Rural Land Use and Land Tenure in New Zealand

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Abstract
Private land-use decisions are critical for a broad spectrum of environmental and social outcomes, ranging from water quality and climate change to rural income distribution. I use a large dataset of the land-use decisions of New Zealand landowners to estimate a cross-sectional multinomial logit model of land use. In this model, the optimal land-use choice depends on geophysical attributes of the land, the cost of access to markets, and on land tenure (Māori freehold title versus general freehold title). I employ the estimated relationship in a counterfactual scenario to assess the overall impact of Māori tenure on the willingness of landowners to supply land for the four most important rural uses in the country: dairying; sheep or beef farming; plantation forestry; and an economically unproductive use, scrub. This allows me to conjecture about the environmental implications of New Zealand's land-tenure system.

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Land use, land tenure, discrete choice model

Contents

1. Introduction ... 5
2. Māori Land Tenure ... 6
3. The Economics Literature on Land Use ... 8
4. An Empirical Model of Land Use ... 9
5. Variables and Data Sources ... 15
    5.1. The Land-use Variable ... 15
    5.2. Geophysical Variables ... 18
    5.3. Cost-of-access Variables ... 20
    5.4. The Land-tenure Variable ... 21
6. Econometric Issues ... 22
    6.1. The Multinomial Logit Model ... 22
    6.2. Endogeneity ... 24
    6.3. Spatial Autocorrelation ... 25
7. Results ... 27
    7.1. Estimation Results ... 27
    7.2. Goodness-of-fit ... 31
    7.3. Counterfactual Land-tenure Scenario ... 34
8. Conclusion ... 36
9. References ... 38
10. Tables ... 42
11. Figures ... 48
12. Appendix ... 56

Index of Tables

Table 1. Summary statistics by land use ... 42
Table 2. Summary statistics by land tenure ... 43
Table 3. Estimation results. ... 44
Table 4. Marginal effects $(dProb/dX_k)$ in model 3 ... 45
Table 5. The fraction of observations in a given land use among all observations with a similar probability prediction for the corresponding use ... 46
Table 6. In-sample aggregate land-use outcomes on Māori freehold land ... 47
Appendix Table 1. Estimation results with facility locations ... 56
Appendix Table 2. Estimation results with spatially lagged variable ... 57

Index of Figures

Figure 1. The geographic distribution of land uses in New Zealand ... 48
Figure 2. The geographic distribution of Māori freehold land in the North Island of New Zealand ... 49
Figure 3. Histograms showing the fraction of all observations with a particular value of SLOPE and LUC, respectively. ... 50
Figure 4. Geographic distributions and histograms of predicted probabilities ... 51
Figure 5. Predicted versus observed land-use shares by territorial authority ... 53
Figure 6. The observed and predicted share of each use within all observations of a given slope ... 54
Figure 7. The observed and predicted share of each use within all observations of a given LUC class ... 55

1. Introduction

Private land-use decisions, even when they are optimal from a landowner's perspective, often produce environmental externalities.[1] These may be positive – the classic example is forestry's contribution to carbon sequestration. More typically, however, land-use externalities are negative. Various agricultural uses are often blamed for their role in non-point source water pollution, greenhouse gas emissions, biodiversity loss and deteriorating ecosystem health. Rural land-use decisions also contribute to aesthetic and cultural values, and affect economic outcomes such as employment and rural income distribution. With agriculture, the sector responsible for nearly half of New Zealand's greenhouse gas emissions, set to enter the country's Emissions Trading Scheme (ETS) in 2015, there exists a pressing need to understand empirically farmers' land-use decisions.

To date, most analyses of land use in New Zealand have been non-spatial or spatially non-quantitative (e.g. Hendy et al., 2007; Todd & Kerr, 2009). The first objective of my study is to estimate a spatially explicit empirical model of land use in order to quantify the effect various geophysical and socio-economic factors have on rural land-use decisions in the country. An important determinant of land use in New Zealand is the country's land-tenure system. Owners of Māori freehold land are part of a complex system that has its roots in customary Māori communal ownership. Accordingly, the second objective of my study is to determine the extent to which New Zealand's unique land-tenure system affects land use.

The economic framework I use to describe landowners' land-use decisions is a discrete choice model. The model is based on the assumption that landowners compare potential economic (and social) returns under different land uses to devote each parcel of land to its highest-valued use. Returns in the model depend on land quality, location relative to population centres and commercial ports, and land tenure. Based on these factors, I model the choice between New Zealand's four most important rural land-use alternatives: dairy farming, sheep or beef farming, plantation forestry and scrub. Qualitatively, estimation results confirm prior expectations regarding the effect of land quality, location and tenure on land-use decisions: in general, intensive cultivation is more attractive in close proximity to markets, and on high-quality land that is not subject to Māori land tenure. Using the parameter estimates from this model, I

[1] The terms "landowner" and "farmer" are both used throughout this paper to refer to the person making land-use decisions.

assess the overall impact of Māori tenure on the willingness of landowners to supply land for the four alternative uses via a counterfactual land-tenure scenario.

In the next section I provide background information on New Zealand's complex land-tenure system. Following that I briefly review the voluminous microeconomic literature on land use. In section 4 I then present the empirical land-use model, as well as its theoretical economic foundations. The model takes spatially disaggregated data from a variety of sources; these are described in section 5. In the following section I consider three econometric issues posed by empirically implementing a discrete choice model of land use, and comment on the feasibility and relative merits of techniques that have been proposed to address them. I then provide estimation results, and offer a heuristic assessment of the model's in-sample predictions in section 7. I also discuss the outcome of the counterfactual land-tenure scenario and its environmental implications. Finally, I present my concluding remarks in section 8.

2. Māori Land Tenure

In pre-European times, land in New Zealand was collectively owned by Māori communities. Following the signing of the Treaty of Waitangi in 1840, the Crown tried to bring Māori land under English common law – with several detrimental consequences to Māori society – and large areas were bought or confiscated from Māori. The land that has remained under Māori ownership (with a few exceptions) is referred to as Māori land. This land is governed under the Te Ture Whenua Māori Act 1993 (also known as the Māori Land Act 1993), one of whose primary objectives is to ensure the retention of land ownership within the Māori community. Meeting this objective has required imposing legal restrictions and protections that do not apply to general land.

Today, about 6 percent of New Zealand's total land area is classified as Māori land. Māori freehold land accounts for the vast majority (about 98 percent) of this. Māori freehold land is almost exclusively owned by the descendants of the original owners (Kingi, 2008).[2] It generally has multiple owners (ranging from 10 percent of titles with only one owner each, to 10 percent with an average of 425 owners each). The ownership of Māori land titles is divided into more than 2 million interests, a number comparable to the interests represented in the other 94 percent of New Zealand's land area, and one that is continuously growing each year (Audit Office, 2004; Kingi, 2008).

[2] In addition to holding interests in their ancestral lands, Māori can, of course, purchase and own general land.

The transfer of Māori freehold land is almost entirely restricted to other Māori with affiliations to the titleholder. Under most circumstances, an interest in Māori freehold land cannot be alienated, disposed of through a will, or taken for payment of an owner's debts or liabilities. As owners die and their descendants succeed to their interests, the fragmentation of ownership continues. Multiple ownership has significantly increased the administrative costs of Māori freehold land because of the need to keep track of the identity and location of a growing number of beneficiaries (Audit Office, 2004). It can also lead to problems with obtaining agreement about land use and development, and reduces the economic return to individual owners.

Māori incorporations and trusts control more than half of all Māori freehold land; at the same time, a significant proportion of land has no formal administration structure (Ministry of Agriculture and Forestry, 2011). The vast majority of owners in large incorporations and trusts do not live on their land or derive their livelihood from it (Kingi, 2008). This often leads to conflict between the shareholders. Under the most common decision-making process, high numbers of minority shareholders tend to out-vote small numbers of majority shareholders. An inherent bias in governance is therefore created towards the small interests, often resulting in a conservative, risk-averse attitude toward land development (Kingi, 2008). In addition to the high administrative and compliance costs, development of Māori freehold land is further arrested because multiple ownership makes it difficult to obtain financing for development.[3]

The historical confiscation of Māori land focused on high-quality land; in consequence, a large fraction of land under Māori freehold tenure today is of poor quality. Around 80 percent of it is classified as non-arable and 30 percent is landlocked (and far from urban centres), reducing the options available for its use (Ministry of Agriculture and Forestry, 2011). Māori freehold land enterprises tend to perform at a level well below comparable general land enterprises (Ministry of Agriculture and Forestry, 2011), and the difficulties faced by Māori freehold landowners in administering their land interests have been recognised by the government as an impediment to the development of the land (Audit Office, 2004).

Various programmes and mechanisms to assist Māori landowners in overcoming barriers to development are proposed from time to time (e.g. Ministry of Agriculture and Forestry, 2011). The degree to which the tenure system contributes to the underdevelopment of Māori freehold land is an important empirical question – it is clear that some of the underdevelopment is simply

[3] It needs to be acknowledged that land is also an important source of identity and cultural pride to Māori. The cultural values of the landowning community can therefore modify economic objectives and influence decisions relating to land use and development.

due to poor land quality and remoteness. Some environmental policies that affect land use could unintentionally penalise Māori owners because the current development of their land does not necessarily reflect its potential. It has been recognised, for example, that the deforestation rules associated with the ETS will further constrain the development options of large areas of Māori freehold land (Ministry of Agriculture and Forestry, 2011). The existing nutrient caps in the Lake Taupo and Lake Rotorua regions also significantly impact owners of Māori freehold land.

3. The Economics Literature on Land Use

Spatially explicit microeconomic analyses of land use are most often framed as discrete choice models. Such models are consistent with utility-maximising behaviour, and they are naturally suited for modelling categorical dependent variables, such as decision-makers' land-use choices (Train, 2009).[4] The approach is data-intensive because it requires location-specific observations of land use as well as of the geophysical, agro-climatic and socio-economic variables that are hypothesised to affect land-use decisions. Despite the popularity of the framework, studying land use in a discrete choice model poses some econometric challenges. I provide an in-depth discussion of some of these issues in section 6.

Dichotomous land-use models consider the choice between a pair of land-use alternatives. Modelling only two land uses is too restrictive in some situations, but it may be appropriate in others. Whether this is the case depends on the questions the researcher wishes to answer. In the context of developing countries, a large body of land-use literature has been driven by an interest in tropical deforestation (e.g. Chomitz & Gray, 1996; Nelson et al., 2001; Munroe et al., 2002; Blackman et al., 2008). At the same time, the focus in developed countries is often on residential development taking place on the rural–urban interface (e.g. Bockstael, 1996; Bell & Irwin, 2002). Both of these environments are characterised by a decision to convert land to a more developed use: in the first case, native forest is cleared for agricultural use; and in the second, an agricultural parcel is converted to urban use. In either setting, it may be sufficient to focus on the development itself, in which case specifying a dichotomous land-use model is appropriate (Munroe et al., 2002; Blackman et al., 2008). When a dichotomous structure does not suit the purposes of the study – for example, when the type of agricultural use to which the land is devoted is important – models with multiple land-use alternatives are estimated.

[4] In the land-use literature, the problem is sometimes presented as one of profit maximisation, and at other times as one of utility maximisation. From a modelling perspective, the two are nearly equivalent, albeit the perspective taken may influence the interpretation of results. I present the theoretical framework in terms of profit maximisation (but allow for the alternative interpretation in discussing the empirical model).

Regardless of the number of land-use alternatives in the choice set, discrete choice models are useful for identifying the location-specific drivers of land-use decisions. Because their predictions can be aggregated to examine land-use outcomes at the regional or national scales, discrete choice models have been employed for policy analysis under a variety of circumstances. Bockstael (1996), for example, uses a binary probit model to assess the impacts of different sewer service provision scenarios on urban conversion. Using the results from her scenario analysis, she also predicts the consequential change in water quality in a Maryland watershed. Chomitz & Gray (1996) use a multinomial logit model with three land-use types to identify the unintended environmental impacts of road construction in southern Belize. Nelson et al. (2001) employ seven alternative uses in their multinomial logit model to simulate the consequences of certain changes in property rights: the elimination of legal protection of a national park, and of two indigenous reserves in a Panamanian province.

Another useful taxonomy is one that distinguishes between models of land-use allocation and models of land-use change (or land-use conversion).[5] The former are estimated on a cross-section of data and are therefore unable to identify time-varying determinants of land-use decisions. The latter require observations from multiple time periods, and can be used to investigate dynamic aspects of choice – for example, conversion decisions that are conditional on initial use. Unlike land-use allocation models, conversion models are sometimes able to link land-use change to its macroeconomic drivers (which are generally constant within any cross-section of data).[6] For instance, Lubowski et al. (2008) simulate counterfactual scenarios to quantify the effect federal farm policies and economic returns have had on land use in the contiguous United States, and Polyakov & Zhang (2008) evaluate the effectiveness of Louisiana's use-value programme by analysing the influence of property taxes on land-use conversions between four alternatives, including three major rural uses and a developed use.

