Modelling Changing Rural Land Use in New Zealand 1997 to 2008 Using a Multinomial Logit Approach

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Abstract
Rural land use in New Zealand is an important driver of economic activity and has clear implications for the environment, including for biodiversity, climate change emissions and water quality. The spatial distribution and aggregate shares of rural land use is always changing, but change occurs slowly. To better understand the drivers of rural land use change, this paper addresses three questions using the popular multinomial logit modelling approach. First, do recent commodity prices have any predictive power on land use conversions? Second, is recently sold land more likely to change use? Third, does land which is marginal between uses have identifiable characteristics? The data used consists of the New Zealand Landcover Database version 3 (LCDB3), with observations in 1997, 2002 and 2008; 6 year average profitability data for dairy, sheep and beef and forestry; QVNZ land sales data; and I control for land quality and Maori tenure. In answering the first and third questions, I evaluate the predictive power of a spatially explicit land use share multinomial logit model, estimated from 2002 cross-sectional variation. To supplement the land use share multinomial logit for questions one and three, and to address question two, I use a land use transition multinomial logit, estimating the likelihood of transition from a single starting land use between 1997 and 2002, similar to Lubowski et al. (2008). Finally, I compare the two modelling approaches.

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Q15

Keywords
Land use, rural, conversion, multinomial logit, land sales, marginal land.

Contents

1. Introduction

There are clear environmental and economic motivations for research into land use. For New Zealand, the agricultural sector is responsible for roughly half of current greenhouse gas emissions, while forestry is an important carbon sink (Ministry for the Environment 2013). In addition, intensification of farming is a primary reason for declining water quality across New Zealand (Verburg *et al.* 2010). Land cover and use are also important for biodiversity and the provision of ecosystem services such as soil conservation (Rutledge *et al.* 2012). Economic activity is fundamentally shaped by a spatial dimension, and rural land use is of high importance to the economic performance of rural communities (Bockstael 1996; Todd and Kerr 2009). Furthermore, agriculture and tourism both benefit from New Zealand's clean green image, activities which are important exports for New Zealand (eg. Saunders *et al.* 2011). Thus, understanding rural land use in New Zealand is important for understanding New Zealand's economic and environmental performance, and how rural land use might change in response to government policy.

The focus of this research is to better understand the dynamics of recent rural land use change in New Zealand, and to evaluate how well the multinomial logit model can predict land use change when estimated using cross-sectional variation of land parcels. In particular, I address three questions: First, do recent commodity prices have any predictive power on land use conversions? Second, is recently sold land more likely to change use? As discussed later, this question is aimed not necessarily at identifying a driver of land use change, but identifying whether land use change is associated with land sales. A land sale may help reduce barriers to a profitable conversion occurring, such as human capital and financial capital constraints. Third, does land which is marginal between uses have identifiable characteristics? To answer these questions, I utilise the multinomial logit model, taking two modelling approaches. First, I estimate a multinomial logit of total land use shares, using the 2002 cross-section of the data. This modelling approach primarily addresses the first question, as well as the third question. Second, I estimate multinomial logit models of the transitions between land use from 1997 to 2002; for example the transitions from pasture are into either pasture, forestry or scrub. This modelling approach can address all three questions. Within the context of these research questions, I discuss the utility of the multinomial logit model, the two modelling approaches and to what extent future land use shares and transitions can be usefully forecast using these models.

Bockstael (1996) outlines some of the reasons why spatially-explicit modelling is important for understanding both ecological and economic processes. The locations of natural and human-made features are important for how ecological processes can function nearby. Land is not moveable, so local natural features and the utilisation of land have important economic implications. Therefore, a spatially-explicit approach has much to offer. However, spatially-explicit modelling has many challenges. Land use change occurs slowly within the context of volatile economic variables. Therefore, associating land use change with changing economic variables is difficult given limited data. Multinomial logit modelling has been a popular approach for modelling discrete land use choice decisions (Tímár 2011). However, given the fact that land use may take decades to adjust to changing economic fundamentals (Kerr and Olssen 2012), it is important to explore how well the multinomial logit can predict land use changes when estimated from the variation in land use and land use transitions at a single snap shot in time.

In the next section of this paper I outline some of the basic theory behind what drives land use decisions. In Section 03 I complete a brief survey on the literature in spatially-explicit land use modelling, particularly those studies using a multinomial logit approach. In the following section, I describe the data used for this project. In Section 5 I explain the multinomial logit model and outline some of its features. Following this is the Results section, where I look at what the two models show about rural land use in New Zealand and discuss how well they perform. Finally, I summarise my findings in the Conclusion.

