The Application of Choice Modelling in Evaluating Sustainable Agriculture Policy and Implications for New Zealand---A Review

by

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Abstract

Agriculture is a vital contributor to the New Zealand economy. However, apart from contributing to economic growth, the increasingly intensive agriculture has also caused environmental degradation. In particular, nutrient discharge from agriculture is a significant challenge for NZ seeking to support sustainable agriculture and protect water quality. As the NZ economy is heavily dependent on agriculture, these problems must surely be addressed. It seems that policy makers should adapt the sustainable development policy, if there is to be a future for NZ agriculture. Significantly, although various programs have been launched to control nutrient discharge, farmers are still hesitant to implement mitigation practices. Hence, to a large degree, this might make it impossible to promote the idea of sustainable agriculture to society. To explore the causes and impacts of the farmer behaviours, this paper reviews the international literature on how choice modelling can be applied to analyse choice within the contest of sustainable agriculture. Furthermore, it will make suggestions for the emerging policy problems for agriculture of NZ. Specifically, the review focuses on two main aspects: the heterogeneity of the farmer preferences under different sustainable agriculture programs, including the latent preference and spatial preference; and the farmer willingness to pay (WTP) for associated cost on nutrient management practices. Significantly, the paper explores how the literature can contribute to the existing understanding of the "peer effects" attribute in the context of choice modelling, including the impacts of "neighbour effects" and "group effects" on the accessibility of relevant information and how these factors affect choice. It also emphasizes the contribution of considering “spatial effects" on payment. Modelling "distance effects" allows us to estimate how the public would trade-off different attribute levels against payment. Last but not least, the paper also highlights potential gaps needed to be filled by future research: particularly, "distance effects" as an attribute in modelling the farmer choices of mitigation practices, including location and soil type.

Key words: Nutrient pollution, Sustainable Agriculture, Choice Modelling, WTP

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1. Introduction

The New Zealand economy is heavily dependent on agriculture, but the nutrient pollution is a significant challenge for the NZ government seeking to support sustainable agriculture and protect water quality. Meanwhile, although various programs have been launched to control nutrient pollution, farmers are still hesitant to implement mitigation practices due to the economic and environmental uncertainty. Therefore, to deal with the emerging policy problems, the government should design a cost-effective policy to adapt to the needs of farmers and promote sustainable development (Segerson & Walker, 2002). Moreover, the policy design should take into account of the farmer preferences, as how farmers choose nutrient management practices (NMPs) and respond to different policies is extremely significant. In this way, it is important to figure out the following questions: what influence the farmer choices; which influencing factors would be the most significant; and what options they would choose under different policy instruments. It is therefore the purpose of this review to explore how choice modelling methods can be used to analyse the heterogeneity of the farmer choices and preferences, and make suggestions for the sustainable agriculture policy in New Zealand.

Specifically, this review will explore how the literature can contribute to the following aspects: choice modelling methods, in the form of choice experiment (CE), consider both the socio-economic characteristics and choice attributes that would influence the decision-maker choices. Thus, the application of choice modelling methods could investigate the heterogeneity of the farmer choices and preferences for mechanism design options (to control nutrient pollution) under different policy scenarios. Besides, payment for mitigation options would be included as one of the attributes so as to estimate how farmers would trade-off different levels of alternatives against their payments (Beharry-Borg et al., 2012). Knowledge of such trade-offs can also inform policy design (Espinosa-Goded et al., 2010). What is more, the farmer choices would be partial estimated if spatial effects being excluded. In this way, we would explore the farmer spatial preferences by estimate the spatial distribution of the farmer willingness to pay (WTP) for the mitigation options. In particular, we can consider the spatial heterogeneity represented as the distance decay effects and differences of soil types. (Bateman et al., 2006; Schaafsma et al., 2012). In the following sections, the review will firstly point out the concept of heterogeneity and the importance of the application of choice modelling methods. And then, it will investigate the farmer heterogeneity by reviewing the empirical studies of latent class model, GIS, and other spatial choice models. Finally, this review will come to conclusions that give the future research direction and implications for New Zealand's sustainable agriculture.