4. An Empirical Model of Land Use

The economic model I use to describe landowners' land-use decisions is based on the bid-rent paradigm. The model assumes that various land uses generate different amounts of economic return, and hypothesises that each piece of land will be devoted to the use earning the

[5] I use the terms "land-use allocation" and "land-use conversion" to describe models only when the context requires that the two are differentiated. In other cases, I simply refer to either kind as a land-use model.
[6] Instead of specifying a conversion model when data from more than one time period are available, the researcher could also estimate a series of independent land-use allocation models and test whether determinants of land use vary between the cross-sections.

highest potential net return at its particular location. It is thus consistent with profit-maximising behaviour: abstracting, for the moment, from any conversion cost between land uses, it assumes the owner chooses a use by comparing the expected return to each land use. Formally, if each land use has a single marketed output,[7] the net present value of return to use *j* on parcel *i* at time *T* can be expressed as

$$R_{ijT} = \int_{t=0}^{\infty} \left(P_{ijT+t} Q_{ijT+t} - \sum_{k} C_{kijT+t} W_{kijT+t} \right) e^{-r_i t}\, dt \tag{1}$$

where *P* and *Q* are the price and quantity of the output, and *C* and *W* represent input costs and optimal input quantities, respectively, for *k* types of inputs. Following Nelson & Hellerstein (1997), who first introduced the time dimension into this framework, the discount rate, *r*, is location-specific to account for any heterogeneity in landowner preferences and socio-economic conditions.

Equation 1 shows that current land-use decisions depend not only on current prices, but also on expectations of future prices. It shows, furthermore, that output prices, production, input costs and the amount of inputs may vary by location. If approximate location-specific returns to each use could be observed, it would be theoretically possible to estimate a land-use model on this information alone. However, this is rarely the case: rather than observing potential returns, the researcher typically has information only on variables that are likely correlated with them – land quality, for example, affects production and returns in obvious ways. Thus, the analysis usually proceeds by assuming a functional form for plot-specific production, prices and costs, and then deriving a reduced-form model for estimation. I follow others (e.g. Chomitz & Gray, 1996; Nelson & Hellerstein, 1997; Nelson et al., 2001; Blackman et al., 2008), with minor modifications, in specifying these functions.

The quantity of output per unit land area that can be produced in use *j* depends on the biological productivity of the parcel and the amount of inputs used in production. Without loss of generality, a Cobb-Douglas production function is assumed with a land-quality index, $\bar{S}$, entering multiplicatively:

$$Q_{ijt} = \bar{S}_{ij} \prod_{k} W_{kijt}^{\phi_{kj}} \tag{2}$$

[7] Alternatively, one could formulate the model in terms of a composite output – for example, meat and wool in the case of a sheep farm.

$$\bar{S}_{ij} = \lambda_{0j} \prod_{n} S_{ni}^{\lambda_{nj}} \tag{3}$$

where, as before, *i* indicates parcel location, *j* indicates the land-use alternatives, *t* the temporal dimension and *k* the inputs to production. The different geophysical and agro-climatic determinants of land quality are indexed by *n*. These are constant over time, but they vary over location. The exponents of each dimension of quality vary by land-use alternative, acknowledging that their effects are use-specific: an increase in soil moisture deficit, for example, may decrease production under both dairy farming and plantation forestry, but not necessarily by the same amount. The parameters ϕ of the production function are normally assumed to fall between zero and one, with their sum over the *k* dimensions totalling one at most.

Effective prices and costs also vary by location, but this heterogeneity is unobserved (or at least incompletely observed). Reflecting the fact that transportation costs create spatial differentials in farm gate prices[8] and factor costs, location-specific prices and costs are approximated by a function that accounts for the parcel's distance from relevant produce and factor markets:

$$P_{ijt} = \exp\left(\gamma_{0jt} + \sum_{m} \gamma_{mjt} D_{mij}\right) \tag{4}$$

$$C_{kijt} = \exp\left(\delta_{0kjt} + \sum_{m} \delta_{mkjt} D_{mkij}\right) \tag{5}$$

where D_{mkij} measures parcel *i*'s distance from, or cost of access to, market *m* relevant to land use *j* (and for input factor *k*). The parameters γ are expected to be negative due to the fact that farm gate prices tend to decline with distance from markets. Conversely, the parameters δ are conventionally thought to be larger than zero, as factor costs typically increase with distance from markets.

Substituting equations 2–5 and the profit-maximising factor demand functions into equation 1, assuming that landowners expect prices and costs to persist over time, and then taking the natural log of both sides yields a reduced-form model for net present return that,

[8] Farm gate prices are the prices at which products are sold by the farm, excluding transportation costs.

following Nelson et al. (2001), simplifies to a linear function of the observed independent variables:[9]

$$\ln(R_{ijT}) = \eta_{0j} + \sum_{n} \eta_{1nj} S_{ni} + \sum_{m} \eta_{2mj} D_{mij} + \eta_{3j} \ln(r_i) \tag{6}$$

The last term is often replaced in practice by a socio-economic indicator variable hypothesised to affect the discount rate. This may relate to institutional settings like membership in marketing cooperatives that affect returns (Blackman et al., 2008), or to the security of legal property rights associated with the location (Nelson et al., 2001).

Because potential returns determine the amount of rent that can be charged on a piece of land, equation 6 incorporates two important economic notions: first, that rent depends on the inherent quality of land; and second, that it depends on the cost of access to relevant markets. Both have an important place in the history of economic thought, and can be traced back to the early 19th century. The idea that differences in rent are created by differences in land quality was originally proposed by David Ricardo (1821). According to Ricardo, the rent charged on the most productive land is based on its advantage over the least productive land. The importance of location was introduced into an economic model by Johann Heinrich von Thünen (1966). As opposed to Ricardo, he visualised a city surrounded by a featureless landscape – that is, by land of homogenous quality. The key feature of von Thünen's model is that transportation costs create systematic differences in farm gate prices, which affect various land uses differently. He demonstrated that, given his original assumptions, land-use choices made by profit-maximising farmers result in concentric rings around the city, each ring being devoted to a particular agricultural activity.

At any time, the observed pattern of land use represents a snapshot of outcomes from a dynamic process. Depending on data availability, a framework based on a reduced-form relationship (like the one presented in equation 6) enables the estimation of a land-use allocation model, as well as of a land-use conversion model. In cases when disaggregate data on land use is available for at least two distinct time periods, farmers' land-use conversion decisions can be

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[9] Chomitz & Gray (1996) and Nelson et al. (2001) derive the exact form of the functional relationship between the reduced-form parameters (the η's) and the underlying structural (production, price and cost function) parameters. Others (e.g. Nelson & Hellerstein, 1997; Munroe at al., 2002; Blackman et al., 2008) specify reduced-form equations similar to equation 6 without explicitly linking the structural and reduced-form parameters. All of the above papers claim to utilise a Cobb-Douglas production function (though Munroe et al. actually mischaracterise theirs as Cobb-Douglas), but the profit-maximising input demands they derive hold only if there is a single factor of production. In the more general case of multiple inputs, the relationship between the structural and reduced-form parameters would be more complex. I therefore regard equation 6 as an approximation.

modelled directly (e.g. Bockstael, 1996; Lubowski et al., 2008; Polyakov & Zhang, 2008). In this case, a parcel currently in use *h* is assumed to be converted to new use *j* if

$$R_{ijt} - Z_{ijt|h} > R_{ikt} - Z_{ikt|h} \tag{7}$$

for all possible uses *k*, including current use *h*. The inequality introduces conversion costs, *Z*, into the model. Conversion costs vary both by initial use and final use, and are naturally assumed to be zero for *k* = *h*. To exploit the time variation present in the data, net return is often specified to include time-dependent explanatory variables such as mean regional profits for any given land use. This approach allows modelling the choice of land use for each parcel conditional on its initial use.

Often, however, time-series geographic land-use data are unavailable. This is the case in my study. Cross-sectional land-use allocation models analyse the current pattern of observed land use, and cannot accommodate dynamic considerations. In essence, they assume that observations represent a stationary state, and thus that all dynamic forces potentially affecting the land-use decision have settled. The decision rule in cross-sectional models is simply to devote parcel *i* to land-use type *j* if returns in land use *j* exceed returns in any other use *k*:

$$R_{ij} > R_{ik} \tag{8}$$

A key difference between models of land-use conversion and models of land-use allocation is the former's ability to account for conversion costs. Depending on the magnitude of these costs, as made clear in equation 7, the expected return needed to induce land-use change may be significantly higher than the return to current use.[10]

My estimating equation is closely based on equation 6. I specify net returns as a linear combination of *k* independent variables (X_{ki}) specific to location *i*, and parameters to be estimated (β_{0j}, β_{kj}) that vary over the land-use alternatives:

$$R_{ij} = \beta_{0j} + \sum_k \beta_{kj} X_{ki} + \varepsilon_{ij} \tag{9}$$

$$R_{ij} = V_{ij} + \varepsilon_{ij}$$

[10] When used for prediction over time, static models tend to overestimate land-use change because of their inability to account for the effect of initial use on conversion costs (De Pinto & Nelson, 2006).

Reflecting the structure of equation 6, the explanatory variables in equation 9 can be grouped into three sets.[11] These include factors associated with land quality characterising terrain, soil properties and climate – components of the land quality index in the structural model specified by equation 3. The second set of variables consists of distance-based measures of the cost of access to relevant markets. These approximate location-specific prices and costs, where the heterogeneity is driven by transportation costs as shown by equations 4–5. Finally, the model also contains an indicator variable for land tenure.

The expression for returns includes a constant term, β_{0j}, for each land use. These choice-specific constants in a discrete choice model play a role similar to that of the constant in an ordinary least squares regression: they control for all factors (unmeasured or unobservable) that are omitted from the specification, but affect the attractiveness of the land uses. The parameters and explanatory variables are grouped into V_{ij}, representing the systematic part of returns.

Equation 9 also introduces ε_{ij}, which is an idiosyncratic component of the return on parcel *i* for land-use type *j*. It represents all factors that matter in the land-use decision, but are not captured in V_{ij}. For example, in most applications the farmer's management skills and sentimental attachment to the land are the private information of the farmer and therefore unobservable to the researcher. This idiosyncratic component is treated as a random error, and is assumed to have a known distribution. Due to the presence of the error term, *ex ante* it is possible only to make probabilistic statements about the choice of land use on any particular piece of land. Denoting by P_{ij} the probability that parcel *i* will be devoted to land use *j*,

$$Prob_{ij} = \text{Prob}(R_{ij} > R_{ik}) \;\; \forall j \neq k$$

$$Prob_{ij} = \text{Prob}(V_{ij} + \varepsilon_{ij} > V_{ik} + \varepsilon_{ik}) \;\; \forall j \neq k$$

$$Prob_{ij} = \text{Prob}(\varepsilon_{ij} - \varepsilon_{ik} > V_{ik} - V_{ij}) \;\; \forall j \neq k \tag{10}$$

The exact functional form this probability takes is determined by the distributional assumptions placed on the error term. I assume in this application that the ε's are independent and identically distributed type I extreme value. With this assumption, the model becomes a

[11] Equation 9 is linear, whereas equation 6 is log-linear. This difference is immaterial: returns are not actually observed in the data and the operation, because it is monotonic, does not affect the order of the most profitable land uses. In fact, one could reinterpret the left-hand-side variable as utility.

multinomial logit (McFadden, 1973). Choice probabilities in a multinomial logit model have a closed-form analytic solution:

$$Prob_{ij} = \frac{\exp(V_{ij})}{\sum_k \exp(V_{ik})} \tag{11}$$

Returns are latent and unobserved, but it is possible to observe an indicator variable, land use, that makes estimation possible. Using this information, the elements of parameter vector $\boldsymbol{\beta}$ can be estimated by maximising the sample log-likelihood function

$$\mathrm{LL}(\boldsymbol{\beta}) = \sum_i \sum_j y_{ij} \ln Prob_{ij}$$

where y_{ij} is the land-use indicator variable (its value is equal to one if the observed land-use choice on parcel *i* is *j*, and zero otherwise). With maximum likelihood, the estimated parameters will be those that, given the assumed structure of the model, are most likely to have resulted in the sample data.

5. Variables and Data Sources

The empirical model specified in equation 9 takes spatially disaggregated data from a variety of sources. As discussed in the previous section, I model the choice of land use as a function of geophysical and climatic factors, location-specific cost-of-access measures, and an indicator controlling for the effects of land tenure. In the remainder of this section, I describe the variables I use to estimate the model. In addition, Tables 1 and 2 provide summary statistics by observed land use and by land tenure, respectively.

5.1. The Land-use Variable

The dependent variable LANDUSE is the observed choice of land use on private, non-covenanted, rural parcels in 2002.[12] Constructing this variable required combining information from several different sources (Zhang, dataset, 2010). These include remote-sensing satellite observations of land cover (Ministry for the Environment and Terralink International, dataset, 2005); land-use information derived from AgriBase, a large database of rural properties (AsureQuality, dataset, 2005); a 2003 map of Department of Conservation (DOC) and other

[12] Geographic land-use data of complete national coverage in New Zealand is available for 2002 only.

conservancy land (Department of Conservation, dataset, 2005); and a 2002 map of land ownership (Landcare Research, dataset, 2008b).

The remote-sensing land-cover dataset was subject to extensive ground-truthing, and is generally considered highly accurate for most types of land cover. The derived land-use information, distinguishing between specific farming activities, is somewhat less accurate because it does not always offer sub-farm-level spatial detail: for most farms, only the dominant use is recorded. In practice, this means that for any farm, only a single land use may be observed within a given land cover type. The exact magnitude of the measurement error thus created is not known, but it is expected to be relatively small as land-cover classes are often very specific, and most New Zealand farms tend to be highly specialised.

