lag	2.68 ($P = 0.12$)			2.43 ($P = 0.16$)		
Robust LM spatial lag	1.21 ($P = 0.45$)			1.21 ($P = 0.45$)		
LM spatial error	1.96 ($P = 0.76$)			1.96 ($P = 0.73$)		
Robust LM spatial error	1.45 ($P = 0.11$)			1.37 ($P = 0.21$)		

***$P < 0.01$, **$P < 0.05$, *$P < 0.1$. Standard errors reported in parentheses.

statistically significant difference for the ATEs, as all the ATEs are statistically significant at a 1 percent level. The ATEs for soil test frequency are between 1.332 and 1.448, and the ATEs for soil test proportion are between 1.231 and 1.249. Given the values of v close to 1, for example $v = 0.9$ and $v = 0.8$, the estimated ATEs of soil test frequency are 1.493 and 1.498, which are close to the value (0.49) estimated by the typical NN matching method shown in Table 4. In addition, a larger value of v produces a smaller ATE for soil test frequency. A larger distance calliper was associated with a larger ATE for soil test proportion, but a large value of v ($v = 0.9$) produces an estimate of ATE (0.289) close to the estimation of the typical NN matching (0.28). Therefore, although the typical NN matching method is associated with risk of bad matching, the estimates in this study are robust and consistent given the spatial effects were controlled in the estimation of matching probabilities.

4.4 Frequency of attendance effect of PEP participation

The results show a positive significant effect of the frequency of meeting attendance on the uptake of soil management practices (Table 7). The odds to conduct soil testing more frequently increase by 38 percent and the soil tested area by 44 percent. The tests for the spatial effects on the uptake of good soil management practices (LM spatial lag and LM spatial error) show no effects for both models. This indicates potential flattening out of spatial effects on farmers' decision-making once joining in the discussion group meetings (Halleck Vega & Elhorst, 2017).

5. Conclusion

Climate change calls for designing and implementing emission reduction policies globally. However, suitable policies must account for stakeholders' heterogeneity within and across industries; the same applies to the evaluation and measurement of policies and programmes. Accounting for spatial effects, we show that a climate change PEP positively affects farmers' adoption of soil management practices in Scotland. Evaluating PEPs as a policy measure is relevant to other countries. The EU has similar market systems and may face similar policy challenges, while light-touch countries such as Australia and New Zealand have a high reliance on farmers' voluntary adoption efforts and therefore benefit from understanding the effect of policies that rely on voluntary action.

We apply novel econometric methods to evaluate PEP participation, while taking into account farmers' interactions. The SPSM method addresses the unobserved confounders in the treatment–outcome relationship by considering the spatial effects and specifying the types of spatial effects in this process. The spatial effects exist in the spatially lagged dependent and independent terms, indicating that farmers participate in the PEP if their neighbouring farmers are also PEP participants, and their participation decisions are affected by their neighbours' characteristics. Note that the scope of the SPSM method extends beyond the evaluation of PEPs and may be used in other areas. When relevant spatial or social information is available, the method can be applied to different extension programmes or practice changes (Läpple et al., 2017; Läpple & Kelley, 2015).

The results have important policy implications for the design of future (climate change) PEPs. First, farmers' interactions need to be considered in the evaluation of PEPs because of the existence of spatial effects in PEP participation. Second, to achieve a higher uptake rate of emission mitigation practices, policy makers should consider ways to stimulate the facilitation of the interactions between the participants and their neighbours, and their neighbours' neighbours, as well as between peers in the PEP group. Third, once farmers are participating in the PEPs, it is important they regularly attend the meetings, as increased meeting frequency has a positive effect on practice adoption.

Future research on social learning and knowledge exchange might provide insight into whether spatial effects arise from direct communication between farmers. The spatial dependence in local participation is related to a dynamic setting where information accumulates, participation rises and eventually flattens out and spatial dependence among local participation rates declines (Halleck Vega & Elhorst, 2017). Due to the data limitation (only cross-sectional data were available), the spatio-temporal dynamic issue was not addressed in this study. Furthermore, previous research has shown that adoption of practices might decrease when participation in the PEP ends (Feder et al., 2004a). Therefore, we suggest that future studies will benefit from longitudinal baseline and follow-up data collected 1–5 years after PEP participation.

