Three Essays on the Spatial Analysis of Sustainable Dairy Farming in New Zealand

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A thesis submitted in fulfilment of the requirements for the degree of Doctor of Philosophy in Economics, the University of Auckland,

2016

Abstract

This Ph.D. thesis consists of three essays on the sustainable development of the New Zealand dairy industry. The first essay focuses on the relationship between dairy yields and intensive inputs. The second and third essays are concerned with farm-level management practices on nutrient pollution, the interactions between farmers, and the impact of farmer choice on the environment. Spatial spillover effects, which are considered as important issues at either the regional level or farm-level decision-making, are addressed in all three essays.

As the New Zealand dairy industry faces the challenge of increasing productivity and dealing with public concerns over nutrient pollution, effective policy needs to address regional dependency and differences in productivity and fertiliser use. The first essay employs spatial panel data models to establish whether unobserved spatial effects exist and investigate how spatial effects influence the relationship between dairy yields and intensive farming inputs across regions. Results show positive spatial spillovers for most intensive inputs. The high level of effluent use and estimated negative yield response to nitrogen suggests that an opportunity exists for the greater use of effluent as a substitute for nitrogen fertiliser. Substitution has the potential to reduce dependence on fertilisers and contribute to a reduction in nutrient pollution.

The second essay analyses spatial dependence in the adoption of best management practices (BMPs) to protect water quality. Bayesian spatial Durbin probit models are

applied to survey data collected from dairy farmers in the Waikato Region of New Zealand. Results show that farmers located in close proximity to each other exhibit similar choice behaviour, indicating that access to industry information is an influential determinant of dairy farmers' adoption of BMPs. In addition, these findings address the importance of farmer interactions in adoption decisions because participation in dairy-related activities is identified as an extension of information acquisition. Financial problems are one of the biggest obstacles for farmers to adopt BMPs. Overall, the second essay highlights the importance of considering spatial interaction effects in farmers' decisions, which is important to the formulation of agri-environmental policy.

The third essay investigates how dairy farmers' social interactions influence the relationship between their environmental performance and nutrient management practices (NMPs). Spatial Durbin error models are employed to analyse farm-level sample data in the Waikato region of New Zealand. Social interactions are modelled by a spatial weights matrix and an adjacent weights matrix. Results show that dairy farmers' environmental performance is positively influenced by geographically close farmers' and socially close farmers' NMPs, such as wintering off cows and increasing the frequency of soil tests. Results also indicate that encouraging the farmer-to-farmer communication improves dairy farmers' environmental performance.

Acknowledgement

First and foremost, I would like to thank my supervisor, Professor Basil Sharp, who has been always supportive throughout the process of my Ph.D. study. Without his support, I cannot finish this thesis. He is open-minded and has always encouraged me to innovatively explore research questions. He has taught me how to do good research. Notably, my academic writing has improved a lot after his countless revisions. He has also offered strong support for me to get access to research resources and application for funds, not to speak of driving me to Hamilton to get research data and do presentations, for so many times!

An early draft of my first essay was presented at the 59th Australian agricultural and resources association conference (AARES). I would like to thank two anonymous reviewers, for their valuable comments. Thanks should also be given to Professor Shida Henneberry, Professor Weiming Tian, Professor Ping Qing and Dr. Michael Delgado, who generously offered helpful comments and ideas for my first essay in the 2015 China Agricultural Economic Review & International Food Policy Institute (CAER-IFPRI) Annual International Conference.

The data for my second and third essays are provided by DairyNZ. I would like to thank Dr. Mike Scarsbrook, Mr. Adrian Brocksopp and Dr. Mike Bramley, for offering the farm-level data and good advice for my research. Thanks should also be given to the Fertiliser and Lime Research Centre (FLRC), Massey University. The FLRC sponsored my attendance and presentation of my second essay in the 29th FLRC annual workshop, where I got lots of valuable comments from the discussion section after my presentation. Mr. Mathew Newman and Mr. Mark Neal also gave good suggestions for my third essay, when we met at the 60th AARES Annual Conference.

I would also like to thank my co-supervisor Dr. Stephen Poletti, Dr. Alan Rogers, Associate Professor John Hillas and other research fellows in the Department of Economics for their valuable comments, advice and support to my thesis. The administration team has also helped me a lot with preparations for conferences, flights booking etc.

I would also like to thank for the support of Chinese Scholarship Council, who has provided a three-year scholarship for my Ph.D. study.

Lastly, I want to thank my father, mother, and my younger sister for the outpouring of support and encouragement. Particularly, special thanks should be given to my beloved husband, Mr. Le Wang. I cannot finish this thesis without his understanding, support and love.

Contents

Abbreviations

ANOVA --------- Analysis of Variance

BMPs ------------- Best Management Practices

GIS ---------------- Geographical Information System

GNS --------------- General Nesting Spatial Model

kg MS/ ha --------- Kilogram Milksolids Per Hectare

LM ----------------- Lagrange Multiplier

Log L -------------- Log-likelihood value

LR ------------------ Likelihood Ratio

MCMC ------------ Markov Chain Monte Carlo

ML ----------------- Maximum Likelihood

N -------------------- Nitrogen

NIWA ------------- National Institute of Water and Atmospheric Research

NMPs -------------- Nutrient Management Practices

NPS ---------------- the National Policy Statement for Freshwater Management

NZ ------------------ New Zealand

OECD -------------- Organisation for Economic Co-operation and Development

OLS ----------------- Ordinary Least Squares

P --------------------- Phosphorus

RMA ---------------- Resource Management Act

SAC ----------------- Spatial Model with the Spatially Lagged Variable and the Spatial Autocorrelated Error Term

SAR --------------- Spatial Autoregressive Model or The Spatial Lag Model

SDEM ------------ Spatial Durbin Error Model

SDM -------------- Spatial Durbin Model

SEM --------------- Spatial Error Model

SLX ---------------- Spatial Lag of X Model

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CHAPTER 1. Introduction

This Ph.D. thesis adopts a three-essay format. All three essays contribute to the fields of agricultural and environmental economics, and are based on empirical studies focusing on nutrient management practices associated with the New Zealand dairy industry. The first essay is concerned with the relationship between dairy production and intensive dairy farming at the regional level; the second and third essays focus on farm-level management practices on nutrient pollution, interactions between farmers, and the impact of farmer choice on the environment. Significantly, an important issue is addressed in all three essays; notably, that policy aimed at nutrient pollution should consider spatial spillovers at either the regional level or farm-level of decision-making.

1.1 Research Background

The dairy industry is a vital contributor to the New Zealand (NZ) economy, but unsustainable farming activities have also caused negative environmental impacts. Significantly, nutrient pollution from dairy farms, predominantly nitrogen and phosphorus, has increasingly become a concern. Although the NZ economy is heavily dependent on agriculture, especially the dairy sector, nutrient pollution is a significant concern for the NZ government seeking to support sustainable agriculture. Therefore, there is no doubt that the NZ dairy industry should adapt its development strategies to sustainable development that has been defined as “development that meets the needs of the present without compromising the ability of future generations to meet their own needs” (the World Commission on Environment and Development, as cited by Department of Prime Minister and Cabinet, 2003, p.6).

To comply with the goal of sustainable growth, the dairy industry faces a great challenge. On the one hand, high productivity is regarded as the international competitive advantage of the NZ dairy industry. Thus, the dairy industry seeks to maintain competitiveness by continued increases in intensification, namely increased use of inputs and stocking rates. On the other hand, unsustainable dairy farming activities are recognised as being responsible for negative environmental impacts, especially the adverse impact on water quality. Therefore, the dairy industry has to balance the increasing intensification in pursuit of high production with its responsibility for environmental degradation due to nutrient pollution.

1.1.1 Intensive Dairy Farming and the Environmental Impact

The dairy industry has increasingly intensified over the last few decades. From the 1990s to date, there has been an increase in the number of farms converted to dairy farming and farms that provide dairy grazing (Statistics New Zealand, n.d.a). The size of dairy farms and the total area of land use in dairy pasture has significantly increased (Ministry for the Environment, 2007). Currently, there are 6.4 million dairy cattle in New Zealand (up to June, 2015), which is about 21 percent higher than the total of 5.3 million in 2007 (Statistics New Zealand, 2015). The additional 1.1 million dairy cows will produce about four times the total amount of milk that New Zealanders consume each year (Statistics New Zealand, n.d.b). As shown in Figure 1.1, the number of dairy cattle has doubled from 2.9 million in 1980 to nearly 6.4 million in June, 2015 (Statistics New Zealand, n.d.c). The above changes indicate an increase in intensive pastoral land use with higher stocking densities.

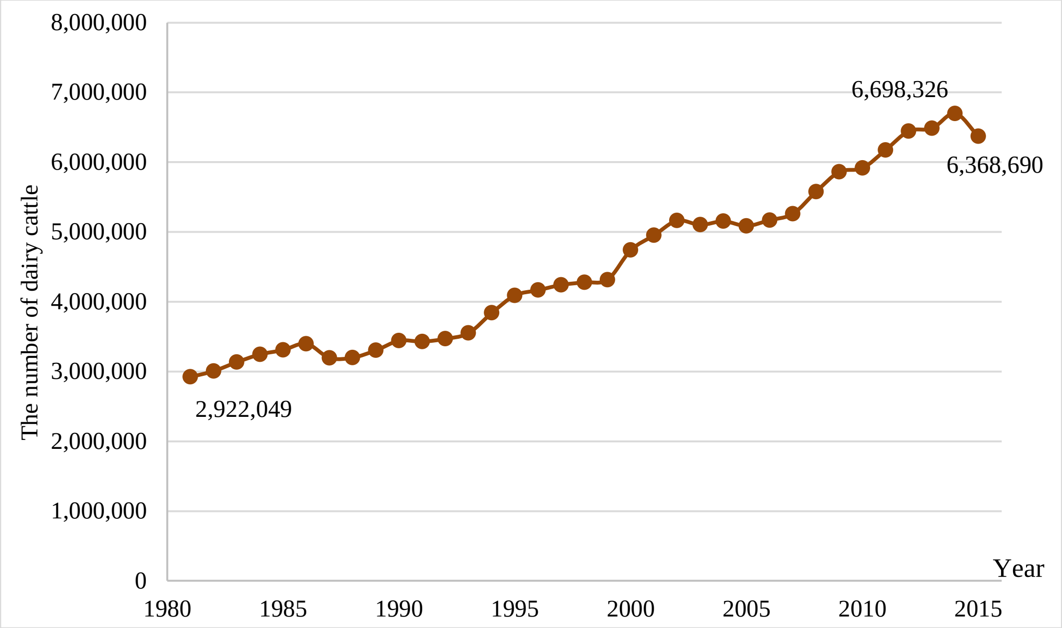

Figure 1.1 The Number of Dairy Cattle from 1980 to 2015

Data Source: Statistics NZ.

High international demand for dairy products is the main driving force behind the increase in dairy cattle numbers (Statistics New Zealand, n.d.a). The value of dairy exports, including milk powder, butter, cheese, and casein, grew significantly over the past years, with exports increasing by about 71 percent (to $12 billion) since 2007 up to June 2015 (Statistics New Zealand, n.d.b). The milksolids price also increased, from $4.05 per kilogram in January 2007 to a record high of $7.95 in April 2011 (Statistics New Zealand, n.d.b). Since then, the price of milksolids has dropped due to fluctuations in international dairy prices affected by oversupply and Russian sanctions on EU dairy exports. The price of milksolids is still expected to reach $5.25 in the 2015/2016 season.

The intensification of dairy farming has led to a significant increase in the use of chemical fertilisers, which have increased the nutrient loss from dairy farms. Gross agricultural nutrient balances increased by about 35 percent from 1998 to 2004 in NZ[1] (OECD, 2008). Notably, the amount of nitrogen fertiliser use has increased tenfold since 1985 and doubled since the mid-1990s to 2007 (Ministry for the Environment, 2007). As can be seen in Figure 1.2, the average nutrient balance of nitrogen and phosphorus of the OECD countries had dropped by 16.9 percent and 37 percent from 1990 to 2004, respectively. In contrast, the nutrient balance of nitrogen and phosphorus had significantly increased by 135.6 percent and 45.9 percent in NZ during the same period.

[1] The nutrient balances are expressed as kg nutrient per hectare of total agricultural land.

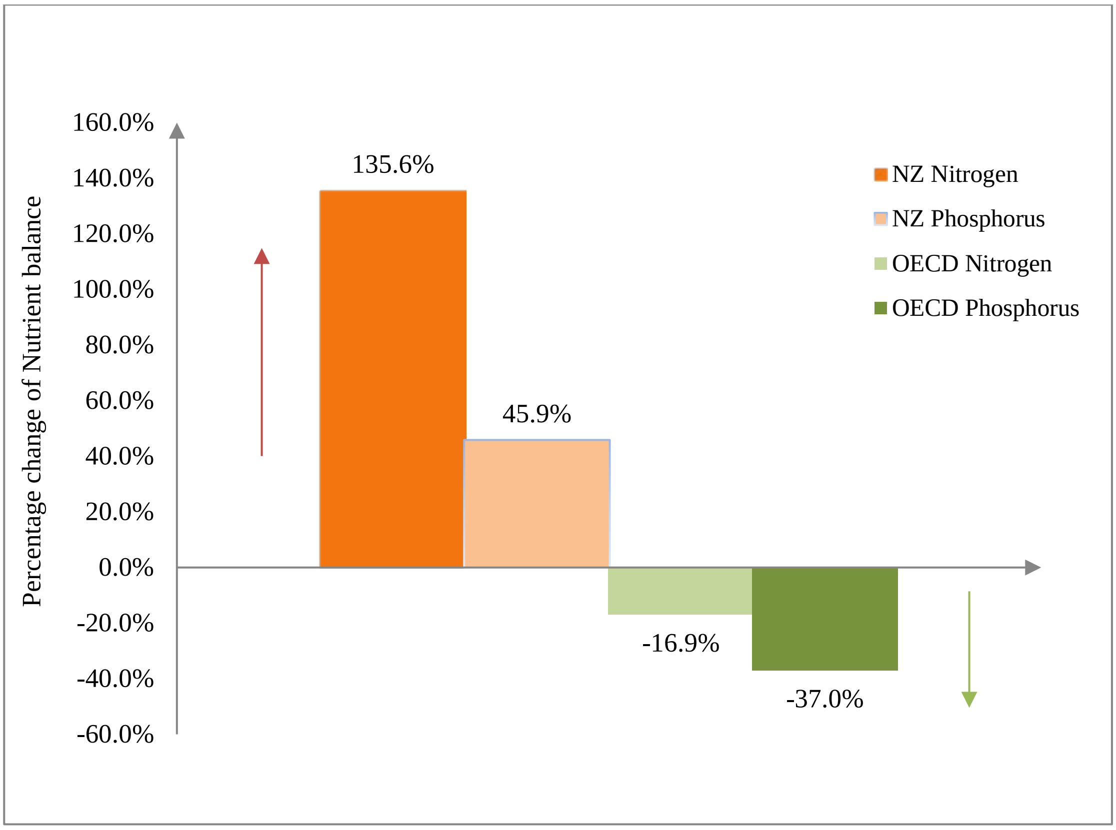

Figure 1.2 Percentage Changes of Nutrient Balance from 1990 to 2004, NZ and OECD Countries

Data source: OECDiLibrary.

Consequently, there is increasing public concern, expressed both locally and nationally, about the adverse environmental impacts of intensive farming, being commensurate with the surge in chemical fertiliser use and the increasing dairy cattle numbers. According to the survey of the public perceptions of New Zealand's Environment, the percentage of NZ residents, who regard farming as the primary cause of damage to fresh waters, increased by about 8 percent. At the regional level, the largest increase (10 percent) was recorded in the central North Island while the largest share of the percentage increase, in 2002, 2007 or 2012, was in the South Island[2] (Cullen, Hughey & Kerr, 2006; Hughey, Kerr & Cullen, 2013). Since water-quality degradation is linked with farming "by-products", more pressure from the public is expected to be placed on the intensive dairy farming in NZ. Accordingly, regulations, such as stock exclusion from waterways, are expected from regional councils in response to public demands for good water quality (Land and Water Forum, 2015).

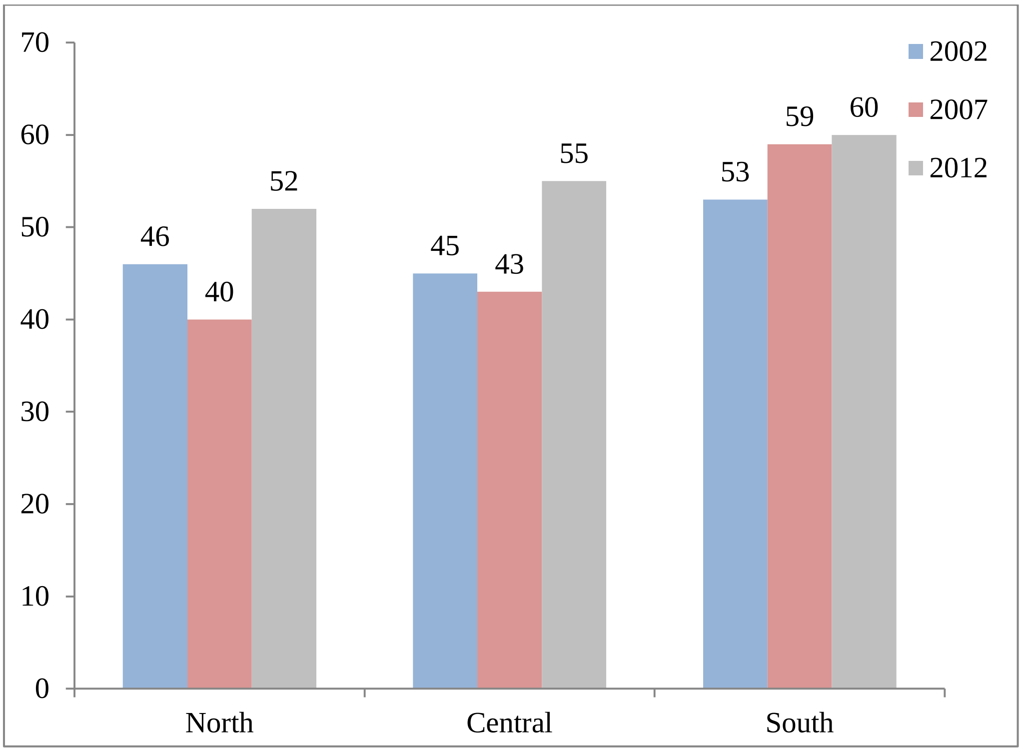

Figure 1.3 Farming Perceived as the Main Cause of Damage to Fresh Waters, by Region

Data source: *the public perceptions of New Zealand's Environment: 2006* (Cullen, Hughey & Kerr, 2006), *the public perceptions of New Zealand's Environment: 2013* (Hughey, Kerr & Cullen, 2013).

[2] In the series of surveys, the results were aggregated to three regions, North area of the North Island, Central area of the North Island, and the South Island.

1.1.2 Farmers' Dilemma

Dairy farmers play a significant role in the development of policy and managing nutrient pollution. Thus, the NZ government has launched various national and regional programs to guide farmers for a better use of intensive inputs and to assist farmers in controlling nutrient discharge. For example, the "Dairy Clean Waterway Accord", which was designed to achieve improved environmental outcomes at a national level; the "Good Management Practices" project and the "Best Practice Dairy Catchments for Sustainable Growth" project, opened a new window of monitoring and controlling nutrient loss at the catchment level. Likewise, government and research institutions have committed to help farmers evaluate the amount of nutrient loss so that farmers can efficiently manage nutrient practices.

Notably, there are a large number of mitigation practices available for controlling nutrient pollution, but one size does not fit all. Farms are different and the effectiveness associated with nutrient management practices depends on the individual farm situation (Howarth & Journeaux, 2016). Hence, some farmers are hesitant to implement mitigation practices due to the uncertainty associated with the environmental performance and the risk of increasing the cost of production.

Moreover, unlike wastewater discharged from factories, nutrient pollution discharged from farms is mostly non-point pollution that cannot be accurately measured. In addition, it is usually costly to implement mitigation practices as farmers need to invest in "hardware", such as installing fences to keep cattle from waterways, and in "software", such as self-learning or staff training for knowledge and skills to implement the practices. All these facts make it difficult for farmers to implement mitigation practices when the mitigation practices cannot be specifically linked to the quantity of pollutant discharge.

1.2 Motivation

Spatial spillover effects have been regarded as one of the important factors that influence the decision-making of spatial units, such as countries and regions[3]. This fact follows Tobler's first law of Geography that close observations are more likely to be connected to each other than distant observations (Tobler, 1970). Spatial spillover effects have been extensively considered in various research fields, such as regional science, transportation and agriculture, since it was first proposed and included in econometric models in 1979 (Anselin, 2010). In spatial models, the relationship among spatial units is captured by using geographical location of the units being observed.

In recent years, many empirical studies have considered spatial spillover effects in the fields of agricultural and environmental economics. This is mostly because agricultural production is, to some extent, dependent on environmental and geographical resources that are closely related to spatial attributes. Consequently, for example, the agricultural policy in one region may be influenced by how similar policies are implemented in the adjacent regions. Therefore, when analysing regional level data, including spatial spillover effects could help to understand the interactions of policies and strategies across different regions.

[3] Spatial spillover effects are also called spatial interaction effects or indirect effects, this thesis regards the three terms to represent the same meaning.

In addition, spatial spillover effects can also be considered in the exploration of behaviour of economic agents, such as individuals and firms (Anselin & Bera, 1998). Specifically, Akerlof (1997) firstly proposed the concept of “social distance” that can be measured either by geographical locations or social network connections among economic agents. That is, the closeness of two individuals can be measured by the inverse of geographical distance between them while it can also be measured by looking at inverse social distance in a social space. In that way, as a special means of “spatial spillover” effects, social interactions among individuals could be investigated through, while not limited to its neighbours, but also through its friends and other social connections.

Therefore, this thesis takes into account spatial spillover effects through essay one to essay three, each contributing to policy design aimed at developing NZ’s dairy industry sustainably and economically. The thesis proposes that spatial considerations would affect the formulation of effective and efficient policy on the sustainable development of the dairy industry. It also suggests that the consideration of spatial spillover effects in policy-making may help farmers to reduce the cost on accessing information and technology on sustainable farming practices, and assist the NZ government to develop national regulations by recognising regional dependence and variance. For each essay, specifically: in essay one, the inclusion of spatial spillover effects aims to capture regional dependence and variation in the relationship between dairy production and the use of intensive inputs; essay two employs geographical locations of dairy farms to verify whether or not spatial dependence exists in farmers’ decision-making on good environmental practices; essay three extends the conventional spatial spillover effects to social network effects in dairy groups.

1.2.1 Essay One

To maintain the international competitiveness of the NZ dairy industry, it is important to understand the relationship between dairy yields and intensive farming inputs regionally and nationally, particularly if policy is to facilitate choice of intensive inputs that can help to increase dairy yields with the least damage to the environment. The problem is that if sufficient nutrients are not provided, then, soil fertility will decrease production. Conversely, excessive nutrients contribute to nutrient loadings that impact the environment. Significantly, farmers will face the challenge of whether or not high dairy yields can be sustained with high intensive inputs, especially on the choice of alternative sources of nutrients, such as the use of dairy shed effluent.

In contrast to the experience of the U.S. and the European Union, there are no regulations or policy instruments aimed at controlling nutrient pollution in NZ at a national level. Policies aimed at controlling nutrient discharge from farms are currently being developed by regional units of government in New Zealand[4]. With the expansion of intensive farming from traditional dairy regions to other regions, the challenge is to take account of the complexity of regional dependency and regional diversity. On the one hand, local conditions influence regional dairy yields. On the other hand, dairy yields in one region might be influenced by its own intensive inputs as well as by neighbouring regions' dairy farming activities. For example, a new technology of

[4] The U.S. has had a national Pollutant Discharge Elimination System (NPDES) since 1972 and the European Union's Agri-environmental schemes has become compulsory among member states since 1992 (United States Environmental Protection Agency, n.d.; European Commission, n.d.).

effluent treatment system developed in one region may increase effluent use in another region. Effluent use may also increase in the adjacent regions due to technology spillovers among regions. Therefore, a good means of dealing with the complexity of regional dependence is to recognise spatial interaction effects among regions, because dairy yields and intensive inputs relationships are better understood by considering both the own region characteristics and spatial spillovers from neighbouring regions.

Therefore, the purpose of essay one is to analyse how dairy yields respond to intensive farming inputs, to establish whether unobserved spatial effects exist, and to investigate how spatial spillover effects influence the relationship between milk production and intensive farming inputs across regions. Moreover, by including interaction terms between effluent and fertiliser use, this essay aims to explore whether trade-offs exist between fertiliser and effluent use and to further reveal the influence of trade-offs on regional dairy yields.

1.2.2 Essay Two

Considering the stochastic characteristic of non-point source pollution, it is impossible to accurately estimate emissions (Kerr & Rutherford, 2008). Therefore, farmers may hesitate to implement mitigation strategies due to economic and environmental uncertainty. In addition, most of the NZ's nutrient regulation programs operate under the premise of voluntary, and the impact of these programs has been doubted. For example, Deans & Hackwell (2008) proposed that the voluntary/ non-regulatory instrument tend to have little influence on the behaviour of farmers who are not interested in changing their practices.

Therefore, it is important to understand factors that affect farmers' choices on the adoption of best practices or participation in agri-environmental programs. Although many studies have explored factors influencing farmer choice, most have used qualitative research methods that provide limited conclusions. Furthermore, the findings are of limited generalizability. Moreover, instead of investing in acquiring technologies, farmers are willing to "look over the fence", chat and learn from their neighbours' experience. Thus, the spatial spillover effects among farmers should be considered as an important factor that influence farmers' decision-making.

Therefore, essay two aims to explore determinants of dairy farmers' willingness to adopt best management practices (BMPs) for water quality protection. Except for testing commonly used determinants, it will test the hypothesis that spatial effects influence farmers' choices. Bayesian spatial Durbin probit models are applied to sample survey data in the Waikato region of NZ. Specifically, this essay will verify the hypothesis from two aspects. Firstly, spatial effects will be modelled according to the distance from farm to the nearest water bodies. The hypothesis examined is whether dairy farmers whose farms are located close to water bodies are more likely to adopt BMPs. Secondly, spatial effects will be presented as the existence of spatial interdependency in dairy farmers' decision-making. It is assumed that dairy farmers observe or learn from nearby farmers thereby reducing uncertainties associated with the performance of BMPs because BMPs are information-intensive farming techniques (Läppl & Kelley, 2015).

1.2.3 Essay Three

To help farmers make better nutrient management plans, OVERSEER® was developed to estimate the amount of nutrient loss to water. Currently, it is applied national-wide by most dairy farmers. Nevertheless, some problems associated with OVERSEER® should not be ignored. For example, nutrient loss to water is estimated by assuming best practices, meaning that any change or transition of on-farm management practices to BMPs does not reduce the nutrient loss predicted by OVERSEER®. Meanwhile, for a given farm system, OVERSEER® estimates the long-term annual average output, assuming the farm management system stays the same (Shepherd et al., 2013). To a great extent, this might stop farmers from investing in some management practices since they are uncertain about whether or not the investment in those practices could improve their environmental performance. Therefore, it is important to investigate whether or not nutrient loss estimated by OVERSEER® is relevant to dairy farmers' real nutrient management practices (NMPs).