My analysis includes "virtual farms". These were created to fill the gaps in AgriBase, and have an inferred land use. The land use assigned to a virtual farm is the dominant use within the region among all land (with existing land-use data from AgriBase) of the same land-cover class (Robert Gibb, pers. comm., 2010). Land cover in some cases clearly identifies land use – forestry, for example, is readily visible in satellite imagery. Moreover, land-cover classes are narrow and specific (the classification differentiates between four types of grassland, for example: high-producing exotic grassland, low-producing grassland, tall tussock grassland and depleted grassland). For these reasons, the inferred land use on virtual farms is expected to be a good predictor of actual land use. Roughly 15 percent of the sample is made up of virtual farms.

I model the choice of land use among a set of four alternatives: dairy farming, sheep or beef farming, plantation forestry and scrub (essentially, uncultivated or non-productive). These comprise the four primary rural uses in New Zealand, collectively covering about half of the land area of the country. The remaining land-use types, about 90 percent of which is DOC or other public land, are considered exogenous. Land-use decisions made on public land are rarely governed by considerations of profit maximisation, and are therefore not amenable to the assumptions of the model. Urban areas have been excluded, as the focus of this study is land allocation among rural uses. Other rural land uses are not modelled because they are relatively unimportant compared to the aforementioned four.[13] A map of land use is displayed in Figure 1.

Dairying is the most intensive (and fastest-growing) land use among those modelled. Dairy conversion demands large investments in infrastructure, and the use has relatively high

[13] A possible exception is horticulture, which has become increasingly significant in recent years, though it is still considerably smaller by area than any of the alternatives in the choice set. In addition, horticulture is more heterogeneous than other uses, and includes groups as diverse as short-rotation crops, perennial crops, orchards and vineyards. These may significantly differ in terms of their intensity and requirements for land quality.

fertiliser and water requirements. Due to its high intensity, dairy farming is often associated with negative environmental externalities, and is consequently the focus of environmental regulations targeting water scarcity and non-point source pollution. The sector is extremely significant economically (dairy products constitute about 25 percent of total merchandise export earnings in New Zealand), as well as in terms of its aggregate land-use share. Around 11 percent of the observations in the sample are under dairy use.

The other pastoral sector, sheep and beef farming, has been experiencing a decline since the mid-1980s but is still the largest by area, occupying nearly 60 percent of the sample. New Zealand sheep and beef cattle are grass fed.[14] They frequently inhabit the same pasture area, so sheep and beef farming are customarily combined into one land-use category. Depending on the quality of their land and other factors, sheep and beef farmers may practise either intensive or extensive farming methods. In terms of land-use intensity, the sector therefore occupies a wide spectrum, with the majority of farms falling between typical dairy and forestry operations. On average, sheep and beef farmers in 2002 applied around one-tenth the amount of nitrogen fertiliser per hectare compared to dairy farmers (Hendy & Kerr, 2006).

Dairy farming is sometimes indistinguishable from other types of livestock farming in satellite measurements of land cover. Therefore, the dominant pastoral use within livestock farms was established using information from AgriBase for this analysis. Focusing on the dominant use may result in an overrepresentation of dairy area: a dairy farmer may theoretically choose to devote lower-quality or less accessible areas within the farm to other livestock, but a livestock farmer would have to incur significant conversion costs (for example, building milking sheds) to establish dairying operations. Under most circumstances, therefore, it is not feasible to practise dairying as a secondary land-use type. Areas known to be drystock or grazing on dairy farms were excluded from the analysis to minimise the potential for such misclassification.

Plantation forestry makes up about 11 percent of the sample land area. The most commonly planted forestry species in New Zealand is Monterey Pine (*Pinus radiata*), with timber being harvested in approximately 30-year rotations. This time lag and the large investments associated with planting mean that a forestry land-use decision is practically irreversible for a significant period of time (and that the land-use choices of profit-maximising owners are complex decisions that involve long-term price expectations and option values). A forestry

[14] If a significant proportion of livestock were crop-fed, the exogeneity of horticultural land uses would be a more tenuous assumption, as crop production would be complementary to dairying and to sheep and beef farming.

observation may thus reflect a land-use decision made decades ago. Therefore, modelling land uses in a static framework is particularly problematic for this sector.

Finally, the remaining roughly 18 percent of observations represent scrub. I define scrub as idle but potentially productive, privately owned land. This definition does not pertain to a specific type of land cover. That is, for the purposes of this study, abandoned pasture (which in some cases may be difficult to identify from satellite imagery – a point I will discuss in more detail in section 7) and blocks of land under indigenous forest land cover both fall into the scrub category. Inherently unproductive land, such as bare mountain tops and swamps, does not fit my definition of scrub and is excluded from estimation.

5.2. Geophysical Variables

Locations are heterogeneous with respect to the bundle of topographic, soil and climate characteristics they offer. I use SLOPE (in degrees) as one of the independent variables. The slope layer was created from a 25m digital elevation model fitted to 20m digital contour data, whose accuracy was assessed using over 2500 independent geographic positioning system data points (Landcare Research, dataset, 2004).

Slope is perhaps the simplest characterisation of terrain. It may affect profitability through productivity as well as through harvest costs, and may render some land uses unfeasible or uneconomic. Dairy farming, for example, is almost always found in relatively flat regions of New Zealand.

Solid curves in the four panels of Figure 6 depict the observed distribution of each land-use type by slope (where the land-use shares within each slope value sum to one). The graphs show, for instance, that nearly a third of all flat (SLOPE = 0) land area in New Zealand is under dairy use, and much of the rest is devoted to sheep or beef farming. In addition, the first histogram in Figure 3 depicts the relative amount of land areas with particular values of slope (rounded to the nearest degree): more than 13 percent of all land is flat, and a quarter of it has a slope of 2 degrees or less. At the same time, the incidence of high slopes is negligible, with an overall share of less than 5 percent for 25 degrees or more, and less than 1 percent for over 30 degrees.

The second geophysical variable, Land Use Capability (LUC) class, is a summary measure of land quality that constitutes part of the New Zealand Land Resource Inventory (Landcare Research and Ministry of Agriculture and Forestry, dataset, 2002). The classification provides an ordinal measure of land quality based on an "assessment of the land's capability for use, while taking into account its physical limitations and its versatility for sustained production" (Lynn et al., 2009).[15] Under this scheme, land is grouped into eight classes, with limitations to use increasing from class 1 to class 8. In general, classes 1–4 are considered suitable for multiple land uses, including arable cropping. Classes 5–7 are unsuitable for arable cropping, but are suitable for pastoral grazing and forestry use. Limitations to use reach a maximum with class 8, which is best managed as conservation land. Higher-intensity uses therefore generally require land of a lower LUC class. This notion is supported by Figure 7, which depicts the observed shares of the four modelled land uses within all observations of a specific LUC class. Most of the private land in New Zealand is of relatively low quality by this classification, as shown by the second histogram of Figure 3.

A different measure of land quality is based directly on the land's biological productivity – i.e. productivity that ultimately leads to economic returns. I employ a "Storie Index"-type variable, PROD, developed for pastoral farming systems (Baisden, dataset, 2003). The variable summarises factors representing climate and soil properties that affect plant growth, and was calibrated via logarithmic regression to satellite measurements of net primary productivity (NPP) in New Zealand (Baisden, 2006).[16] The productivity index, unlike LUC class, is therefore an objective and cardinal representation of land quality. It is measured in tonnes of grass biomass grown per square metre per year.

A similarly calibrated productivity index is available, but not included in the estimation, for New Zealand plantation forestry. The reason for omitting this variable is that it is highly correlated with the pastoral productivity index (correlation coefficient $r = 0.973$). The two indices have different absolute scales: the amount of grass biomass that can be grown on a piece of land usually differs from the amount of woody biomass that can be grown on the same piece of land. However, as shown by equation 9, the parameters of the model vary by land-use alternative, and the difference in scale will therefore be reflected in the scaling of the estimated coefficient on the pasture productivity variable for forestry use.[17]

The LUC class and the productivity index both provide a complex summary measure of land quality, as determined by a range of underlying geophysical and climatic factors. Nevertheless, they capture different dimensions of quality, and the two are nearly orthogonal

[15] Although slope is one of several geophysical inputs to the LUC classification, Todd & Kerr (2009) find that slope affects land use beyond its effect through LUC class. This finding justifies the treatment of slope as a separate independent variable.

[16] Satellite observations of NPP measure productivity under current land use. The calibration procedure is necessary for estimating productivity on parcels not currently under a pastoral use.

[17] Despite the high correlation, the significance of the productivity variable is expected to be lower in the forestry equation: Baisden (2006) found that the relationship between observed NPP and the calibrated pasture productivity index was much stronger than that between NPP and the calibrated exotic forestry productivity index.

(correlation coefficient r = -0.0013). The LUC classification is based primarily on an assessment of local geophysical conditions (rock types, soils, landforms and slopes, erosion types and severities), while PROD is strongly affected by climatic factors (it is calculated from growing degree days, soil moisture deficit and soil particle size). Accordingly, LUC classes are fairly evenly distributed across larger regions, but pastoral productivity exhibits a strong north–south gradient. It is likely that the calibration procedure used for deriving the productivity index masks large-scale variation in land quality. This dimension of quality is mostly reflected in LUC.[18]

The exact combination of geophysical variables employed by researchers varies across studies, but in general slope and different land-quality measures have consistently been found to be significant determinants of land-use decisions (e.g. Chomitz & Gray, 1996; Nelson & Hellerstein, 1997; Lubowski et al., 2008).

5.3. Cost-of-access Variables

I use two distance measures to account for transportation costs thought to be relevant for certain land-use types. As in equations 4–5, TOWN_DIST is intended to capture the cost of access to local factor and produce markets and other amenities typically provided by population centres.[19] It is an impedance-weighted distance to the nearest (in the least-cost sense) supermarket. Most New Zealand agricultural and forestry products are exported, and so PORT_DIST is an analogous measure of distance to the nearest major commercial port. Proximity to towns is hypothesised to be more important for intensive types of land use, and proximity to ports is hypothesised to be important for industries that produce more for export and are more expensive to transport (dairy farming and forestry).

In calculating both cost-of-access variables, I follow an approach similar to that of previous studies (e.g. Chomitz & Gray, 1996; Nelson & Hellerstein, 1997; Blackman et al., 2008). Impedance weights were assumed to depend on two factors: the existence of roads; and, in the absence of roads, the underlying terrain. Travelling along roads is assigned a significantly lower cost than travelling on terrain. In addition, traversing flat terrain is considered less costly

[18] An alternative rationale for using two comprehensive quality measures is that one may think of land-use capability as a constraint: it is about limitations to use and not about production per se. There is no inherent reason that land without any limitations should grow more grass than land with a limitation that does not affect grass growth, but makes it less than ideal for tillage. This argument is precisely why the productivity indices were developed in the first place (Troy Baisden, pers. comm., 2010).

[19] Grimes & Aitken (2008), for example, show that water access to New Zealand farms is more valuable closer to towns, and attribute this finding to water-intensive land uses (such as dairying and cropping) that require access to processing facilities and an urban labour pool.

than traversing hilly terrain.[20] Although the weighting is arbitrary, this method of calculating least-cost distances has the desirable property of producing values closely related to road distance, especially for parcels located near road features. Access costs are considerably higher in remote areas because of the large impedance costs accumulated before reaching the nearest road. The cost-distance calculations were carried out in ArcGIS using a road centre-line layer (Land Information New Zealand, dataset, 2010).

5.4. The Land-tenure Variable

An indicator variable, MAORI, provides information on land tenure: its value equals zero for general private land, and one for Māori freehold land. Approximately 5.4 percent of the sample land area falls in the latter category. As explained earlier, the tenure system may contribute to the underdevelopment of this land. It is, for example, difficult for owners of Māori freehold land to obtain a loan or mortgage from financial institutions. The various characteristics associated with Māori freehold land are not observed separately: the indicator variable captures the effect of all aspects of Māori tenure, including matters of ownership, succession, governance, administration and finance.

Māori own general land as well, thus the variable should not be interpreted as a socio-economic indicator for the ethnicity of the parcel's owner. It is, however, possible that some Māori communities may express distinct cultural values in their land-use decisions on land inherited from their ancestors. These arguments bring up the possibility of a behavioural objective distinct from profit maximisation. As I have argued, the model in equation 9 is compatible with utility-maximising behaviour as well – as long as one component of the utility-function is determined by economic returns, which seems plausible. The environmental and cultural preferences of owners, inasmuch as they affect the use of Māori freehold land, will also be reflected in the parameter estimate of the indicator variable.

Figure 2 shows the geographic distribution of Māori freehold land in the North Island of New Zealand (the area of Māori land in the South Island is negligible). As can be seen in Table 2, this land is, on average, under less intensive cultivation than general land. At the same time, the majority of Māori freehold land is in the poorest, non-arable LUC classes, and often in remote regions of the country. These differences in land quality and location therefore need to be controlled for when studying land tenure and its effects on land use. The ownership and land-

[20] For every 500m travelled, the impedance weight assigned to road travel is $w = 1$. The impedance weight for travelling the same distance across terrain is calculated as w = SLOPE + 10.

tenure data (Landcare Research, dataset, 2008b) are based on information from the Māori Land Information Base.