2. Heterogeneous of the farmer preferences and the impacts on agri-environmental programs

The impacts of the farmer behaviours and choices have been increasingly addressed in the evaluation of sustainable agriculture policy. Notably, more and more studies have emphasized how the heterogeneity of the farmer preferences would influence the choices. Researchers explore the impacts of the farmer choices from various perspectives by applying qualitative methods and quantitative methods. Qualitative studies use the interview method to investigate the heterogeneity of the farmer behaviours and the associated socio-economic characteristics (e.g. Moon & Cocklin, 2011; Bewsell & Brown, 2011). Although the conclusions may be of significance for re-estimating agri-environmental programs, the qualitative research methods have greatly restricted the size of the research population so that the analysis results are of limited generalizability (Blackstock et al., 2010). Also, two streams of quantitative research point to the importance of the impacts of heterogeneity. By using optimization methods, the first highlights how the farm characteristics influence the efficiency of controlling nutrient pollution and the mitigation cost under sustainable agriculture policies (Ekman, 2005; Doole, 2012). These papers, however, ignore the farmer choices which would directly or indirectly impact the implementation of polices. The second avenue in explaining heterogeneity employs choice modelling methods. In particular, the choice models (CMs) method and the contingent valuation (CV) method are most commonly used in choice modelling. In the form of choice experiment (CE), CMs are applied to explore the household and the farmer participation willingness for environmental protection programs (e.g. Baskaran et al., 2009); and contingent valuation (CV) are used to evaluate willingness to pay (WTP) or willingness to accept (WTA) increments or decrements of, typically, public goods, saying water, air, land and etc. (Bateman et al., 2006).

CE is a survey-based method, and one major advantage has been the use of stated-preference (SP) data. Compared with Revealed-preference (PR) data, which relate to individual's actual choices in real-world situations, SP data are collected in experimental or survey situations where respondents are presented with hypothetical choice situations (Train, 2009). For example, a farmer might be presented with three NMPs with different investment cost and other attributes. The farmer would be asked which of the three practices he/she would choose if offered only these three choices in the real world. The answer the farmer would like to give is his/her stated choice.

It is undeniable that RP data have the advantage that they reflect decision-makers' actual choices. However, such data are limited to the choice situations and attributes of alternatives that currently exist or have existed historically. SP data can complement this, as SP data based experiments can be designed to contain as much variation in each attribute as the researcher thinks is appropriate. Significantly, it is possible to combine the SP data and RP data in research. Therefore, farmers' real NMPs can be seen as the RP data and set as the baseline or "current alternative" (Hensher et al., 2005); while the stated preference can be also captured within the framework of SP choice experiment design. Given the potential mechanism designs (associated with the sustainable development project) that have never been offered before, or for new attributes of old projects, stated-preference data would allow the estimation of choice models when combined with revealed-preference (Louviere et al., 2000).

3. Understanding heterogeneous preferences in choice modelling

3.1 Choice modelling basics---the multinomial logit model

Discrete choice models (DCMs), which are derived under an assumption of utility-maximizing behaviour by the decision maker, are the most commonly used models in choice modeling (Train, 2009). Based on the random utility theory, the most standard econometric model used to analyse the results from the discrete choice experiment is the multinomial logit (MNL) model. The MNL model scribes the decision maker's[2] choices among alternatives. A farmer selects the alternative from the choice set that has the highest utility value. As is shown in Equation 1, the indirect utility function (U) which represents the satisfaction that farmer (n) receives (e.g., from the nutrient mitigation regulation programs) offered by alternative (j) as:

$$U_{nj} = V_{nj} + \varepsilon_{nj} \tag{1}$$

2. As we explore the application of choice modelling methods in evaluating the farmer choices, we would like to use "farmers" to substitute "decision makers" for simplicity.

Here, the indirect function is composed of two parts: V_{nj} represents the deterministic element of farmers' utility, which is typically specified as a linear index of the attributes (X) of the j alternatives in the choice set; and ε_{nj} is the stochastic disturbance term which represents all the unobserved influences on a farmer's choice.

Importantly, the main assumption should be noticed that each farmer perceives a level of utility (U) or "attractiveness" from each alternative j and then, on each of the choice cards, selects the alternative which delivers the highest level of utility from those available on that card. In this way, the probability (P_{nj}) that farmer n choose alternative (i) in preference to any other alternative (j), can be expressed as the probability that the utility associated with alternative (i) is greater than that associated with all other alternatives. This is shown in equation 2:

$$\begin{aligned} P_{ni} &= Pr\left(V_{ni} + \varepsilon_{ni} > V_{nj} + \varepsilon_{nj}, \forall\, j \neq i\right) \\ &= Pr(\varepsilon_{nj} - \varepsilon_{ni} < V_{ni} - V_{nj}, \forall\, j \neq i) \end{aligned} \tag{2}$$