Social interactions, such as communication with neighbours, dairy group discussions, or talking with friends in dairy groups, may also influence farmers' decision-making. This might be evident in a small community, where farmers know and meet with each other frequently. Although nutrient management issues are often invisible and difficult to monitor, farmers often have a 'fair idea' of what each other is doing (Ritchie, 2007). Besides, dairy farmers may exchange their experience in dairy groups on a particular NMP with other farmers facing a similar choice. Consequently, whenever a dairy farmer is making a decision on NMPs, the farmer may compare his/ her own environmental performance with his/ her peers' performance. Furthermore, Oreszczyn, Lane & Carr (2010) suggest that learning might occur during interaction activities among farmers. Hence, we may assume that dairy farmers share or learn from the experience on NMPs from other farmers, as they tend to develop farming knowledge with observations on other farmers' practices (Wood et al., 2014).

The aim of the third essay is to explore the relationship between dairy farmers' environmental performance and their NMPs, to understand how social interaction effects influence this relationship, and to provide suggestions for the design of nutrient control policy. Specifically, it will address the following questions: how does environmental performance respond to dairy farmers' real NMPs? To what extent, has one dairy farm's nutrient loss been influenced by the NMPs of its neighbouring farms? And, whether spatial interactions or social network interactions have a greater impact on the relationship between nutrient loss and NMPs. It firstly adopts a spatial econometric model with typical spatial interaction effects as a point of departure and then extends the model to include social network interactions among dairy farmers.

1.3 Structure of the Thesis

The structure of this thesis is shown in Figure 1.4. Followed by the introduction section, an overview of method is presented in Chapter 2. Chapter 2 introduces spatial econometric models that are used as main analysis methods in all three essays. The three essays, in sequence, are presented in Chapters 3, Chapter 4 and Chapter 5. Each essay includes an introduction, a relevant review of the literature, empirical analysis, and a brief summary. Conclusions for this thesis are presented in Chapter 6, where contributions of each essay are addressed and policy implications are provided according to conclusions of the thesis.

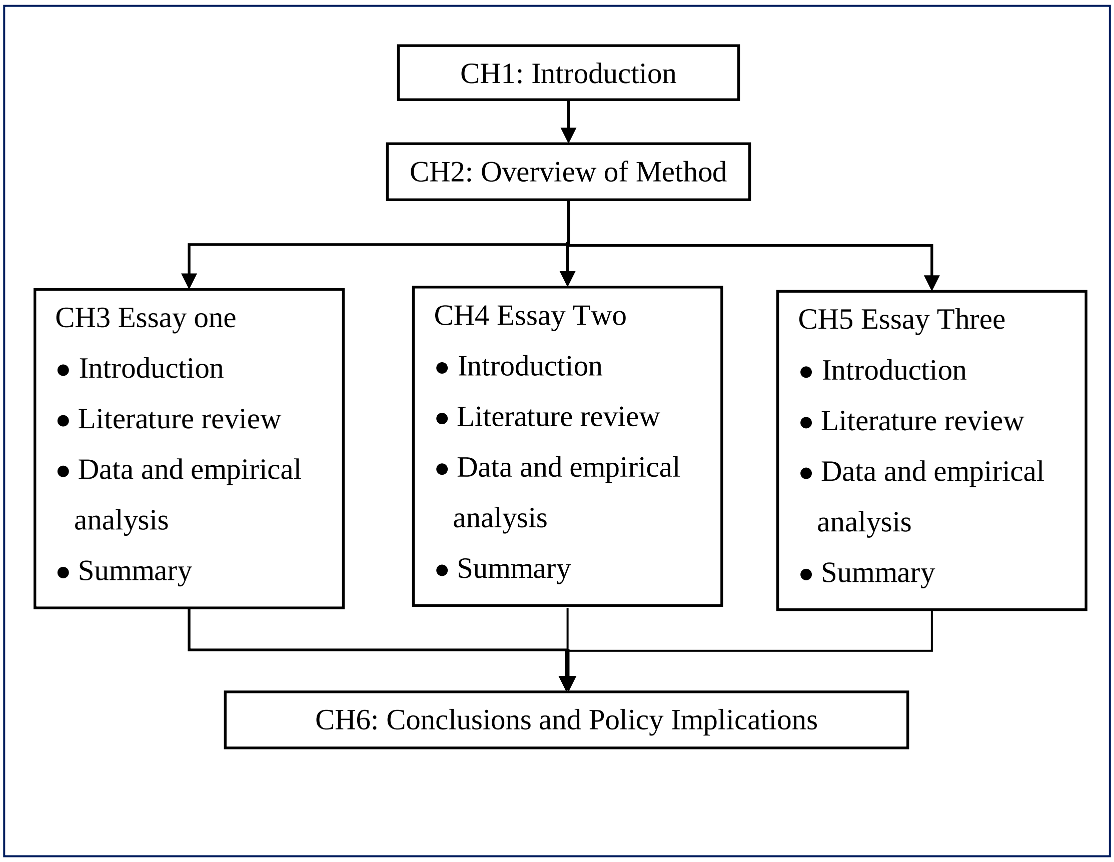

Figure 1.4 Structure of the Thesis

In the following Chapter, spatial econometric models, which are used in all three essays, will be introduced. Specifically, it starts with an introduction of model specifications for different spatial models, details model interpretations, and provides some empirical applications of spatial econometric models in economics.

CHAPTER 2. Overview of Method

2.1 Introduction

Spatial econometric methods are employed as the main method of analysis for the thesis. This chapter provides a literature review of model specifications of different spatial econometric models and gives an overview of model selection methods to include appropriate spatial interaction effects. In addition, it specifies different ways to construct a spatial weights matrix to model spatial interactions among observations and discusses extensions of spatial weights matrix that can be applied to model social interaction effects among observations. Finally, it presents some empirical applications of spatial econometric methods in economics, particularly in agricultural and environmental economics.

2.2 Spatial Econometric Models

Spatial econometric analysis methods have been extensively studied and broadly applied in various research fields since it was firstly proposed in 1979 (Anselin, 2010). Specifically, spatial econometric models include different spatial interaction effects over different geographical units, which can be expressed as point locations (e.g., zip codes, buildings and residences) or aggregated data over specific geographic areas (e.g., countries, regions, and land parcels). In addition to geographic units, spatial econometric methods can also be used to explore the behaviour of economic agents, such as individuals, firms or governments (Anselin, 2010). In the early phase of development, the spatial lag model was the main focus of spatial econometric models, which is also known as the spatial autoregressive (SAR) model, and the spatial error model (SEM)[5]. The two models are shown in Equation 2.1 and Equation 2.2 for cross-sectional data, respectively.

(2.1) $$Y = \lambda WY + \alpha\iota + X\beta + \varepsilon$$

(2.2) $$\begin{aligned} Y &= \alpha\iota + X\beta + u, \\ u &= \rho Wu + \varepsilon \end{aligned}$$

In Equation 2.1, Y is an $n \times 1$ vector of the dependent variable; $\alpha\iota$ is the constant term with an $n \times 1$ vector of ones ι associated with the parameter α to be estimated; X denotes an $n \times k$ vector of k independent variables, with the associated coefficient parameters β, and ε is the disturbance term. Unlike conventional econometric models, the SAR model includes an endogenous dependent term WY representing a linear combination of values of the dependent variable Y constructed from neighbouring observations. W is an $n \times n$ matrix called spatial weights (the detail of which will be specified in the next section), and λ is an unknown spatial parameter to be estimated. Different from the SAR model, the SEM model captures the spatial interaction effect in

[5] The acronyms used in this thesis are those most commonly used in the spatial econometrics literature to refer to the model specification (see e.g. Elhorst, 2014).

a spatially autocorrelated error term u, with the unknown spatial parameter ρ to be estimated.

The spatial lag of X model (SLX), not often been used in empirical studies, provides another way to model spatial spillover effects. The SLX model is shown in Equation 2.3, where the spatial spillover effect is presented in the form of a spatially lagged independent term WX. The spatially lagged independent term is set to capture impacts of the neighbouring observations' characteristics, with the associated coefficient parameters θ to be estimated.

(2.3) $$Y = \alpha\iota + X\beta + WX\theta + \varepsilon$$

The above three models include three spatial spillover effects, i.e. a spatially lagged dependent term, a spatially autocorrelated error term, and a spatially lagged independent term. However, early on researchers started to believe that two or more spatial spillover effects could exist in real world applications, and it is possible to include those effects in one spatial model. Ideally, one spatial econometric model may include all the three effects, called the general nesting spatial (GNS) mode, but most studies have agreed that at least one interaction effect should be excluded or else the parameters are unidentified. However, divergence in opinion exists with regard to the selection of which interaction effects should be included (Elhorst and Fréret, 2009).

LeSage & Pace (2009) and Elhorst (2014) have proposed that the best option for empirical studies is to choose the spatial Durbin model (SDM) that excludes the spatially autocorrelated error term. LeSage (2014) has further argued that the SDM is the only model specification worth considering for empirical work to measure global spillover effects; while the spatial Durbin error model (SDEM) is the only one that needs to be estimated if one can narrow down the relationship being investigated as reflecting local spillover effects[6]. As shown in Equation 2.4, the SDM model considers two spatial spillover effects, i.e. a spatially lagged dependent term and spatially lagged independent variables.

$$Y = \lambda WY + \alpha\iota + X\beta + WX\theta + \varepsilon \tag{2.4}$$

The SDEM model excludes the endogenous spatially lagged dependent variable and includes the spatially lagged independent variables and the spatially autocorrelated error term, shown in Equation 2.5.

$$\begin{aligned} Y &= \alpha\iota + X\beta + WX\theta + u \\ u &= \rho Wu + \varepsilon \end{aligned} \tag{2.5}$$

A complete description of the relationship between a general linear model/ non-spatial model and the extensions to spatial models are shown in Figure 2.1.

[6] Please find the details of model selection in LeSage (2014), who has also introduced the SAC model that includes both the spatially lagged variable and the spatial autocorrelated error term, and explained the disadvantages of the SAC model.

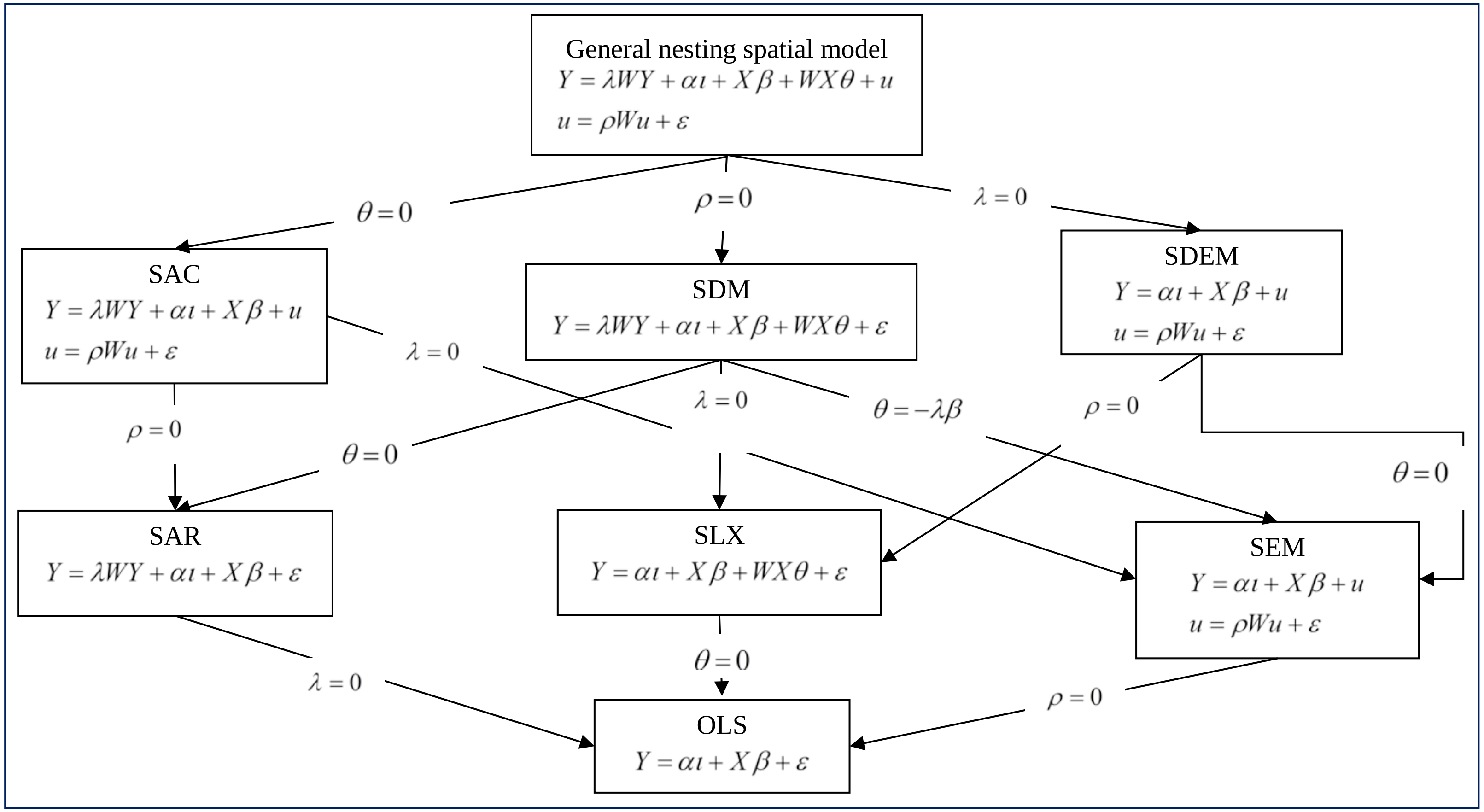

Figure 2.1 Relationships between Different Spatial Models for Cross-sectional Data

Source: Elhorst & Vega, 2013.

According to the relationships depicted in Figure 2.1, diagnostic tests have been developed for selecting the appropriate spatial model best fitting the targeted research questions and data. Generally, tests can start with the benchmark model, a non-spatial linear model at the bottom of Figure 2.1, to test for the spatial spillover effects presented as a spatially lagged term of the dependent variable and a spatial autocorrelated error term by using both the Lagrange Multiplier (LM) test and the robust LM test (Anselin et al., 1996). This testing process is used to determine whether or not the non-spatial model needs to include spatial interaction effects. Moran's I test can also be used to test for the existence of spatial autocorrelation in cross-sectional data (Moran, 1950).

Except for testing for spatial interaction effects in the non-spatial model, diagnostic tests can also start from the top. As spatial models used in empirical studies often include two spatial effects, the test can start from, for example, the SDM model. By using the Wald test, it is possible to verify the hypothesis whether it is proper to simplify the SDM to the SAR as well as the hypothesis whether the SDM can be simplified to the SEM (Elhorst & Fréret, 2009).

I follow the above testing processes to choose the best spatial econometric models that best fit the data used in each essay. In my first essay, I used the SDM model in a panel data setting for regional dairy yields and intensive inputs; a transformed SDM model is used in the second essay, where the dependent variable is a binary variable representing dairy farmers' choices on the adoption of best management practices for water protection; and an SDEM model is used in essay three, which attempts to explore spatial spillover effects (from geographically close neighbours and socially close contacts in dairy groups) of neighbouring farmers' choices of nutrient management practices, and how spillover effects influence farmers' environmental performance.

2.2.1 Spatial Weights Matrix

As discussed in the previous section, a spatial weights matrix is used in spatial econometric models to model the spatial relevance among spatial units. The spatial weights matrix $W = (w_{ij}; i, j = 1, \ldots, n)$ is an $n \times n$ positive matrix, where each spatial unit w_{ij} appears both in rows and columns. Here, each spatial weight reflects the ''neighbouring'' relationship defined for the corresponding observations *i* and *j* (LeSage & Pace, 2009). It is noted that "self-influence" is excluded by assuming that $w_{ii} = 0$ for all $i = 1, \ldots, n$.

There are several ways of building a spatial weights matrix in practice, but all these approaches adopt distances and boundaries. Generally, boundary-based weights matrix, such as queen contiguity and rook contiguity approach, is used to capture local effects. In this case, the usual focus is on interaction effects among the adjacent neighbours who share boundaries with each other.

The simplest way to construct a boundary-based weight matrix is the queen contiguity approach. If the set of boundary points of spatial unit *i* is denoted as $bin(i)$, then, the queen contiguity weights are expressed in Equation 2.6.

$$w_{ij} = \begin{cases} 1, & bin(i) \cap bin(j) \neq \varnothing \\ 0, & bin(i) \cap bin(j) = \varnothing \end{cases} \tag{2.6}$$

Although it is straightforward to understand the relationship between two spatial units through the above expression, queen contiguity weights define neighbouring units as those sharing only a single boundary point, such as a shared corner point on a grid of spatial units (Getis, 2009). Thus, a much more powerful approach is developed to require that some positive portion of their boundary be shared. As defined in Equation 2.7, l_{ij} denotes the length of shared boundary between spatial units *i* and *j*, which is called the rook contiguity weights.

(2.7)
$$w_{ij} = \begin{cases} 1, & l_{ij} > 0 \\ 0, & l_{ij} < 0 \end{cases}$$

However, sometimes, researchers attempt to model the impact of a neighbour's neighbour or even a neighbour of neighbour's neighbour so that distance-based weights matrix is developed for this purpose. One of the most commonly used distance-based matrixes is defined on the basis of a powered inverse distance d_{ij}^{-c} (*c* usually equals to 1 or 2 in empirical studies) between observation *i* and *j* ($i \neq j$). Practically, it measures a distance decay effect among the spatial units. For example, an inverse distance weights matrix may take the form shown in Equation 2.8.

(2.8)
$$w_{ij} = \begin{cases} d_{ij}^{-1}, & 0 \le d_{ij} \le d \\ 0, & d_{ij} > d \end{cases}$$

Here, *d* denotes a threshold distance beyond which spatial effects are assumed to be zero.

Another commonly used distance-based approach is k^{th} nearest neighbours weights matrix, which takes the form shown in Equation 2.9.

$$w_{ij} = \begin{cases} 1, & j \in N_k(i) \\ 0, & otherwise \end{cases} \qquad (2.9)$$

where distances from each spatial unit i to other units j ($i \neq j$) can be ranked as: $d_{ij(1)} \leq d_{ij(2)} \leq \ldots \leq d_{ij(\mathrm{n}-1)}$. Thus, for each $k = 1, \ldots, n-1$, $N(k_i) = \{j(1), j(2), \ldots, j(k)\}$ contains k closest neighbours to i.

In the above two spatial weights matrixes, either the threshold distance or the number of k^{th} nearest neighbours is determined on the basis of several aspects, such as requirements to address the research question, size of the data set, and previous literature on the specification of distance. By using the distance-based weights matrix, the impact of a neighbour's neighbour can be captured, even though it is assumed to decay with the increase of the distance.

Except for boundary-based and distance-based weights matrix, a spatial weights matrix based on social connections has extended the use of the conventional spatial scope to consider social locations among spatial units. That is, instead of observing physical distance, interactions with respect to socioeconomic characteristics are measured and modelled by using "economic distance" or "social distance". For example, inversed trade share, inverse distance between GDP per capita, and migration flow information are typical indicators to model the interactive relationships between observed countries rather than modelling boundary connections among these countries. (e.g. Crabbé, 2013;

Corrado & Fingleton, 2012). The construction of spatial weights matrix based on social locations can follow the distance-based weights matrix, shown in Equation 2.8, while d_{ij}^{-1} is no longer the geographical distance but "economic distance" or "social distance". For example, to measure the "economic distance" between country *i* and *j*, the inverse distance d_{ij}^{-1} between the two countries can be substituted by using inverse difference in GDP per capita between the two countries.

Another example of social-related weights matrix is to consider social network connections among individuals. Assuming that there is an individual, who meets and makes friend with another individual in a social event on a specific topic. The individual's attitude on this topic may be influenced by that of the friend met in the social event (even though this one lives far away) rather than that of the individual's neighbour. Accordingly, a spatial weights matrix can be built according to relationships of individuals in different social events, based on the rook contiguity approach shown in Equation 2.7.

In empirical studies, "the best" spatial weights matrix is usually determined according to comparing indicators of goodness of fit of models, such as R^2 or Adjusted R^2, with different matrix specifications. However, LeSage (2014) suggests that researchers should choose "the best" spatial weights matrix based on the research questions, and a simple form of spatial weights matrix is preferred. In this thesis, to select "the best" spatial weights matrix for each essay, I firstly consider the focus of the research question for each essay. For example, in the first essay, a distance-based spatial weights matrix is chosen to model spatial interactions among regions considering only 55 regions are included. If a boundary-based matrix was used, some regions may be isolated with no neighbours. In the third essay, in order to model social interactions among dairy farmers, a boundary-based spatial weights matrix is built to capture interactions among geographically close farmers, while a social-related matrix is built to capture interactions among farmers in the same dairy groups. Meanwhile, I also compare indicators of goodness of fit of models with different spatial weights matrixes. Hence, in the first essay, different thresholds of distance are tested and compared according to the values of R^2. Similarly, in the third essay, the spatial model with a rook contiguity weights matrix outperforms other spatial models, indicating the rook contiguity weights matrix is “the best” matrix.

2.2.2 Interpreting Direct and Indirect Effects

Spatial econometric models consider spatial spillover effects from neighbouring spatial units, which makes it different from results interpretation of conventional least square regressions. Considering an SDM model, to better present the impacts of spatial spillover effects, Equation 2.4 can be transformed to:

(2.10) $$Y = (I - \lambda W)^{-1}(X\beta + WX\theta) + (I - \lambda W)^{-1}\iota\alpha + (I - \lambda W)^{-1}\varepsilon$$

where I is an $n \times n$ identity matrix. Furthermore, Equation 2.10 can be presented as a simple form shown in Equation 2.11, where x_k stands for the k^{th} independent variable.

(2.11) $$Y = \sum_{k=1}^{r} S_k(W)x_k + V(W)\iota\alpha + V(W)\varepsilon$$

where $S_k(W) = V(W)(I\beta_k + W\theta_k)$ and $V(W) = (I - \lambda W)^{-1} = I + \lambda W + \lambda^2 W^2 + \lambda^3 W^3 + ...$

Specifically, $S_k(W)$ can be further expanded to:

$$S_k(W) = \begin{pmatrix} S_k(W)_{11} & S_k(W)_{12} & ... & S_k(W)_{1n} \\ S_k(W)_{21} & S_k(W)_{22} & \cdots & S_k(W)_{22} \\ \vdots & \vdots & \ddots & \\ S_k(W)_{n1} & S_k(W)_{n2} & \cdots & S_k(W)_{nn} \end{pmatrix} \tag{2.12}$$

According to Equation 2.11 and 2.12, derivative of the i^{th} dependent variable y_i regarding x_{ik} does not equal to β_k but takes the form $S_k(W)_{ii}$. Thus, in contrast to a conventional non-spatial linear model, it is not valid to use the estimated coefficients β_k to interpret the impacts of the explanatory variables. Here, $S_k(W)_{ii}$ includes the impact on the i^{th} dependent variable y_i from a change in x_{ik}, consisting of direct (of own) and indirect effects (of neighbouring spatial units).

Pace and LeSage (2006) firstly proposed a summary measurement method to interpret direct and indirect effects, considering the influence of changes in an independent variable varies over observations. Thus, a scalar summary measure is based on summing the total impacts over the rows (or columns) of the matrix $S_k(W)$ and taking an average over all observations. Specifically, the average total impact to an observation is measured as the average of row sums from $S_k(W)$; the average direct impact is measured as the average of the diagonal of matrix $S_k(W)$; and the average indirect impact is referred to the difference between the average total impact and average direct impact. Details of calculating these effects can be found in the study of LeSage & Pace (2009).

Formulas to calculate direct and indirect effects calculation for different spatial model specifications are presented in Table 2.1, according to model specifications of the spatial models shown from Equation 2.1 to 2.5 and the summary measure method.

Table 2.1 Direct and Indirect Effects of Different Model Specifications

Effects / Models	Direct effects	Indirect effects
OLS/SEM	β_k	0
SAR/SAC	Diagonal elements of $(I - \lambda W)^{-1} \beta_k$	Off-diagonal elements of $(I - \lambda W)^{-1} \beta_k$
SLX/SDEM	β_k	θ_k
SDM/GNS	Diagonal elements of $(I - \lambda W)^{-1}(\beta_k + W\theta_k)$	Off-diagonal elements of $(I - \lambda W)^{-1}(\beta_k + W\theta_k)$

Source: Elhorst & Vega (2013)

2.3 Overview of Empirical Applications of Spatial Econometric Models

As stated by Anselin (2010), when reviewing the development of spatial econometric models, a significant move can be observed from applications on a small scale of research fields, such as urban and regional development, to applications in the mainstream of social science studies. In the early stage, spatial econometric models were applied in regional science, environment and geography studies, but barely attracted attentions from economists and social scientists. In recent years, however, things have changed. Research interest in the application of spatial econometric models, especially in the fields of social science, has rapidly increased. Anselin (2010) believes that the growth of interest in applied spatial analysis was stimulated by the emergence of several articles in econometric journals, such as Econometrica and Econometric Reviews and Econometric Theory[7]. In particular, the Journal of Econometrics held a special issue, 'Analysis of spatially dependent data', which has facilitated the prevalence of the application of spatial econometric models (Baltagi, Kelejian & Prucha, 2007).

Spatial econometric models have been applied in almost all the subfields of agricultural and environmental economics, such as production economics and land economics. Weiss (1996) developed models that incorporate spatial effects to enable incorporation of spatial cost and output surfaces into production theory in a study of precision farming. Following Weiss's suggestion, Bongiovanni (2002) and Bullock, Lowenberg-DeBoer & Swinton (2002) applied geographical information system (GIS) to control for site-specific variable rates of fertiliser application to achieve better management of nutrient inputs and to increase crop production. Their results show potential benefits from precision agriculture by allowing for spatially customized rates of fertiliser application. Using spatial econometric models in a case study of site-specific nitrogen application in corn production, Anselin, Bongiovanni & Lowenberg-DeBoer (2004) also demonstrated the potential for improving nitrogen management. Their results show

[7] A list was made by Anselin, Florax & Rey (2004) on theoretical and empirical studies in the main econometrics journals from the late 1990s to the early 21st century.

that nitrogen response differs by landscape position, and the returns for nitrogen use and site-specific management practices are different when analysed in spatial models and non-spatial models, where all spatial models indicate profitability while the non-spatial models do not.

Spatial econometric models have also been used to examine the impact of climate change on agricultural production. For example, Baylis, Paulson & Piras (2011) use a spatial panel data model, incorporating climatic factors, such as annual rainfall, to capture the spatial variance in climate change. Their results indicate great potential for the application of spatial panel econometric models for applied researchers. Cai, Yu & Oppenheimer (2014) used a spatially weighted model to examine the impact of weather variation on corn yields across different regions in the US. Their results show that corn yields negatively respond to temperature in warmer regions but positively respond to temperature in cooler regions, indicating spatially heterogeneous impacts of regional temperature.

The above studies are good examples that show the advantages of including spatial information in the study of agricultural and environmental economics, and furthermore, illustrate the potential of extending spatial analysis to other topics.