Nelson et al. (2001) use a similar strategy with land-tenure indicators to investigate the effect of the tenure system on land-use decisions in Panama. They employ a set of four indicator variables (denoting locations inside a national park, each of two indigenous reserves, and mineral or forest concession areas) to classify parcels by land tenure, and conclude that legal property rights for an indigenous population can influence land-use outcomes. Their results are, of course, not directly transferrable to the context of a developed country – for example, in their application, unlike in New Zealand, the enforceability and security of property rights is an important issue.

To select observations for estimation, geographic sampling was performed by placing a 500m × 500m rectangular grid over the country and recording the value of each variable at each grid point. The traditional way of visualising the resultant sample is to think of each observation as a homogeneous 25ha cell.[21] The sampling procedure described above yields 519,251 observations, which corresponds to approximately 13 million hectares, or close to half of the total land area of New Zealand's two main islands. A sample of this size preserves a great amount of spatial detail for a national-scale analysis, but does not pose serious computational constraints in a multinomial logit estimation. The omitted observations represent either public land or land under unknown ownership (485,683), private land in exogenous uses (54,076), or private land in one of the modelled uses with incomplete data on the explanatory variables (16,838).

6. Econometric Issues

This section briefly considers some of the econometric challenges posed by empirically implementing a spatial discrete choice land-use model. The issues I review revolve around the implications of using a multinomial logit model, the potential endogeneity of certain independent variables, and spatial effects giving rise to spatial autocorrelation. In each case, I examine methods that have been proposed to address these issues from a theoretical as well as an empirical standpoint.

6.1. The Multinomial Logit Model

Due to its assumption of independent and identically distributed errors, the behavioural implications of the multinomial logit model are restrictive and, in many situations, unrealistic.

[21] All data sources have an original resolution that is finer than this.

The model exhibits what is known as "independence from irrelevant alternatives"; that is, the relative odds of choosing one alternative over a second alternative do not depend on the existence or attributes of any other alternative (Train, 2009). Intuitively, the multinomial logit model does not allow for the possibility that certain alternatives are more similar than others. Despite its limitations in representing choice behaviour, the multinomial logit model has been a popular choice for modelling land-use decisions (e.g. Chomitz & Gray, 1996; Nelson & Hellerstein, 1997; Nelson et al., 2001; Carrión-Flores et al., 2009).

Other discrete choice models relax the restrictive assumptions of the multinomial logit and allow more complex substitution patterns to emerge. Probit models offer a lot of behavioural flexibility, but require normally distributed errors, and can be cumbersome to deal with. They are most often estimated in dichotomous choice situations (Bockstael, 1996; Munroe et al., 2002; Blackman et al., 2008). In a nested logit model, the independence from irrelevant alternatives property holds only within the nests, but not necessarily across nests. The practical significance of this is that in a nested logit, alternatives grouped into the same nest are allowed to be closer substitutes. Lubowski et al. (2008) estimate a model with three nests specified according to the land-quality requirements of their modelled uses. The greatest amount of behavioural flexibility is offered by the random parameter logit model, which can approximate any random utility model (McFadden & Train, 2000). Polyakov & Zhang (2008) employ this specification in estimating a model of land-use conversion to analyse the effect of property taxes on the conversion decision.

It is not clear to what degree the conceptual advantages provided by the more flexible models are empirically significant. Nelson et al. (2004) compare the performance of three alternative models, and find that the nested logit model is superior to both the multinomial and random parameters logit models in terms of its predictions in their application. However, De Pinto & Nelson (2006) revisit the same study and, using a slightly different method of evaluation, discover that the nested logit does not perform significantly better than the simpler multinomial logit. Likewise, Lubowski et al. (2008) perform specification tests that support their use of the nested logit model as opposed to the multinomial logit model. At the same time, they also find that the nested specification is not critical for their overall findings, and that the simpler non-nested model yields qualitatively similar results in their simulations. The same conclusion has been reached in other applications as well: for example, in the location choice literature, Miyamoto et al. (2004) observe that their random parameters logit model does not perform significantly better than a standard logit model in either a practical or a statistical sense. These findings suggest that despite its restrictive assumptions, the multinomial logit model performs relatively well in empirical applications.

In addition, a desirable feature of the multinomial logit model is that it can be specified in a manner that ensures that its predictions match the data perfectly. The inclusion of a full set of alternative-specific constants (one less than the number of choice alternatives) achieves this outcome. Due to their different distributional assumptions, random parameter logit models, regardless of whether they contain alternative-specific constants, will not necessarily generate in-sample predictions that aggregate to the observed choice shares (Klaiber & von Haefen, 2008). This is an important difference, because predictions from land-use models are often aggregated to focus on overall land-use shares.

6.2. Endogeneity

The location of a parcel of land relative to dairy-, meat- or wood-processing facilities may affect the land-use decision. Proximity to a pulp or panel mill, for example, can greatly reduce log transportation costs, thereby increasing the potential profitability of plantation forestry in the area. Distances to processing plants therefore contribute to the creation of spatial differentials in farm gate prices, as shown by equations 4–5. The concern with these variables is that they are endogenous, because processing facility locations are not independent of land-use decisions. In fact, it would be natural to expect that plants are strategically built near their suppliers of raw materials. In other words, facility locations are simultaneously determined with land-use outcomes.

Chomitz & Gray (1996) and Nelson et al. (2001) face a similar issue. In their applications, the problem arises because of the possibility that road construction through the rainforest is not completely independent of the land's suitability for agricultural production. Their measures of access costs will be endogenous if roads are preferentially routed through regions more suited for agricultural production, and if not all aspects of land quality are observed (and controlled for).[22]

Endogeneity in linear regression models leads to biased parameter estimates. The method of instrumental variables and two-stage least squares regression are the conventional solutions to this problem (Greene, 1990). It is tempting for the econometrician to attempt to control for

[22] By an analogous argument, my TOWN_DIST and PORT_DIST variables could be subject to the same criticism. My maintained assumption is that in New Zealand road construction is less affected by unobserved dimensions of land quality than in the context of tropical deforestation. Towns are also not affected by the simultaneity problem to the same degree as processing facilities. Likewise, the location of major commercial ports is determined primarily by geophysical factors. The exogeneity of TOWN_DIST and PORT_DIST in my application is therefore a more tenable assumption.

endogeneity in discrete choice models by selecting appropriate instruments and applying an analogous two-stage procedure: Chomitz & Gray (1996) and Nelson et al. (2001) use such an approach. However, Foster (1997) argues that the technique does not apply to non-linear models, and that it will not result in consistent parameter estimates in a discrete choice framework. I therefore exclude cost of access measures to processing facilities from the main set of regressors, and relegate results from a model that includes these variables to the Appendix (Table A1).

6.3. Spatial Autocorrelation

Under spatial randomness, the location of observations may be altered without affecting the information content of the data (Anselin, 1988). The converse, spatial autocorrelation, is more realistic to expect in a land-use model. Spatial autocorrelation can arise from spillovers among the dependent variables or among the error terms. In the former case, local land-use outcomes are interdependent, and in the latter, unobserved determinants of land-use choices are correlated across space.[23]

In linear regression models, spatial autocorrelation leads to inefficient parameter estimates and inaccurate measures of statistical significance. The problem is readily addressed via a spatial weights matrix: by assuming a structure for the spatial relationship and estimating additional parameters that characterise this structure. This technique is almost always computationally unfeasible in discrete choice models (it could involve solving integrals of the dimension of the sample), and has been applied only to small datasets (e.g. Carrión-Flores & Irwin, 2004). Alas, the consequences of spatial autocorrelation are also more severe: it results in heteroskedastic errors, which lead to inconsistent parameter estimates in discrete choice models (McMillen, 1992).

In the absence of a readily accessible yet rigorous solution to deal with spatial autocorrelation, researchers have developed various ad hoc methods to mitigate its effects. The most widely used of these is systematic spatial sub-sampling: to select only observations for estimation that are a certain minimum distance from one another. This strategy has been employed by Nelson & Hellerstein (1997), Munroe et al. (2002) and Lubowski et al. (2008), among others. The rationale usually given for systematic sub-sampling is that spatial autocorrelation decays with distance and may be minimised by using observations located

[23] For this reason, spatial autocorrelation can virtually be taken for granted. All observed independent variables exhibit some level of spatial correlation – it would be unrealistic to expect the opposite of omitted variables of importance.

sufficiently far apart.[24,25] In an effort to account for the influence of the surrounding environment on land-use outcomes, some authors also construct spatially lagged independent variables (e.g. Nelson et al., 2001; Munroe et al., 2002).[26]

Robertson et al. (2009) investigate the effectiveness of these techniques in discrete choice models. Their Monte Carlo simulation results advocate the use of spatially lagged explanatory variables. However, the approach makes very little practical difference in their empirical application. This seems to be a ubiquitous finding with regard to spatial effects in land-use models. Blackman et al. (2008) find that their Bayesian heteroskedastic spatial autoregressive model produces qualitatively virtually identical results to those from an ordinary probit. Likewise, Robertson & Nelson (2006) claim that leaving spatial effects unmodelled does not significantly affect the predictive ability of their model. Using systematic spatial sub-sampling, Munroe et al. (2002) successfully reduce the extent of spatial autocorrelation, yet they discover that the overall predictive accuracy of their model changes only slightly. At the same time, sub-sampling greatly reduces their overall predictive power owing to the reduction in the number of observations. Lubowski et al. (2008) also establish that results based on a spatial sub-sample are very similar to those based on the full sample (and conclude that spatial dependence is not a critical concern in their application). Similarly, Nelson et al. (2001) see little evidence for the effectiveness of using independent variables with spatial lags in the model they estimate. Finally, a more recent working paper by Carrión-Flores et al. (2009) introduces a more complex two-step procedure to account for spatial dependence in multinomial discrete choice models. However, they find that it produces bias and does not lead to a marked improvement in performance relative to a non-spatial model.

Despite the mixed empirical evidence for the effectiveness of systematic spatial sub-sampling and spatially lagged independent variables, I experiment with both techniques in my model. Results based on the sub-sample are presented in the next section, along with other results; those from a model with spatial lags are in the Appendix (Table A2).

[24] In most applications, the full sample is already systematically drawn (by a grid, for example). The implicit assumption in subsampling is that the original grid is not coarse enough to eliminate the autocorrelation.

[25] Robertson et al. (2009) remark that subsampling amounts to undercounting the effect of neighbouring error terms, and does not result in the use of the "proper" distribution in the estimation.

[26] More advanced techniques have been implemented in dichotomous choice models. For example, Blackman et al. (2008) estimate a land use model with a Bayesian heteroskedastic spatial autoregressive procedure. It is often not straightforward to transfer these techniques to multinomial choice situations.

7. Results

In this section, I describe estimation results from several specifications of the multinomial logit model. I start with the simplest specification, and gradually expand the set of explanatory variables. Objectively evaluating the performance of discrete choice models is difficult because goodness-of-fit statistics in these models are often not comparable across applications, or even different specifications in the same application. I examine the in-sample predictions of the model along several dimensions to obtain an intuitive (though subjective) understanding of its strengths and weaknesses. Finally, using the estimated relationships, I analyse a counterfactual scenario to establish the impact of Māori land tenure on national land use in New Zealand.

7.1. Estimation Results

One of the objectives of my study is to quantify the effect Māori tenure has on land-use decisions in New Zealand. To motivate the discussion, the first model I estimate includes only the land-tenure indicator variable along with an alternative-specific constant for each use. The maximum likelihood estimation results from this, as well as subsequent model runs, are displayed in Table 3 and discussed below.

Equation 10 shows that discrete choice models operate on differences in the latent variable. The absolute scale and level of rent (or utility) are immaterial – from a modelling perspective, that is. Stated informally, choice outcomes are based on which alternative wins, and not by how much. A practical consequence of this is that the only parameters that can be estimated in discrete choice models are those that capture differences across the alternatives. I designate scrub the base outcome, and accordingly normalise all scrub coefficients to zero. Although these are omitted from Table 3, the parameter estimates for all other land uses should be interpreted relative to the normalised scrub parameters.

Estimation results from model 1 support the observation that Māori freehold land tends to be associated with lower-intensity uses. This relationship is apparent from the estimated negative coefficients on the MAORI variable. In addition, the relative magnitude of these coefficients for the various land-use alternatives is also informative: it indicates that more intensive uses become increasingly less likely under Māori tenure. Results from model 1 therefore constitute proof that Māori freehold land is, on average, less developed than other private land. However, tenure is only partially driving these results in light of the fact that Māori freehold land also tends to be associated with lower-quality soils.

A more complete understanding of tenure requires that other characteristics of the land be controlled for. Model 2 introduces geophysical land attributes as independent variables, and thereby enables the investigation of how these dimensions of land quality affect private land-use decisions. One feature of the specification in model 2 that merits some discussion is that LUC class appears in it as a cardinal variable rather than a set of categorical indicators. This intentional misspecification greatly reduces the number of parameters that need to be estimated, and has negligible effects on model fit.[27] It also results in a conceptually simpler monotonic relationship. Despite the fact that the land-use capability classification does not have a cardinal interpretation, it appears that the effect of LUC class on land-use decisions is appropriately approximated by a continuous variable – more evidence for this claim is offered in section 7.2.