The MNL model is derived by assuming that the individual error terms ε_{nj} are independently and identically distributed and follow a Gumbel distribution (McFadden & Train, 2000). This gives rise to the following choice probability, and it is a general form of the MNL model:

$$P_{ni} = e^{\beta' x_{ni}} \Big/ \sum_j e^{\beta' x_{nj}} \tag{3}$$

This model can be estimated using maximum likelihood procedures. The analyst can capture the observed taste heterogeneity in this model by interacting the preference for the choice attributes, or an alternative specific constant, with observable data such as farmers' socio-economic characteristics (include age, gender and annual income), and the farm specific characteristics (for example: the stock rate).

3.2 Latent preferences

The MNL model has provided a foundation for the analysis of discrete choice modelling in many previous studies, but it also been criticized for the Independence of Irrelevant Alternatives (IIA) assumptions and its limited ability to accommodate heterogeneous preferences (e.g., McFadden & Train, 2000; Carlsson et al., 2003). Hence, the principle of latent class model (LCM) is a promising avenue for solving these problems, for heterogeneous taste intensities are employed in this model when the researcher assumes the presence of latent variables which take the form of discrete constructs (Boxall & Adamowicz, 1999). Basically, it evaluates choice behaviour as a function of observable attributes of the choices and latent heterogeneity in respondent characteristics (Greene & Hensher, 2003). To examine the latent preference, the latent class choice model is comprised of two components: a class membership model and a class-special choice model as shown in figure 1. In the analysis, respondents are sorted into s groups (s = (1, 2, …, S)). The number of groups (classes) is not determined endogenously but estimated with various numbers of classes (Milon & Scrogin, 2006). In addition, the numbers are based on statistical information criteria (Swait, 1994).

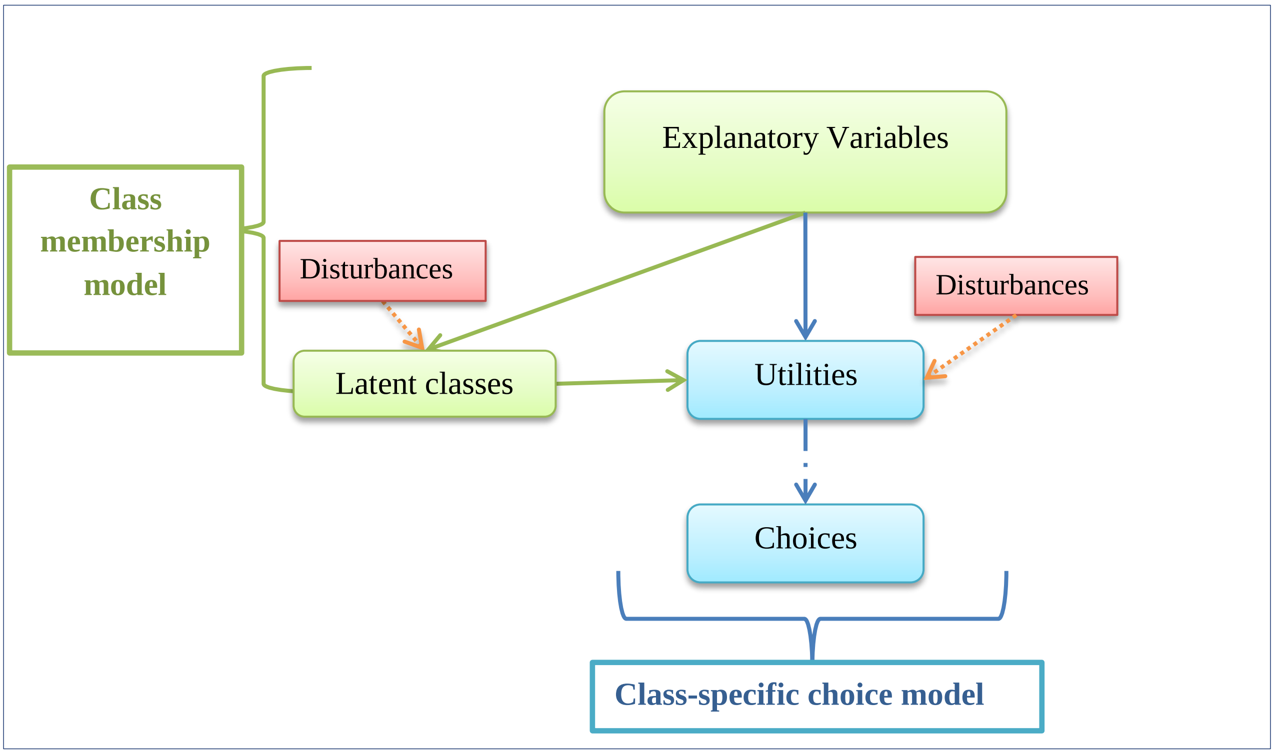

Figure 1 latent class choice model framework (Walker and Li, 2007)