Furthermore, although few, some empirical studies have started to employ spatial econometric models built for discrete dependent variables to model spatial dependence in farmer choice or behaviour. According to the concept of neighbourhood effect defined by Manski (1993), spatial dependence means that farmers located nearby show similar choice preferences. The dependence might be due to communication between farmers, which may raise awareness or reduce information costs, for example. Case (1992) was one of the first to apply a spatial probit model to explore the neighbourhood effect on Indonesian farmers' adoption of the sickle. In recent studies, spatial dependence has also been considered in spatial econometric models in farmers' adoption of organic farming. For example, Wollni & Andersson (2014) use survey data to analyse factors affecting farmers' decision on organic conversion in Honduras; Lewis, Barham & Robinson (2011) examine the neighbourhood effect in the organic conversion decision in southwestern Wisconsin of the U.S; and La¨pple & Kelley (2015) apply Bayesian spatial Durbin probit models to account for spatial dependence in Irish drystock farmers' adoption of organic farming. Results of all these articles indicate that significant spatial dependence exists in farmer choice, and suggest that policy implications might be biased if spatial effects are ignored.

Applications of the spatial econometric models, presented in the above, imply the importance and potential benefits of taking into account spatial spillover effects in econometric models. Significantly, these studies illustrate why it is important to consider spatial issues in agricultural and environmental economics studies: for example, agricultural production is highly dependent on geographical and environmental resources; and farmers' farming practices are observable when they are located in close proximity. Spatial issues, therefore, should not be ignored in empirical studies focusing on agricultural and environmental economics.

Hence, in Chapter 3, I will apply spatial econometric models in the first essay to address the importance of spatial effects in the relationship between regional dairy yields and intensive inputs.

CHAPTER 3. Essay One: Spatial Analysis of Dairy Yields Response to Intensive Farming in New Zealand

3.1 Introduction

3.1.1 Background

Following the removal of export incentive subsidies in the 1980s, New Zealand (NZ) experienced an "agricultural revolution" (Baskaran, Cullen & Colombo, 2009). Meanwhile, in recent years, international demand for dairy products has further fuelled the expansion of the NZ dairy sector (Tímár, 2011). Significantly, the dairy industry has expanded from traditional dairy regions, such as the central North Island and the east coast of South Island, to other regions (Clark et al., 2007). This has led to more intensive dairy farming, represented by higher stocking densities as well as a significant increase in the use of chemical fertilisers (Evans, 2004). While there is a wide public recognition of the benefits associated with increasing production and the sector's contribution to the economy, there are growing concerns about environmental degradation. Currently, the dairy industry is facing tremendous pressure from the public arising from an increasing public awareness of water quality degradation associated with intensive farming (Land and Water Forum, 2015). According to surveys of the public's perception of New Zealand's Environment, the proportion of NZ residents, who regard farming as the major cause of damage to freshwaters, increased from 48% in 2002 to 57% in 2013 (Cullen, Hughey & Kerr, 2006; Hughey, Kerr & Cullen, 2013). Thus, controlling nutrient discharge from dairy farms is now a crucial issue for regional and central government.

In order to maintain the international competitiveness of the NZ dairy industry, it is important to understand the relationship between dairy production and intensive farming regionally and nationally, particularly if policy is to facilitate choice of intensive inputs that can help increase dairy yields with the least damage to the environment. If sufficient nutrients are not provided then, soil fertility and production will decrease, which affects profits. Conversely, if excessive nutrients are provided, there can be negative effects on the environment. Specifically, farmers will face the challenge of whether or not high dairy yields can be sustained with high intensive inputs, particularly in respect to the choice of alternative sources of nutrients.

Farmers have the option of choosing between using more chemical fertilisers, such as nitrogenous fertiliser, and more farm effluent. In particular, as shown in Figure 3.1 and Figure 3.2, the price of chemical fertiliser has increased from 369 NZD per hectare per year (36,761 NZD per farm per year) in 2000 to 607 NZD per hectare per year (86,711 NZD per farm per year) in 2014 (DairyNZ, 2015). Alternatively, farmers can use effluent to supply nutrients to pasture, as it contains various nutrients, including nitrogen, phosphorus, potassium, and magnesium. Moreover, when appropriately applied on land, effluent can substitute chemical fertilisers with a lower cost. Based on the fertiliser prices in 2010, the effluent of one hundred dairy cows can help farmers to save up to 2,200 NZD in fertiliser per year (Waikato Regional Council, n.d.). In the meantime, the cost of installing and maintaining on effluent pond has decreased with the development of new technologies. Meanwhile, new technologies for effluent management have presented the potential to reduce environmental degradation (DairyNZ, 2014). According to an analysis result of the Good Management Practices project, there are some improvements in water quality because of an increase in the use of farm effluent sprayed over land during a ten-year period (NIWA, 2016)[8].

Therefore, by substituting manufactured sources of fertiliser with dairy effluent, farmers may be able to lower on-farm costs and contribute to improved water quality. In that way, improved understanding of the relationship between dairy yields and intensive farming practices may assist the dairy industry to optimize intensive inputs, ensure increased milk production, and contribute to improvements in water quality.

[8] The Good Management Practices (GMP) is a voluntary project, which was launched in 2001. It aims to develop and/or implement good management practices to maintain acceptable water quality standards at catchment-level. The project includes five catchments in Taranaki, Waikato, Canterbury, West Coast, and Southland.

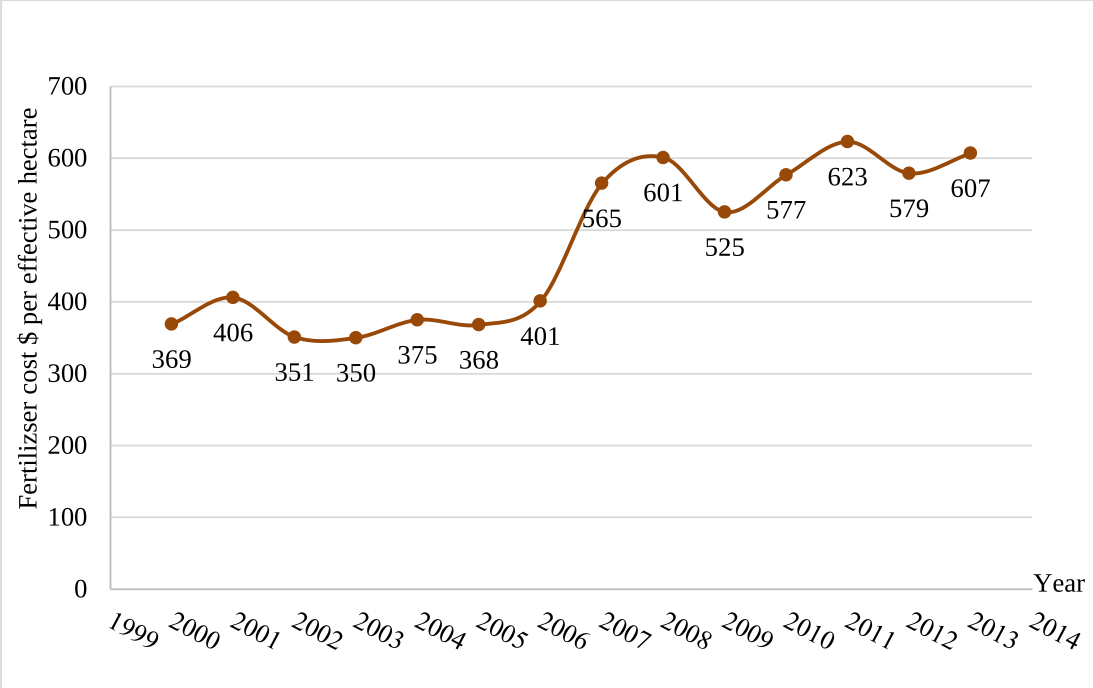

Figure 3.1 Fertiliser Cost $ Per Effective Hectare from Season 2001/ 2002 to Season 2013/ 2014

Source: DairyNZ

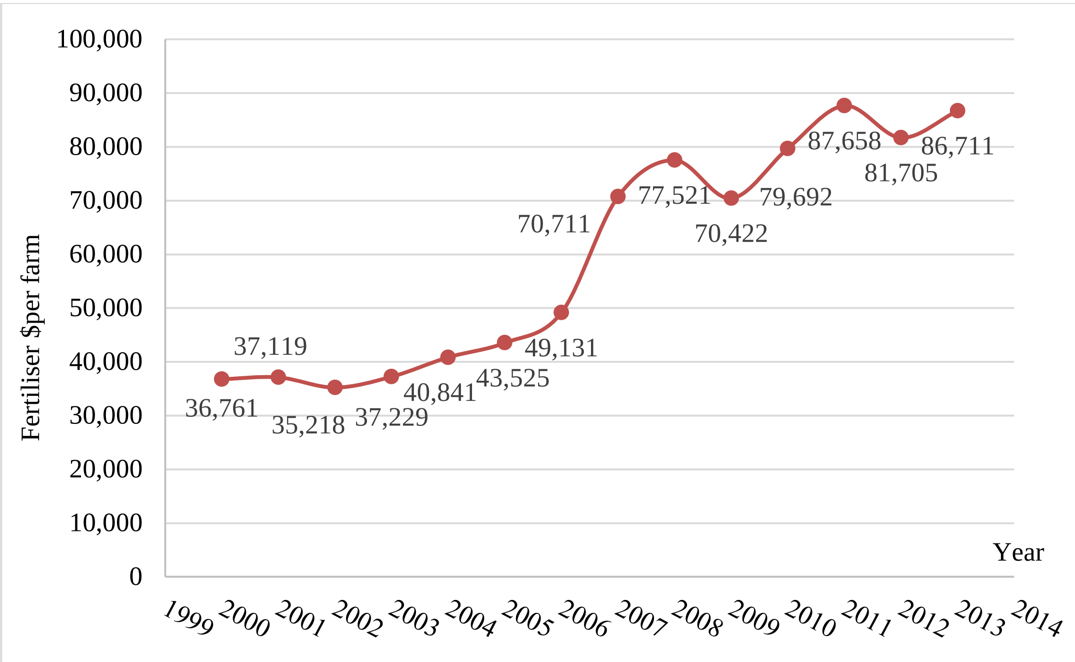

Figure 3.2 Fertiliser Cost $ Per Farm from Season 2001/ 2002 to Season 2013/ 2014

Source: DairyNZ

Policies aimed at controlling nutrient influx from intensive dairy farming are currently being developed by regional units of government in New Zealand. To better inform policy, the challenge is to take account of the complexity of regional dependence and regional diversity. On the one hand, dairy yields in one region might be influenced by its own intensive inputs and by neighbouring regions' dairy yields and intensive inputs. On the other hand, the variety of regional conditions could also influence regional dairy yields. Thus, a good means of dealing with the complexity is to recognise the impacts of spatial interaction effects, because dairy yields and intensive inputs relationships are better understood by considering both the own region characteristics and spatial spillovers from neighbouring regions.

3.1.2 Literature Review

Literature on the relationship between dairy yields, productivity and intensive inputs is summarized as follows. In the field of agriculture and the environment, most studies focus on the scientific or technical aspects of intensive farming and its impacts on production and productivity. These studies typically utilize an average dairy farm system or example farm system for a given region to assess production and environmental impacts. These impacts are quantified as environmental efficiency which is measured in terms of greenhouse gas emissions or nitrate leached per ton of milksolids. From the perspective of environmental emissions, Ledgard et al. (2003) and Ledgard et al. (2004) used a life-cycle method to evaluate resource use efficiency of the average Waikato dairy farm, and compared environmental efficiency with a typical Swedish dairy farm. The conclusions show that the difference in environmental efficiency between the two farming systems is small while the Swedish dairy farming system was more energy efficient. Basset-Mens, Ledgard & Boyes (2009) compared the average NZ dairy farm system with three other dairy systems of various ranges of intensification. Low-input systems in some areas of New Zealand using innovative energy use technologies were shown to represent a promising option for intensive farming. Similarly, Matthew, Horne & Baker (2010) observed and evaluated two examples of dairy farms specifying the evolution of intensification and nitrogen loss during the past thirty years in New Zealand. Their results showed a significant increase in production as well as nitrogen loss. Significantly, the results also indicated the importance of a change in effluent disposal management, which offsets nitrogen loss and increases environment-efficiency.

In contrast, economic studies have not only focused on production and environmental impacts but also economic efficiency. Typically, stochastic frontier analysis and data envelope analysis have been used to investigate the relationship between dairy production, technical efficiency, and environmental efficiency. Apart from labour and capital inputs, some studies also considered environmentally detrimental indicators, including stocking rates, effective farming areas, and nitrogen fertiliser use (De Koeijer et al., 2003; Reinhard, Lovell & Thijssen, 2000; Reinhard, Lovell & Thijssen, 2002). These studies arrived at similar conclusions, notably, that better farm management practices can improve both economic and environmental efficiency. Using a sample of Australian dairy farms, Graham (2004) employed a dynamic fixed effects panel model to estimate the environmental effects of undesirable inputs, where nitrogen surplus is treated as a detrimental input associated with dairy farms. The results show that it is possible to ensure that higher dairy production is associated with environment-friendly farming activities.

However, all the above studies do not consider spatial issues, although some have used climatic factors, for example, annual rainfall, to model spatial variations (Baylis, Paulson & Piras, 2011). Intuitively, with the expansion of the dairy industry from traditional dairy regions to other regions, dairy yields as well as intensive inputs in those regions may be influenced by the spillovers from traditional regions. Thus, ignoring spatial effects may cause inaccuracy in the analysis of regional dairy yields response to intensive inputs. Indeed, spatial econometric methods have been applied in production economics for crops, such as corn and wheat. For example, using spatial econometric models in a case study of site-specific nitrogen application in corn production, Anselin, Bongiovanni & Lowenberg-DeBoer (2004) demonstrated the potential for improving nitrogen management with the consideration of spatial effects. Their results show that nitrogen response differs by landscape position, and the returns for nitrogen use and site-specific management practices are different when analysed in spatial models and non-spatial models, where all spatial models indicate profitability while the non-spatial models do not. Cai, Yu & Oppenheimer (2014) used a spatially weighted model to examine the impact of weather variation on corn yields across different regions in the US. Their results show that there are spatially heterogeneous effects of regional temperature on corn yields, as corn yields negatively respond to temperature in warmer regions but positively respond to temperature in cooler regions. Although not focusing on the dairy industry, the above studies are good examples that show the advantages of including spatial information in the study of production-intensive agriculture, and furthermore, illustrate the potential of using spatial econometric models to analyse the response of dairy yields to intensive inputs.

Only a few papers have related spatial issues to dairy production at a regional level.

Peterson (2002) has employed spatial econometric models to examine the impacts of environmental regulations and traditional location factors in determining county-level dairy production in the U.S. Their results show that dairy production levels are positively correlated across different counties in the U.S. Importantly, the results indicate that the extent to which current changes in dairy production levels have been influenced by differences in the environmental regulations across the U.S. states. Furthermore, Mosnier & Wieck (2010) have reviewed studies emphasizing spatial dynamic and the determinants of regional dairy production. The review proposes that research focusing on the change of farm structure and regional production may assist to better understand regional production changes. Up to now, there has been no study on the relationship between dairy production and intensive inputs in NZ that considers spatial effects. Thus, by testing for the existence of the spatial effects in the relationship between regional dairy yields and intensive inputs in NZ, this essay can contribute to the formation of regional environmental regulation.

In this essay I seek to analyse how dairy yields respond to intensive farming inputs, to establish whether unobserved spatial effects exist, and to investigate how spatial spillover effects influence the relationship between dairy yields and intensive farming across different NZ regions[9]. This essay contributes to the existing literature in two ways. First, this is the first empirical application of spatial econometric methods to examine the spatial relevance of dairy yields and intensive inputs in NZ. In particular, the spatial panel data model accounts for cross-sectional dependence and controls for heterogeneity. Second, the essay not only takes into account traditional intensive inputs but also innovatively includes the areas of effluent sprayed over effective farm areas as

[9] In this paper, regions refer to territorial units of government.

one of the intensive farming indicators[10]. By including effluent and nitrogen use in the model, I can indicate whether or not there are trade-offs between these two intensive inputs and further reveal the influence of trade-offs regarding dairy yield. The results contribute to an understanding of how farmers can improve their management of intensive inputs and contribute to the formation of regional environmental policy that recognises regional dependence and heterogeneity.

3.1.3 Structure of Essay One

This essay is structured as follows. In section 3.2, it details the approach of spatial econometric modelling. Section 3.3 describes the data, presents the empirical models, and selects the best model. Section 3.4 gives results of the empirical models. Section 3.5 concludes and provides policy suggestions.

3.2 Model Specifications

The application of spatial econometric models in policy analysis typically calls for the inclusion of more than one spatial interaction relationship. For example, a policy change by one regional unit of government may not only directly influence its own economy but indirectly affect the economy of the neighbouring regions, and vice versa. In this context, the spatial Durbin model (SDM) allows for the inclusion of both spatially lagged dependent and independent variables (e.g., Mur & Angulo, 2006; Elhorst & Fréret, 2009; Beer & Riedl, 2012). This is especially applicable in policy

[10] For simplicity, effluent application and effluent use are also used in this essay, which represent “areas of effluent sprayed over effective farm areas”.

analysis when the research interest focuses on estimating the impacts of neighbouring policy in terms of two spatial interaction effects in contrast to a spatial lag model (SAR) that includes only an endogenously spatially lagged dependent variable, and the spatial error model (SEM) where the spatial autoregressive error terms may not give meaningful interpretations (Anselin, 2010). Moreover, the inclusion of the spatially lagged independent variables in the SDM could help to avoid omitted variable issues in empirical studies. Therefore, the SDM is chosen for empirical analysis since I am concerned about not only the impacts of one region's own intensive farming practice on its dairy production but also impacts from the neighbouring regions' intensive farming activities.

For this essay, I consider a fixed effects model, including spatial fixed effects (individual effects) and time fixed effects, to be appropriate for the following reasons[11]. Firstly, spatial fixed effects are designed to control for time-invariant variables, and time fixed effects to control for spatial-invariant variables. Thus, excluding spatial fixed effects may lead to bias in cross-sectional studies, and omitting time fixed effects may cause bias in time-series studies (Baltagi, Song & Koh, 2003). Additionally, the random effects model is particularly restrictive. One of the strictest assumptions for random effects model is zero correlation between the random effects terms and the explanatory variables. This, however, may not be satisfied in empirical studies (Debarsy & Ertur, 2010). Furthermore, there are no time-invariant variables included in the analysis, but this is usually the main reason for most empirical studies that include random effects in order to avoid the problem of omitting time-invariant variables (Elhorst, 2014).

[11] I will also use hypothesis tests to support the choice in the following section.

To date, many empirical studies have used coefficient estimation to test whether or not spatial spillover effects exist, and to derive inferences regarding the significance of spillover effects. Nevertheless, some recent studies, including LeSage & Pace (2009), LeSage (2014) and Elhorst (2014), have demonstrated that erroneous interpretations and conclusions may be made based on coefficient estimation. According to LeSage & Pace (2009), a scalar summary approach, which measures the average direct impact from own region and the average indirect effect from neighbouring regions, may be more valid. This essay will follow the estimation method proposed by LeSage & Fischer (2008) and Elhorst (2014), and the empirical analysis will report direct effects, indirect effects (spatial spillover effects) and total effects (the summation of direct effects and indirect effects) for the response of regional dairy yields to intensive inputs.

3.2.1 Empirical Models

For comparison purposes, I have four empirical regression models: the non-spatial pooled linear model with no fixed effects in the form of Equation 3.1, the one-way SDM with time fixed effects included, the one-way SDM with spatial fixed effects included, and the two-way SDM with time and spatial specific effects included (the following three models are in the form of Equation 3.2).

Following the specifications of Elhorst (2014), a non-spatial pooled linear regression model, shown in Equation 3.1 in a panel setting, can be extended to an SDM as shown in Equation 3.2. Here, spatial interaction effects of the SDM are presented as a spatially lagged endogenous variable and exogenous independent variables, and the fixed effects include both spatial fixed effects and time fixed effects.

(3.1) $$Y_t = \alpha\iota_n + X_t\beta + \varepsilon_t$$

(3.2) $$Y_t = \lambda WY_t + \alpha\iota_n + X_t\beta + WX_t\theta + \mu(optional) + \delta_t(optional) + \varepsilon_t$$

Here, $Y_t = \left(y_{1,t}, y_{2,t}, \ldots, y_{n,t}\right)$ is the $n \times 1$ vector of the dependent variable representing the dairy yield for all regions in period $t\left(t = 1, \ldots, T\right)$; and WY_t is the spatially lagged term representing the values of dependent variables in neighbouring observations, where $W = (w_{ij}; i, j = 1, \ldots, n)$ is a $n \times n$ positive spatial weights matrix and each spatial weight w_{ij} reflects connections for the corresponding observations *i* and *j* according to either boundary or distance (LeSage & Pace, 2009). Due to an incomplete coverage of the NZ regions included in this essay, I consider a distance-based weights matrix instead of boundary-based matrix. I employ an inversed distance weights matrix, as shown in Equation 2.8 in Chapter 2, to keep the weight matrix simple (LeSage, 2014). The threshold distance chosen is 92 km indicating travel distance among regions according to comparing indicators of goodness of fit, such as R^2, of models with a distance radius ranging from 50 km to 120 km; λ is the corresponding spatial parameter of the interaction effect; $\alpha\iota_n$ is the constant term, with an $n \times 1$ unit vector ι_n associated with the parameter α to be estimated; and X_t denotes an $n \times k$ vector of exogenous variables, describing its own characteristics, associated with an $n \times k$ coefficient vector β to be estimated. Accordingly, WX_t denotes the neighbouring region's characteristics, with θ as the unknown coefficient parameter; $\mu = (\mu_1, \mu_2, ..., \mu_n)$ and δ_t represents the spatial specific and time-period effects, respectively, and ε_t is an error term (i.i.d.) with zero mean and variance σ^2.

In addition, considering trade-offs between the quantity of chemical fertiliser applied and the area of irrigated effluent, I allow for interactive terms between fertiliser application and effluent use by centring these variables. In other words, effects of chemical fertiliser application on dairy yields depend on the level of effluent sprayed over effective areas, and vice versa. For example, the interactive term for nitrogen fertiliser (N) and effluent use (E) can be formulated from Equation 3.3 to Equation 3.5. In that way, the impact of nitrogen on dairy yields is interpreted given an average level of effluent application (i.e. the average level has a score of 0 on the centred effluent variable), and vice versa. The interactive terms between the other three chemical fertiliser variables, i.e. phosphorus, potassium, and lime (P, K, L), and effluent use are formed following the same process as for nitrogen and effluent.

(3.3) $$N_{centred} = N_i - \sum_{i=1}^{n} N_i$$

(3.4) $$E_{centred} = E_i - \sum_{i=1}^{n} E_i$$

(3.5) $$NE = N_{centred} \times E_{centred}$$

3.2.2 Model Selection

I follow three commonly used testing processes in the spatial econometric literature to verify that the two-way SDM best fits our data[12].

I firstly start with the benchmark model, a non-spatial pooled linear model shown in Equation 3.1, to test for two spatial interaction effects presented as a spatially lagged term of the dependent variable and a spatial autocorrelated error term by using both the Lagrange Multiplier (LM) test and the robust LM test (Anselin et al., 1996; Elhorst, 2014)[13]. This testing process is used to determine whether or not the benchmark model needs to include the two spatial interaction effects. Table 3.1 reports the estimation results of a non-spatial model to determine whether it should be extended to a spatial lag model or a spatial error model. When employing the LM tests, both the hypothesis of no spatially lagged term and no spatial autocorrelated error must be rejected at the 5 percent level of significance, regardless of the inclusion of spatial fixed effects and/ or time fixed effects. Similarly, when adopting the robust LM tests, the hypothesis of no spatially lagged term must be rejected at the 5 percent level of significance. Nevertheless, the hypothesis of no spatial error term cannot be rejected at the 5 percent level of significance, provided that no fixed effects, or either spatial fixed effects or time fixed effects are included.

[12] Except for the test processes listed below, this paper also uses Moran's I test, developed for cross-sectional data, to test for the existence of spatial autocorrelation in regional dairy yields for the year 2002, 2007 and 2012, respectively. Results of Moran's I test indicate the existence of spatial autocorrelation in the data, details of the results are presented in the Appendix.

[13] I take the base-10 Logarithms of both dependent and independent variables.

Table 3.1 LM and Robust LM Test for Panel Data Models without Spatial Interaction Effects

Explanatory variables	Pooled OLS	Time fixed effects	Spatial fixed effects	Spatial and time fixed effects
Spatial fixed effects	NO	YES	NO	YES
Time fixed effects	NO	NO	YES	YES
Log L	298.91	380.29	327.72	873.82
LM spatial lag	56.42 (p=0.021)	133.73 (p<0.012)	34.05 (p<0.032)	64.08 (p<0.018)
LM spatial error	134.1 (p=0.016)	213.28 (p=0.011)	74.65 (p=0.026)	47.29 (p=0.02)
Robust LM spatial lag	68.29 (p=0.036)	33.22 (p=0.02)	1.98 (p=0.038)	3.18 (p=0.022)
Robust LM spatial error	1.65 (p=0.056)	1.01 (p=0.089)	1.97 (p=0.051)	1.02 (p=0.062)

Except for testing for the two spatial interaction effects from the benchmark model, I can also start from the two-way SDM. By using the Wald test, I can verify the hypothesis whether it is proper to simplify the SDM to the SAR as well as the hypothesis whether the SDM can be simplified to the SEM. The Wald test for the spatially lagged term (64.08, p=0.018) indicates that the hypothesis that SDM can be simplified to the SAR must be rejected at the 5 percent significance. Additionally, the hypothesis of SDM can be simplified to the SEM must also be rejected at the 5 percent significance (47.29, p=0.02). These results confirm that both the SAR and SEM must be rejected in favour of the SDM.

Lastly, I test for the appropriateness of including fixed effects and determine which fixed effects (spatial fixed effects and/ or time fixed effects) should be included. I use

Hausman's specification test to test for the random effects model against the fixed effects model. The results (40.96, $p<0.01$) show that the random effects model must be rejected. Also, the likelihood ratio (LR) test on the two-way SDM is used to test for the null hypothesis that the spatial fixed effects are not jointly significant. The results (935.21, $p<0.05$) indicate that this hypothesis must be rejected. Similarly, the null hypothesis that the time fixed effects are not jointly significant must also be rejected (27.72, $p<0.05$). These further justify the inclusion of spatial fixed effects and time fixed effects for the SDM specification. The above test results point to use the SDM with two-way fixed effects that is called the two-way SDM.

3.3 Data

Data used in this essay come from three main sources, the agricultural production census (Statistics NZ), dairy statistics (DairyNZ), and the national climate database (the National Institute of Water and Atmospheric Research (NIWA)). I utilize 2002, 2007 and 2012 data from fifty-five NZ regional authorities. Statistics NZ ran a full agricultural production census in 2002, 2007 and 2012, which is consistent with the data obtained from DairyNZ. The annual climate data of the year 2002, 2007 and 2012 is from the combined statistics calculated from regional observation stations by NIWA.