Data Availability Statement

Research data cannot be shared due to third party restrictions.

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Appendix 1

Table A1 Effects estimates of the SDM probit model

Variable	Non-spatial probit model			Spatial Durbin probit model		
	Coefficient	Std. error	Sig.	Coefficient	Std. error	Sig.
Intercept	−0.06	0.08		−4.63	0.009	***
Age of the farmer	−0.18	0.12		−0.11	0.01	***
Farm size	−0.00001	0.00007		0.00003	0.00001	***
Farming experience	0.10	0.18		0.06	0.03	*
Presence of successor	0.08	0.29		0.05	0.02	***
Agricultural training	0.54	0.16	***	0.32	0.10	***
Rented land	0.11	0.29		0.04	0.02	**
Distance to focus farm	−0.03	0.008	***	−0.018	0.004	***
Sheep and beef farm	0.53	0.39		0.27	0.20	
Arable and forage farm	0.37	0.40		0.10	0.12	
Mixed livestock	0.76	0.38	**	0.32	0.29	
Mixed farm	−2.07	0.86	**	−1.17	0.44	***
W*Age of the farmer				−0.06	0.03	***
W*Farm size				0.0001	0.0000	***
W*Farming experience				0.02	0.08	**
W*Presence of successor				−1.58	1.02	
W*Agricultural training				0.09	0.20	***
W*Rented land				0.07	0.03	**
W*Distance to focus farm				−0.015	0.007	**
W*Sheep and beef farm				−0.35	0.15	
W*Arable and forage farm				0.46	0.17	
W*Mixed livestock farm				1.44	0.84	
W*Mixed farm				−0.27	0.12	**
Wy (λ)				0.12	0.04	**
LogLik	−159.19			−165.54		
McFadden R^2	0.24			0.35		
LM spatial lag	23.68 ($P < 0.0001$)					
Robust LM spatial lag	19.21 ($P < .0001$)					
LM spatial error	34.9 ($P < 0.0001$)					
Robust LM spatial error	21.45 ($P < 0.0001$)					
Wald test spatial lag				10.86 ($P < 0.0001$)		
Wald test spatial error				7.69 ($P < 0.0001$)		

Table A2 Regression results of other spatial models

Variable	SAR			SEM			SLX			SDEM		
	Coef.	Std. error	Sig.	Coef.	Std. error	Sig.	Coef.	Std. error	Sig.	Coef	Std. error	Sig.
Intercept	−0.2	0.47		−0.06	0.48		−1.13	5.16		−6.42	4.11	*
Age of the farmer	−0.18	0.12		−0.1	0.07		−0.28	0.13	**	−0.16	0.08	**
Farm size	−0.000006	0.00005		−0.000007	0.00004		−0.00009	0.00009		−0.00003	1.06	
Farming experience	0.04	0.1		0.05	0.11		0.28	0.19		0.15	1.87	
Presence of successor	0.04	0.17		0.04	0.81		−0.2	0.32		0.1	0.33	
Agricultural training	0.36	0.1	***	0.32	0.10	***	0.64	0.17	***	0.38	0.07	***
Rented land	0.06	0.17		0.06	0.17		−0.01	0.31		−0.04	0.03	
Distance to focus farm	−0.02	0.004	***	−0.03	0.005	***	−0.03	0.02	*	−0.02	0.01	**
Sheep and beef farm	0.53	0.39		0.33	0.23		1.44	0.52	***	0.84	0.04	***
Arable and forage farm	0.37	0.40		0.10	0.24		0.65	0.5		0.35	1.4	
Mixed livestock	0.76	0.38	**	0.46	0.24	**	1.47	0.52	***	0.85	0.05	***
Mixed farm	−2.07	0.86	**	−1.17	0.47	***	1.57	0.48	***	0.89	0.04	***
W*Age of the farmer							0.3	0.67		1.7	1.18	
W*Farm size							0.000003	0.0005		0.0001	0.009	
W*Farming experience							1.04	1.17		0.6	0.71	
W*Presence of successor							−2.42	2.02		−1.34	1.14	
W*Agricultural training							1.48	0.97	*	0.82	0.44	*
W*Rented land							2.17	2.25		−0.04	0.06	
W*Distance to focus farm							−0.04	0.03	*	−0.02	1.55	
W*Sheep and beef farm							0.58	2.67		0.92	2.51	
W*Arable and forage farm							−2.13	1.8		−1.17	1.38	
W*Mixed livestock farm							2.1	2.33		1.22	0.93	
W*Mixed farm							1.84	1.62		1.04	1.29	
Wy (λ)	0.37	0.03	***									
Wu (λ)				0.17	0.02	***				0.12	0.04	**
LogLik	−167.71			−169.47			−150.43			−159.44		
McFadden R^2	0.25	0.24	0.31	0.33								