Generally, the LCM model is also specified as a random utility model comprised of an observable, deterministic component of utility and an unobservable random component. Actually, there are many variants of latent class models, but the one used in the analysis of this figure is based on the influence of choice based attributes in the estimation of latent segments used by Boxall & Adamowicz (2002). Briefly, the LCM model is specified as a random utility model where respondent n belongs to latent class s = (1,2,….S). The utility function can now be expressed as:

$$U_{nj|s} = V_{nj} + \varepsilon_{nj} = \beta_s X_{nj} + \varepsilon_{nj|s} \tag{4}$$

As described before, U also denotes utility received by farmer n from the alternative j. But it is different from the MNL model as the utility is conditional on the farmer being in group s, and β is also a vector of parameters over j alternatives specific to group s (Ben-Akiva et al., 2002). Therefore, the utility parameters are now segment specific, and equation 3 can be expressed as:

$$P_{ni|s} = {e^{\beta_s X_{ni}}} \Big/ {\sum_j e^{\beta_s X_{nj}}} \tag{5}$$

3.3 Spatial preferences

In experimental studies, it is generally believed that heterogeneity of the farmer choices can be addressed in choice experiment (with SP scenarios), and policy makers can better understand and adapt preference-oriented policy to the farmer behaviours (Jeffords, 2011). Nevertheless, though lots of differences are considered across farmers, one of the most important factors, spatial issues, have been ignored in choice experiment design of agri-environmental policy.

3.3.1 Applications of spatial analysis in choice experiment

Actually, spatial analysis has already been broadly applied in choice experiment in various research fields, including marketing and environmental valuation assessment. Researchers regarded spatial effects to be complex and significant, as the effects would influence consumers purchasing choice, households travelling choice, tourists destination choice, and the public participating intend (for certain environmental improvement projects) (E.g. Bateman & Langford, 1997; Bateman et al., 2006; Campbell et al., 2007). Indeed, some researchers have started to take “space heterogeneity” into the consideration of environmental value evaluation. Actually, Schaafsma and Marije (2009) have already reviewed the application of spatial choice experiment in environmental valuation in detail. In these studies, spatial effects were considered to be reflected from two aspects: the distance decay and the geopolitical threshold effects. The former treated decision makers' WTP decays as monotonic function. (E.g. Brouwer et al., 2010; Jørgensen et al., 2012; Pate & Loomis, 1997). For example, the public willingness to pay for the improvement of water quality of a lake would decay due to the distance to the lake or the park; while the latter one regarded that WTP displays discrete thresholds over geopolitical boundaries (E.g. Hanley et al., 2003; Morrison & Bennett, 2004; Georgiou et al., 2000). Although all these papers only focused on the public choice spatially, these analysing methods can be further extended and used to explore the farmer behaviours and choices.

The farmer choices, as well, would be influenced by spatial effects. Nevertheless, researchers have devoted little attention to examining the spatial patterns that result from the profit or utility-maximizing choices of farmers. First and foremost, farms are located in different sites, where various situations (for example, soil types and their distance to rivers) could spatially influence the nutrient loss. Consequently, farmers would make choices based on their locations. In addition, the accessibility to information on nutrient regulation can affect the farmer choices because neighbours' behaviours might influence the farmer choices. Given the complexity of spatial issues across farmers, the spatial effects can be concluded into two categories: spatial dependence and spatial heterogeneity (Van Bueren & Bennett, 2004). The former generally represents the spatial effects between neighbouring areas or locations while the latter means different preferences spatially across different regions or locations (LeSage, 1999).