Fifty-five out of sixty-seven regions are included in the analysis due to information being incomplete for the other eleven territories. In this essay, I use kilogram milk solids per hectare (kg MS/ ha) to measure dairy yields, i.e. the dependent variable. Kg MS/ ha is the most commonly used variable in empirical studies of dairy production (e.g. Ledgard et al., 2004; Jay & Meorad, 2007; Basset-Mens, Ledgard & Boyes, 2009;

Bryant et al., 2010). Variables representing regional intensive farming inputs are average stocking rate, fertiliser use (including nitrogen, phosphorus, lime, and potassium) and effluent use[14]. Theses independent variables are also measured per hectare corresponding to the dependent variable. In addition, except for regional intensive input variables, I also include two commonly used climate variables, which are annual (total) rainfall and average soil moisture (December to February). To some extent, these two variables may control for regional climate variation, particularly the average soil moisture in summer season that may capture the impact of summer drought on dairy yields[15]. Descriptions and descriptive statistics of the variables are shown in Table 3.2 and Table 3.3, respectively.

[14] Although labour and machinery are important inputs to dairy yields, there are no territorial level data on those indicators. Thus, this study does not include these as explanatory variables.

[15] Note that I intend to use climate variables to control for regional climate variance, but do not declare that the results reflect the effects of climate change on regional dairy yields in NZ.

Table 3.2 Descriptions of Variables

Variable name	Descriptions	Data Source
Dairy yields (Y)	kilogram milksolids per hectare (kg MS/ ha)	DairyNZ
Nitrogen fertiliser (N)	Total urea use and all other nitrogen containing fertilisers (tonnes/ ha).	Statistics NZ
Phosphorus fertiliser (P)	Total phosphatic fertiliser, diammonium phosphate and ammonium sulphate (tonnes/ ha).	Statistics NZ
Lime (L)	Total lime use (tonnes/ ha).	Statistics NZ
Potassic fertiliser (K)	Total potassic fertiliser (tonnes/ ha).	Statistics NZ
Effluent use (E)	Areas sprayed by effluent over total effective farm areas (percentage).	Statistics NZ
Average stocking rate (SR)	Regional average number of peak cows milked divided by effective areas.	DairyNZ
Annual rainfall (RF)	Annual (total) rainfall (millimetres).	NIWA
Average soil moisture (SM)	Average soil moisture in summer season (%).	NIWA

Table 3.3 Descriptive Statistics of Variables

Variable name	Counts	Min.	Max.	Mean	S.D.
Y	165	496	1436	918.50	176.20
N	165	0.01	0.78	0.45	0.43
P	165	0.006	16.46	0.58	0.61
L	165	0.009	4.08	0.63	0.59
K	165	0.001	3.27	0.36	0.33
E	165	0.05	1	0.28	0.22
SR	165	1.89	3.56	2.71	0.32
RF	165	335.30	6715.40	1364.33	1284.54
SM	165	6.43	51.23	24.34	10.69

3.3.2 Visualization of Dairy Production and Intensive Farming

Maps are used to visualize the spatial distribution of regional dairy yields and some intensive inputs[16]. Figure 3.3 is the map of dairy yields distribution coloured according to kg MS/ ha of fifty-five New Zealand territorial authorities, where the darker colour represents higher production. Similarly, in Figure 3.4, Figures 3.5 and Figure 3.6, the average stocking rate, nitrogen and effluent use mapped with the darker colour stands for higher level of intensive inputs, respectively.

[16] In the maps, the regional dairy yields and intensive inputs are the average of those in the year 2002, 2007 and 2012.

Figure 3.3 Average Dairy Yields

Figure 3.4 Average Stocking Rates

Figure 3.5 Average Nitrogen Use

Figure 3.6 Average Effluent Use

The maps illustrate the following facts. Firstly, there is a significant variation in dairy yields. Regions with low dairy production are in the far north, the east coast of the North Island, and the west coast of the South Island, while regions with high production are in the central and the south area of the North Island and the east coast of the South Island. Additionally, a spatially clustered pattern can be observed. For example, dairy yields in the far north show a low-low clustered pattern while those in the central and southern areas show a high-high clustered pattern. Thirdly, comparing the shade of colours in Figures 3.4-3.6 with that in Figure 3.3, a similar spatial distribution can be clearly discerned. To some degree, the spatial distribution of regional stocking rates shows a pattern most similar to regional dairy yields, which might indicate a highly correlated relationship between regional dairy yields and stocking rates. However, for the other two intensive inputs, differences can be discerned with regard to dairy yields. For example, nitrogen use at an average level is in the northern areas of the North Island, even though the dairy yields are low; effluent use in the south-east areas of the North Island is low given high levels of dairy production. Lastly, dairy yields are characterized by differences between South Island and North Island. It can be observed that the average regional dairy yield in the South Island is higher than that in the North Island, which might be considered as a consequence of land use practices and intensive inputs.

These observations indicate that spatial variance exists in regional dairy yields and intensive farming inputs. The obvious spatial patterns shown in the maps further confirm to use spatial econometric methods to analyse the data used in this essay.

3.4 Results and Discussions

3.4.1 Coefficient Estimation Results

Although I have already verified that the two-way SDM specification best suits the data, I list coefficient estimation results of the four empirical models for comparison purposes. As shown in Table 3.4, the pooled model (the non-spatial model) results are estimated using OLS and the other three spatial models are all regressed using maximum likelihood estimation.

Table 3.4 shows that the two-way SDM outperforms the other models in terms of R^2 (0.96), adjusted R^2 (0.89), and log-likelihood value (425.24), which is consistent with the test results shown in section 3.2.2 for model selection. The spatial autoregressive parameter λ is statistically significant in all three spatial models, which implies the existence of spatial dependence in regional dairy yields. Also, differences between the coefficient estimates of the pooled OLS and the two-way SDM are obvious. For example, the sign of nitrogen use in the non-spatial model is not as expected and opposite to those of the spatial models. All these indicate that ignoring spatial interaction effects can result in biased estimates and lead to inaccurate interpretations of the relationship between dairy yields and intensive inputs.

Table 3.4 Coefficient Estimation Results for Regional Dairy Yields Response to Intensive Inputs

Explanatory variables	Pooled OLS	One-way SDM (time fixed effects)	One-way SDM (spatial fixed effects)	Two-way SDM (spatial and time fixed effects)
Intercept	1.91*** (11.08)	-	-	-
N	-3.60e-02** (-2.35)	1.68e-01 (1.18)	2.75e-01* (1.71)	3.09e-01* (2.08)
P	4.67e-03 (4.28e-01)	1.96e-02* (1.86)	6.58e-02*** (4.04)	8.04e-02*** (4.12)
L	2.09e-02 (1.29)	1.49e-02 (9.31e-01)	3.59e-02 (1.12)	3.58e-02 (1.21)
K	-9.05e-03 (-8.79e-01)	-1.59e-02 (-1.45)	3.40e-02*** (2.73e-02)	2.81e-02** (2.17)
E	3.45e-01*** (3.09)	4.09e-01*** (3.53)	5.83e-01*** (3.33)	6.21e-01*** (3.49)
SR	1.29e-01*** (15.58)	1.07*** (11.55)	9.97e-01*** (5.34)	9.95e-01** (5.31)
NE	-1.09e-01*** (-4.66)	-1.04e-01** (-4.83)	-1.47e-01*** (-6.51)	-1.45e-01*** (-6.35)
PE	-9.01e-03 (-4.25e-01)	-5.55e-03 (-2.71e-02)	-5.17e-02** (-2.19)	-5.07e-02** (-2.16)
LE	-7.23e-02** (-3.05)	-6.71e-02*** (-3.21)	-1.09e-02*** (-3.04)	-1.11e-02*** (-3.08)
KE	-4.34e-02*** (-2.79)	-3.09-02** (-2.23)	-1.95e-02 (-1.07e-01)	-1.41e-02 (-2.22e-01)
RF	6.31e-02 (1.53)	2.28e-03 (5.13e-01)	1.76e-02 (2.44e-01)	1.29e-02 (2.22e-01)
SM	2.03e-02*** (2.76)	3.23e-02*** (2.38)	3.91e-02* (1.98)	3.27e-02** (2.34)

Table 3.4 Coefficient Estimation Results for Regional Dairy Yields Response to Intensive Inputs (continued)

W*N		2.15e-01	3.04e-02*	2.85e-02*
		(1.05)	(1.76)	(1.83)
W*P		5.21e-02**	2.79e-02*	2.87e-02**
		(3.19)	(1.91)	(1.96)
W*L		3.05e-02	1.09e-02	1.39e-02
		(1.15)	(4.05e-01)	(4.67e-01)
W*K		2.93e-02	1.86e-02	2.20e-02
		(1.49)	(1.04)	(1.22)
W*E		2.98e-02*	6.21e-02	3.95e-02**
		(1.69)	(3.65e-01)	(2.67)
W*SR		5.47e-01	1.71e-01	1.62e-01*
		(7.43e-01)	(1.34)	(1.89)
W*NE		-2.02e-02	-4.45e-02	-4.75e-02
		(-3.85e-01)	(-2.27e-01)	(-8.90e-01)
W* PE		-3.89e-02	-3.76e-02	-3.92e-02
		(-1.32)	(-1.42)	(-1.37)
W*LE		-1.73e-02	-1.82e-02	-1.79e-02
		(-8.12e-01)	(-9.63e-01)	(-6.23e-01)
W*KE		-1.93e-02	-4.09e-02***	-4.21e-02**
		(-1.32)	(-3.01)	(-2.18)
W*RF		1.88e-02	1.66e-02	1.59e-02
		(1.49e-01)	(1.58e-01)	(1.43e-01)
W*SM		2.16e-02*	1.72e-02*	1.91e-02*
		(1.72)	(1.81)	(1.98)
Lambda	-	4.08e-01***	2.23e-01*	3.78e-01**
		(4.01)	(1.91)	(3.01)
R^2	0.87	0.89	0.95	0.96
Adjusted R^2	0.81	0.83	0.87	0.89
Log L	312.91	353.81	432.22	439.93

Source: author's elaboration based on Matlab software; '***', '**', '*' indicate coefficients that are significant at 1%, 5% and 10%, respectively; figures in parentheses represent t-values.

3.4.2 Effects Estimation and Interpretation

To investigate magnitude of the differences between the non-spatial model and the two-way SDM, one can compare coefficient estimates of the pooled OLS in Table 3.4 to those of the effects estimated in Table 3.5. Significantly, it is invalid to compare coefficient estimates in the non-spatial model with their counterparts in the two-way SDM in Table 3.4. That is because the parameter estimates in the non-spatial model represent the marginal effect of a change in intensive inputs on dairy yields, but the coefficients in the SDM do not (the reason has already been detailed in section 2.2.2, chapter two). Fortunately, I can use effects estimation of the two-way SDM to explore the marginal effect of a change in intensive inputs on regional dairy yields. The direct and indirect effects are derived using the methods of LeSage and Pace (2009). Results of the effects estimation are reported in Table 3.5.

Direct effects measure the own impacts of intensive inputs and own regional characteristics on one region's dairy yield, and the indirect effects measure the neighbouring impacts on dairy yield of this region. Thus, if I interpret the coefficients estimation results from the pooled OLS model, I will draw incorrect conclusions. For example, I will mistakenly conclude that higher nitrogen use could lead to lower regional dairy yields given an average effluent use. Another example is that, though obtaining the same sign for effluent use, I would underestimate its impact by about 0.6 percent (comparing the coefficient of effluent in the pooled OLS in Table 3.4 and the total effect of effluent use in Table 3.5). The difference is due to inaccurate coefficient estimations of the pooled OLS as well as the omission of spatial spillover effects.

Table 3.5 Direct, Indirect and Total Effects Estimates Based on the Coefficient Estimates of the Two-Way SDM Model Reported in Table 3.4

Explanatory variables	Direct effects	Indirect effects	Total effects
N	3.10e-01*	2.89e-01*	5.99e-01**
	(2.11)	(1.89)	(2.74)
P	8.63e-02***	2.93e-02**	1.16e-01***
	(3.96)	(1.99)	(3.83)
L	3.89e-02	1.32e-02	5.21e-02
	(1.27)	(6.72e-01)	(5.70e-01)
K	2.61e-02**	2.32e-02	4.93e-02
	(2.51)	(1.13)	(1.39)
E	6.34e-01***	3.49e-01*	9.83e-01**
	(3.58)	(2.81)	(2.90)
SR	9.96e-01***	1.92e-01**	1.19**
	(5.03)	(2.89)	(4.14)
NE	-1.35e-01***	-4.42e-02	-1.97e-01**
	(-5.90)	(-8.68e-01)	(-3.19)
PE	-5.52e-02***	-4.94e-02**	-1.05e-01*
	(-3.58)	(-3.23)	(-2.35)
LE	-1.21e-02*	-4.81e-02	-6.02e-02*
	(-2.68)	(6.16e-01)	(-2.06)
KE	-1.40e-02	-4.09e-02*	-5.49e-02*
	(-2.87e-01)	(-1.12)	(-2.61)
RF	1.42e-02	2.09e-02	3.51e-02
	(1.02)	(2.43e-01)	(5.13e-01)
SM	3.53e-02***	2.11e-02**	5.64e-02**
	(2.62)	(2.31)	(2.38)

Source: author's elaboration based on Matlab software; '***', '**', '*' indicate coefficients that are significant at 0%, 1% and 5%, respectively; figures in parentheses represent t-values.

According to results of the effects estimation presented in Table 3.5, I firstly look at the impacts of intensive inputs on dairy yields. Total effects of most of the intensive input variables are positive and statistically significant. Furthermore, there are also significantly positive spillover effects of the intensive input variables across regions, except for lime and potassic fertiliser. These imply that regional dairy yields highly depend on intensive inputs, and spatial dependence exists in regional intensive dairy farming. Specifically, among all the intensive input variables, stocking rate has the greatest influence on regional dairy production, with regional dairy yields increase 1.2 percent in response to 1 percent increase in stocking rate.

The interpretation of the magnitude of chemical fertiliser use should be considered together with the interactive terms between fertiliser and effluent use. For nitrogen and phosphorus use, direct, indirect and total effects of the two fertilisers are all positive and statistically significant given an average level of effluent use (*E* equals 0). In particular, the total effect of nitrogen on dairy yields increases by 0.6 percent for a 1 percentage increase in nitrogen use, where the total effect can be decomposed to 0.3 percent direct effect and 0.3 percent indirect effect. And associated with a 1 percentage increase in the use of phosphorus fertiliser, there is a 0.11 percent total effect on dairy yields, coming from a positive direct effect (0.8 percent) and a positive indirect effect (0.3 percent). However, when the proportion of effluent irrigation areas increases, I find that the positive response of yields to either nitrogen or phosphorus turns out to be negative, considering the negative interactive terms (*NE* and *PE*). Meanwhile, regional dairy yields increase by about 1 percent for 1 percent increase in effluent irrigation areas, given the average level of nitrogen and phosphorus use. Similarly, when either nitrogen or phosphorus use is increased, the results show that the response of dairy yields to effluent use are negative due to the negative interactive term (*NE* and *PE*). These can be interpreted as trade-offs between nitrogen and effluent use and trade-offs between phosphorus and effluent use, indicating that there is no need to apply as much as nitrogen and phosphorus when effluent use can achieve the expected level of dairy yields.

There is no spatial spillover effect associated with potassic fertiliser use on dairy yields; regional dairy yields increase by 0.3 percent due to a 1 percent increase in own region use. None of the three effects (direct, indirect and total effects) are statistically significant for lime use. According to the results, there is no influence of regional rainfall on dairy yields, indicating that total annual rainfall may not explain the variance of regional dairy yields. This is because dairy yields vary with changes in seasonal rainfall patterns to a large extent (García-Ispierto et al., 2007). Both the direct and indirect impacts of soil moisture on dairy yields are statistically significant. Specifically, with 1 percent rise in the average soil moisture in summer, regional dairy yields are expected to increase by 0.06 percent, with 0.04 percent direct effect and 0.02 percent spillover effect.

3.4.3 Effects Estimation for North Island and South Island

Bearing in mind that land area, climate, and development status differ in the North Island and South Island, the impacts of different intensive inputs on dairy yields may also vary (Tables of the descriptive statistics of variables for the North Island and South Island can be found in the Appendix). Thus, I present and compare effects estimation results for the North Island and South Island and observe whether the variation exists.

Table 3.6 and Table 3.7 show direct, indirect and total effects estimation for the North Island and South Island, respectively.

Table 3.6 Direct, Indirect and Total Effects Estimation-North Island

Explanatory variables	Direct effects	Indirect effects	Total effects
N	3.09e-01*	1.99e-01*	5.09e-01**
	(2.23)	(2.01)	(2.74)
P	7.31e-02***	2.37e-02**	9.68e-02***
	(3.62)	(1.99)	(3.73)
L	3.23e-02	1.31e-02	4.54e-02
	(1.07)	(5.22e-01)	(4.01e-01)
K	2.11e-02*	1.76e-02	3.87e-02
	(2.23)	(1.03)	(1.39)
E	6.28e-01***	3.21e-01*	9.49e-01**
	(3.81)	(2.81)	(2.90)
SR	9.99e-01***	1.98e-01**	1.18**
	(5.22)	(2.89)	(5.11)
NE	-1.33e-01***	-4.22e-02	-1.75e-01**
	(-5.92)	(-7.28e-01)	(-3.19)
PE	-4.98e-02***	-4.74e-02**	-9.72e-01*
	(-3.62)	(-3.03)	(-2.51)
LE	-1.11e-02*	-5.12e-02	-6.23e-02*
	(-2.28)	(-8.16e-01)	(-2.11)
KE	-1.40e-02	-4.09e-02*	-5.49e-02*
	(-2.87e-01)	(-1.12)	(-2.61)
RF	1.41e-02	2.09e-02	3.50e-02
	(1.00)	(2.48e-01)	(5.15e-01)
SM	3.46e-02***	2.09e-02**	5.55e-02**
	(2.63)	(2.32)	(2.38)

Source: author's elaboration based on Matlab software; '***', '**', '*' indicate coefficients that are significant at 0%, 1% and 5%, respectively; figures in parentheses represent t-values.

Table 3.7 Direct, Indirect and Total Effects Estimation-South Island

Explanatory variables	Direct effects	Indirect effects	Total effects
N	4.67e-01*	3.09e-01*	7.67e-01**
	(2.31)	(1.92)	(2.89)
P	9.38e-02***	3.01e-02**	1.24e-01***
	(3.96)	(1.99)	(3.83)
L	4.89e-02	1.28e-02	6.17e-02
	(1.07)	(4.22e-01)	(5.70e-01)
K	3.25e-02***	1.21e-02	4.46e-02
	(3.51)	(1.13)	(1.29)
E	8.13e-01***	4.91e-01*	1.30e-01**
	(4.16)	(2.83)	(2.90)
SR	9.99e-01***	2.02e-01**	1.21**
	(6.21)	(3.01)	(3.14)
NE	-1.01e-01***	-3.13e-02	-1.14e-01**
	(-4.86)	(-7.21e-01)	(-3.19)
PE	-5.42e-02	-3.24e-02**	-8.66e-02*
	(-3.18)	(-3.43)	(-2.37)
LE	-1.12e-02*	-5.81e-02	-6.93e-02*
	(-2.48)	(8.22e-01)	(-2.06)
KE	-1.78e-02	-3.45e-02*	-5.23e-02*
	(-3.87e-01)	(-1.35)	(-2.61)
RF	2.09e-02	1.12e-02	4.21e-02
	(1.07)	(4.35e-01)	(5.13e-01)
SM	4.34e-02***	2.11e-02**	6.45e-02**
	(3.09)	(2.52)	(2.38)

Source: author’s elaboration based on Matlab software; ‘***’, ‘**’, ‘*’ indicate coefficients that are significant at 0%, 1% and 5%, respectively; figures in parentheses represent t-values.

Comparing Table 3.6 and Table 3.7 to Table 3.5, the estimation results present consistency. It can be observed that either the signs or the level of statistical significance show a similar trend as those in Table 3.5. Likewise, ups and downs of the magnitudes of the effects are not significant, around 0.1 to 0.3 percent. Except for lime and potassic fertiliser, total effects of the intensive input variables are positive and statistically significant for both North Island and South Island. Similarly, for all the intensive input variables, stocking rate still has a great impact on regional dairy production, no matter for North Island or South Island, with regional dairy yields increase about 1.2 percent in response to 1 percent increase in stocking rate. Trade-offs exist between nitrogen, phosphorus use and effluent use in both North Island and South Island.

However, although not significant, differences can be observed from the results shown in Table 3.6 and Table 3.7. Intensive inputs, including nitrogen, phosphorus and effluent use, seem to be more influential to regional dairy yields in North Island than those in South Island. This finding is consistent with Jiang (2011), results of which indicate that dairy farming in South Island is associated with higher fertiliser elasticity. Given an average level of effluent use, regional dairy yields increase by 0.5 percent in North Island but 0.7 percent in South Island in regard to 1 percent increase in nitrogen use. In the same way, increases in the use of phosphorus contribute more to the increase in dairy yields in South Island, of about 0.3 percent. Given an average level of chemical fertiliser use, 1 percent increase in effluent use leads to 0.95 percent increase in milk production in North Island. Significantly, the same amount of increase in effluent use contributes to about 1.3 percent increase in dairy production in South Island. However, this estimate might be overestimated due to the lack of data on technology. As indicated by Jiang (2011) farming technology in South Island is more technologically advanced compared to that in North Island. Lastly, regional dairy yields in North Island are more dependent on stocking rate, with about 1.2 percent increase in dairy yield in response to 1 percent increase in stocking rate.

3.5 Summary

In essay one, I analysed the response of regional dairy yields to intensive farming inputs spatially in New Zealand. Regional dairy yields are characterized by substantial differences in regard to intensive inputs including chemical fertiliser use, stocking rates, effluent use and regional climate factors. To avoid biased estimates, I applied spatial panel data models to the data and compared the results to those obtained from the non-spatial model. The results clearly show that all the three spatial panel data models (the one-way SDM with time fixed effects, the one-way SDM with spatial fixed effects and the two-way SDM) perform better than the non-spatial model for the analysis of the relationship between regional dairy yields and intensive inputs. Ignoring spatial interaction effects among regions can provide misleading estimates of the impacts of intensive inputs on regional dairy yields. The results also show that there are significant spatial spillover effects associated with dairy yield, nitrogen use, effluent use and stocking rate. Moreover, South Island dairy farming gets more in return through increasing intensive inputs.

This essay leads to several conclusions for policy, as well. To begin with, I find significant spatial spillover effects on regional dairy yields regarding some intensive inputs. This indicates that although the regional governments might have different policies and regulations, spatial dependence exists between neighbouring regions. From a national perspective, to reduce nutrient pollution, results of this essay indicate that policy makers should take into account interactive influence between neighbouring regions. Consequently, political decisions may not only affect the region to which they are targeted but also neighbouring regions. This calls for political cooperation between different regional authorities. In addition, the significant and positive impacts of intensive inputs, especially stocking rate, indicate a close relationship between dairy yields and intensification of dairy farming. This reminds policy makers to consider the balance between the pursuit of dairy production and pollution regulation, as intensive inputs are significant factors for achieving higher dairy yields. Fortunately, however, results of the essay indicate trade-offs between the use of chemical fertilisers and effluent use. Considering the trade-off, the high level of effluent use and estimated negative yield response to nitrogen and phosphorus suggests that an opportunity exists for greater use of effluent as a substitute for chemical fertilisers. This, from a regional level, verifies the conclusion of Matthew, Horne & Baker (2010), who found out that a change in effluent disposal management could offset nitrogen loss and increases environmental efficiency at the individual farm level. Particularly, in South Island, the use of effluent can provides an alternative source to keep soil fertile and offer irrigation water for dairy pasture. Thus, it is wise for regional governments to highlight the trade-off in the policy making process, as rational utilization of effluent may help dairy farmers to save money on chemical fertilisers and help the dairy industry to better maintain its international competitive advantage.

The existence of spatial dependence in farmer choice of good management practices may lead to positive spillovers of good management practices from one region to another region. Furthermore, understanding the determinants of farmer choice associated with different mitigation practices may promote positive regional spillovers. Thus, in the following chapter, essay two will extend the exploration of spatial spillover effects from the regional level to farm-level, and investigate the impacts of spatial spillover effects on farmers' adoption of good management practices for water protection.

CHAPTER 4. Essay Two: Spatial Dependence and Determinants of Dairy Farmers' Adoption of Best Management Practices for Water Protection

4.1 Introduction

4.1.1 Background

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

Therefore, the dairy industry is under increasing pressure to make a commitment to improving the environmental performance of farming practices to protect water quality in waterways. Among all the good practices, keeping stock out of waterways and riparian planting are regarded as the most direct and efficient practices for the NZ dairy farmers. The former avoids direct pollution of cow dung and urine to waterways, and the latter assists by filtering cow dung and slowing the flow of effluent and chemical fertilisers to waterways. In 2013, the dairy industry agreed to set a new voluntary project called "sustainable dairying: Water Accord" (the new Accord) to support the sustainable development of the NZ's economy (Dairy NZ, n.d.a)[17]. Compared to the old Accord, the new Accord continues to focus on protecting water quality in waterways but with broader and more stringent requirements. Previously, dairy farmers were required to have stock excluded from waterways that are "deeper than a red band gumboot (ankle deep), wider than a stride, and permanently flowing" (the Ministry for Primary Industries, 2013). It set a target that 90 percent exclusion of stock from waterways be met by 31st May 2012, but only 87 percent exclusion was achieved (the

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

Ministry for Primary Industries, 2013). The new Accord, however, has clearly defined waterways as “rivers, streams, drains and springs over one metre wide and 30 centimetres deep that permanently contain water, all lakes, and wetlands”. The new Accord target is set at 100 percent exclusion of stock from waterways by 31st May 2017. Moreover, farmers are expected to prepare riparian planting plans to adopt to protect water quality (Dairy NZ, n.d.a).

Under the new Accord, dairy farmers have greater responsibilities to comply with Best Management Practices (BMPs) to meet the new targets for sustainable growth. Hence, farmer’s choice behaviour should be considered as one of the most important determinants of the success of policy aimed at water quality protection. In this way, farmers may face a significant challenge of balancing profitability and the cost of adopting BMPs. However, the main focus of water quality protection has been on the public’s opinion on the impacts of dairy farming on water quality. Studies have paid attentions to either the public’s perception of environmental degradation due to unsustainable agricultural practices or the NZ residents’ willingness to pay for water quality protection (e.g. Tait et al., 2011; Marsh, Mkwara & Scarpa, 2011; Hughey, Kerr & Cullen, 2013). However, it is equally important to explore the issues associated with water quality degradation from the perspective of dairy farmers and to understand what factors influence farmers’ decisions as to their compliance with water protection requirements. Failing to understand this may make it difficult to reach the new Accord targets by the expected date.

To explore reasons for farmers’ adoption and non-adoption of BMPs, literature on this question provides insights into a number of determinants (Knowler & Bradshaw, 2007).