Table A2 (*Continued*)

Variable	SAR			SEM			SLX			SDEM		
	Coef.	Std. error	Sig.	Coef.	Std. error	Sig.	Coef.	Std. error	Sig.	Coef	Std. error	Sig.
Wald test spatial lag	8.21 ($P < 0.001$)											
Wald test spatial error		15.37 ($P < 0.001$)		8.63 ($P < 0.001$)								

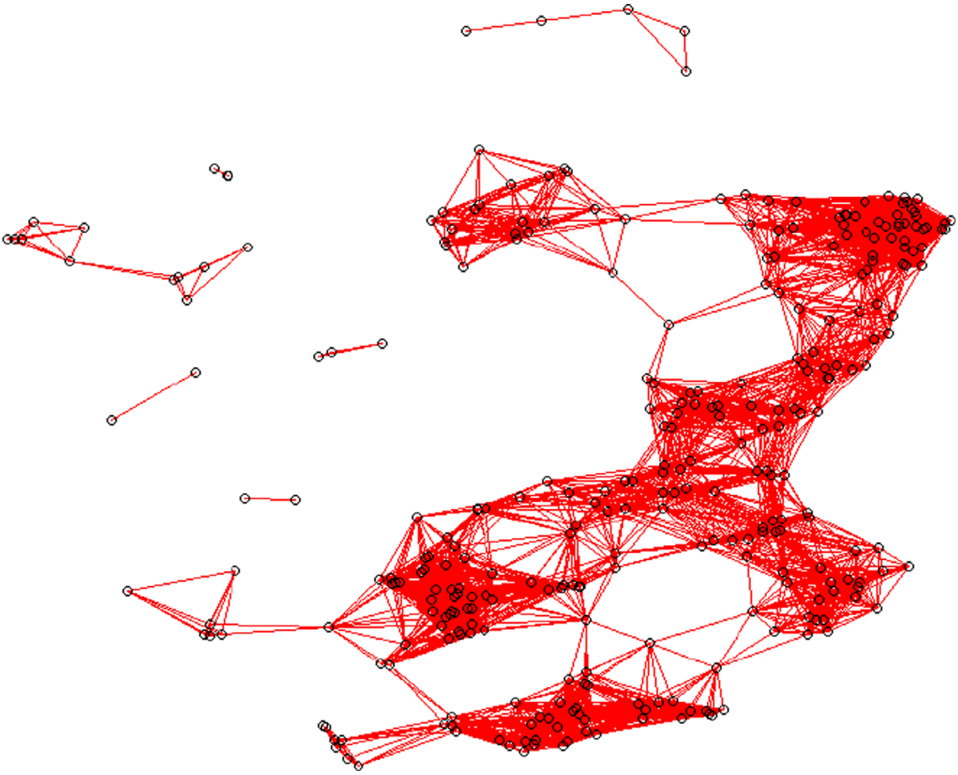

Figure A1 Density plot of spatial weights matrix. [Colour figure can be viewed at wileyonlinelibrary.com]