Most parameters have the expected sign, and all of them are statistically significant at the 1 percent level. As shown in Table 3, accounting for slope, LUC class and biological productivity causes little change in the previously estimated relationship with regard to land tenure: its effect remains qualitatively the same conditional on these geophysical factors. Nonetheless, controlling for land quality does result in slightly higher (i.e. lower in absolute value) tenure coefficients because Māori freehold land is of lower quality on average.

Steeper terrain reduces the attractiveness of all three productive uses relative to scrub, as reflected by the negative SLOPE coefficients. The effect is larger for more intensive land-use types. All three LUC class coefficients are negative as well, indicating that land with more limitations to use is less likely to be devoted to production. As with the SLOPE coefficients, the absolute magnitude of the LUC class coefficient is largest for dairy and smallest for forestry. These findings confirm prior expectations regarding the overall relationship between land-use intensity and land quality.

Biological productivity is highly and positively significant for dairying. It enters with a negative coefficient in the sheep-beef equation, however, implying that the ability to grow grass biomass matters more for scrub than it does for sheep or beef farming. This certainly should not lead to the conclusion that additional productivity is undesirable for livestock farms.[28] A couple of different factors could contribute to the perverse finding (though it is unlikely to be fully explained by either of them). It may be a manifestation of misclassification that affects scrub and pasture in the land-cover data. In certain regions of the South Island, abandoned pasture does

[27] A specification with separate indicators for each LUC class achieves a slightly higher log-likelihood value, but more than doubles the number of parameters. Model fit with four LUC class indicators (each representing two classes) is poorer than the fit achieved by the misspecified model.

[28] It is true, however, that extensively managed pasture land has very limited requirements with regard to productivity.

not grow woody biomass due to a lack of seed sources: what appears as pasture in satellite imagery may actually be scrubland in these areas. With no differences in land cover, abandoned land would be assigned the primary use of the farm on which it is located. Because of the strong influence of climate on the productivity variable, the affected regions are those with relatively low biological productivity; consequently, sheep and beef farming appear less sensitive to productivity reductions.[29] To a lesser degree, another type of misclassification may also play a role in explaining the perverse productivity outcome: some of the scrub area in the sample may represent unidentified lifestyle blocks and land awaiting development for subdivision. Quite conceivably, these are more prevalent in regions with a pleasant climate (which generally coincides with high productivity). Lifestyle blocks could thereby cause scrub to appear a more attractive alternative on productive land.[30]

As already discussed in the previous section, the alternative-specific constants (ASC) ensure that modelled aggregate land-use shares add up to their observed sample counterparts in a multinomial logit model. To the extent that omitted factors systematically affect the desirability of the land-use alternatives, their effects will be soaked up by the estimated constants. *Ceteris paribus*, a higher constant leads to a higher choice probability, but its value has no inherent economic meaning.

Model 3 incorporates the full set of explanatory variables, including measures of access cost to population centres and major commercial ports. All previous results, including those on the effect of land tenure, hold in this specification as well. TOWN_DIST has a negative effect on dairy attractiveness, reflecting dairy farming's greater reliance on local produce and factor markets. As expected from their lower level of land-use intensity, sheep and beef farming and plantation forestry are less sensitive to proximity to population centres. The estimated coefficient on PORT_DIST is also significant and negative for dairy and forestry (the two large export industries, whose products, per unit of value, are more expensive to transport). A likelihood ratio test comparing models 2 and 3 firmly rejects the null hypothesis that the cost-of-access variables do not matter in land-use decisions.[31,32]

[29] This hypothesis is supported by the geographic distribution of marginal land without seed sources (Landcare Research, dataset, 2008a). Marginal land with no potential seed sources to allow reversion to a different land cover makes up just over 60 percent of all marginal land (excluding mountain tops) by area on the North Island, and as much as 95 percent on the South Island.

[30] Misclassification resulting from a failure to observe lifestyle blocks could also contribute to the explanation of the negative productivity coefficient in forestry use. However, in light of the weak relationship between remote sensing measurements of NPP and the productivity index for exotic forestry (Baisden, 2006), the perverse forestry relationship is less of a concern.

[31] The test statistic is calculated as $\mathrm{LR} = -2\left[\mathrm{LL}\left(\hat{\beta}^{H}\right) - \mathrm{LL}\left(\hat{\beta}\right)\right]$, where $\mathrm{LL}\left(\hat{\beta}^{H}\right)$ is the maximised log-likelihood value from the constrained model (model 2, in this case), and $\mathrm{LL}\left(\hat{\beta}\right)$ is the maximised log-likelihood value from

The issue of spatial autocorrelation and the relative merits of strategies that have been proposed to mitigate its effects have already been discussed in section 6.3. The most widely applied technique involves re-estimating the model on a sub-sample drawn to maximise the distance between observations. Estimates displayed under the model 4 heading in Table 3 have been obtained by implementing this strategy. The sub-sample includes only about 3 percent of the original observations – this means that the straight-line distance between the nearest neighbours is around 3km. It is clear that the results established in model 3 are robust to systematic spatial sub-sampling. In fact, the 95 percent confidence interval for each parameter in model 4 includes its point estimate from model 3. This finding suggests that spatial autocorrelation is not a major problem in my application.[33]

Although significant and largely consistent with underlying economic theory, the coefficients from the multinomial logit model can be difficult to interpret because they are relative to the base outcome. A more intuitive way to evaluate the effect of covariates is to examine the marginal effect of changing their values on the probability of observing an outcome. Because of the non-linearity of the logit model, marginal effects depend on the values of all independent variables. For each land use, I evaluate marginal effects from model 3 at the median values of the covariates within that particular use. These are shown in Table 4. Marginal effects for the land-tenure indicator suggest that Māori tenure reduces the probability of observing dairy use by 27 percent on a piece of land that has the attributes of the median dairy land. Likewise, it reduces the probability of sheep or beef farming by about 23 percent on land that is identical to the median sheep or beef farmland. Plantation forestry and scrub become more likely under Māori freehold land tenure (on the median-quality land corresponding to the use), as indicated by the tenure variable's positive marginal effect for these two alternatives.[34]

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the unconstrained model. It is distributed chi-squared with degrees of freedom given by the number of restrictions implied by the constrained model (Train, 2009).

[32] Excluding virtual farms from the estimation does not qualitatively change any of the results.

[33] As noted in the previous section, a similar conclusion is frequently drawn in the land-use literature. This would be a remarkable outcome considering what it implies – that spatially correlated unobserved factors have no major influence on land-use decisions. A more probable explanation may be that other specification errors disguise the effect of spatial autocorrelation.

[34] Māori iwi (tribes) have in recent years received land transfers from the New Zealand government as a compensation for land taken from them in the 19th century. Some of today's Māori freehold forests were acquired in such transfers, meaning that the land-use decision was actually made before the land came under Māori ownership. This could bias the forestry coefficient on MAORI (and the variable's marginal effect) upward. Most transfers have taken place since 2002, however, and are therefore not represented in the land-use data. Although the forestry use of this land may not reflect the preferences of current owners, Dickson et al. (2009) argue that the carbon liability they face under the ETS for deforestation makes it relatively unlikely that the land will transition out of forestry.

7.2. Goodness-of-fit

Estimation results are qualitatively robust to different subsets of the explanatory variables and to deleting a large numbers of observations. Assessing model fit is difficult, however, because in discrete choice models a statistical equivalent to the familiar R-squared of ordinary least squares regression does not exist. The two most common alternative measures of goodness-of-fit are the likelihood ratio index and the proportion correctly predicted (or hit rate). When comparing discrete choice models estimated on the same data, it is generally correct to claim that the model with the higher log-likelihood value fits the data better.[35] The likelihood ratio index is based on a transformation of the log-likelihood value, and measures how well the model performs relative to a null model in which all the parameters are zero. Its value ranges from zero to one, with higher values indicating better fit. However, its similarity to R-squared stops here – the likelihood ratio index does not indicate the proportion of variation in the response variable that is explained by the model, and it has no intuitively obvious meaning. Therefore, likelihood ratio indices from non-nested models are not comparable, which limits its usefulness as a goodness-of-fit measure. It is, for example, technically incorrect to compare model 3 to model 4 on the basis of the likelihood ratio index.

In the second common goodness-of-fit measure, the proportion correctly predicted, the predicted outcome for each observation is assumed to be the alternative with the highest predicted probability. Train (2009) recommends avoiding this statistic because, despite its apparent intuitive appeal, it is meaningless in a probabilistic context. For this reason, I do not report proportion correctly predicted in the estimation results section.[36]

For lack of a general goodness-of-fit statistic, I evaluate the model's predictive ability in various heuristic and intuitive ways. These informal checks are useful in pointing out some of the strengths and weaknesses of the model, but it is important to note that none of them constitutes a rigorous means of testing its predictions. Figure 4 shows histograms and geographic distributions of the predicted choice probabilities for each land-use alternative. The vast majority of the country's land area is seen by the model as virtually unsuitable for dairy farming, as reflected by the abundance of near-zero dairy choice probabilities. On the other hand, a small fraction of observations do have relatively high dairy probabilities, and these occur almost without exception in traditional dairy-producing regions. In particular, areas in Taranaki and

[35] The likelihood ratio test formalises this concept for hypothesis testing.

[36] One problem with the statistic can easily be demonstrated by observing that, in model 3, the proportion correctly predicted equals 0.6460. This seems fairly high, especially in a choice situation with four alternatives. But note that simply predicting sheep or beef farming for each observation, without estimating any model at all, would achieve a similarly high hit rate (0.5942) due to the alternative's large land-use share.

Waikato have the highest dairy probabilities. Dairy-producing regions on the South Island (and especially in Canterbury) tend to display lower choice probabilities for dairy farming. This finding may be explained by the fact that a large fraction of dairy land in these regions is irrigated (the model does not include artificial improvements to land).[37]

The distribution of predicted sheep and beef probabilities paints a different picture. The median value is over 0.6, and for certain combinations of the independent variables the model predicts this land-use type with a high probability. Very few observations have a low predicted probability for sheep or beef farming. The model's predictions thus reflect reality in the sense that the land use is a popular alternative under most geophysical and socio-economic conditions and in all regions of the country.

Forestry, like dairy, has a low median probability of being chosen. Unlike dairy, it is never predicted to be a particularly attractive choice. The 99th percentile of forestry probabilities is under 0.25, and the number of observations for which it is the highest-probability land use is less than 100 – even in those cases, forestry probability is only marginally higher than scrub probability. This means that the model is unable to identify conditions under which forestry would be a notably attractive land-use choice. At the other end of the spectrum, forestry is seldom predicted to be completely unfeasible either. It is an unlikely land-use choice in most situations, but the predictions rarely imply a degree of certainty akin to that implied by the low dairy probabilities. In this sense, the distribution of forestry probabilities is more similar to that of sheep or beef probabilities, but with a lower probability mass. According to the model, forestry is most likely in the upper North Island, where, indeed, most forestry production takes place.

The histogram of scrub probabilities resembles that of dairy probabilities. For many pieces of land, scrub is an extremely unlikely choice, but the range of probability predictions is large. Therefore, there exist situations in which it is clearly the most attractive land-use type (which, given the definition of scrub, implies that a productive use is unlikely to be economic in these situations). High scrub probability invariably occurs on low-quality parcels of land in more remote regions, as indicated by the geographic distribution shown in Figure 4. This mirrors the general pattern of the land use's observed distribution.

How well do the model's predictions match actual land-use outcomes? Table 5 sheds further light on this question. The large sample size facilitates the evaluation of predictions in a

[37] If irrigation is productivity-enhancing, its presence will be reflected in satellite measurements of NPP. However, its derived effect on PROD is not analogous because of the calibration procedure used in the variable's calculation.

manner that, unlike a hit-rate-based statistic, is not contrary to the meaning of choice probabilities. The table shows the fraction of observations in a given land use among all observations with a similar probability prediction for the corresponding use. The grouping is based on 100 probability intervals, not all of which are represented in the table. For example, 30.8 percent of all observations with a predicted dairy probability in the range of 0.30–0.31 are indeed in dairy use, and 84.4 percent of all observations with a predicted scrub probability in the range of 0.80–0.81 are indeed scrub. Overall, there is a high degree of correspondence between predictions and observations. The only possible exception is dairying, for which predictions get less accurate in the upper range of probability values. That the information carried in choice probabilities is correct on average should not be surprising (after all, the parameter estimates are those that maximise the likelihood function), but it is reassuring to find that the close relationship applies to the whole range of probability values in each land-use alternative.

For any individual parcel of land, the model implies potentially high levels of uncertainty surrounding the choice of land use: for nearly a quarter of all observations, the value of the highest-probability outcome is less than 0.5, while the median value is 0.64. As indicated by the results in Table 5, aggregating predictions over a large number of observations may be a useful strategy to address this uncertainty – at the cost of losing spatial detail. At the national level, modelled land-use shares exactly equal observed land-use shares due to the inclusion of fixed effects for each land use. The equality does not necessarily hold at a regional level, which suggests another means of testing the model's predictions. Figure 5 compares predicted and observed land-use shares within the 55 territorial authorities that contain at least 2000 observations.[38] The relationship is reasonably strong for dairy and scrub, but weak for forestry, suggesting that unobserved factors may play an especially important role for land-use decisions in forestry. Some of these unobserved factors are inevitably associated with the near-term irreversibility of forestry (meaning that it is the land use most likely to be out of equilibrium). The biggest outliers in the forestry panel of Figure 5 represent territorial authorities in the central North Island where forestry has historically been very significant. In some of these areas, large forests were planted during the 20th century because their selenium- and cobalt-deficient soils were thought to be unsuitable for pastoral uses.