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

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

Therefore, the aim of this essay is to explore determinants of dairy farmers' willingness to adopt BMPs for water quality protection. In addition, except for testing the commonly used determinants, such as farm characteristics, it will test the hypothesis that spatial effects influence farmers' choices. Bayesian spatial Durbin probit models are applied to sample survey data in the Waikato region of NZ. Specifically, this essay will verify the above hypothesis from two aspects. Firstly, spatial effects will be modelled according to the distance from the farm to the nearest water bodies. It is assumed that dairy farmers whose farms are located close to water bodies are more inclined to be willing to adopt BMPs. Secondly, spatial effects will be presented as the existence of spatial interdependency in dairy farmers' decision-making. It is hypothesised that dairy farmers observe or learn from nearby farmers thereby reducing the uncertainty of the performance of BMPs since BMPs are information-intensive farming techniques (Läppl & Kelley, 2015).

4.1.2 Structure of Essay Two

This essay is structured as follows. Relevant literature is reviewed in section 4.2. Section 4.3 details the econometric models, including a basic probit model of farmer choice and a spatial Durbin probit model of farmer choice with spatial spillover effects considered. Section 4.4 describes empirical models and data. Section 4.5 presents results and discussions. Conclusions are presented in section 4.6.

4.2 Literature Review

An abundance of studies use qualitative research methods based on interviews to explore factors affecting farmers' willingness to adopt best (good) environmental practices or participate in agri-environmental programs[18]. These studies propose the following determinants are worthy of attention. Firstly, it is proposed that farmers' cognitions or perceptions of given environmental policies or management practices are decisive factors to implement programs on BMPs successfully (Schoon & Te Grotenhuis, 2000; Moon & Cocklin, 2011; Blackstock et al., 2010). Likewise, it is believed that farmers hold various goals that lead to different motivations to take part in agri-environmental programs (Fairweather, 1999; Bergevoet et al., 2004;). Also, farmers' attitude–behaviour differences are associated with the heterogeneity of

[18] The terms "good management practices" and "best management practices", referring to management practices used on farm to protect the environment, are interchangeably used in studies. For simplicity purpose, the abbreviation BMPs will be used to represent either good management practices or best management practices.

socioeconomic attributes. In addition, factor analysis and segmentation analysis were usually combined with interviews in some studies. Result of these studies revealed that heterogeneous farm characteristics affect farmers' decision-making differently (e.g. Farmar-Bowers & Lane, 2009, Zalidis et al., 2004; Prager & Nagel, 2008; Wilson, Harper & Darling, 2013).

In short, qualitative studies, to some extent, provide an intuition for understanding the relationship between farmer's choice behaviour and farmer's willingness to adopt best BMPs. Moreover, these studies agree that policies should focus on farmer's attitudes, values, cognitions, and the decision-making process. Hence, conclusions of these studies may be of significance for re-estimating environmental protection programs and shed light on future policy making. Nevertheless, the conclusions are usually limited by the research methods because almost all the above studies used a limited number of interviews with farmers, which greatly restricted the size of the research population and limited the generalizability of the results.

Choice modelling analysis is another commonly used method in the literature on farmers' adoption of BMPs or participation in agri-environmental programs. In choice modelling studies, heterogeneity of farmer choice can be demonstrated by estimating farmers' utility functions according to farm and household characteristics and other attributes (Haile & Slangen, 2009). A number of empirical studies have illustrated that farm and household characteristics, the quantity of production, policy changes, as well as farmers' perceptions of given programs, all contributed to the uptake of BMPs (e.g. Rahelizatovo & Gillespie, 2004; Hassan & Nhemachena, 2008; Kurkalova & Wade, 2013). Nevertheless, despite offering valuable insights into the factors that influence the adoption of BMPs, the above studies ignore spatial dependence that is important for farmers' adoption decisions.

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

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

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

This essay contributes to the literature in the following aspects. First, it contributes to the empirical literature on the determinants of farmer's adoption of BMPs in NZ by using spatial econometric analysis methods, which considers various determinants, including drivers and barriers for farmers to adopt BMPs, farm and household characteristics as well as spatial issues[19]. Significantly, dairy farms are geographically located. Thus, spatial effects are presented as the distance from the farm to the nearest water bodies and neighbourhood effect, which is measured according to spatial relationships among dairy farms. Secondly, direct impacts (from own characteristics) and indirect impacts (from neighbours' characteristics) will be captured because I

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

examine the determinants of adoption by using a spatial Durbin probit model that allows for the inclusion of direct and indirect effects of each independent variable on the probability of adoption.

4.3 Econometric Models

4.3.1 Modelling Framework

This essay assumes that dairy farmers make decisions on the adoption BMPs according to the difference in utility derived from the adoption and non-adoption of BMPs. Thus, for the i^{th} farmer, the difference in utility is constructed by $y_i^* = U_{1i} - U_{0i}$, where U_{1i} and U_{0i} is the utility associated with observed 1 (to adopt BMPs) and 0 (not to adopt BMPs) indicators. y_i^* is an $n \times 1$ latent variable that cannot be observed, and $y_i(0,1)$ denotes the binary outcome variable that can be observed and expressed in Equation 4.1:

$$\begin{cases} y_i = 1, \ if \ y_i^* \geq 0 \\ y_i = 0, \ if \ y_i^* < 0 \end{cases} \tag{4.1}$$

According to a traditional choice model, y_i^* is assumed as a function of the observed decision-making characteristics and farm characteristics. These characteristics are denoted by an $n \times k$ matrix X_i. Figure 4.1 shows the modelling framework of farmers' decision-making (on adoption/ non-adoption) under the circumstance of a standard choice modelling context, and the extension of farmer choice in a spatial context. Here, the terms in blue rectangles represent unobservable variables, while those in orange boxes represent observable variables. The relationships between y_i^*, y_i and X_i in a standard choice model are depicted in the upper portion of Figure 4.1.

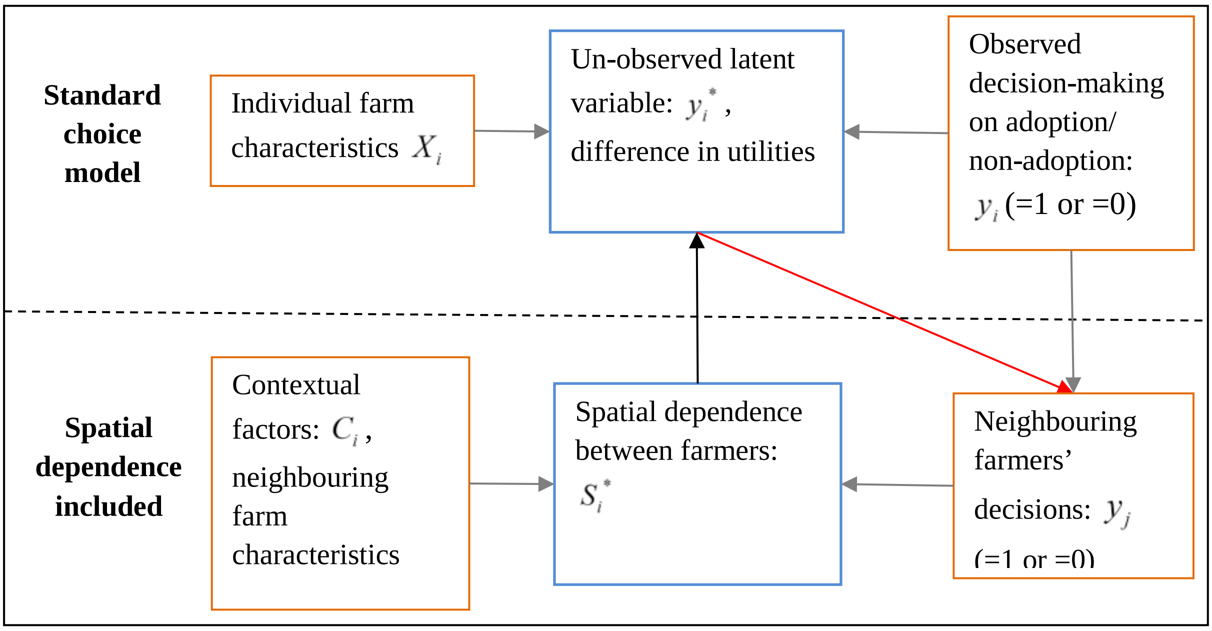

Figure 4.1 Modelling Framework of Farmers' Decision-making

The interpretation of the relationships between y_i^*, y_i and X_i depend on utility maximization that the i^{th} farmer chooses to adopt BMPs when:

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

Therefore, as illustrated in the upper part of Figure 4.1, the relationships can be regressed on the basis of Equation 4.3, in a non-spatial choice model.

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

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

The lower portion of Figure 4.1 describes the contextual factors (also known as contextual effects in the sociological literature), i.e. characteristics of neighbouring farms, and spatial spillover effects from neighbouring farmers' decisions. In other words, y_i^* depends on the own farm and household characteristics as well as on the spatial dependence between the farmer and his/ her neighbours. Then, y_i^* can be constructed as:

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

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

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

Here, Z_k denotes the vector of the exogenous characteristics of the group *k* or in the area *k* to which farm *i* belongs, and $y_j(i)$ denotes the vector of decisions of his/ her neighbours ($i \neq j$). Notably, when the spatial dependence is included, the decisions of farmer *i's* neighbours influence his/ her decision that, in return, affects the decisions of the neighbours. It is called the feedback effect, as shown in red arrow in Figure 4.1.

4.3.2 Spatial Durbin Probit Model

As illustrated in the previous section, this essay uses a spatial Durbin probit model (SDM probit model) to analyse how interdependence in farmers' decisions contributes to their adoption of BMPs. The SDM probit model was designed by LeSage and Pace (2009) to include spatial dependence that takes the form shown in Equation 4.6.

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

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

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

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

In this essay, the SDM probit model is regressed by using the Bayesian Markov Chain Monte Carlo (MCMC) estimation, and a detailed description of the estimation procedure for the model is provided in LeSage and Pace (2009) and LeSage (2014). Regarding the choice of the most appropriate spatial weights matrix, several models with different thresholds d are run and compared using posterior model probability (LeSage and Pace, 2009). The range of the threshold values is from 1.5 km to 4 km (in intervals of 0.5 km), which is chosen on the basis of the distance band calculation in Arc GIS 10.2. This range is consistent with previous studies, such as van Meijl & van Tongeren (1998) and Srinivasan, Shankar & Holloway (2002) who indicate a reasonable radius for technology spillover is 2 to 3 km in rural areas. The model with the highest posterior probability with a threshold value of 1.5 km is the preferred model fitting the data best (results will be shown in section 4.5.1).

4.4 Data

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

In addition to farmers' adoption and non-adoption choices, dairy farmers also gave answers on what motivates them to adopt BMPs and what prevents them from implementing BMPs. Hence, drivers and barriers associated with the adoption choices are grouped to form categorical variables considered as explanatory variables in this essay. There are three main drivers, including self-initiated, access to industry information (such as access to the advice of experts, access to the knowledge of BMPs, and access to local government plans for BMPs), and other motivations. Also, there are three main barriers, including financial problems (such as capital shortage and high expenditures), lack of information, and personal reasons and others. Other explanatory variables include farm and household characteristics. The survey data on farm characteristics included farm size, farm contour and participation in dairy-related social activities. Unfortunately, the survey did not cover household characteristics, which are regarded as important factors affecting farmers' decision-making. Meshblock data from the NZ 2013 census are used for the purpose of capturing household characteristics. Although the meshblock data cannot completely describe the variance of the individual (farm-level) data, 141 counts are collected from the meshblock data[20]. The 171 farms are located in rural areas instead of city blocks in the Waikato region. Thus, it is not a perfect but acceptable alternative to represent household characteristics. Three types of spatial variables are also included as explanatory variables: the lagged dependent variable Wy_i^*, the lagged explanatory variables WX_i (shown in Equation 4.6), and the distance from the farm to the nearest water bodies, which are calculated in Arc GIS 10.2 using the coordinates of the 171 dairy farms[21]. A detailed description of all the explanatory variables is shown in Table 4.1. Accordingly, the expected signs of the coefficients associated with the variables are also given in the third column of Table 4.1. Where it is a priori difficult to set the expected sign of coefficients, "+ or –" and "– or +" are used. However, the preference for the signs is offered given the orders. For example, DR1, "+ or –" indicates self-motivated farmers are more likely to adopt BMPs compared to farmers who find other reasons as the primary motivation to adopt BMPs.

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

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

Statistics descriptions of the dependent and explanatory variables are presented in Table 4.2.

Table 4.1 Descriptions of Variables

Explanatory variables	**Descriptions**	**Expected signs**
Drivers for adopting BMPs (DR)	Categorical variables: DR1: self-initiated, coded as 1. DR2: industry information, coded as 2. DR3: others, coded as 3 (set as the base).	 + or - + or -
Barriers to adopting BMPs (BA)	Categorical variables: BA1: financial problems, coded as 1. BA2: lack of information, coded as 2. BA3: personal reasons and others, coded as 3 (set as the base).	 - or + - or +
Farm size	Effective areas of dairy farms (hectares).	+
Farm contour	Percentage of flat areas over total farm areas.	-
Social activities	The number of dairy-related activities, such as discussion group and field days that farmers participated in the past year (2012).	+
Distance	The distance from the dairy farm to the nearest water bodies (km). To control for the non-linear relationship between distance and the farmer's adoption of BMPs, the distance is natural log transformed in the empirical analysis.	-
Staff training	Binary variable=1, if there are staffs who have been trained or are being trained toward BMPs.	+
Income (Proximity)	The median income of people (in 1000 dollar), who are greater than 16, in meshblocks.	+
Age (Proximity)	The average age of people, who are greater than 16, in meshblocks.	-
Education level (Proximity)	Education level, which is the proportion of people (who are greater than 16) educated at and over level 5, in meshblocks.	+

Table 4.2 Statistics Descriptions of Variables

Variable name	Min.	Max.	Mean	SD.
Dependent variable	0	1	0.41	0.49
DR1	0	1	0.24	0.35
DR2	0	1	0.39	0.49
DR3	0	1	0.37	0.48
BA1	0	1	0.51	0.39
BA2	0	1	0.28	0.45
BA3	0	1	0.21	0.41
Farm Size	25	874	169.63	122.88
Farm Contour	0	100	38.94	33.25
Social event	0	33	4.83	7.10
Distance	0.55	11.10	3.93	2.44
Staff training	0	1	0.46	0.34
Income	36700	125000	82833.13	18678.13
Age	17.5	57.2	36.10	7.84
Education	0	0.46	0.24	0.12

4.5 Results and Discussions

4.5.1 Model Comparison and Coefficient Estimation

As discussed in section 4.3.2, an SDM probit model with a 1.5 km threshold *d* is chosen as the preferred model due to the highest posterior model probability. Table 4.3 presents results of the posterior model probabilities comparing alternative SDM probit models with threshold values ranging from 1 km to 4 km (in intervals of 0.5 km). The results indicate that spatial spillover effects are assumed to be zero beyond the 1.5 km threshold distance. Comparing parameters across different model specifications, it is observed that as *d* increased, and thus increasingly distant farmers included into the neighborhood, the parameter λ in relation to the spatially lagged dependent variable decreases in statistical significance and magnitude.

Table 4.3 Comparison of Models with Different Threshold Values

Threshold values	Model probability	The coefficient values of λ
$d = 1$	0.467	0.389 ($p = 0.011$)
$d = 1.5$	0.621	0.412 ($p = 0.021$)
$d = 2$	0.214	0.121 ($p = 0.051$)
$d = 2.5$	0.098	0.098 ($p = 0.064$)
$d = 3$	0.0842	0.088 ($p = 0.095$)
$d = 3.5$	0.0594	0.046 ($p = 0.112$)
$d = 4$	0.0623	0.048 ($p = 0.123$)

The comparison of different spatial model specifications is given in Table 4.4. Similarly, the posterior model probabilities of the spatial autoregressive (SAR) probit model, spatial error (SEM) probit model, the spatial lag of *X* (SLX) probit model and the SDM probit are compared, with a threshold value of 1.5 km. Model specifications of the other three spatial models are shown in section 2.2, Chapter 2.

Table 4.4 Comparison of Spatial Models

Spatial models	Model probability
The SAR probit model	0.513
The SEM probit model	0.414
The SLX probit model	0.398
The SDM probit model	0.621

The coefficient estimates for the parameters β, λ, and γ in the preferred SDM probit model are shown in Table 4.5. It is noted that λ is statistically significant at the 1 percent level indicating the existence of spatial dependence in the adoption of BMPs among dairy farmers. Moreover, the positive sign of λ implies that a dairy farmer is more likely to adopt if his/ her neighbours are also BMPs adopters. Furthermore, most of the explanatory variables are statistically significant at different statistically significant levels (1 percent, 5 percent and 10 percent level as shown in the fourth column in Table 4.5), and the signs of the coefficients are as expected in Table 4.1.

Table 4.5 Coefficient Estimates of the SDM Probit Model

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

Although the statistical inference of magnitudes of the explanatory variables cannot be made according to the coefficient estimates shown in Table 4.5, expectations on the signs of the coefficients, which is made in Table 4.1 in the previous section, can be verified. With respect to the drivers to adopt BMPs, the results in Table 4.5 show, as expected, that self-motivated farmers and those who get access to industry information, including access to the advice of specialist and knowledge of regional council plans, are more likely to adopt BMPs. Regarding the barriers, financial problems and difficulty to get information decrease the likelihood of BMPs adoption. In line with these findings, the positive sign of the social activities variable indicates that participating in dairy-related activities seem to be another way that farmers gain access to information on BMPs.

Different farm characteristics have different impacts on the adoption of BMPs. Farmers operating bigger farms in terms of farm area are more likely to adopt BMPs, while farmers whose farms have flat contour tend not to adopt BMPs. Staff training is a positive indicator of BMPs adapter. According to the negative sign of the distance variable, the distance decay effect exists in the adoption of BMPs.

All three household characteristics, except for median income, have a significant effect on the choice to adopt BMPs. As expected, younger farmers are more likely to adopt BMPs, and farmers with higher education are more likely to adopt BMPs. This accords with intuition as new technologies are often more readily adopted by younger farmers. Likewise, educated farmers might pay more attention to the environmental impacts of unsustainable dairy farming and be willing to adopt good practices for water protection.

Lastly, most of the spatially lagged independent variables are statistically significant, indicating that a farmer's adoption of BMPs is affected by his/ her neighbours' characteristics. Discussions on magnitudes of the effects of the explanatory variables on the adoption of BMPs are detailed in the following section.

4.5.2 Effects Estimation

In the non-spatial probit model, marginal effects are estimated at the mean for continuous variables and for a change from zero to one for dummy variables. The SDM probit model, however, accounts for both direct and indirect effects (LeSage, 2014). The direct effects represent the impact of a change in the explanatory variables of farmer *i* on the adoption probability of farmer *i*, and the indirect effects (spatial spillovers) express the cumulative effect of a change in the explanatory variables of neighbouring farms on the adoption probability of farmer *i*. The indirect effects come from the interdependence in decision-making among farmers, i.e., a change in the independent variable has an effect on farmer *j's* probability to adopt BMPs and thereby also on farmer *i's* probability to adopt. To what extent changes in the neighbourhood influence the adoption probability of farmer *i* depends on the spatial proximity defined by the spatial weights matrix. The total effect of an explanatory variable is thus the sum of its direct effect and its indirect effect (LeSage and Pace, 2009).

Table 4.6 shows the marginal effect estimates, including direct, indirect and total effects as well as Bayesian 95 percent credible intervals for total effect estimates. The results show that for all explanatory variables, direct effects are about 1.5 times larger than the indirect effects, on average. According to magnitudes of the total effects, the most influential determinants are access to industry information (in the category of drivers), financial problems (in the category of barriers), participation in dairy related social activities, and staff training.

Table 4.6 Direct, Indirect and Total Effects Estimates of the SDM Probit Model

Variable	Direct effects	Indirect effects	Total effects
DR1: self-initiated	0.123	0.082	0.205 [0.005, 0.405]
DR2: industry information	0.223	0.041	0.264 [0.236, 0.702]
BA1: financial problems	-0.367	-0.098	-0.465 [-0.585, -0.345]
BA2: lack of information	-0.049	-0.017	-0.066 [-0.089, -0.043]
Farm size	0.062	0.031	0.093 [0.001, 0.185]
Farm contour	-0.014	-0.009	-0.023 [-0.053, 0.007]
Social activities	0.313	0.021	0.334 [0.114, 0.554]
Log Distance	-4.42	-1.95	-6.37 [-8.18, -4.16]
Staff training	0.173	0.115	0.288 [0.101, 0.475]
Income	0.004	0.002	0.006 [-0.002, 0.014]
Age	-0.041	-0.019	-0.06 [-0.08, -0.04]
Education level	0.016	0.010	0.027 [0.015, 0.039]

Source: author's elaboration based on Matlab software.

Driver and Barrier Variables:

Among all the drivers, access to industry information is regarded as the most important determinant of dairy farmers' adoption of BMPs. Compared to farmers choosing other motivations, farmers, who regard access to industry information as the most important driver, are 26.4 percent more likely to adopt BMPs. The 26.4 percent total effects can be further broken down to 22.3 percent direct effects and 4.1 percent indirect effects. This finding is consistent with results of previous studies on technology adoption as information exchange between neighbours is an important determinant of technology diffusion (e.g. Bandiera & Rasul, 2006; Case, 1992; Wollni & Andersson, 2014). Likewise, self-motivated farmers' adoption probability increases by 20.5 percent, with about 8 percent coming from the spillovers of self-motivated neighbours.

Relative to personal and other reasons, financial problems, such as capital shortage and high expenditures, seem to be the biggest obstacle that prevents dairy farmers from adopting BMPs. Farmers who have financial difficulties are 46.5 percent less possible to adopt BMPs, and about 9.8 percent is from impacts of the neighbouring farmers who are also constrained by their budget. Although less influential, lack of information could also decrease farmers' adoption probability by 6.6 percent.

Farm Characteristic Variables:

Among all the farm characteristics, staff training and participation in social activities that are related to dairy farming, such as discussion groups and workshops, are important determinants of farmers' decision-making on the adoption of BMPs. A farmer's adoption likelihood increases by 33.4 percent in total when he/ she participated in one more social activities in the previous year. This finding indicates that farmers may exchange experience and knowledge on BMPs in these social activities. Being an alternative channel for information acquisition, participating in social events provides opportunities for dairy farmers to reduce the risk of adoption by learning from people they meet at social events. Staff training is also a positive indicator of a farmer's adoption of BMPs. A farmer, whose staff have been trained or are being trained to master BMPs, is 28.8 percent more likely to adopt BMPs. Part of the increase in the probability, about 40 percent (indirect effects divided by total effect), is because the farmers' neighbours are also keen to train staff on the merits of BMPs.

The impacts of the physical characteristics of farms, including farm size and farm contour, are less significant compared to the above variables. The likelihood of a farmer's adoption choice rises by 9.3 percent with an increase of one hectare of the effective farm area, but it decreases with an increase in one percent of flat areas over total farm areas. A possible reason to explain the positive response of farmer's adoption choice to farm area is that large farms demand better management. Thus, fencing stocks off waterways may be seen as one of the good management practices either to protect water quality or to prevent the lost of livestock. In addition, farmers may focus on soil-water conservation, and thus, concern more about sustainable development of their farms, if most of their farm land is rolling or steep.

As expected, the hypothesis that farmers who live closer to water bodies tend to be more willing to adopt BMPs to protect water quality cannot be neglected. Here, with one-kilometer increase in the distance from a farm to the nearest water bodies, the probability of the farmer's adoption of BMPs decreases by about 6.4 percent. This finding confirms the existence of distance decay effect of farmers' demands for clean waterways.

Household Characteristic Variables

Higher education level and median income have positive impacts on farmers' adoption of BMPs. In particular, education level has the greatest impact. With a 1 percent increase in education level, a farmer located in the meshblock is 2.7 percent more likely to adopt BMPs. The adoption probability only increases by 0.6 percent with a rise in $1000 in median income in the meshblock. On the contrary, the average age negatively affects the adoption of BMPs. 6 percent decrease is observed in the probability of adoption due to one year increase in age.

4.6 Summary

This essay uses a spatial Durbin probit model to empirically analyse spatial dependence and determinants of dairy farmers' adoption of BMPs. Data used in this essay were obtained from a survey of 171 farms in the Waikato region of New Zealand; socioeconomic data were drawn from the 2013 Census. The advantage of the SDM probit model is that it allows for the inclusion of both the spatially lagged dependent variable and spatially lagged independent variables, which takes account of impacts of the neighbouring farmers' decisions as well as neighbouring farmers' characteristics. Therefore, different from non-spatial probit models, the SDM probit model accounts for both direct and indirect effects. Significantly, the indirect effects (spatial spillovers) help to measure to what extent a change in the neighbouring farmers' characteristics affect the adoption probability of a dairy farmer. The statistically significant and positive parameter λ indicates that spatial spillover effects exist, and farmers are more likely to adopt BMPs if their neighbours are also adopters. Spatial spillover effects are also observed through impacts of the neighbouring farmers' characteristics. In addition, a farmer's willingness to adopt BMPs decay with the increase in the distance from the farm to the nearest water bodies.

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

Based on the results and findings presented in this essay, policy implications can be made as follows. To begin with, an understanding of dairy farmers' drivers and barriers to adopting BMPs could assist policy makers to focus on specific strategies and deliver support to solve problems that are badly in the need of help. For example, financial problems are regarded as the biggest obstacle for farmers to adopt BMPs in the empirical analysis, which is consistent with reality not only in the Waikato region but elsewhere of NZ. Thus, it is worthwhile for regional governments to figure out ways of reducing the cost of dairy farmers to adopt BMPs, such as offering free channels for information acquisition, which could significantly reduce the uncertainty of adoption BMPs. Also, the importance of information availability in the neighbourhood network and social activities suggests that policies and strategies that address the whole community may be more efficient than targeting individual farmers to induce behavioural changes in adopting BMPs. Joint neighbourhood initiatives are also most appropriate to address the positive externalities of sustainable management practices. Although individual farmers could not internalize the full benefits of the adoption of BMPs and, therefore, incline to delay adoption, integrated activities in one community can help to overcome such problems of collective action. Assuming all farmers in a neighbourhood commit to implementing mitigation practices against water pollution, individuals do not have to fear that neighbouring farmers may free ride on their investments into BMPs. Lastly, the existence of a distance decay effect in dairy farmers' adoption of BMPs provides a different point of view of education as a vehicle for regional governments to use in the promotion of BMPs. That is, during the education and promotion process, instead of treating dairy farmers as polluters, they could also be seen as individuals who also demand good water quality for recreation purposes. Stimulating dairy farmers' desire for clean waterways may encourage them to re-evaluate their farming practices and adjust to the requirements of sustainable dairy farming.

Social interactions among farmers can be captured through both geographical distances and social network connections among farmers. Thus, in the next chapter, essay three will extend the exploration of social interactions among farmers from spatial interactions to social network interactions. Furthermore, it will investigate how social interactions among farmers affect environmental performance.