3.3.2 Geographic information system (GIS) for measuring spatial effects in CE

Geographic information has been employed in the analysis of nutrient pollution regulation for a long time, since GIS can combine water quality data, soil type data, and climate changing data to estimate the amount of emissions (Kovacs & Honti, 2008). It is not uncommon that both the coordinates and the continuity of the locations are used for analysis of spatial effects (LeSage, 1999). Moreover, GIS offers a powerful set of tools for analyzing spatial data. In the literature of applying GIS in choice modeling, spatial choice of the decision-maker is usually illustrated by setting associated spatial information (for example, the location) as one of the attributes in the choice set or one of the extraneous factors (Ancev & Odeh, 2005).

Distance decay is generally used in analyzing spatial effects, especially in CVs literature for non-market goods. Several studies have indicated that the requirement for environmental quality is possibly to decrease with the distance from residency of the respondents to the resource in focus (Georgiou et al., 2000; Mouranaka, 2004; Bliem & Getzner, 2008). For example, it is illustrated that residence living near by the park would show higher demand for enjoying the beautiful scenery and clear water of the lake (in the park), and the distance decay effect was evaluated by using the GIS. Instead of using straight-line or network distance, estimates of the relevant travel times are also used to show this spatial effect (Bateman et al., 2006). Furthermore, some researchers have also concentrated on exploring direction effects. Schaafsma et al.(2012) presented "directional heterogeneity in preferences" by measuring the spatial properties by defining the location of the residence in terms of being in the north, northeast etc. direction relative to each of the lakes.

There are also other ways of measuring the spatial effects in CE literature. Geographical threshold, for instance, can also be used to measure spatial issues. To measure the residence choice of land use, researchers believed that geographic thresholds trigger major changes in land use patterns (Bradonjic et al., 2009). Geographical threshold graphs are a rich model with the possibility of controlling structural properties by choosing specific weight distributions and tuning threshold values. Specifically, the regional boundary is usually the geographic threshold to be considered in modeling spatial effects in choice modeling (Kenny et al., 2000). Another way of considering the spatial preference is to define the spatial weight matrix by regional boundary or electoral division. As stated by Campbell et al.(2008), electoral division can be conceived as spatial dependence, which might extend beyond administrative concepts. And it assumed that respondents sampled nearby are more likely to have WTP values than those far apart. For testing this spatial dependence, Moran's I test statistic is used for measuring in addition to distance measurement between two nearby respondents (Campbell et al., 2007).

In combined with the methods above, some other spatial data are applied in Arc GIS to address the spatial effects. Specifically, when modelling the respondent choice, water quality data and farm land use data are applied in choice modelling. Especially, water quality is quantitatively ranked for recreation purpose of different levels (e.g., Bateman et al., 2002; Tait et al., 2011; Brouwer et al., 2010); and parcel level data were aggregated to the farm level to investigate the farmer preference for participating land preservation programs (Lynch & Lovell, 2003).

3.4 Willingness to pay and willingness to accept

A common objective of the use of discrete choice model is the derivation of measures designed to determine the amount of money individuals are willing to forfeit in order to obtain some benefit from the understanding of some specific action or task (Hensher et al., 2005). Such measurements are referred to as measures of willingness to pay. Generally, WTP measurements are calculated as the ratio of two parameter estimates, holding all else constant. Significantly, measuring WTP is important to environmental economics research as non-monetary attributes, such as evaluating water quality (Tait et al., 2011). Given at least one attribute is measured in monetary units, the ratio of the two parameters will give a financial indicator of WTP. While in environmental economics literature, especially pollution (waste disposal) right studies, WTA is usually assumed to be larger than WTP (Jason et al., 1994). WTP is, for example, to measure the public willingness to pay for the improvement of the water quality of a lake, as they would be the gainer when enjoying the good views of the lake; WTA is, here, to measure the factories willingness to accept for compensating the degradation of the water quality, since they should be responsible for disposing effluent to the lake (Horowitz & McConnell, 2002)[3].