2. Theory of land use

This section covers the basic theory behind land use allocation and conversion. First, I clarify the important distinction between land use and land cover. I then cover the bid-rent theory and how land use decisions can be modelled within a utility maximisation framework. Finally, I add the dimension of land use conversion costs, which slow the optimal pace of land use conversion.

2.1. Land use versus land cover

For this project I am conceptually interested in land use. However, the dataset I have available is a land cover dataset. Therefore, it is useful to clarify the difference at the beginning of the section.

In simple terms, land use is the human activity on a given piece of land at a given time, whereas land cover is a description of what is on that land. Thus, land use includes the economic activity taking place on the land – for example dairy farming or industrial production. Land cover on the other hand reflects the interaction between human and ecological processes. Therefore, land cover usually reflects the economic use of a piece of land – for example, the land cover for dairy farming is likely to be pasture. Alternatively, land cover could also reflect the absence of economic production – for example, scrub. Scrub represents the first plant colonisers of land which has been cleared, and is now regenerating back into bush. Therefore, scrub may be indicative of land recently in pastoral farming but no longer being used that way, cleared through natural means (such as fire) or any number of other scenarios (Rutledge *et al.* 2012).

Land cover is commonly used in the literature to infer land use, given land cover is more easily observable, and the relationship that exists between land cover and land use. How strong this relationship is depends on the type of relationship between the particular land uses and land covers of interest. Land use can alter the land cover, but it may also be determined or constrained by the land cover. Further complicating matters is the relationship between economic variables and land use, and linking that to land cover, given land may be used more or less intensively, but land cover may not reflect that change in intensity (Cihlar and Jansen 2001; Verburg *et al.* 2009).

For this paper I use the New Zealand Land Cover Database version 3 (LCDB3) as a proxy for land use. The LCDB is frequently used for New Zealand land use studies as there is no equivalent national land use database (Rutledge, Price, and Herzig 2012). While some studies in the international literature use models and further data to infer land use from land cover (Chakir 2009; Cihlar and Jansen 2001), I argue in this study that approach is unnecessary. A strong link between land use and land cover can be assumed, and this study is not focussing on land use intensity.

The biggest limitation from using the LCDB3 is that for the land cover of pasture, I cannot distinguish between sheep and beef farms, and dairy farms. Therefore, the data is not as fine scale as would be preferred for this major land cover type, though for simplicity I do not try to infer land use within the category of pasture. In terms of land cover reflecting land use, there are unlikely to be significant discrepancies between the two. Some exotic forest may be wild, or be part of a wind break, and therefore not be forestry. There is also abandoned pasture in some parts of the South Island where there is not enough seed source for scrub to regenerate (Tímár 2011). Given the extent of pasture and forestry in New Zealand, I argue these issues are unlikely to substantially affect my results. Furthermore, there is no available way to improve the data for this study, though it is important to note the limitations of the data. Thus, I will talk theoretically in terms of land *use* and use the terms *use* and *cover* interchangeably in the empirical sections.

2.2. Bid-rent theory

Land use theory has its roots in the works of David Ricardo (1821) and Heinrich von Thünen (1966, cited by Tímár 2011). Ricardo proposed the idea that land of higher quality will accord its owner higher rents relative to land of lower quality. Von Thünen added to this the dimension of distance to market (Tímár 2011).

Von Thünen imagined the simplest case, in which there is one main market centre within a flat, uniform region. In this case, land use is dependent solely on distance to the main centre, given uniform land quality and transport access. Thus, one can imagine that land closest to the main centre will be in urban and industrial uses, land farther out will be in agricultural uses – dependent on the value of the agricultural products and their transport costs – and finally land farthest away will be left to natural uses. Land will be allocated to its highest value use through market mechanisms, with land managers wishing to maximise the net present value of their return.[1] In a uniform region, distance to market will affect farmgate price – the commodity price which the land manager observes, given their distance to market. Von Thünen postulated that this would create concentric rings around the city of different types of agriculture (Tímár 2011).