CHAPTER 5. Essay Three: Social Interaction Effects on the Relationship between Dairy Farmers' Environmental Performance and Nutrient Management Practices

5.1 Introduction

5.1.1 Background

Sustainable development of the NZ dairy industry needs active participation by dairy farmers in best management practices and policy support. The current decline in international dairy price has impacted profitability of the NZ dairy industry. Dairy farmers also face the challenge of maintaining high productivity and minimizing environmental pollution due to intensive farming activities. Thus, farmers have to use intensive inputs efficiently to control cost and avoid adverse environmental impacts. Indeed, the National Policy Statement for Freshwater Management (NPS), which was issued in 2011 by the NZ government, requires all regional councils to set quality limits on all water bodies within their regions by December 2030[22] (Ministry for the Environment, 2011). This regulation indicates that nutrient loss to water, predominantly nitrate leaching and phosphate loss, needs to be better managed to protect water quality. Consequently, a drive can be expected for dairy farmers to improve their nutrient management practices (NMPs) to meet imminent regulations.

Nevertheless, due to the uncertainty of economic and environmental performance associated with changes in management plans, dairy farmers may be cautiously hesitant when it comes to the implementation of NMPs. This is because attempts to improve NMPs and reduce nutrient loss might have an adverse impact on production or profitability. Currently, most of the NZ dairy farmers manage their nutrient plans and budgets on OVERSEER®, which produces both production and environmental indices to help assess whether productive or environmental outcomes are being met. OVERSEER® is seen as a reliable tool applied nationally because it reduces unnecessary cost associated with implementing NMPs[23].

OVERSEER® estimates nutrient loss to water based on the assumption of best practices, where any change or transition of on-farm management practice does not reduce the nutrient loss predicted by OVERSEER®. For example, OVERSEER® considers fencing

[22] In this statement a water body refers to anything that holds water, whether water is: still, such as lake, wetland, on-farm dam, pond; flowing, such as stream, creek, river; manmade, such as drain; intermittent only holds water in wet periods or over the winter; and underground/ sub-surface, e.g. aquifer (Ministry for the Environment, 2011).

[23] Overseer® was developed in New Zealand for NZ farming systems in the early 1990s, firstly named Overseer, and has since undergone repeated revisions to improve the model as new science and knowledge is incorporated.

off waterways and wetland as effective methods to avoid nutrient loss to water (OVERSEER Management Services, 2015). Nevertheless, some management practices, such as fencing cattle out of puddles on farm at any time, do not count as valid method to achieve best environmental performance in OVERSEER®. For a given farm system, OVERSEER® estimates the long-term annual average outputs, assuming the farm management system stays the same (Shepherd et al., 2013). For example, increasing soil test frequency helps farmers to understand soil conditions on farm, particularly during the year of extreme climate events such as floods or droughts. But it will not change the nutrient loss predicted by OVERSEER®. To a great extent, this might stop farmers from investing in some NMPs since they are uncertain about whether or not the investment in NMPs could improve their environmental performance. Therefore, it is important to investigate whether or not the nutrient loss estimated by OVERSEER® is relevant to dairy farmers' real NMPs.

Another non-ignorable factor, which may influence dairy farmers' environmental performance, is social interactions among dairy farmers. This can arise when dairy farmers' choices of NMPs are highly likely influenced by their peers' opinions. It is especially evident in a small community, where farmers know and meet with each other frequently. Although nutrient management issues are often invisible and difficult to monitor, farmers often have a 'fair idea' of what each other is doing (Ritchie, 2007). Besides, social networks, often established by fielddays and discussion groups, provides another source of ideas regarding nutrient management. Dairy farmers may exchange their experience in dairy farming with other farmers who take part in the same dairy groups. Furthermore, as proposed by Oreszczyn, Lane & Carr (2010), learning might occur during interaction activities among farmers. Consequently, whenever a dairy farmer is making a decision on NMPs, it is possible that the farmer may compare his/ her own environmental performance with that of his/ her peers' environmental performance. Hence, we may assume that dairy farmers share or learn from the experience in NMPs from other farmers.

This essay uses a spatial analysis method to explore the relationship between dairy farmers' environmental performance and their NMPs, to understand how social interaction effects influence this relationship, and to provide suggestions for the design of nutrient control policy. Specifically, the essay will address the following questions: how does environmental performance respond to dairy farmers' NMPs? To what extent, has one dairy farm's nutrient loss been influenced by the NMPs of its neighbouring farms[24]? And, whether spatial interactions or social network interactions have an impact on the relationship between nutrient loss and NMPs. I firstly adopt a spatial econometric model with typical spatial interaction effects as a point of departure and extend the model to include social network interactions among dairy farmers.

5.1.2 Framework

Figure 5.1 shows the framework for this essay. Dairy farmers' NMPs are represented by three categories, including six types of NMP variables on the upper left; four intensive inputs are shown on the upper right. Both may influence nutrient loss to water, which is the primary indicator to estimate the relationship between dairy farmers' environmental performance and farmers' own NMPs and intensive inputs. Notably, social interaction

[24] Neighbouring farms/ farmers in this essay refer to farms/ farmers that are geographically close and socially close.

effects are considered from both a spatial interaction and a social network perspective. Accordingly, a spatial weights matrix and adjacent weights matrix are used to create social effects variables as well as social autocorrelated error term, which will be specified in section 5.3, to model how environmental performance responds to their neighbours' NMPs and intensive inputs.

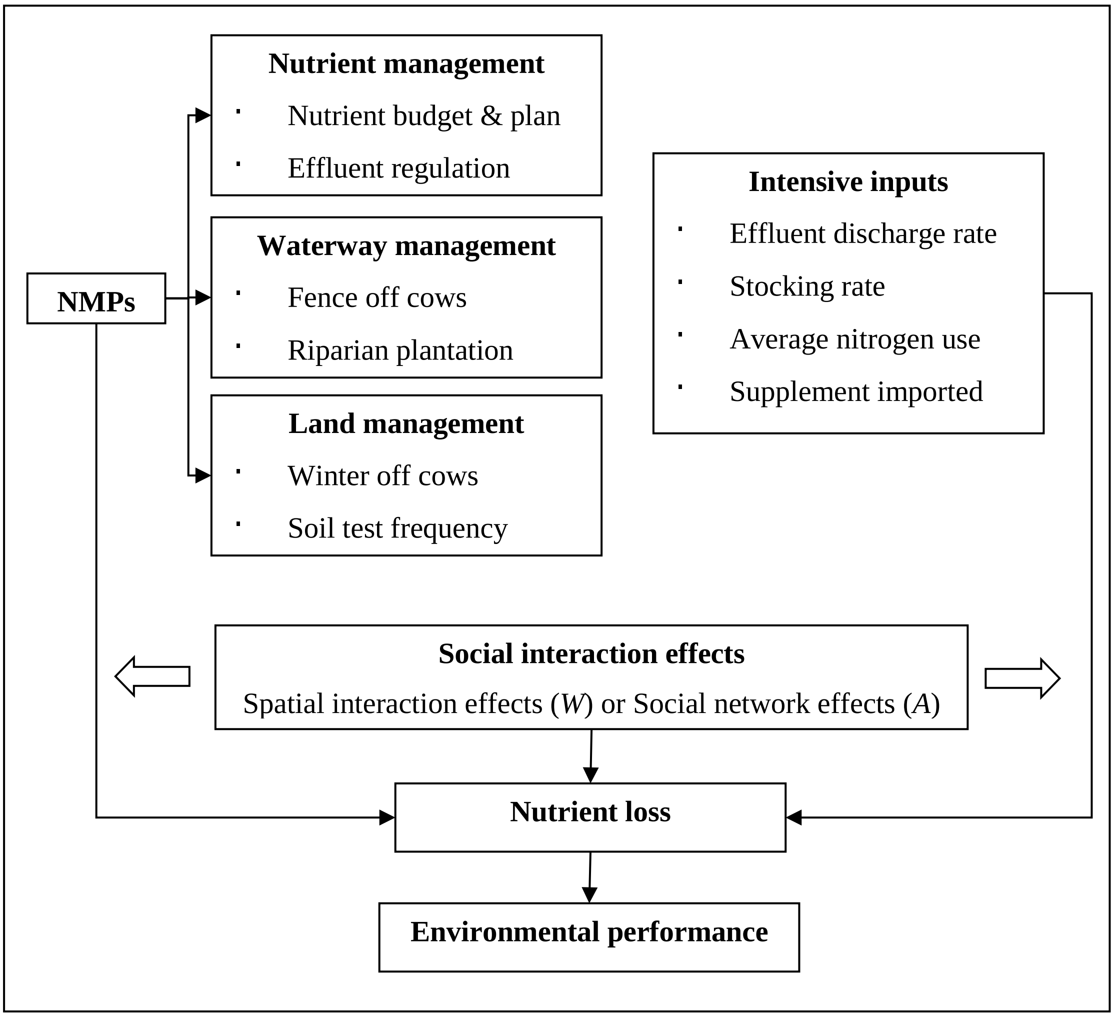

Figure 5.1 Framework for Essay Three

5.1.3 Structure of Essay Three

The remainder part of the essay is organized as follows. Relevant literature is reviewed in section 5.2. Section 5.3 describes the method of constructing a spatial weights matrix and adjacent weights matrix to model social interaction effects among dairy farmers and details the spatial econometric models. Section 5.4 describes the data and variables for empirical analysis. Section 5.5 presents results and discussions. Conclusions are presented in section 5.6.

5.2 Literature Review

There are two parts to this section. First, literature on the relationship between dairy farmers' environmental performance and NMPs, including the definition of environmental performance and different approaches applied in the analysis of the relationship is reviewed. The second part provides an overview of the literature on how social interaction effects influence farmers' decision-making and how social interaction effects can be used in the analysis of the relationship between dairy farmers' environmental performance and NMPs.

5.2.1 Environmental Performance

From an input-oriented perspective, good environmental performance implies the use of intensive inputs, such as nitrogen, to achieve a given level of output at low levels of nutrient pollution. One of the most commonly used indicators is nitrogen surplus, which is the difference between external nitrogen inputs and nitrogen contained in outputs (e.g. milk and meat). Nitrogen surplus is regarded as a good means of measuring resource use efficiency, where all the intensive inputs such as manure and nitrogenous fertiliser use are included as detrimental inputs (Reinhard, Lovell & Thijssen, 1999). Another traditional indicator is nitrogen conversion rate, which can be represented in different forms. Three commonly used forms include: (1) feed conversion rate = nitrogen in milk/ nitrogen consumed as feed by cows, (2) manure and fertiliser conversion rate = nitrogen uptake by crops and pasture/ manure and fertiliser use, and (3) whole-farm nitrogen conversion rate = sum of nitrogen exported off-farm/ sum of nitrogen imported to farm (Powell et al., 2010). These indicators provide insights into understanding nitrogen use efficiency by relating intensive inputs to desired nitrogen outputs. However, these indicators may not directly measure the impacts of intensive inputs on the environment.

Environmental efficiency indicators, from an output-oriented perspective, offer another means of evaluating dairy farmers' environmental performance. In the field of agricultural and environmental studies, scientists are interested in measuring or estimating the quantity of nutrient loss to water, and use these environmental indices to evaluate environmental performance. Thus, low nutrient pollution is related to good environmental performance. In contrast, an economic framework views off-farm practices as an external cost associated with milk production. Whether the external cost is sufficient to warrant policy interruption is, of course, an empirical matter. Specifically, research on the regulation of greenhouse gas emissions have used emission indicators to assess environmental performance. Here, the emission indicator is calculated by using greenhouse gas emissions divided by milk production (Zaim &

Taskin, 2000). A similar approach used a ratio of nitrate leaching to milk production as an indicator to compare environmental efficiency between different dairy farms (Ledgard et al. 2004). Therefore, a reduction in this ratio indicates a decrease in nitrate leaching per kilogram milk solids.

This essay uses the ratio of nitrate leaching to milk production to assess dairy farmers' environmental performance. This is mostly because the output-oriented perspective is regarded as the main measure to assess environmental performance in NZ, for both dairy farmers and regional councils. For example, to measure the reduction of nutrient pollution, farmers and regional governments primarily rely on estimations by OVERSEER®, which is output-oriented. Thus, the ratios can help to directly measure the adverse impacts of nutrient pollution on the environment as well as relate undesired products with milk production.

5.2.2 The Relationship between Environmental Performance and NMPs

Optimization and econometric methods are two main approaches used to analyse the relationship between dairy farmers' environmental performance and NMPs.

A number of studies have examined the connection between farmers' environmental performance and NMPs using optimization methods, where the abatement cost of pollution is estimated under the assumption of farm profit maximization (e.g. Bratt, 2002; Brady, 2003; Ekman, 2005). In New Zealand, most studies have used a cost-minimized framework to test for changes in nutrient loss or abatement cost under different policy scenarios. From this perspective, three main approaches have been developed to integrate farmer's environmental performance at a catchment level by using linear/ non-linear programming methods. One is to use the NZ Whole Farm Model and extensions of the model. For example, Ramilan et al. (2011) developed a hybrid model to simulate different impacts of nutrient control policies on nutrient loss at a catchment level. They have further derived the farm-level marginal abatement cost by considering three types of farm systems, which are labelled as extensive, moderate and intensive systems. They found that abatement costs for intensive farms are lower for moderate and extensive farming systems, and either a compulsory standard or threshold tax outperforms a standard emissions tax[25]. However, Doole (2012) and Holland & Doole (2014) have argued that the NZ Whole Farm Model ignored the heterogeneous characteristics of dairy farms. Thus, they have estimated the relationship between farm characteristics and abatement level under a differentiated policy, a uniform policy, and a thresholds policy[26]. Their conclusions have emphasized the need to consider heterogeneity among dairy farms, and the lowest abatement cost was achieved under the differentiated policy. Motu Economic and Public Policy Research focused on the application of nutrient trading prototype to control nutrient loss at Lake Taupo and the Lake Rotorua catchment. These studies have simulated groundwater lags for nutrient loss travelling to ground water, and shown the importance of considering a

[25] The three policies are: a compulsory standard sets standard tax on emissions; a threshold tax sets a tax on emissions above the allowable standard; a standard emission sets tax on the allowable level of emissions.

[26] The differentiated policy sets different abatement level for each farm; the uniform policy sets a uniform abatement level for every farm; and a thresholds policy set a same threshold for every farm.

time-frame in the analysis of farm-level environmental performance and NMPs [27] (McDonald & Kerr, 2011; Anastasiadis et al., 2011).

All the above studies used optimization methods to simulate farmers' environmental performance under different policy scenarios. Problem is, however, to aggregate up to catchment/ regional level, which assumes that catchment/ regional level is appropriate for considering environmental impacts, but NMP decisions are ideally related to farm-level decision-making. Moreover, simulations used in these studies may be indicative but may not reflect true relationships between environmental performance and farmers' NMP decisions.

Studies using econometric methods have focused on measuring the correlation between good management practices and nutrient input efficiency, such as nitrogenous fertiliser use and effluent use. Stochastic frontier analysis (SFA) and data envelopment analysis (DEA) have been used to measure technical efficiency or environmental efficiency by comparing the distance of the individual farms to the frontier (e.g. Reinhard, Lovell & Thijssen, 2000; Graham, 2004; Picazo-Tadeo, Gómez-Limón & Reig-Martínez, 2011). For example, De Koeijer et al. (2003) applied DEA to assess the relationship of nutrient management and nitrogen use efficiency in a sample of Dutch arable farms in Netherlands. Their results show a significant positive correlation between nutrient management practices and nitrogen use efficiency. Most of these studies have concluded that better farm management practices improve both economic and environmental efficiency. Meanwhile, some studies have found that good environment

[27] It is estimated that it would take at most 150-200 years for nutrient loss travelling to Lake Rotorua because of groundwater lags.

performance is negatively correlated with the increased use of nitrogen fertiliser or maize silage (e.g. Basset-Mens, Ledgard & Boyes, 2009; Cederberg & Mattsson, 2000).

The above studies illustrate the importance of relating NMPs and heterogeneous farm characteristics to environmental performance. They also suggest various nutrient abatement policies for different NMPs. However, they ignore the possibility that a dairy farmer's decision-making on NMPs is influenced not only by his/ her own judgement but also by his/ her neighbours' experience. Therefore, ignoring social interaction effects among dairy farmers may lead to inaccurate estimations on the relationship between environmental performance and farmers' NMPs.

5.2.3 Social Interaction Effects on Farmers' Decision-making

A small number of studies show the significance of considering social interactions among farmers in the analysis of farmers' decision-making. Rijswijk (2013) has reviewed four surveys undertaken by the Pasture Renewal Leadership Group (PRLG) among its members, dairy farmers, seed retailers and contractors. This study focused on the social interactions between respondent groups and explored how interactions among farmers influence their pasture renewal practices. It found that farmers' decision-making is influenced by the social interactions on the basis of their perceived credibility of the information sources. Small, Brown & Montes de Oca Munguia (2013) quantified farmers' social interactions according to the size of their social network, defined as the number of participation in dairy-related events. In this study, farmers participating in six or more farming activities in a year are regarded as socially connected to other farmers. They employed probit models to investigate social connections among farmers for various types of farmers, including sheep and beef farmers and dairy farmers. Notably, this research revealed that dairy farmers are significantly more connected by the means of their social networks than other farmers. These studies confirmed the necessity of modelling social interactions among farmers, but they did not indicated to what extent and how the social interaction effects influence dairy farmers' environmental performance.

Social interaction effects are usually modelled in terms of spatial interactive relationships and social network relationships among observations. Specifically, spatial interactions are constructed in the form of a spatial weights matrix to capture interactive relationships over observations in spatial econometric literature. Following Tobler's first law of Geography, close observations are more likely to be connected to each other than distant observations (Tobler, 1970). Thus, dairy farmers' NMPs may be influenced by neighbouring farmers. In contrast to interactions derived from geographical characteristics, some social science studies have stated that observations, which are economically similar, are more likely to have an influence on each other than those geographically related (Case, 1991). Notably, in economics studies, neighbouring interactive relationships have been extended to a broader definition, where social network relationships can also be seen as another form of spatial interaction. That is, instead of observing physical distance, interactions with respect to socioeconomic characteristics are measured and modelled by using "economic distance" or "social distance". For example, inverse trade share, inverse distance between GDP per capita, and migration flow information are typical indicators to model the interactive relationships between observed countries rather than modelling boundary connections among these countries. (Crabbé, 2013; Corrado & Fingleton, 2012). These studies have concluded that the inclusion of socioeconomic information in spatial analysis deepens the understanding of social interactive relationships among observations.

5.2.4 Contributions to Existing Literature

This essay contributes to the existing literature as follows. Firstly, for studies on the relationship between environmental performance/ nutrient loss and NMPs, it contributes to the literature on the application of spatial analysis methods to examine the correlates between nutrient loss and NMPs. Compared to studies using optimization simulation, survey data are used in this essay to reflect farmers' revealed-preference on NMPs, and its impact on their environmental performance. Social interactions among dairy farmers are considered as a way of reducing fixed cost of acquiring knowledge on NMPs. Additionally, this essay quantitatively models social interactions among dairy farmers according to spatial interactions and social network interactions. This gives insights into a different perspective on regulating nutrient loss, not only focusing on better NMPs in a geographical area but also promoting better nutrient management through different dairy-related social events or social groups. Neighbouring farms are not only referred as farms geographically close but also those belonging to the same social groups. In other words, in addition to model spatial interactions, this essay also considers modelling farmers' interactions through their participation in dairy groups and dairy-related activities. Hence, it indicates how the influence of geographically neighbouring farmers is different from the influence of socially neighbouring farmers on environmental performance.

5.3 Model Specifications

5.3.1 Modelling Social Interactions among Farmers

Dairy farmers' social interactions are modelled in two ways in this study. It firstly utilizes a spatial weights matrix to model social interactions among neighbouring farmers, according to geographical positions.

Spatial Interactions-Spatial Weights Matrix: I firstly construct an $n \times n$ spatial weights matrix $W = (w_{ij}; i, j = 1, \ldots, n)$, where each spatial weight w_{ij} captures the spatial interactive relationship of the corresponding farms i and j. It is noted that "self-influence" is excluded by assuming $w_{ij} = 0$ for all $i, j = 1, \ldots, n$. As stated in Chapter 2, the boundary-based and distance-based approaches are commonly used to construct the spatial weights matrix, where the former defines neighbours according to shared boundary among spatial units and the latter defines neighbours according to distance among spatial units.

The "best spatial weights matrix" should be selected with the consideration of requirements addressed in the research question, data size of the empirical analysis and comparison of the goodness of fit of models with different spatial weights matrixes. In reality, dairy farmers can directly observe other farmers' NMPs when they share a common boundary. Therefore, I assume that the boundary-based approach is appropriate to model spatial interactions among dairy farmers in this analysis. In addition, the best fitting spatial weights matrix is the rook contiguity weights matrix, which is chosen by comparing the goodness of fit of spatial models using different spatial weight matrixes. Comparison of the results are shown in Appendix.

It is straightforward to understand the spatial relationship between two spatial units through the expression of rook contiguity weights, where dairy farms share a positive portion of the boundary. As defined in Equation 5.1, l_{ij} denotes the length of shared boundary between farm i and j, when it is greater than zero they are neighbours to each other. I assume that farmer i could interact with farmer j more often than farmer i does with other distant farmers.

(5.1) $$w_{ij} = \begin{cases} 1, l_{ij} > 0 \\ 0, l_{ij} < 0 \end{cases}$$

Furthermore, this essay uses an adjacent weights matrix to model social interactions among farmers in terms of their participation in different dairy groups or dairy-related events. For simplicity, I will use dairy group(s) to represent both dairy groups and dairy-related events in the following part of this essay. Eleven kinds of dairy groups are included in this study. When participating in these dairy groups, dairy farmers are able to learn various knowledge on dairy farming as well as to share their experience with other farmers. Descriptions of these groups are listed as follows. (More details of the dairy groups can be found at http://www.dairynz.co.nz/events/).

- **Dairy Conference**, such as farmers' Forum and the Once-a-Day Milking Conference.
- **Farm system group** is designed for discussion of topics on farm systems.

- **Field day** is usually a one-day event where dairy farmers learn about up-to-date information on dairy-related technologies or progress of dairy programmes. Topics are various, including nutrient efficiency on farm and farm profit.
- **Focus Farm** is set up by a committee of farmers to demonstrate the profitability gains and sustainable development on different dairy farms. Meetings are usually held on focus farms.
- **Meeting** is similar to Field day. The difference is that this event may consist of a series of meetings, where farmers may have in-depth knowledge of given topics, such as a series of 7 meetings on the issue of healthy rivers.
- **Pasture plus** provides grazing decision makers with opportunities to discuss about their local areas and take advantage of the planning tools and advice.
- **Progression group** is for farmers who would like to enhance their business skills and career options.
- **Rapid response** is specified for discussion on issues which need timely response, such as dry conditions and emergency herd test.
- **Regional project meeting** is for dairy farmers participating in regional projects to meet and discuss about their experience on the project. They are also informed of achievements of the project by experts and staffs who are responsible for the project.
- **Specialist group** provides a forum for group members and guest speakers who have relevant experience on the given topic to discuss and share experiences.
- **Workshop** offers courses and discussions on various topics.

Social Network Interactions-Adjacent Weights Matrix: I use an $n \times n$ adjacent matrix $A = (a_{ij}; i, j = 1, \ldots, n)$ to model the social network connections obtained from participating in dairy groups between farmer i and j. It is also assumed that $a_{ij} = 0$ for all $i, j = 1, \dots, n$ to exclude "self-influence". As shown in Equation 5.2, it indicates farmer i and j are in the same dairy group g, when $a_{ij} = 1$; $a_{ij} = 0$, otherwise. Notably, the adjacent matrix used in this essay is undirected, meaning $a_{ij} = a_{ji}$. Thus, $a_{ij} = a_{ji} = 1$ means farmer i's decision-making is influenced by farmer j and vice versa.

(5.2) $$a_{ij} = \begin{cases} 1, if \ \ i \in g, j \in g \\ 0, if \ \ i \notin g, j \notin g \end{cases}$$

Furthermore, instead of using "1s" to model the undirected interactions among dairy farmers, I extend Equation 5.2 to Equation 5.3 so as to model the closeness among farmers within the same dairy group. In Equation 5.3, c ($c = 1, 2, ..., k$) represents the number of same groups to which both farm i and j belong, where a larger c indicates a closer relationship between farmer i and j.

(5.3) $$a_{ij} = \begin{cases} c, if \ \ i \in g_1, g_2, ..., g_k, j \in g_1, g_2, ..., g_k \\ 0, if \ \ i \notin g, j \notin g \end{cases}$$

For example, according to Equation 5.3, an adjacent weights matrix can be formed for a small social network with six farmers who participate in dairy groups. The social interactive relationship is modelled by the adjacent weights matrix shown in Equation 5.4. The "2" in row one column two indicates that farmer 1 and farmer 2 participate in two of the same dairy groups; the "1" in row two column three indicates that farmer 2 and farmer 3 participate in one of the same dairy groups; the "0" in row one column three indicates that farm 1 and farm 3 are not neighbours to each other, as they do not go to the same dairy group.

(5.4)
$$A = \begin{pmatrix} 0 & 2 & 0 \\ 2 & 0 & 1 \\ 0 & 1 & 0 \end{pmatrix}$$

5.3.2 Econometric Models

Nutrient loss to water is regarded as a by-product for dairy farms. I model the relationship between nutrient loss and NMPs using a Cobb-Douglas production function $Y = f(M, I)$, where nutrient loss Y varies with changes in intensive inputs I and NMPs M. According to the production function, the "contribution" of intensive inputs and NMPs to nutrient loss can be estimated using a linear regression model presented in Equation 5.5.

(5.5)
$$\ln(Y) = \alpha\iota + I\beta_1 + M\beta_2 + \varepsilon$$

The linear regression model can be extended to include social interaction effects among farmers by using a spatial analysis approach. A spatial Durbin error model (SDEM) is employed to explore the influence of social interaction effects on the relationship of farmers' environmental performance and NMPs[28]. Particularly, two empirical models are specified with a spatial weights matrix W shown in Equation 5.6 and an adjacent

[28] Explanations and test results for choosing different spatial models are presented in the Appendix.

weights matrix A shown in Equation 5.7, respectively. The SDEM models the spatial interaction effects (also known as spatial spillover effects) in two ways, i.e. the spatially lagged independent variables $WX\theta$ as in Equation 5.6 ($AX\theta$ as in Equation 5.7) and the spatial autocorrelated error term u. For simplicity, X is used to represent all independent variables, including NMPs M and intensive inputs I.

$$\begin{aligned} \ln(Y) &= \alpha\iota + X\beta + WX\theta + u \\ u &= \rho Wu + \varepsilon \end{aligned} \tag{5.6}$$

$$\begin{aligned} \ln(Y) &= \alpha\iota + X\beta + AX\theta + u \\ u &= \rho Au + \varepsilon \end{aligned} \tag{5.7}$$

Here, $Y = (y_1, y_2, \ldots, y_n)$ is an $n \times 1$ vector of the dependent variable representing dairy farmers' environmental performance (nitrate leaching/ kg MS); $\alpha\iota$ is the constant term, with an $n \times 1$ unit vector ι associated with the parameter α to be estimated; X denotes an $n \times k$ vector of independent variables, describing farmers' own intensive inputs and NMPs, associated with an $n \times k$ coefficient vector β to be estimated. Accordingly, WX (AX) denotes the neighbouring farmers' intensive inputs and NMPs, with θ as the unknown coefficient parameter; u is the spatial autocorrelated error term expressed with the spatial lag term Wu (Au). ρ is the corresponding spatial parameter of this interaction effect, and ε is an independently and identically distributed error term with zero mean and variance σ^2.