Therefore, the estimated coefficient by using MNL model (from equation 1) on the pay attribute can be interpreted as the marginal utility of income; dividing any other attribute parameter estimate by this value will therefore produce an "implicit price", which could be interpreted as a WTA requirement for delivery of a particular level of change in management practice from baseline behaviour. Therefore, the WTA requirement for a certain management practice attribute k can be computed as the negative of the ratio of k's coefficient divided by the coefficient on the pay variable β_{pay}, it can be expressed in equation 6:

$$WTA = -({}^{\beta_k}/_{\beta_{cost}}) \tag{6}$$

In that way, farmers' WTA for the improvement of NMPs can be calculated in the form of money. While for the LCM model, one can also calculated the individual-specific conditional estimates of the marginal WTA for level of each attribute k. And this can be expressed as:

3. Details about the difference between WTP and WPA can be seen in *A Review of WTA / WTP Studies* (Horowitz & McConnell, 2002).

$$WTA_n = \hat{E}\left({}^{-\beta_{\mathrm{nk}}}/_{\beta_{\mathrm{cost}}}\right) = \sum_{s=1}^{S} \widehat{Q_{nk}}\,({}^{-\beta_{\mathrm{nk}}}/_{\beta_{\mathrm{cost}}}) \quad (7)$$

In this equation, Q is a matrix of individual-specific posterior probability of segment membership. Compared with the MNL model, the LMC model can further illustrate the heterogeneity of the farmer WTA in different groups. And it assumes that farmers easily access to information would have more WTP for reducing nutrient pollution.

4. Conclusions and the application in NZ---exploration of the dairy farmer preferences on nutrient management practices

In the above sections, according to the review of the application of choice modelling methods, the studies generally concluded that the heterogeneity was demonstrated by estimating the farmer utility functions according to the farmer characteristics and other attributes in different choice sets (Haile & Slangen, 2009). Thus, considering the dairy farming is a crucial contributor to nutrient pollution, it would be innovative to apply the choice modelling methods to investigate the dairy farmer preferences for nutrient management practices. Specifically, the future research can focus on the analysis of the dairy farmer latent preferences and spatial preferences. Taking into account of the CE methodology, a good questionnaire should be designed firstly to collect the data for analysing the dairy farmer choices. Several stages are needed for the CE design. For example, as shown in table 1, there may be 5 nutrient management practices included in the choice set. For each practices, the coefficients of MNL models can tell the relationship between the dairy farmer choices and the associated attributes. In addition, for the associated management practices, the cost coefficient can be connected with each management practice attribute as shown in equation 6, and calculate the dairy farmer WTP for each practice.

Table 1 attributes and levels used in choice sets

Attribute	Levels	Description of levels
Fertilizer management	3	no management reduce the application of fertilizer apply nitrification inhibitors
Soil management	3	no management drain wet areas apply stand-off or feed pad
Effluent management	3	no management apply sprinkler or irrigator to use effluent apply effluent pond
Waterways management	3	no management fence off cows from waterways create riparian or buffer strips
Data monitoring	3	no monitor monitor data occasionally monitor data regularly
Annual cost (per hectare)	7	0, 20, 40, 60, 80, 100, 120 (NZ$)

As for the implication of latent class analysis, dairy farmers could be segmented by groups (e.g. if we want to explore whether **“**the accessibility to information would influence the farmer choices on nutrient management practices” or not, the LMC model can be used). Consequently, here, the accessibility to information will be the criteria for sorting farmers to different groups. Neighbour relationship is a commonly used factor influencing farmers' decisions, as it is assumed individuals would like to share information with neighbours (Edwards & Wallmo, 2008). Different from the consideration of "neighbour effects", some studies also point out that the social networks would be more important (Ter Wal & Boschma, 2009). As people in the same group, saying participation in certain groups, might share the information the other members would like. Thus, the New Zealand's farmer preference of participating discussion groups (either held by Fonterra or DairyNZ) or training courses could be set as the criteria for latent class. That means farmers will be sorted according to their membership of the discussion group or training courses.

For the consideration of spatial effects, although it is complex to model the spatial effects, the exploration of spatial dependence and spatial heterogeneity would be achieved with the comprehensive consideration of the literature and the reality. The survey data of the dairy farmer choices would be combined with the GIS metadata. Thus, the choice experiment design of NMPs (of dairy farmers) would not only be quantitatively measured but also explored with spatial effects. More specifically, neighbouring effects (the distance) between nearby farms (and their relative distance to the nearest water body) can both be seen as spatial dependence, while farms located in various regions base on different administrative distinct (and soil type) could be regarded as the spatial heterogeneity (see an example of land management in figure 2). In practical, the future research would compare the two ways of measuring distance decay effects (nearby farm distance and the relative distance to rivers) by using the distance decay model; and also compare the regional effects and soil type difference by using the spatial weight matrix and Moran's I test statistic.