A final informal in-sample test one may wish to perform is to examine the predicted distribution of land uses by the modelled attributes of land. Figures 6 and 7 illustrate this distribution for slope and LUC class, respectively. For low and moderate values of slope,

[38] Territorial authorities are either city councils or district councils, representing the second tier of local government in New Zealand.

predictions follow actual land-use shares very closely. The errors are large in the upper half of the slope range, but they seem disproportionately large because the graphs depict shares instead of land areas: recall from Figure 3 that less than 5 percent of all observations in the sample have a slope of 25 degrees or more, and less than 1 percent have a slope of over 30 degrees. In addition, it is possible that some of the observations on extreme slopes actually correspond to unproductive areas of sheep or beef farms, and are therefore misclassified in the land-use data (recall that only the primary use from AgriBase is recorded in the data).

The distribution of land uses within different LUC classes is of particular interest because LUC is used as a cardinal variable in estimation. The conceptually correct means of modelling the effect of LUC class on the land-use decision would be via a set of seven indicators (one for each LUC class, less one for normalisation), because the classification has only an ordinal meaning. However, the close match between predicted and actual land-use shares in Figure 7 suggests that the relationship is well approximated by a cardinal interpretation of the LUC classification.

7.3. Counterfactual Land-tenure Scenario

The model includes a full set of alternative-specific constants. Therefore, aggregating the land-use probabilities across individual decision-makers results exactly in the national (in-sample) supply of land, s_j, in the alternative uses:

$$s_j = \sum_i Prob_{ij}(\boldsymbol{\beta}, \boldsymbol{X})$$

Given any change in the independent variables, the choice probabilities can be recalculated using the formula in equation 11 along with the estimated parameters. The sum of these probabilities (over decision-makers) yields an estimate of the overall land-use shares under the conditions represented by the new set of independent variables, $\widehat{\boldsymbol{X}}$:

$$\widehat{s_j} = \sum_i Prob_{ij}(\boldsymbol{\beta}, \widehat{\boldsymbol{X}})$$

I take advantage of this property of the multinomial logit model to assess the overall impact of Māori tenure on land use in New Zealand. Achieving this involves employing the estimated parameters from model 3 in a scenario in which the MAORI variable is constrained to equal zero for each observation (while all other geophysical and cost-of-access variables are kept at their original values). This combination of the parameters and independent variables is used to predict the counterfactual choice probabilities, which are then aggregated over all observations to arrive at national-level land-use share estimates.

The results in Table 6 suggest that the current land-tenure system reduces the aggregate shares of dairying and sheep and beef farming. If all Māori freehold land were general land, an additional 32,000ha of New Zealand's land area could be expected to be in dairy use. This is nearly three times the total dairy area on Māori freehold land, and over 2 percent of the country's current dairy area. Conversely, forestry and scrub areas are larger than they would be without Māori tenure. Note that the tenure system is predicted to increase overall plantation forestry area, even though the estimated coefficient on MAORI is negative in the forestry equation.[39] This happens because the probability (and land-use share) responses are highly non-linear, as shown by equation 11. The amount of predicted change in forestry area depends on the parameter estimates of all four land-use alternatives, not only on those of forestry.

Using the counterfactual land-use area estimates, it is also possible to assess the environmental implications of Māori land tenure. Rough calculations suggest that it leads to an approximate reduction of over 1 million tonnes of carbon dioxide equivalent emissions per year within the sample land area.[40] At a carbon price of NZ$25 per tonne, the estimated reduction in emissions could save New Zealand around $27 million in emission liabilities annually. The other side of the coin, of course, is that rural incomes are negatively affected by the underdevelopment of Māori freehold land.

The estimated land-use and environmental effects of Māori freehold tenure should, of course, be interpreted with caution. In particular, note that they do not represent the expected impact of removing legislation affecting Māori freehold land today (if it were possible to do so). The results are based on a static model, and they are conditional on unobserved economic factors, which have changed since the land-use decisions registered in the data were taken. Legislative changes would also have no effect on the preferences of landowners, yet these could partially explain the underdevelopment of Māori land. The results of the counterfactual scenario are thus best viewed as the land-use outcomes one would expect to observe if, *ceteris paribus*,

[39] It was shown in section 7.1 that the marginal effect of MAORI on forestry use is also positive. That marginal effect was calculated while holding constant the values of all other independent variables at a specified level. Area responses in Table 5, on the other hand, are calculated at the actual values of other covariates for each observation.

[40] I calculate dairy and sheep-beef emissions per hectare per year using average stocking rates and average carbon dioxide equivalent emissions from stock as well as from fertiliser per stock unit. Sequestration per hectare per year for forestry is calculated from the age-class distribution of forests in 2002 and the average carbon dioxide stock contained per hectare by age class. In the counterfactual scenario, the total area in each age class is scaled proportionately. I assume scrub sequestration to equal 3 tonnes of carbon dioxide per hectare per year – the figure currently used by the Ministry of Agriculture and Forestry (MAF Policy, 2010).

owners of Māori freehold land had the same preferences and faced the same regulations as owners of general private land.

Despite its hypothetical nature, the above scenario is informative because it quantifies the degree of underdevelopment of Māori freehold land. Knowledge of this information is important for environmental policy-making. For example, the results reinforce the view that a historical-emissions-based allocation mechanism of free emission permits in the ETS would penalise owners of Māori freehold land because their land use is of low intensity relative to the land's potential. (Note that for such arguments, it does not matter whether the underdevelopment is a result of the preferences of landowners or the regulations affecting them.) Further, the results could also be used to estimate the amount of aggregate loss imposed by such an allocation mechanism on owners of Māori freehold land.

8. Conclusion

I have estimated a spatially explicit microeconomic model of national land use in New Zealand, a country with a diverse landscape and climate. The model admits multiple rural land uses, including an economically non-productive use, and controls for land quality, location and land tenure. It is the first such model in New Zealand, and it represents the most detailed econometric evaluation of the impact of location-specific land attributes on private land-use decisions in the country. The results suggest that geophysical and socio-economic factors affect land use in largely expected ways.

Data availability constrains my analysis to a static one. It is based on factors that vary within the cross-section, though many determinants of land use vary over time. It is impossible to address these within a static framework. For example, without additional information the model presented in this paper cannot be used to simulate land-use change in response to variations in the carbon price under the ETS. Its predictions are conditional on all time-dependent factors. However, if the amount of overall land-use change could somehow be known or estimated, the framework would potentially be useful for geographically "allocating" that overall change. This may be the case when it is used in combination with dynamic land-use share models, for example.

This study also contributes to discussions around the potential development of Māori freehold land (e.g. Kingi, 2008; Dickson et al., 2009; Ministry of Agriculture and Forestry, 2011), and its results support anecdotal evidence for the importance of tenure in determining land-use decisions. I provide strong and quantitative evidence that Māori freehold land is underdeveloped relative to general land, even after taking into account differences in land quality and location. These findings are relevant for policy-makers because they could have important equity implications.

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10. Tables

Table 1. Summary statistics by land use

LANDUSE	Variable	Obs.	Mean	Median	Min.	Max.
Dairy		55,940				
	MAORI		0.01	0	0	1
	SLOPE		2.76	1	0	38
	LUC		3.48	3	1	8
	PROD		1.39	1.48	0.37	2
	DIST_TOWN		1.65	1.40	0	14.44
	DIST_PORT		12.37	9.61	0.24	52.69
Sheep or beef		308,524				
	MAORI		0.02	0	0	1
	SLOPE		8.47	7	0	47
	LUC		4.89	6	1	8
	PROD		1.08	1.04	0.05	2.02
	DIST_TOWN		3.76	2.68	0	64.02
	DIST_PORT		14.05	12.50	0.05	75.55
Forestry		59,615				
	MAORI		0.08	0	0	1
	SLOPE		10.65	10	0	41
	LUC		5.79	6	1	8
	PROD		1.26	1.28	0.24	1.98
	DIST_TOWN		4.05	3.29	0	36.20
	DIST_PORT		15.61	13.11	0	71.01
Scrub		95,172				
	MAORI		0.16	0	0	1
	SLOPE		14.86	15	0	47
	LUC		6.32	6	1	8
	PROD		1.26	1.29	0.07	2.01
	DIST_TOWN		6.52	4.36	0	147.85
	DIST_PORT		19.08	16.26	0.05	164.61
Total		519,251				

Table 2. Summary statistics by land tenure

Statistic		MAORI = 0	MAORI = 1
Share			
	Dairy	0.11	0.02
	Sheep or beef	0.61	0.27
	Forestry	0.11	0.16
	Scrub	0.16	0.55
Mean			
	SLOPE	9.04	13.43
	LUC	5.04	6.19
	PROD	1.16	1.35
	DIST_TOWN	3.81	8.61
	DIST_PORT	14.52	22.75
Obs.		490,849	28,402

Table 3. Estimation results (t-statistics shown in parentheses).

LANDUSE	Variable	Model 1	Model 2	Model 3	Model 4
Dairy					
	MAORI	-2.7543	-2.5123	-2.2950	-2.3834
		(-69.99)	(-57.83)	(-51.64)	(-9.01)
	SLOPE		-0.2435	-0.2200	-0.2190
			(-149.12)	(-131.01)	(-23.66)
	LUC		-0.7611	-0.6484	-0.6344
			(-143.67)	(-119.50)	(-20.96)
	PROD		1.1758	1.5141	1.4677
			(59.62)	(65.49)	(11.15)
	DIST_TOW			-0.1978	-0.1902
				(-45.26)	(-7.84)
	DIST_POR			-0.0443	-0.0465
				(-60.47)	(-11.23)
	ASC	-0.3651	3.6521	3.6637	3.7254
		(-65.94)	(100.81)	(97.06)	(17.30)
Sheep or beef					
	MAORI	-2.0449	-1.4229	-1.3054	-1.2923
		(-140.64)	(-88.32)	(-78.97)	(-13.81)
	SLOPE		-0.0704	-0.0646	-0.0680
			(-105.97)	(-93.37)	(-17.22)
	LUC		-0.5172	-0.4943	-0.4793
			(-126.81)	(-119.55)	(-20.64)
	PROD		-1.6786	-1.7966	-1.8985
			(-132.89)	(-121.44)	(-22.25)
	DIST_TOW			-0.0279	-0.0311
				(-25.77)	(-5.02)
	DIST_POR			-0.0010	-0.0009
				(-2.10)	(-0.33)
	ASC	1.3298	7.0496	7.1354	7.2495
		(333.64)	(247.60)	(248.60)	(43.93)
Forestry					
	MAORI	-0.8673	-0.6917	-0.5118	-0.4784
		(-48.80)	(-37.67)	(-27.01)	(-4.49)
	SLOPE		-0.0663	-0.0581	-0.0595
			(-76.22)	(-63.79)	(-11.54)
	LUC		-0.1511	-0.1085	-0.0854
			(-29.72)	(-20.95)	(-2.94)
	PROD		-0.3095	-0.3267	-0.4150
			(-19.16)	(-17.13)	(-3.81)
	DIST_TOW			-0.0382	-0.0479
				(-23.41)	(-5.10)
	DIST_POR			-0.0153	-0.0136
				(-24.57)	(-3.89)
	ASC	-0.3681	1.7620	1.8524	1.8920
		(-66.42)	(50.34)	(52.32)	(9.33)
Observations		519,251	519,251	519,251	161,86
Log-likelihood value		-563475	-465492	-460365	-14342
Likelihood ratio index[41]		0.0214	0.1915	0.2004	0.2014

[41] The likelihood ratio index is also known as McFadden's pseudo R-squared.