5.4 Data

The Waikato region is regarded as the heart of NZ's dairy industry. The majority of dairy herds (76%) are in the North Island, with the greatest concentration (30%) situated in the Waikato Region (DairyNZ, 2014). 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. Among all the projects, the Upper Waikato Sustainable Milk Project is the largest environmental good practice project ever undertaken by the dairy industry. With $685,000 co-funded by DairyNZ, 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 (2012-2015), to control nutrient loss going into the Waikato River as well as to improve water use efficiency on farm (DairyNZ, n.d.b). Farmers voluntarily made commitments to adopting mitigation practices at the start of the project. Follow-ups are made by face to face interviews and questionnaires to see if farmers have completed their commitments.

The data used in this essay come from the Upper Waikato Sustainable Milk Project. There are 163 observations in the data, including environmental performance, NMPs, and intensive inputs. The NMPs data are from 163 questionnaires randomly collected from the face to face interviews in 2014, and it is coded to form NMP variables. In the questionnaires, dairy farmers gave answers about their NMPs from several aspects, including nutrient management, land management and waterways management. I choose six NMP variables to present dairy farmers' NMPs considering the usability of the questionnaires and the advice offered by experts from DairyNZ. Environmental performance data (the nitrate leaching to water) are from the 2012-2013 estimation by OVERSEER®. Data on intensive inputs were abstracted from DairyNZ.

5.4.1 Variables

The dependent variable describes dairy farmers' environmental performance, which is the nitrate leaching to water (kg/ ha) divided by per kg MS per hectare per year[29]. The independent variables include the NMP variables, intensive input variables and social interaction variables.

All the NMP variables are categorical variables that describe NMPs from three aspects, including nutrient management, land management and waterways management. In particular, nutrient management includes variables on nutrient budgets & nutrient plans and variables on effluent management; land management includes variables on wintering off cows and variables on soil test frequency; waterways management includes variables on fencing off cows from waterways and variables on riparian planting. Here, waterways is defined according to the statement of NPS that waterways are not only limited to rivers, streams, drains and springs over one metre wide and 30 centimeters deep that permanently contain water, all lakes, and wetlands, but also referred to any wet areas that may cause nutrient pollution.

In accordance with the NMPs sorted from the 163 questionnaires, four intensive inputs

[29] For simplicity, nitrate leaching will be used to substitute the nitrate leaching to water per kg MS per hectare per year in the following parts of the essay.

are included, which are regarded as the most influential factors contributing to nitrate leaching. These variables are nitrogenous fertiliser use, effluent discharge rate, stocking rate and imported supplements. The above variables represent dairy farmer’s own NMPs and intensive inputs, while social interaction variables denote the weighted average neighbouring farmers’ NMPs and intensive inputs. Taking stocking rate as an example, S*stocking rate, as one of the social interaction variables, presents the average stocking rate of neighbouring farms. S represents social interactions among dairy farmers, which has been specified in section 5.3.1. Detailed explanations of all variables are presented in Table 5.1, and statistic descriptions of NMPs and intensive inputs are reported in Table 5.2.

Table 5.1 Descriptions of Variables

Variable name	Descriptions
The dependent variable (Nitrate leaching)	Nitrate leaching to water per kg MS per hectare per year, which is calculated by nitrate leaching (kg/ ha/ yr) divided by MS (kg/ ha/ yr).
NMP variables	**Six types of NMPs (Categorical variable)**
Nutrient budgets & plans (NU)	NU1, have neither had an up to date nutrient budget nor completed a nutrient management plan, coded as 1 (set as base). NU2, have either an up to date nutrient budget or has already completed a nutrient management plan, coded as 2. NU3, have not only had an up to date nutrient budget but also have already completed a nutrient management plan, coded as 3.
Winter off cows (WIFF)	WIFF1, no cows wintered off, coded as 1 (set as base). WIFF2, a part of cows wintered off, coded as 2. WIFF3, all cows wintered off, coded as 3.
Soil test frequency (ST)	ST1, soil test frequency is more than two years, coded as 1 (set as base). ST2, soil test frequency is between 1 year and two years, coded as 2. ST3, the frequency is less or equal to 1 year, coded as 3.
Waterways management (WW)	WW1, no waterways fenced, coded as 1 (set as base). WW2, parts of the significant waterways fenced, coded as 2. WW3, all significant waterways fenced, coded as 2.
Riparian plant (RP)	RP1, no riparian plant plan, coded as 1 (set as base). RP2, having riparian plant plan, coded as 2.
Effluent management (EM)	EM1, the limit of effluent discharge (150 kg N/ ha/ yr) is not satisfied, coded as 1 (set as base). EM2, the limit is satisfied, coded as 1.

Table 5.1 Descriptions of Variables (continued)

Intensive input variables	**Four intensive input variables**
Effluent discharges rate (EFF)	Farm effluent irrigation areas (hectares)/ effective areas (hectares).
Stocking rate (SR)	Peak cow numbers/ effective areas.
Average nitrogen use (AN)	Whole farm average nitrogenous fertiliser use (kg/ ha/ yr).
Supplements (SP)	The amount of imported supplements (tonnes).
Social interaction variables	**NMPs and Intensive input Variables of neighbouring farms**
S* Nutrient budgets & plans	S*NU1: neighbouring farmers have neither had an up to date nutrient budget nor completed a nutrient management plan, coded as 1 (set as base). S*NU2, neighbouring farmers have either an up to date nutrient budget or has already completed a nutrient management plan, coded as 2. S*NU3, neighbouring farmers have not only had an up to date nutrient budget but also have already completed a nutrient management plan, coded as 3.
S*Winter off cows	S*WIFF1, neighbouring farmers have no cows wintered off, coded as 1 (set as base). S*WIFF2, neighbouring farmers have a part of cows wintered off, coded as 2. S*WIFF3, neighbouring farmers have all cows wintered off, coded as 3.
S*Soil test frequency	S*ST1, soil test frequency of neighbouring farmers is more than 2 years, coded as 1 (set as base). S*ST2, soil test frequency of neighbouring farmers is between 1 year and two years, coded as 2. S*ST3, the frequency of neighbouring farmers is less or equal to 1 year, coded as 3.

Table 5.1 Descriptions of Variables (continued)

S*Waterways management	S*WW1, neighbouring farmers have no waterways fenced, coded as 1 (set as base). S*WW2, neighbouring farmers have parts of the significant waterways fenced, coded as 2. S*WW3, neighbouring farmers have all significant waterways fenced, coded as 2.
S*Riparian plant	S*RP1, neighbouring farmers have no riparian plant plan, coded as 1 (set as base). S*RP2, neighbouring farmers have riparian plant plan, coded as 2.
S*Effluent management	S*EM1, neighbouring farmers do not achieve the limit of effluent discharge (150 kg N/ha/yr), coded as 1 (set as base). S*EM2, neighbouring farmers achieve the limit, coded as 1.
S*EFF	Average Effluent discharges rate (percentage) of neighbouring farms.
S*SR	Average stocking rate of neighbouring farms.
S*AN	Average whole farm average nitrogen use (kg/ ha/ yr) of neighbouring farms.
S*SP	Average imported supplements (tonnes) of neighbouring farms.

Table 5.2 Statistics Description of Variables

Variable name	Min.	Max.	Mean	SD.
Nutrient loss	2.03e-03	0.26	4.56e-03	4.33e-03
NU1	0	1	0.24	0.39
NU2	0	1	0.39	0.49
NU3	0	1	0.37	0.48
WIFF1	0	1	0.51	0.39
WIFF2	0	1	0.28	0.45
WIFF3	0	1	0.21	0.41
ST1	0	1	0.20	0.42
ST2	0	1	0.33	0.47
ST3	0	1	0.47	0.49
WW1	0	1	0.30	0.43
WW2	0	1	0.23	0.42
WW3	0	1	0.47	0.49
RP1	0	1	0.65	0.49
RP2	0	1	0.35	0.48
EM1	0	1	0.25	0.37
EM2	0	1	0.75	0.43
EFF	0	100	25.63	17.34
SR	1.29	4.05	2.80	0.51
AN	10.00	250.00	115.81	49.66
SP	0.10	1966	358.04	363.71

5.5 Results and Discussions

For comparison purposes, I list results of the three empirical models in Table 5.3. The first model is the linear non-spatial model. The SDEM-W model is the SDEM regressed with the spatial weights matrix, and the SDEM-A model is the SDEM regressed with the adjacent weights matrix. The non-spatial model is estimated using OLS and the other two SDEM models are regressed using maximum likelihood estimation.

Table 5.3 shows that the SDEM models outperform the non-spatial model in terms of R^2, adjusted R^2 and log-likelihood value. Meanwhile, the spatial autocorrelation coefficient parameter ρ is statistically significant in the SDEM models. Moreover, most of the coefficient estimates of social interaction variables in the SDEM models are statistically significant as indicated by t−statistics values at different levels. All these suggest that ignoring social interaction effects (spatial effects and social network effects) in the data might result in biased and inefficient estimates. For example, in the non-spatial model, nitrate leaching from a dairy farm where parts of cows have been wintered off is 11 percent lower than that from farms where cows have not been wintered off. However, this number is 7.9 percent and 8 percent in the SDEM-W and SDEM-A model, respectively, suggesting that the coefficient is overestimated for about 3 percent in the non-spatial model. Thus, choosing the non-spatial model may lead to inaccurate estimations and interpretations.

Table 5.3 Coefficient Estimation Results for Nutrient Loss Response to NMPs and Intensive Inputs

Explanatory variables	OLS	SDEM-W	SDEM-A
Intercept	-1.74*** (-8.61)	-1.67*** (-6.56)	-1.24*** (-3.69)
NU2	-5.58e-02 (0.77)	-3.95e-02 (-0.51)	-3.83e-02 (-0.49)
NU3	-2.92e-02 (0.38)	-4.44e-03 (-0.58)	-4.05e-02 (-0.29)
WIFF2	-1.84e-02 (-0.24)	- 2.18e-02* (-1.62)	-2.23e-02* (-1.73)
WIFF3	-0.11** (-2.18)	-7.98e-02** (-2.48)	-8.03e-02** (-2.84)
ST2	-9.16e-02* (-2.06)	-7.83 e-02** (-2.38)	-7.91e-02** (-2.32)
ST3	-5.23e-02*** (-3.08)	-4.05e-02*** (-3.56)	-4.01e-02*** (-3.17)
WW2	-1.36e-02 (-0.16)	-5.29e-02 (-0.64)	-5.25e-02(-0.85)
WW3	-7.91e-02* (-1.98)	-5.04e-02** (-2.18)	-5.13e-02* (-1.84)
RP	6.49e-02 (1.03)	-4.30e-02 (-0.69)	-4.07e-02 (-0.93)
EM	-7.26e-02* (-2.01)	-6.11e-02* (-1.75)	-7.02e-02* (-1.76)
EFF	5.77e-03*** (3.43)	5.56e-03*** (3.38)	5.74e-03*** (3.75)
SR	1.76e-02**(2.85)	5.17e-02** (2.40)	5.29 e-02** (2.18)
AN	4.40e-02* (2.02)	1.52e-02* (1.89)	1.54e-02* (1.79)
SP	3.38e-04***(4.40)	3.23e-03*** (4.59)	3.42e-03*** (2.82)
S*NU2	-	-0.31(-1.55)	-0.59 (-0.83)
S*NU3	-	9.04e-02 (0.43)	-0.38 (-0.67)
S*WIFF2	-	-1.35e-02 (-0.48)	-2.02e-02* (-1.92)
S*WIFF3	-	-2.02e-02* (-1.91)	-1.33e-02** (-2.00)
S*ST2	-	-1.51e-02 (-0.69)	-1.71e-02* (-1.86)
S*ST3	-	-2.24e-02** (-1.97)	-3.33e-02** (-2.89)
S*WW2	-	-2.03e-03 (-0.12)	-1.11e-02* (-1.79)
S*WW3	-	-2.22* (-1.90)	-2.44e-02* (-1.81)
S*RP	-	0.16 (0.99)	0.49 (1.03)
S*EM	-	-1.04** (-2.03)	-2.61e-02* (-1.91)
S*EFF	-	2.19e-03 (0.58)	8.26e-02 (1.07)

Table 5.3 Coefficient Estimation Results for Nutrient Loss Response to NMPs and Intensive Inputs (Continued)

S*SR	-	1.53e-02*** (3.83)	5.78e-02 (1.01)
S*AN	-	2.79e-02 (0.59)	0.29 (0.47)
S*SP	-	3.90e-03** (2.29)	3.29 (0.59)
Rho	-	0.21*** (5.07)	0.32*** (7.44)
R^2	0.68	0.76	0.79
Adjusted R^2	0.63	0.71	0.73
Log L	-368.9	-452.1	-579.72

Source: author's elaboration based on Matlab software; '***', '**', '*' indicate coefficients that are significant at 1%, 5% and 10%, respectively; figures in parentheses represent t-values.

Considering the SDEM models outperform the non-spatial model, I only interpret the coefficients estimated in the SDEM models. The SDEM model allows to use measures of dispersion such as the t-statistic for these regression parameters as a basis for inference regarding significance of the direct impacts (from farmers' own NMPs and intensive inputs) and indirect impacts (from neighbouring farmers' NMPs and intensive inputs).

5.5.1 Direct Impacts - Farmers' Own NMPs and Intensive Inputs

According to the estimation results in Table 5.3, most of the NMP variables (except for nutrient budget & plan and riparian plant) and all of the intensive input variables are statistically significant, and the signs of these coefficients are as expected in both of the two spatial models. Magnitudes of these coefficients represent the direct impacts of dairy farmers' own NMPs and intensive inputs on environmental performance. Notably, there are only small differences between the NMP coefficient estimates and intensive input variables in the SDEM-W model and those in the SDEM-A model. For example, coefficient estimated for WIFF2 is -2.18e-02 in the SDEM-W model and -2.23e-02 in the SDEM-A model. Thus, the estimation results for the direct effects of NMPs and intensive inputs are consistent in the two spatial models. Figure 4.2 shows the direct effects in regard to farmers' own NMPs and intensive inputs on nitrate leaching.

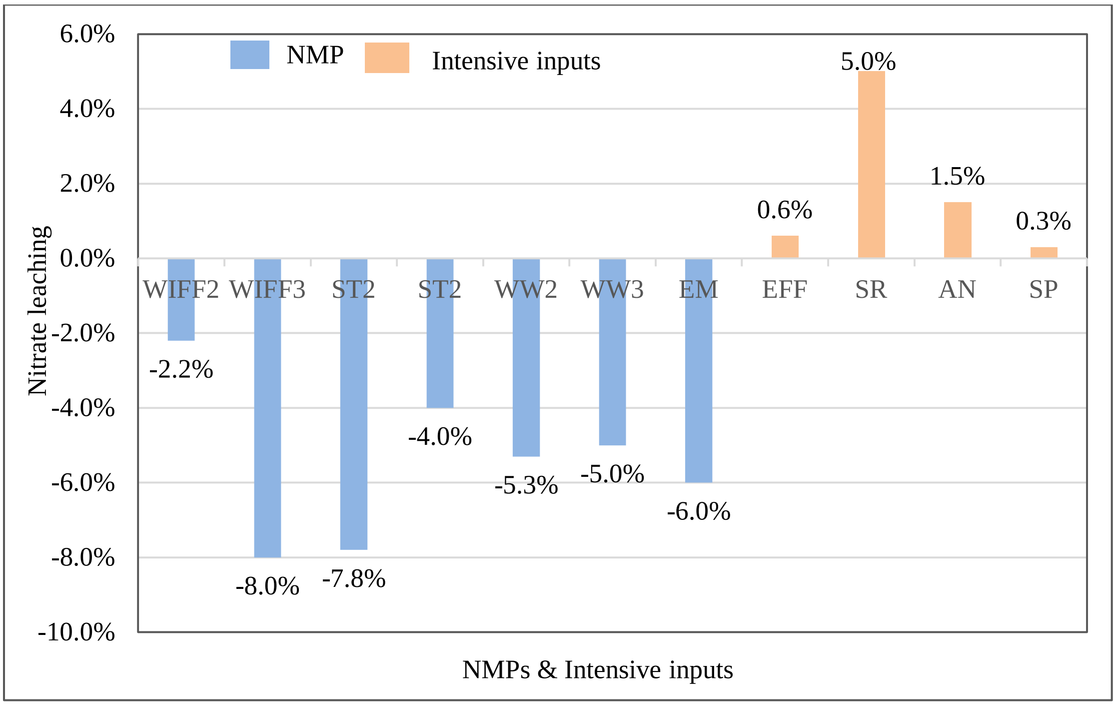

Figure 5.2 Dairy Farmers' Nitrate Leaching Response to Their Own NMPs and Intensive Inputs

NMP Variables: As shown in Figure 5.2, the coefficients estimated for NMPs, including wintering off cows, soil tests, fencing off all cows and effluent management, are statistically significant. Specifically, when wintering off a part or all of the cows, dairy farmers' nitrate leaching is about 2.2 and 8 percent lower, respectively, than that of farmers who have no cows wintered off. When soil test frequency is between one and two years, nitrate leaching is about 7.8 percent lower than that of farmers who have soil tested longer than 2 years. Similarly, with a soil test frequency less than, or equals to one year, nitrate leaching may be 4 percent lower than that of farmers having lower soil test frequency. Farmers, who have fenced off all cows from waterways, achieved nitrate leaching that is 5 percent lower compared to that of those who have no cows fenced. Lastly, when effluent discharge satisfying the regulation (150 kg N/ ha/ yr) imposed by the Waikato regional council, nitrate leaching is about 6 to 7 percent lower than that of farmers whose effluent discharge do not satisfy the requirement of effluent discharge regulation.

Intensive Input Variables: All the coefficient estimates for intensive input variables are positive and statistically significant. Positive signs of the coefficients indicate that high intensive inputs lead to an increase in nitrate leaching. Particularly, nitrate leaching rises by 0.6 and 5 percent with one percent increase in effluent discharge rate and stocking rate, respectively. 1.5 percent and 0.3 percent increase in nitrate leaching is associated with an increase in 1 kg nitrogen use per hectare and 1 tonne imported supplements.

5.5.2 Indirect Impacts - Social Interaction Effects

Indirect impacts (also known as spatial spillover effects) from neighbouring farmers are measured by social effects variables in the two spatial models. Magnitudes of these coefficients represent the indirect impacts of neighbouring farmers' NMPs and intensive inputs. As shown in Table 5.3, the estimated coefficients of the social interaction effects variables in the two spatial models are different, as those in the SDEM-W model explain the social interaction effects from 'real' neighbours (geographically), while those in the SDEM-A model present the influence from socially close neighbours. These facts indicate that the extent of influence from geographically close farmers and socially close farmers are different. Figure 5.3 presents how nitrate leaching responds to geographically close farmers' and socially close farmers' NMPs and intensive inputs. I will interpret the indirect effects regarding neighbouring farmers' NMPs and intensive inputs for the SDEM-W model and the SDEM-A model separately.

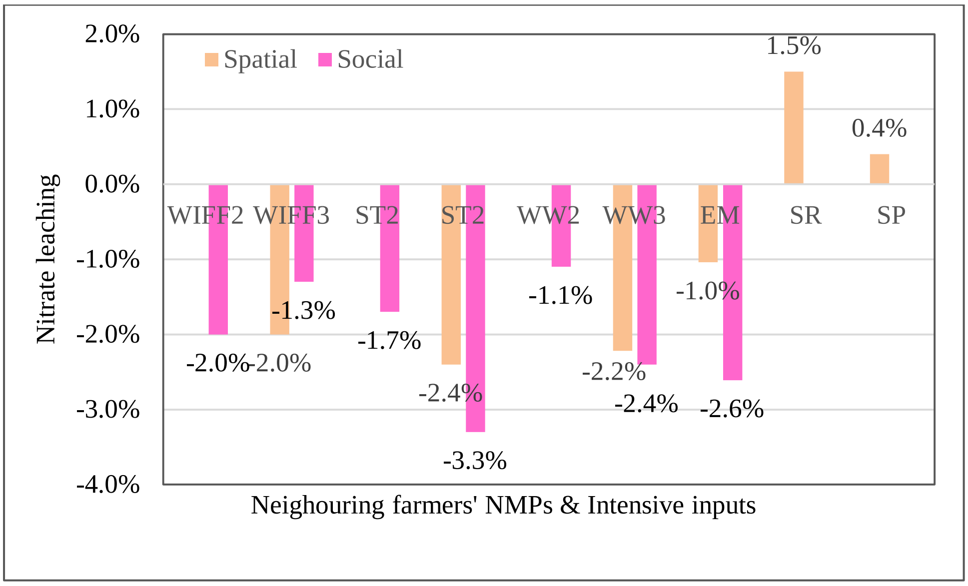

Figure 5.3 Dairy Farmers' Nitrate Leaching Response to Their Neighbours' NMPs and Intensive Inputs

Spatial Interaction Effects: As shown in the SDEM-W model in Table 5.3, dairy farmers' NMPs are positively influenced by neighbouring farmers' NMPs in the following aspects. Firstly, when surrounded by neighbours who have all cows wintered off, dairy farmers' nitrate leaching is 2 percent lower than that of farmers whose neighbours have no cows wintered off. In addition, compared to farmers whose neighbours have soil tested over 2 years, dairy farmers' nitrate leaching is 1.5 and 2.2 percent lower if their neighbours have a shorter soil tests frequency (test frequency is between 1 to 2 years and less than or equal to 1 year). Dairy farmers may also observe and learn from their neighbours' waterways and effluent management practices. A 2.2 percent decrease in nitrate leaching may be associated with neighbours' good waterways management practices, i.e. fencing all cows off waterways. When neighbours have met the effluent discharge limit (150 kg N/ ha/ yr) imposed by the Waikato regional council, nitrate leaching is 1 percent lower than that of farmers whose neighbours' effluent discharge exceed the effluent regulation. Likewise, spatial dependency exists in intensive input variables, including stocking rate and imported supplements, but there are no spatial spillover effects in nitrogen use and effluent discharge rate. This is mostly because it may be easy for farmers to observe their geographical neighbours' choices on stocking rate and imported supplements, while it may not easy for them to observe their neighbours' choice of nitrogen use and effluent application. In particular, around 1.5 percent increase in nitrate leaching is associated with 1 percent increase in neighbouring farmers' stocking rate; and 0.4 percent rise in nitrate leaching is due to 1 tonne increase in neighbouring farmers' imported supplements.

Social Network Effects: Positive influence of socially close neighbours' good NMPs are also observed in the SDEM-A model in Table 5.3. For dairy farmers who are connected to farmers having a part or all cows wintered off, the average nitrate leaching is 2 and 1.3 percent lower than that of farmers whose social contacts choose not to winter off cows. It is also true for soil tests, waterways management and effluent management. When socially close farmers' soil test frequency is between 1 and 2 years or less than 1 year, nitrate leaching is 1.7 and 3.3 percent lower than that of dairy farmers whose social contacts have soil test frequency over 2 years. Dairy farmers, whose socially close neighbours fence a part or all cows off waterways, produce nitrate leaching 1.1 and 2.4 percent less than that of farmers whose socially close neighbours have no waterways management practices. Additionally, there is about 2.6 percent difference between nitrate leaching of dairy farmers whose social contacts satisfy the Waikato regional council's effluent discharge limit and that of farmers whose contacts does not. The latter's nitrate leaching is greater than that of the former. Notably, socially close farmers' choices on intensive inputs have no impact on dairy farmers' intensive inputs, as all the estimates for social interaction variables in regard to intensive inputs are not statistically significant.

5.6 Summary

This essay aims to use a spatial analysis approach to explore the relationship between nutrient loss and NMPs, and to investigate whether or not social interactions between farmers influence this relationship considering heterogeneous intensive inputs of farms in the Waikato region of New Zealand. Social interaction effects are modelled in terms of a spatial weights matrix capturing neighbouring farmers' impacts as well as an adjacent weights matrix capturing the influence from farmers participating in the same dairy groups. To avoid biased and inefficient estimates, I applied spatial econometric models to the data and compared the results to the non-spatial model results. Results of the essay clearly show that the spatial Durbin error model suits the data best.

Results of this essay also show that good NMPs are positively associated with environmental performance that is measured by kg nitrate leaching divided by kg milksolids. With the application of various good NMPs, nitrate leaching is lower than (ranging from 1 percent to 8 percent) that of farmers who have no good NMPs. Although some NMPs, such as soil test frequency, are not considered contributing to reducing nutrient loss estimated by OVERSEER®. Those practices, however, are actually associated with good environmental performance. This fact indicates the requirement of adjustment of the OVERSEER® estimation. For example, during the time of extreme climate events such as floods or droughts, increasing soil test frequency can assist farmers to adapt to special weather conditions, which should be taken into account of the OVERSEER® estimation for nutrient loss to water.

Moreover, the results demonstrate that spatial dependence exists among geographically close farmers and socially close farmers, as significantly positive spillover effects are observed from geographically close farmers and farmers participating in the same dairy groups. Notably, environmental performance is negatively influenced by an increase in stocking rate and imported supplements of geographically close farmers, but there is no significant influence from socially close farmers. This indicates that dairy farmers may observe geographically close farmers' farming activities, such as their stocking rate, and make decisions on the choice of their own intensive inputs.

Furthermore, the results suggest a role of government policy to motivate more farm-level communication and cooperation. Additionally, interactive activities are not restricted to a small area, such as one catchment or region but also broader dairy groups, which may facilitate learning among farmers. This finding also implies that social network interactions among farmers may promote positive spillovers of good NMPs from regions to regions, which explains one of the important reasons of regional level spillovers stated in the first essay.

For the Waikato regional council, particularly, dairy groups may be a proper place to test for dairy farmers' response to more rigid regulations for nutrient pollution or new technologies on NMPs that are expected to implement in the near future. Except for interactive discussions in dairy groups, dairy farmers may also spread what they have discussed and what they have learnt from dairy groups to their neighbouring farmers. The regional council may also consider developing different ways to facilitate social interactions among dairy farmers. For example, dairy farmers, especially young farmers, may prefer to communicate with others through social media, such as Facebook and Twitter.

CHAPTER 6. Conclusions and Policy Implications

6.1 Introduction

High productivity is the core competitiveness of the NZ dairy industry, while the “100% pure and healthy” brand keeps attracting international demand for dairy products. With these advantages, the NZ dairy industry has rapidly developed and expanded over the past few decades. Nevertheless, the expansion of the dairy industry has been accompanied with concerns about negative impacts of intensive dairy farming on the environment. Criticisms have concentrated on the side effects of increasing stocking density, chemical fertiliser use and effluent discharge on water quality of the NZ’s waterways. Improved understanding of the relationship between dairy yields and intensive farming practices may assist the dairy industry to meet the challenge of ensuring high yields with the least damage to the environment.

High production may be achieved by a continued increase in stocking rate and fertiliser use, but unsustainable activities associated with intensive farming may cost farmers. Currently, unsustainable farming practices have been labelled as “dirty dairy”. To control for nutrient pollution, regional councils in NZ have already issued regulations and implemented projects in response to “dirty dairy”. More stringent regulations are expected to be implemented in some dairy intensive regions, such as the Waikato region (DairyNZ, n.d.c).