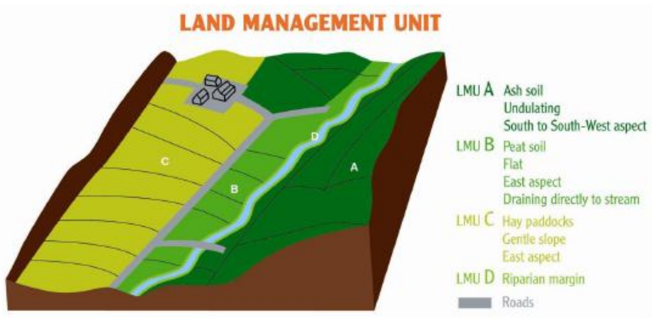

Figure 2 land management unit of NZ, source from NZ Fertiliser Manufacturers' Research Association 2007

To model the spatial heterogeneity for dairy farmers, the first variable is the distance between a farm to the nearest water body (e.g. a lake or a river), and the next potential variable could be the soil type of the farm. Here, the random parameter logit (RPL) model could be used to capture the individual specific difference for different dairy farmers. One of the advances of RPL model is that it represents a full relaxation of the IID assumption (required by MNL model). Moreover, as combined with geographic data, the RPL model can be used to capture the uncontrolled heterogeneity across dairy farms when considering the spatial effects. The general form of the RPL model is presented in equation 8:

$$U_{nj} = \beta' X_{nj} + \eta' X_{nj} + \varepsilon_{nj} \tag{8}$$

The first part, $\beta' X_{nj}$ is the deterministic part of the utility function and has the same specification as the MNL model. The second part, η' is an idiosyncratic random term associated with taste intensity with zero mean whose distribution over farmers and alternatives depends (in general) on the underlying parameters and observable data relating to alternatives j and farmer n. And ε_{nj}, is a random term that is IID Gumbel over alternatives and does not depend on the underlying parameters or data (McFadden & Train, 2000). The underlying assumption for the RPL model is that η' takes a general distribution such as normal, log normal, uniform or triangular (McFadden & Train, 2000). In order to consider the spatial heterogeneity, equation 8 can be written as equation 9. And this is the main model used in the future study to model distance effects and soil types.

$$U_{nj} = ASC_j + \sum_k \beta_k X_{njk} + \sum_k \eta_{kn} X_{njk} + \sum_m \omega_{jm} ASC_j * S_{mn} + \sum_s \delta_{ks} X_{njk} * S_{sn} + \varepsilon_{nj} \quad (9)$$

Where

ASC_j is an alternative specific constant for alternative *j*;

β_k is a vector of coefficients associated with the *k*th attribute;

X_{njk} are *k*th attribute that describe the alternative *j* (NMPs) of farmer *n*;

η_{kn} is a vector of *k* deviation parameters which represents how the tastes of farmer *n* differ from the average taste β_k;

ω_{jm} is the vector of coefficients of the interactions between the ASC_j and the *m*th farm characteristic of farmer *n*(S_{mn});

δ_{ks} is the vector of coefficients of the interactions between the *k*th attribute and the *s*th local spatial characteristic of farm n (S_{sn}).

Specifically, the farm characteristic could be described in terms of the stock rate of the farm (numbers of cows on farm/ the efficient area of farm land). These data will be also collected from the questionnaire. The spatial characteristic will be measured by two parameters: one is the distance between the dairy farm and the nearest water body; the other is the soil type of the dairy farm. These data can be obtained by using GIS analysis (in ArcGIS). Equation 9 can also be written as the form of probability as in equation 2, and probability (P_{nj}) that farmer n choose alternative (i) in preference to any other alternative (j) can be estimated by using maximum likelihood procedures (for RPL model) in NLOGIT. Importantly, the last term of equation 9 will be used to estimate the farmer spatial preference (marginal WTA) in the similar form of WTA presented in equation 4, and both the distance effect and the soil type effect can be estimated. With the estimation of the dairy farmer preferences for different attributes, the possible profiles of nutrient management attributes can be used for nutrient control policy design. Combining the spatial effects, policy makers can better adapt the policy mechanism to the preferences of different regions, as well.

In short, this study reviews the applications of choice modelling methods in exploring the farmer choices and evaluating the associated sustainable development policies. We can come to the conclusion that choice modelling methods may reveal the heterogeneity of the farmer choices and preferences and help to identify what farmers' trade-offs. Moreover, this review further points out the application of CE in analysis of New Zealand's dairy farmers. Furthermore, the consideration of the dairy farmer latent class preferences and spatial preferences would be filled with the future study.

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