Table 4. Marginal effects $(dProb/dX_k)$ in model 3

Variable	Dairy	Sheep/beef	Forestry	Scrub
MAORI	-0.2697	-0.2269	0.0502	0.2498
SLOPE	-0.0392	-0.0028	-0.0005	0.0129
LUC	-0.0542	-0.0787	0.0383	0.0808
PROD	0.7528	-0.3810	0.1265	0.2794
DIST_TOWN	-0.0419	0.0024	-0.0015	0.0065
DIST_PORT	-0.0103	0.0023	-0.0019	0.0010

Table 5. The fraction of observations in a given land use among all observations with a similar probability prediction for the corresponding use

Predicted probability	Fraction in use: Dairy	Sheep/beef	Forestry	Scrub
0.01–0.02	0.011	0.000	0.012	0.015
0.05–0.06	0.047	0.041	0.062	0.069
0.10–0.11	0.127	0.086	0.097	0.125
0.20–0.21	0.220	0.228	0.169	0.192
0.30–0.31	0.308	0.307	0.282	0.267
0.40–0.41	0.394	0.393		0.394
0.50–0.51	0.564	0.514		0.540
0.60–0.61	0.622	0.624		0.650
0.70–0.71	0.636	0.719		0.766
0.80–0.81	0.619	0.807		0.844
0.90–0.91		0.898		0.905
0.95–0.96		0.926		1.000
0.99–1.00				

Table 6. In-sample aggregate land-use outcomes on Māori freehold land (area in hectares)

Land use	Actual area	Counterfactual area	% change
Dairy	17,200	49,232	186.23
Sheep or beef	190,400	323,867	70.10
Forestry	113,175	98,258	-13.18
Scrub	389,275	238,694	-38.68

11. Figures

Figure 1. The geographic distribution of land uses in New Zealand

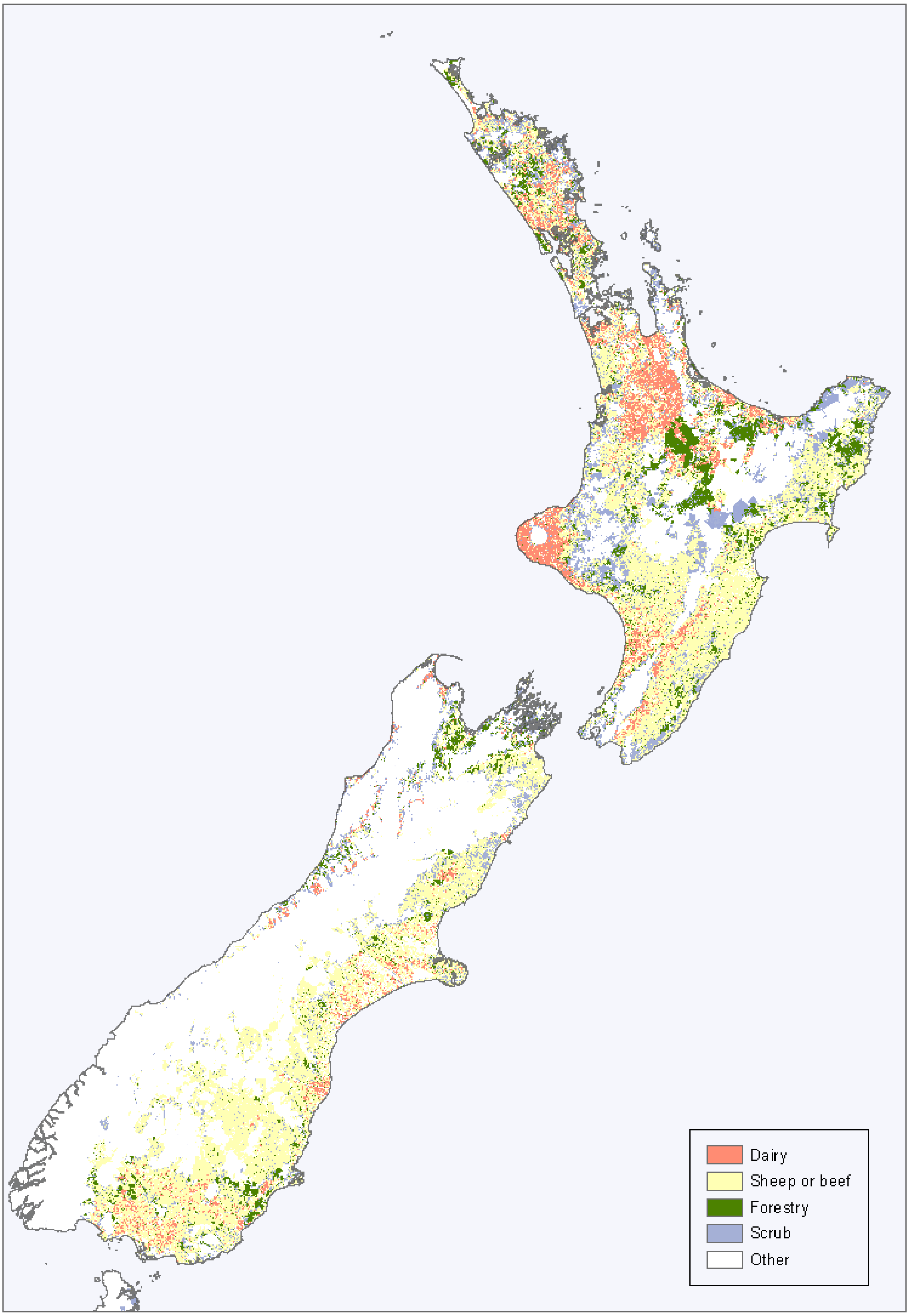


Figure 2. The geographic distribution of Māori freehold land in the North Island of New Zealand

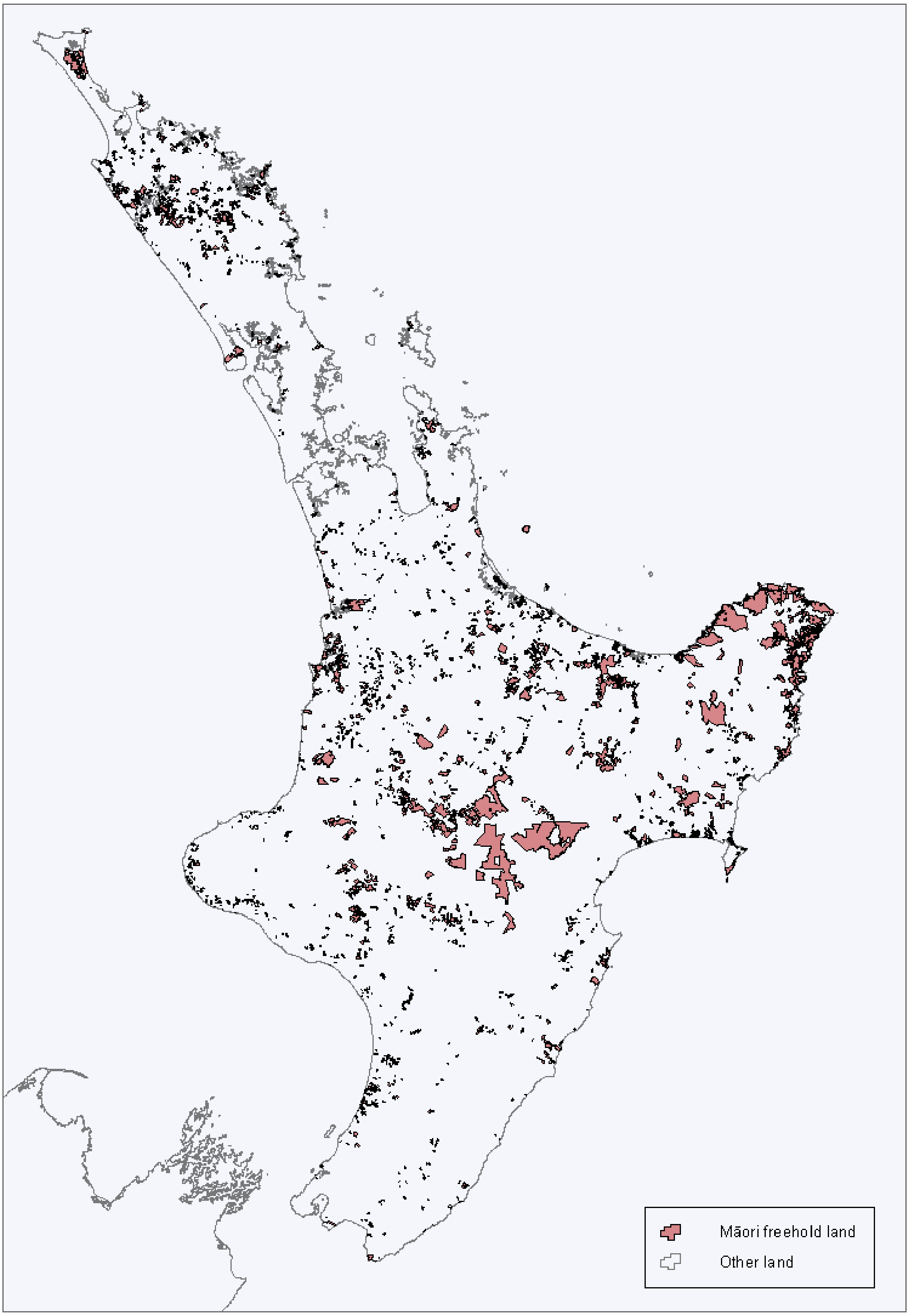


Figure 3. Histograms showing the fraction of all observations with a particular value of SLOPE and LUC, respectively.

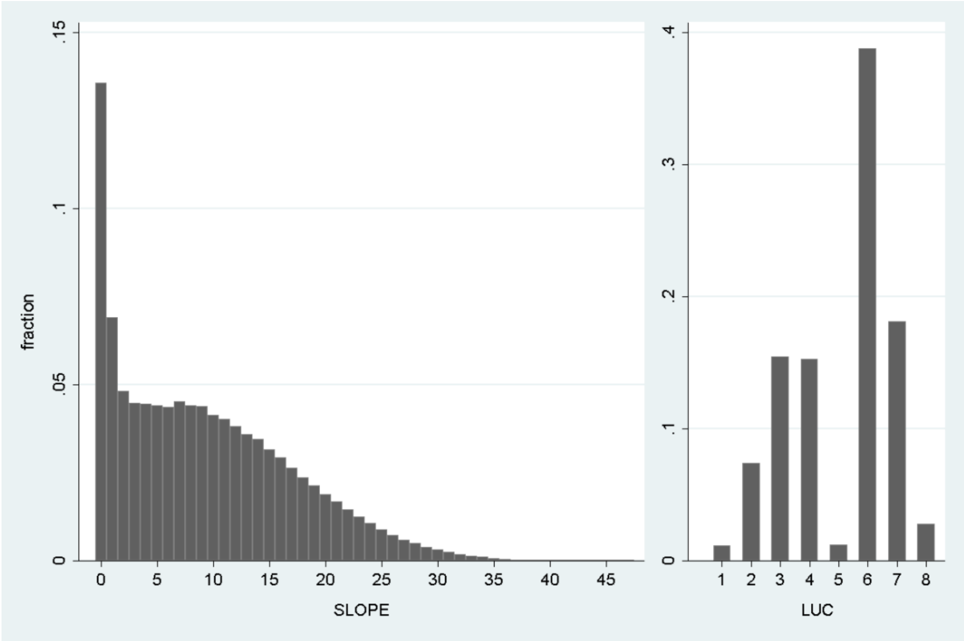


Figure 4. Geographic distributions and histograms of predicted probabilities

In the top panels, white areas are not modelled; darker shades indicate a higher probability. In the bottom panels, vertical lines denote the 10th, 50th, 90th and 99th percentiles of predicted values.

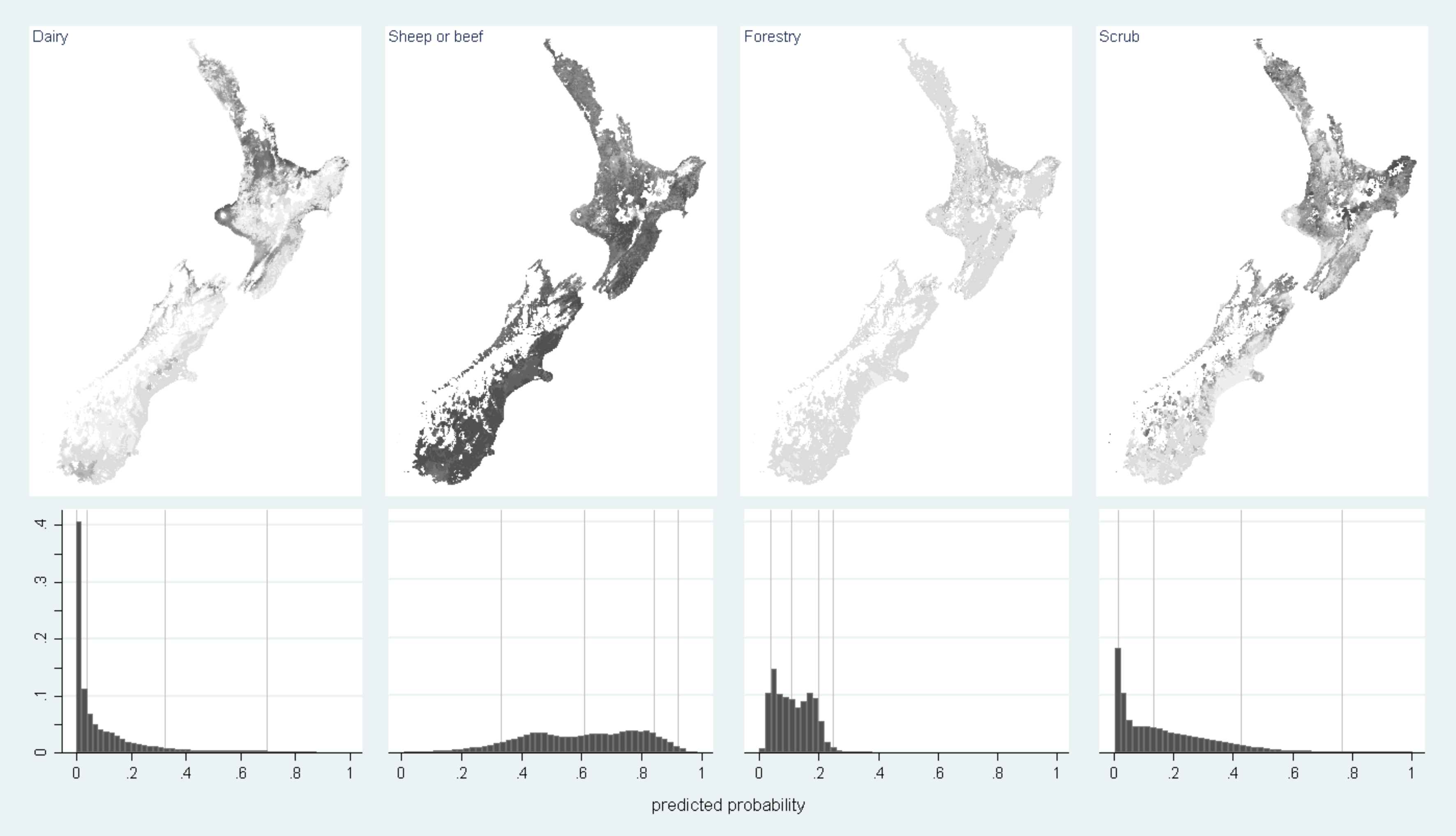


Figure 5. Predicted versus observed land-use shares by territorial authority
(45-degree line drawn for reference)