For dairy farmers, being blind to these problems is neither sustainable nor economically efficient. In recent years, some farmers have already paid the price. In 2010, a dairy company was given a $120,000 fine for repeated breaches discharging effluent to tributaries of the Whataroa River (TVNZ, 2010); in 2015, the largest fine of $66,000 was given to a farmer who discharged effluent into ground water and a stream on one of his farms in the Taranaki region (Slater, 2015). Fonterra, the largest dairy exporter in the world, has developed “The Supply Fonterra Programme” to help its suppliers on the continuous improvement of sustainable milk production. According to the programme, Fonterra may refuse to collect milk from non-compliant farms in regard to their nutrient management performance (Swannfriday, 2009). Therefore, one must question is dairy farmers need to be equipped with the knowledge on nutrient management in order to upgrade farm management systems sustainably in response to the increasingly stringent regulations.

Considering the situations as stated above, this Ph.D. thesis contributes three essays on agricultural and environmental economics regarding sustainable development of the NZ dairy industry. Particularly, the three essays are empirical studies addressing the impacts of spatial spillover effects on regional dairy yields, intensive farming practices and farmers’ decision-making on good environmental practices. To conclude the thesis, I will present main findings and highlight the contributions of each essay in section 6.2, and provide policy implications of this thesis for the regulation of nutrient pollution and sustainable development of the NZ dairy industry in section 6.4.

6.2 Summary of Contributions to Literature

6.2.1 Essay one

The first essay analysed the relationship between regional dairy yields and intensive inputs in New Zealand. Previous studies on this question focused on estimating dairy production and assessing environmental impacts under different scenarios by using the average farm system in a given region in NZ. Results of these studies are helpful for sustainable development of individual farms, but the results are limited to the specific situations of the given farm system and the given region. To extend the relationship to a broader level, this essay used spatial econometric models to analyse aggregated regional data to address regional dependence and differences in regard to intensive inputs, such as chemical fertiliser use, stocking rate, and effluent application.

The expansion of dairy industry has led to growing conversion of land use from, for example forestry, to dairy pasture. During this process, intensive dairy farming has expanded to unconventional dairy regions. Indeed, spatial effects may play an important role in this process. Thus, when analysing regional dairy yields response to intensive farming, this essay innovatively proposed to consider potential spatial spillover effects among regions, which assists to capture spatial dependence in regional dairy yields and spillovers from neighbouring regions' intensive practices.

Until now, there has been no research on the relationship between dairy yields and intensive inputs in NZ that considers spatial spillover effects. Hence, by testing for the existence of the spatial spillover effects in the relationship between regional dairy yields and intensive inputs, this essay can establish whether unobserved spatial effects exist, and to investigate how spatial spillover effects influence the relationship between dairy yields and intensive farming across regions.

The first essay contributes to the existing literature in two ways. First, this is the first empirical application of spatial econometric methods to examine the spatial relevance of dairy yields and intensive farming in New Zealand. Particularly, the spatial panel data model accounts for cross-sectional dependence and controls for heterogeneity. Second, the essay not only takes into account traditional intensive inputs but also innovatively includes the areas of effluent sprayed over farms as one of the intensive farming indicators. By including the interaction term of effluent and nitrogen use in the model, results of the first essay indicate that there are trade-offs between these two intensive inputs and further reveal the influence of trade-offs on regional dairy yield. The results contribute to an understanding of how farmers can improve their management of intensive inputs and contribute to the formation of regional environmental policy that recognises regional dependence and heterogeneity.

6.2.2 Essay Two

Dairy farmers play an important role in the implementation of water protection projects. However, considering the cost and uncertain performance associated with different environmental practices, dairy farmers may be hesitant to apply BMPs to comply with the requirements for controlling nutrient pollution. Therefore, understanding the impact of determinants of farmers' decision-making on the adoption of BMPs could help to assist farmers to better comply with water protection requirements, such as those stated in the new water accord.

Previous studies provided a wide scope of factors, including farmers' attitudes, perceptions, and farm and household characteristics, which may influence farmers' decision-making on BMPs. These studies failed to address spatial interactions that play a crucial role in farmers' decision-making. Significantly, knowledge on BMPs is information intensive. Interactions among farmers may reduce their fixed cost on acquiring BMPs information and reduce risks associated with the implementation of BMPs.

The second essay, therefore, used a spatial Durbin probit model to empirically analyse the spatial dependence and determinants of dairy farmers' adoption of BMPs. The results show that spatial dependence exists in farmers' adoption of BMPS, and spatial spillovers are also observed through the impacts of neighbouring farmers' characteristics. In addition, a farmer's willingness to adopt BMPs decay with the increase in the distance from the farm to the nearest water bodies. The results also show that information acquisition is the most important driver for farmers to adopt BMPs, while financial problems, to the greatest extent, hinder dairy farmers' adoption of BMPs.

The second essay contributes to the literature as follows. First, it contributes to the empirical literature on the determinants of farmer's adoption of BMPs in NZ by using spatial econometric methods, which considers various determinants, including drivers and barriers for farmers to adopt BMPs, farm and household characteristics. Significantly, this essay addressed that spatial effects should be considered as one of the determinants. When dairy farms are geographically located, spatial effects are presented as the distance from the farm to the nearest water bodies, and the neighbourhood effect that exists in farmers' adoption choices. Secondly, direct effects (from own characteristics) and spatial spillover effects (from neighbours' characteristics) of the determinants are captured. When adopting the SDM probit model, this essay examined to what extent the direct and indirect effects of each determinant affects the probability to adopt BMPs.

6.2.3 Essay Three

Currently in NZ, dairy farmers' environmental performances are evaluated by the results estimated by OVERSEER®, which is the only tool applied nationally. The output-oriented results estimated by OVERSEER® help farmers manage their nutrient budget and assist regional councils to set standards for controlling nutrient pollution. Debates, however, often come from doubts on the reliability of the estimation results since OVERSEER® estimates nutrient loss to water based on the assumption of best practices. Additionally, concerns have also concentrated on the consistency of OVERSEER® estimations, considering it has kept upgrading to higher versions (the most recent version is Version 6.2). Thus, it is necessary to explore the relationship between nutrient loss and NMPs implemented by farmers, especially for those NMPs that have not been included in OVERSEER®.

When analysing this relationship, social interactions among dairy farmers should also be included. As indicated in the second essay, spatial dependence exists in farmers' adoption of BMPs. It also indicated that participating in dairy-related activities could facilitate farmers' adoption of BMPs. Consequently, dairy farmers' decisions on NMPs may also be influenced by their neighbours.

The third essay extends social interactions among farmers from those, who are geographically close, to farmers in the same dairy group, who are socially close. It used a spatial analysis approach to explore the relationship between nutrient loss and NMPs, and to investigate whether or not social interactions between farmers affect this relationship considering heterogeneous intensive inputs of farms. Results of the third essay show that dairy farmers' good NMPs is positively associated with their environmental performance. Although some NMPs, such as soil test frequency, are not considered contributing to reducing nutrient loss estimated by OVERSEER®, they are actually associated with good environmental performance. The results also demonstrate that positive spatial spillover effects exist in NMPs among geographically close farmers and socially close farmers.

Contributions of the third essay to the literature are shown as follows. To begin with, for studies on the relationship between environmental performance/ nutrient loss and NMPs, it contributes to the literature on the application of spatial analysis methods to examine the correlates between nutrient loss and NMPs. It verified that some NMPs that are not considered as BMPs by OVERSEER® do influence farmers' environmental performance. Additionally, this essay quantitatively modelled social interactions among dairy farmers and examined how social interactions influence dairy farmers' environmental performance. In addition to model spatial interactions among farmers, this essay also considered farmers' interactions through their participating in dairy-related activities, as neighbouring farms are not only referred to farms geographically close but also those belonging to the same dairy groups. According to the results, the influence of geographically close farmers on environmental performance is different from that of socially close farmers.

6.3 Policy Implications

This thesis leads to several policy implications regarding nutrient regulation and sustainable development of the dairy industry in NZ. Significantly, the existence of spatial dependence in regional dairy yields and the use of intensive inputs indicates the use of spatial spillover effects in regulations on regional nutrient management. For example, the effect of nutrient pollution regulation in one region may be spilled to its neighbouring regions. The thesis also finds out trade-offs between the use of nitrogenous fertiliser and effluent use and the positive response of environmental performance to good NMPs, which lead to policies associated with effluent management and the use of OVERSEER®. Moreover, the existence of social interactions among dairy farmers may shed a light on promoting sustainable milk production. An example of utilizing the interactions in policy-making is to explore different ways, through which farmers communicate with each other, and to understand how farmers learn and exchange experience in different social situations. This section will specify policy implications associated with the main findings of this thesis.

6.3.1 Spatial Dependency and Heterogeneity in Nutrient Pollution Regulation

The Resource Management Act (RMA) is the primary legislation in NZ setting rules on how to manage the environment and the natural resources at a national level. Moreover, in 2009, the central government announced a new strategy for the management of NZ's freshwater resources. The RMA, however, has not specified a national-level regulation for controlling nutrient pollutions. Instead, rules and regulations that must be consistent with the goals set by the RMA have been made by regional and territorial councils. According to the RMA, regional councils can regulate nutrient discharges to land and water and regulate activities that can lead to nutrient discharges. The good side is that regional strategies can provide local knowledge, accountability, and flexibility to regulate nutrient pollution. However, it is not easy to evaluate performance of nutrient pollution control at a national level, considering differences of regulations and projects across regions.

It is possible to form a national policy to control nutrient pollution considering the existence of positive spillover effects in regional dairy yields and the use of intensive inputs. Although the regional governments have different policies and regulations, spatial dependence exists between neighbouring regions. From a national perspective, to reduce nutrient pollution, policy makers should take into account the spillover effects between regions. Specifically, a maximal limit on farm-gate nutrient discharge could be set at a national level for water protection. The limit provides a standard to evaluate regional environmental performance along with the water quality data monitored across NZ's waterways. Cooperation is needed for setting the limit. A reliable tool, which can be applied, accepted and interpreted nationally, for estimating farm-gate nutrient loss is also a necessity. OVERSEER® is a wise choice, even though it still needs to be improved.

Meanwhile, regional variation has to be considered when setting a national limit. In Europe, the measures of Good Agricultural and Environmental Condition impose minimum conditions but leave considerable implementation leverage for every member state (Mosnier & Wieck, 2010). In NZ, more stringent limits can be set in dairy intensification regions. Since 2014, the Horizons regional council, Environment Bay of Plenty and Environment Canterbury have had nitrogen targets in place for specific parts of their catchments. It is expected that the impacts of these targets will spillover to adjacent areas and regions.

Another good example of considering regional differences is the "Nutrient vulnerable zone" policy in the UK, which aims to better manage the use of nitrogen fertiliser or manure. The NZ government can also identifies "nutrient vulnerable zone" or "nutrient sensitive zone", which helps regions within the zone to set higher standards for water quality protection. Actually, an innovative move has been made in two nutrient vulnerable areas, Lake Taupo catchment and Lake Rotorua. A nutrient trading system was firstly introduced to Lake Taupo catchment, where the Lake Taupo Protection Trust was established with a goal of a 20 percent permanent reduction in nitrogen leaching by 2018 (Duhon & Kerr, 2012). Under a benchmark assessed by OVERSEER®, farmers can either choose to mitigate nutrient loss or negotiate with others or the Lake Taupo Trust (to buy or sell allowances). The system used in Lake Rotorua catchment adopts the essence of the Lake Taupo project and extends the trading to include phosphorus loss (McDonald & Kerr, 2011). It is clearly that successful implementation of the Lake Taupo nutrient trading system set forth a new move to regulate nutrient emissions, which stimulated the development of trading prototype in Lake Rotorua catchment. It is very possible that other nutrient sensitive areas may follow the steps of these two catchments.

6.3.2 Effluent Use for High Milk Production with the Least Damage to the Environment

Results of this thesis, illustrated in the first essay, indicate trade-offs between chemical fertilisers and effluent use. Considering the trade-off, the high level of effluent use and estimated negative yield response to nitrogen and phosphorus suggests that an opportunity exists for greater use of effluent as a substitute for chemical fertilisers. Particularly, the use of effluent can, on one hand, provides an alternative source for fertilization. On the other hand, it also offers irrigation water for pasture.

Indeed, this finding is consistent with the conclusions made by Matthew, Horne & Baker (2010), who found out that a change in effluent disposal management could offset nitrogen loss and increases environmental efficiency at the individual farm level. Also, Lowe, Cass & Horswell (2016) propose that farm dairy effluent has the potential to benefit productivity land and contribute to improved waterways quality.

Specifically, according to the Waikato Regional Council (n.d.), assuming that the maximum amount of N from effluent (150 kg N/ per hectare/ year) is applied, dairy shed effluent may provide the amount of nutrients shown as follows:

- 20 kg of phosphate per hectare.
- 117 kg of potassium per hectare.
- Approximately 20-30 kg of sulphur per hectare.
- Smaller amounts of magnesium and calcium.

Thus, it is wise for regional governments to highlight the trade-off in policy making process. Notably, wastewater treatment systems have increasingly developed, and currently, some systems require less capital outlay, which may make effluent treatment systems become more acceptable by dairy farmers. Rational utilization of effluent may help dairy farmers to save money on chemical fertilisers and help the dairy industry to better maintain the high productivity. Notably, special care should also be taken into account in the process of effluent application, especially when applying effluent in winter.

6.3.3 Improvements in OVERSEER®

The OVERSEER® nutrient budget model was developed by Agresearch and has been upgraded according to actual conditions over the past decade (Wheeler et al., 2010). Most farmers use OVERSEER® to make nutrient plans, and regional governments use it to formulate regulations for nutrient pollution, as it is the only tool applied in NZ, nationally.

However, as stated in essay two, OVERSEER® estimate nutrient loss to water on the basis of BMPs, even though some good NMPs do positively related to environmental performance. Adjustments, therefore, are necessary to be made for more accurate estimations of nutrient loss. One suggestion for the adjustment is that special variables or parameters are suggested to adapt for extreme weather events. For example, in the year of drought or flood, climate and soil parameters could be variable instead of stable long-term readings. Gary et al. (2016) suggest that some individual components of farm systems can be taken into account to be included or updated in OVERSEER®.

Although debates and doubts exist in the accuracy of nutrient loss estimated by OVERSEER®, quite a lot of researchers see it as the best tool currently available for estimating nutrient loss across the diversity and complexity of farming systems in NZ. I do believe it is wise to improve OVERSEER® instead of inventing new tools, considering time and money invested in the development process. Furthermore, it is easier and faster for farmers to accept an updated OVERSEER® and to get it work, compared to learning new tools.

It is promising to set a national-level standard for nutrient pollution when the accountability of OVERSEER® is ensured. At present, some scientists are working on the consistency of the estimations made by different versions of OVERSEER®. Additionally, a collaborative project is now underway to offer guidance on the better use of OVERSEER® information in policy, planning and compliance. This project is governed by various members including five regional councils, the Ministry for Primary Industries, the Ministry for the Environment, OVERSEER Management Services, Dairy companies Associated of NZ, Beef & Lamb NZ, HortNZ and the Foundation for Arable Research (Murray et al., 2016). Besides, spillovers from the five regional councils in participating in the project may further impact adjacent or similar regions to improve the understanding of OVERSEER®.

6.3.4 The Role of Social Interactions in Farmers' Adoption of BMPs

A good understanding of dairy farmers' drivers and barriers to adopting BMPs could assist policy makers to specify strategies and deliver support to solve the problems that are most in the need of help. As stated in this thesis, for example, financial problems are regarded as the largest obstacle for farmers to adopt good practices in the Waikato region, while access to industry information facilitates farmers' adoption of BMPs.

Social interactions between farmers are found to be another important driver for farmers to adopt BMPs. The existence of social interactions in decision-making between farmers, which is stated in the second and third essay, indicates the information exchange among farmers. The second essay addresses that spatial dependence exists in decision-making among farmer who live in close proximity, and the third essay further states that spatial dependence also exists in the choice of NMPs between socially close farmers, who participate in the same dairy groups. Furthermore, access to industry information, as one of the drivers, is found to has the greatest impact on farmers' adoption of BMPs. Participation in different (dairy-related) social activities, as another means of getting information, also facilitates farmers to adopt BMPs.

All these findings highlight the importance of information acquisition for dairy farmers to adopt BMPs, as it could reduce the cost for dairy farmers to adopt BMPs. Thus, the NZ government may consider offering free channels for information acquisition, which could significantly reduce risks and uncertainties associated with the adoption of BMPs.

Moreover, joint neighbourhood initiatives are also appropriate to address the positive externalities of sustainable management practices. That is to say, interactive activities are not restricted to a small area, such as one catchment or region but can be extended to broader dairy groups, which may facilitate learning among farmers across regions. While individual farmers cannot internalize the full benefits of their adoption decisions and, therefore, tend to delay adoption, coordinated activities can help to overcome such problems of collective action. If all farmers in a neighbourhood commit to establishing measures against water pollution, individuals do not have to fear that neighbouring farmers may free ride on their investments into good management practices.

It is noted that, although policy implications made in this section are based on the analysis in the Waikato region, it can be tested and applied to elsewhere in NZ. The only difference is that different regional councils may develop different ways to facilitate social interactions among dairy farmers. For the Waikato regional council, it may be appropriate to test for, in dairy groups, farmers' response to more rigid nutrient loss regulations or new technologies on nutrient management that are expected to implement in the near future. In addition, social media, such as Facebook and Twitter, may be a practical information source for farmers to acquire and exchange information on sustainable milk production. Regional governments may target different dairy groups in social media, explore characteristics of the groups and promote sustainable development projects.

Lastly, the existence of distance decay effect in dairy farmers' adoption of BMPs provides a different point of view of education as a vehicle for regional governments to use in the promotion of BMPs. That is, during the education and promotion process, instead of treating dairy farmers as polluters, they could also be seen as individuals who also demand good water quality for recreation purposes. Stimulating dairy farmers' desire for clean waterways may encourage them to re-evaluate their farming practices and adjust to the requirements of sustainable dairy farming.

6.4 Future Research

Overall, this thesis contributes three essays on agricultural and environmental economics with the application of different spatial econometric models. Results of the thesis lead to many policy implications regarding nutrient pollution control and sustainable development of the NZ dairy industry. In particular, essay one provides insights into the understanding of how regional dairy yields respond to intensive inputs, and how to use the spillovers among regions to control nutrient pollution. One limit of the first essay comes from the accessibility of data, as variables such as labour and machine input are not included in the model. It would be worthwhile to include those variables when the data are available. The second essay verifies the existence of spatial spillover effects in decision-making of farmers' adoption of BMPs, while the third essay extends the spatial spillovers to social network effects among dairy farmers. Furthermore, results of these two essays confirm the conclusion that a good understanding of spatial spillover effects among regions could assist to design policies for nutrient pollution control, as farmers may play an important role in the spillover of regional regulations. A future direction to further these two essays is to extend the study of farmer decisions at a national level with more observations, which could help to draw more powerful conclusions. Another direction is to explore connections among farmers through the internet, considering social media has become an increasingly acceptable form of communication.

In regard to spatial spillover effects, future research could consider using the flow direction of waterways to model spatial interactions among regions. The geographical location of farms can also be related to upstream, midstream and downstream of nearby waterways. This is another way to model spatial effects, which may also influence dairy farmers' choices of BMPs.

Appendix

Appendix lists all the tables, test results (with explanations), statistical tests, and estimation methods stated in the thesis in orders. Contents shown in A1 are for essay one, A2 for essay two, and A3 for essay three.

A1. Essay one

Effluent as a Natural Source of Fertiliser

In the first essay, I proposed that effluent, when appropriately applied on land, can be seen as a substitution of chemical fertiliser to supply nutrients to pasture. It contains various nutrients, such as nitrogen, phosphorus, potassium, magnesium, sulphur and trace elements, which are required for the growth of pasture. Appendix Table 1 indicates the potential nutrient contents within different sources of dairy effluent.

Appendix Table 1 Nutrient Contents of Different Sources of Effluent

Effluent source \ Nutrient content	% dry matter	kg N/m^3	kg P/m^3	kg K/m^3
Dairy shed effluent	0.8	0.45	0.06	0.35
Feed pad and dairy effluent sludge	4.0	1.35	0.3	1.05
Effluent from unstirred pond or effluent after separation	0.3	0.25	0.03	0.35
Separated solids	20	4.5	0.72	2.1
Solids from wintering barn	40	5.0	1.5	5.6

Source: Waikato Regional Council

Descriptive Statistics of Variables: Appendix Table 2 and Table 3 shows the descriptive statistics of variables for North Island and South Island in essay one, respectively.

Appendix Table 2 Descriptive Statistics of Variables-North Island

Variable name	Counts	Min.	Max.	Mean	S.D.
Y	108	496	1336	918.50	175.10
N	108	0.02	0.78	0.44	0.41
P	108	0.006	16.46	0.56	0.60
L	108	0.009	4.08	0.63	0.59
K	108	0.001	3.27	0.39	0.34
E	108	0.05	1	0.30	0.21
SR	108	1.89	3.56	2.92	0.33
RF	108	338.87	6715.40	1464.67	1332.14
SM	108	6.78	51.23	28.46	12.95

Appendix Table 3 Descriptive Statistics of Variables- South Island

Variable name	Counts	Min.	Max.	Mean	S.D.
Y	57	534	1436	1005.80	179.43
N	57	0.01	0.76	0.43	0.42
P	57	0.006	16.46	0.58	0.61
L	57	0.008	4.07	0.62	0.57
K	57	0.001	3.21	0.34	0.32
E	57	0.04	1	0.26	0.20
SR	57	1.89	3.51	2.70	0.31
RF	57	335.30	6315.40	1345.23	1267.14
SM	57	6.03	48.06	20.15	9.98

Results and Explanations of Moran's I Test

Moran's I test is used to test for the existence of spatial dependence in cross-sectional data. The null hypothesis is that there is no spatial autocorrelation. The test statistic Moran's I is shown in Equation A.1.

(A.1)

$$I = (n/Z)[\sum_{i}^{n}\sum_{j}^{n} w_{ij}(y_i - \bar{y})(y_j - \bar{y}) \Big/ \sum_{j}^{n}(y_i - \bar{y})^2];$$

$$\bar{y} = \frac{1}{n}\sum_{i}^{n} y_i;$$

$$Z = \sum_{i}^{n}\sum_{j}^{n} w_{ij}$$

Where, y_i and y_j are the levels of regional dairy yields of region *i* and *j*, w_{ij} is one of the elements constituting a spatial weights matrix, which indicates the spatial interaction between region *i* and *j*, and Z is the sum of w_{ij}.

I test for the existence of spatial autocorrelation in regional dairy yields. Although the test is developed to explore the spatial interaction for cross-sectional data, I calculate it for the years of 2002, 2007 and 2012, respectively. The results of Moran’s I test are presented in Appendix Table 4. By observing the p-values, the results are statistically significant, indicating the existence of spatial dependence of dairy yields across regions. Thus, a spatially lagged dependent term should be included in the model.

Appendix Table 4 Moran's I Test for Regional Dairy Yields

Year	Moran's I	p-value
2002	0.4101	1.07e-05
2007	0.5400	1.55e-08
2012	0.4336	3.35e-06

Source: author’s elaboration based on ArcGIS 10.2.

A2. Essay Two

Bayesian MCMC Estimation

In essay two, the SDM probit model is regressed by using the Bayesian MCMC estimation. Here, I only give a simple description of Bayesian MCMC estimation methods. A detailed description of the estimation procedure for the model can be found in LeSage and Pace (2009).

As stated in essay two, y is the binary dependent variable representing farmer choice of adoption or non-adoption of BMPs, y^* is an $n \times 1$ latent variable that cannot be observed, and β, θ, λ are all unknown parameters.

Bayesian estimation methods are based on a combination of the likelihood of the model $p(y|\tau)$ and prior distributional assumptions $p(\tau)$, where $\tau = (\beta, \theta, \lambda)$ are unknown parameters. The prior distribution indicates how likely different values of the parameters are, before observing the data. Prior distributions for the parameters have to be specified, which will yield $p(\tau|y)$: $p(\tau|y) \propto p(y|\tau)p(\tau)$, when combined with the likelihood according to Bayesian rule. According to LeSage and Pace (2009), for the spatial probit model, sampling from the resulting posterior distribution needs to use an MCMC sampler approach. In that way, conditional posterior distributions for the parameters are derived and sampled sequentially.

To model binary choice models, the Bayesian method treats the observed binary dependent variable y as an indicator of unobserved utility y^*. Hence, the sampled continuous values y^* are used instead of the observed binary values y. If y^* is known, it follows that $p(\beta, \theta, \lambda | y^*) = p(\beta, \theta, \lambda | y^*, y)$ that allows estimation of the remaining parameters using the same conditional posterior distributions as for a continuous model. The insight here is that if y^* is seen as an additional set of parameters to be estimated, then the conditional posterior distribution for the model parameters β, θ, λ takes the same form as a Bayesian regression problem involving a continuous dependent variable rather than the problem involving the discrete-valued vector y. Given the resulting conditional posterior distributions for the spatial probit model, the model is estimated in several steps. That is, the MCMC technique samples from the conditional posterior distributions for the model parameters, starting with arbitrary values.

A3. Essay Three

Test Results and Explanations of Choosing Different Spatial Models

Test results for model selection in essay three are shown in Appendix Table 5. According to the test result of LM spatial and Robust LM spatial lag, the hypothesis of no spatial lag term cannot be rejected at the 5 percent level of significance; according to the test result of LM spatial error and Robust LM spatial error, the hypothesis of no spatial autocorrelated error must be rejected at 5 percent. These results indicate that a spatial lagged dependent variable should not be included while the spatial error term should be considered.

Appendix Table 5 LM and Robust LM Test for Spatial Effects in Non-Spatial Model

LM and Robust LM Test	Tests Results
LM spatial lag	1.21 (p=0.11)
LM spatial error	36.11 (p=0.006)
Robust LM spatial lag	0.98 (p=0.021)
Robust LM spatial error	6.65 (p=0.034)
Source: author's elaboration based on Matlab software.	

Additionally, I use the Wald test to verify the hypothesis whether it is proper to simplify the SDEM model to the spatial lag of X model (SLX, only the spatially lagged independent variables be considered) as well as the hypothesis whether the SDEM model can be simplified to the spatial error model (SEM). The Wald test for the joint significance of spatially lagged independent variables (42.25, p=0.001) indicates that the hypothesis that SDEM model can be simplified to the SLX must be rejected at 5 percent significance. Meanwhile, the hypothesis of SDEM simplified to the SEM must also be rejected at 5 percent significance (37.56, p=0.01). These results confirm that both the SLX and SEM model must be rejected in favour of the SDEM.

Test Results for Choosing Spatial Weights Matrix

As shown in Appendix Table 6, according to the values of Log L, R^2 and Adjusted R^2, the rook contiguity weights matrix is chosen to be used in the SDEM model in essay three to capture spatial interactions among dairy farmers.

Appendix Table 6 Estimation Results for SDEM Models with Different Spatial Weights Matrix

Weights / Indicators	Model -rook contiguity	Model -Queen contiguity	Model - 5 nearest neighbours	Model - 10 nearest neighbours
Log L	-452.1	-383.2	-215.9	-324.6
R^2	0.71	0.70	0.67	0.69
Adjusted R^2	0.76	0.74	0.71	0.73

Source: author's elaboration based on Matlab software.

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