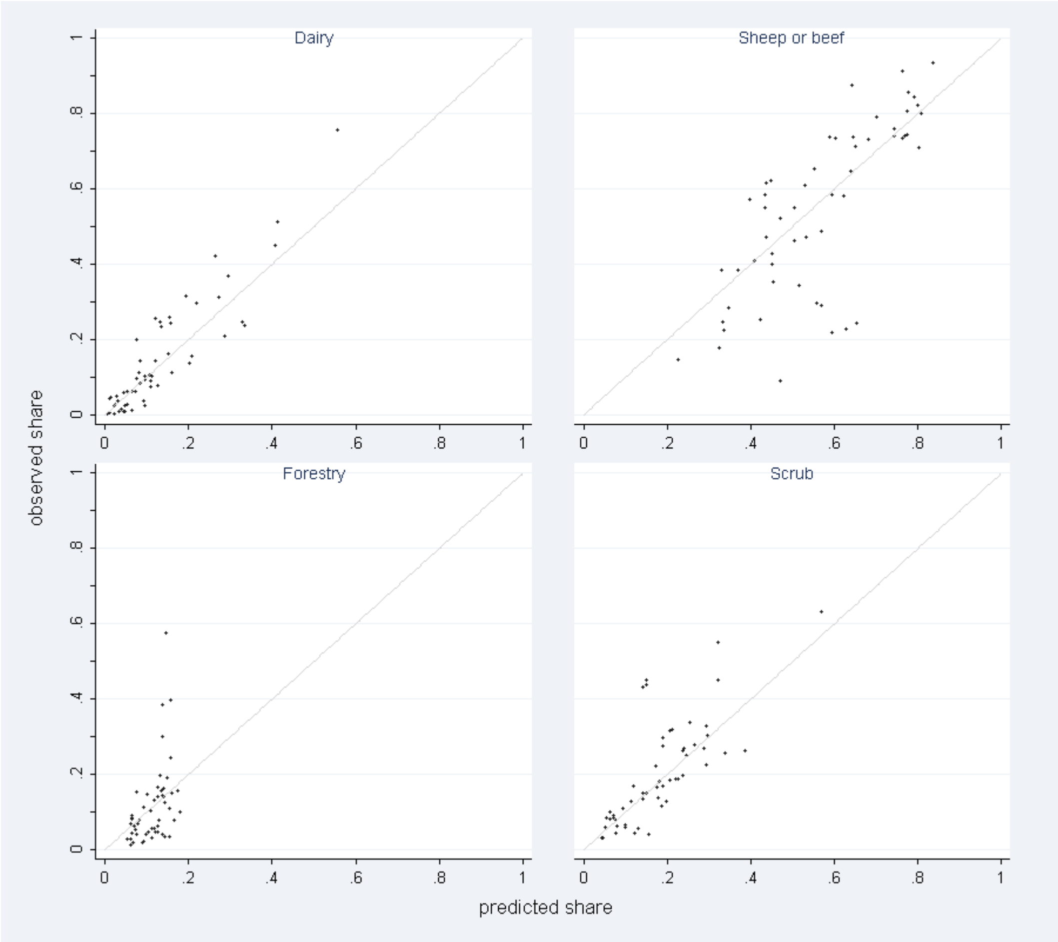


Figure 6. The observed (solid line) and predicted (dashed line) share of each use within all observations of a given slope

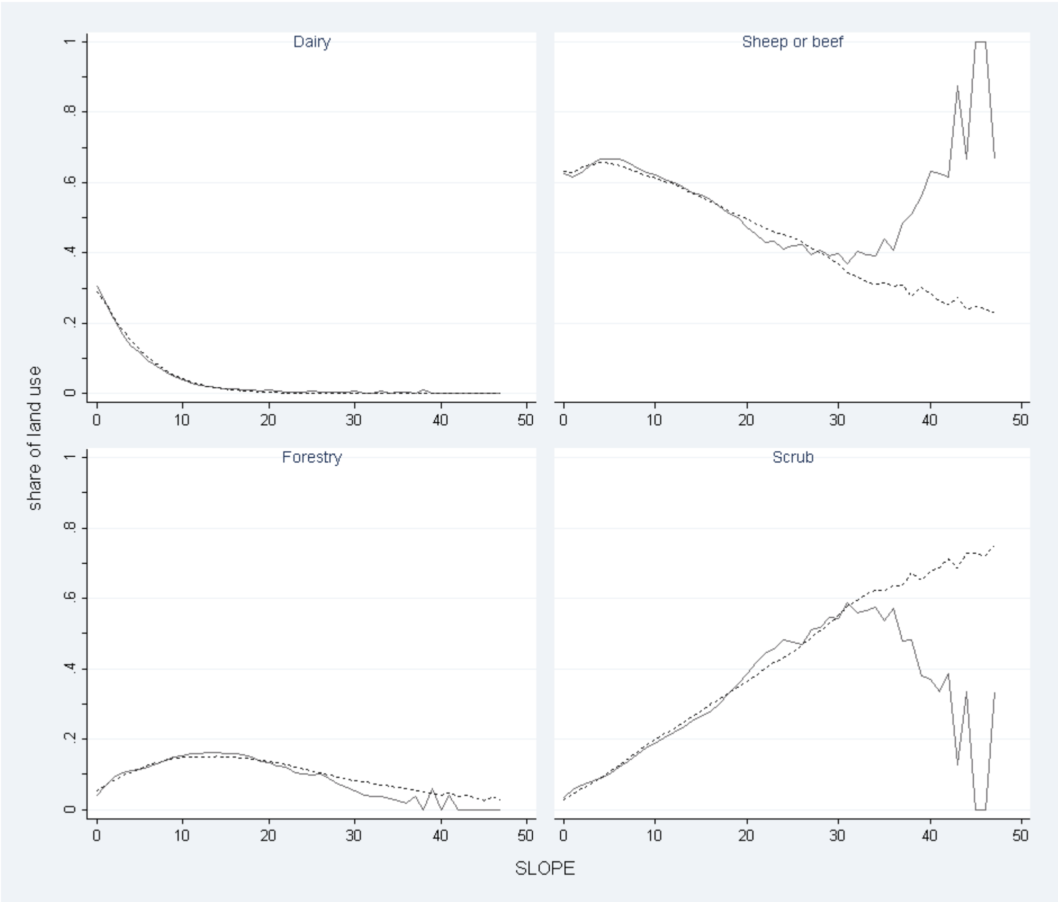
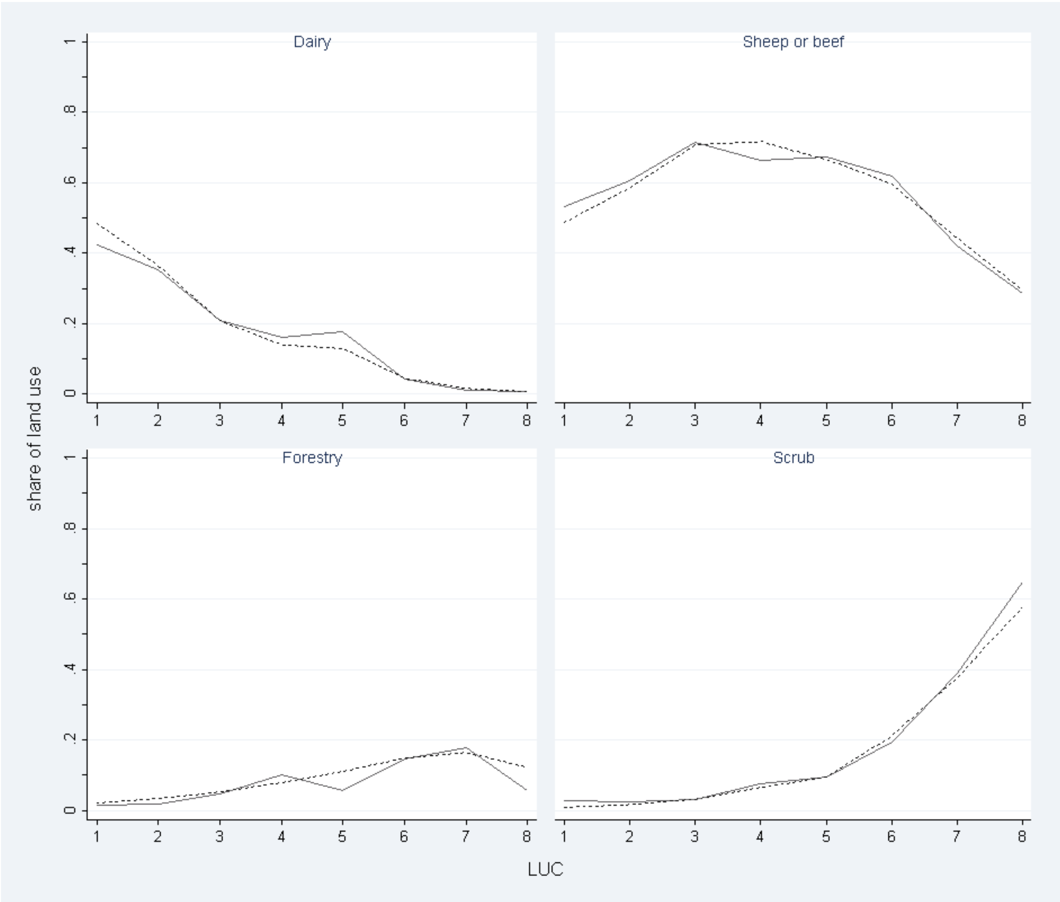


Figure 7. The observed (solid line) and predicted (dashed line) share of each use within all observations of a given LUC class



12. Appendix

Appendix Table 1. Estimation results with facility locations (t-statistics shown in parentheses)

Variable	Dairy	Sheep/beef	Forestry
MAORI	-1.9827	-1.1429	-0.5305
	(-43.38)	(-68.02)	(-27.73)
SLOPE	-0.2053	-0.0631	-0.0568
	(-121.97)	(-91.50)	(-61.59)
LUC	-0.6438	-0.4865	-0.0974
	(-117.61)	(-117.92)	(-18.71)
PROD	0.9707	-1.9318	-0.5905
	(40.78)	(-128.93)	(-29.87)
DIST_TOWN	-0.0395	0.0348	0.0451
	(-8.24)	(23.08)	(22.89)
DIST_PORT	-0.0218	0.0075	-0.0089
	(-27.31)	(14.49)	(-14.18)
DIST_D	-0.1772		
	(-89.42)		
DIST_SB		-0.0733	
		(-58.18)	
DIST_F			-0.1012
			(-79.91)
ASC	4.5842	7.3162	2.5139
	(117.09)	(252.45)	(69.34)
Observations	519,251	519,251	519,251
Log-likelihood value	-450867	-450867	-450867

DIST_D, DIST_SB and DIST_F are impedance-weighted distance measures to the nearest dairy plant, meat plant and major wood-processing facility, respectively (Ministry of Agriculture and Forestry, dataset 2009). The cross-coefficients of the facility–distance variables are constrained to zero on theoretical grounds: for a plantation forestry plot, its distance from the nearest dairy-processing facility should not matter. An analogous argument can be made for the other cross-coefficients. Parameter estimates from this model are significant and qualitatively credible, but the locations of processing facilities are endogenous.

Appendix Table 2. Estimation results with spatially lagged variables (t-statistics shown in parentheses)

Variable	Dairy	Sheep/beef	Forestry
MAORI	-2.4472	-1.3834	-0.7144
	(-55.98)	(-85.26)	(-38.54)
SLOPE	-0.0173	-0.0095	-0.0049
	(-6.04)	(-7.49)	(-2.91)
SLOPE_LAG	-0.2725	-0.0768	-0.1038
	(-75.63)	(-48.21)	(-49.61)
LUC	-0.4913	-0.3994	-0.2120
	(-71.37)	(-77.33)	(-32.23)
LUC_LAG	-0.2796	-0.1175	0.2589
	(-30.05)	(-17.30)	(29.63)
PROD	1.1659	-1.7720	-0.4159
	(57.79)	(-137.38)	(-25.44)
ASC	4.0376	7.3284	1.2581
	(98.19)	(225.56)	(31.05)
Observations	519,251	519,251	519,251
Log-likelihood value	-458692	-458692	-458692

Spatial lags for SLOPE and LUC were calculated by taking the mean of the variable in the eight locations immediately neighbouring the observation. There is evidence for multicollinearity between the independent variables and their spatial lags; it is especially severe for slope. Therefore, the spatial lag variables (at least in their current form) fail to improve estimation results.

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