Land use is complicated by a quality dimension, especially in a country such as New Zealand, which is renowned for its huge diversity of landscapes, soil types and climates within a relatively small area. Land quality will affect the level of returns possible from each use. For example, in rural New Zealand, dairy farming is an intensive land use requiring highly fertile land. Rotational crops also require fertile land, along with flat land to make efficient harvesting practicable. Extensive sheep and beef and forestry are uses which do not require such fertile land and are profitable on rugged high country land (Todd and Kerr 2009). Furthermore, given that agricultural produce and logs are important exports for New Zealand, the relevant distance to market may be distance to port or distance to a processing facility (Tímár 2011). Thus, there is an interaction between the distance from markets, the productive potential of the land and the optimal land use.

2.3. Land use choice

The land use decision can be more formally modelled within a utility maximisation framework. Utilising this framework allows the various factors within the bid-rent theory to be modelled in terms of how a land manager optimises their land use choice. It also allows other factors which determine land use decisions to be added, such as the amenity value preferences of

[1] Given the land owner may not be the one managing the property, I refer to the land manager as the person making the land use decision throughout this paper.

the land manager. In describing the optimal land use choice, I ignore conversion costs until the next subsection.

Given a discrete choice of J land use types, suppose land manager i's return to land use j at time t is:

$$\boldsymbol{\pi_{ij,t} = p_{ij,t} \cdot q_{ij,t}(a, h, k, l) - c_{ij,t}(a, h, k, l)} \tag{1}$$

where π represents profits and $\boldsymbol{p_{ij,t}}$ is the farmgate price. The production function $\boldsymbol{q(.)}$ depends on various factors, such as land quality (a), production technology and human capital (h) (Parks 1995), capital (k) and labour (l). The cost function, $\boldsymbol{c(.)}$**,** also depends on these factors, and the market prices of inputs.

A land manager is concerned about present value, V, of these profits, which is the sum of their total expected discounted value. For time t, this looks like:

$$\boldsymbol{V_{ij,t} = \sum_{s=0}^{\infty} \delta^s E_t[\pi_{ij,t+s}]} \tag{2}$$

where δ is their discount factor.

Finally, there are other factors which affect land use. These reflect the preferences of land managers. Land managers may prefer certain types of land uses given their family history with the land, amenity value preferences, level of environmental concern and so on.

Therefore, total expected utility U received by land manager i for her property being in use j can be represented as:

$$\boldsymbol{U_{ij,t} = V_{ij,t} + \epsilon_{ij,t}} \tag{3}$$

where $\epsilon_{ij,t}$ represents other factors which determine expected utility.

Therefore, in choosing the land use for her property at time t, a land manager will set out to maximise the present value of her expected utility. Land manager i will achieve this by choosing land use j, when the following inequality holds for all other land uses, k:

$$\boldsymbol{U_{ij,t} \geq U_{ik,t}} \quad \text{for all } \boldsymbol{j \neq k} \tag{4}$$

The model in this subsection represents a simple model without conversion costs (and was developed from Tímár (2011) and McFadden (1973)). Holding all factors constant, land use allocations could be expected to converge to the point where Equation (4) holds for all land parcels. However, land use conversion is costly and risky (Parks 1995), including due to the evidence that commodity prices follow a random walk (Schatzki 2003). Thus, in the next subsection I discuss how land use conversion costs can be added to the model.

2.4. Land use conversion

Given the costly and risky nature of land use conversion, land use conversions tend to be gradual in practice (Kerr and Olssen 2012; Parks 1995). Conversion costs can therefore be added into Equation (4). Land will be converted by the land manager when expected conversion costs are less than the expected benefits from conversion. Therefore, the land manager will convert to land use j if:

$$\boldsymbol{U_{ij,t} - Z_{ij,t} \geq U_{ik,t} - Z_{ik,t}} \quad \text{for all } \boldsymbol{j \neq k} \tag{5}$$

where $Z_{ij,t}$ is the expected cost of conversion for land manager i to land use j at time t (Bockstael 1996; Tímár 2011). Note that if land manager i is in land use j at time t, then $Z_{ij,t} = 0$. Thus, each period can be thought of as a conversion; staying in the same land use can be thought as converting from land use j in the previous period, to land use j in the current period.

While the net present value of a conversion may be worthwhile purely on a profitability basis, there are many reasons why a land owner may not convert or may delay conversion. I suggest that these reasons include option value – the value of delaying a decision given the costs and risks of the decision; risk aversion – the land owner may wish to reduce risks of conversion not paying off by maintaining current use; the human capital of land manager – the land manager may not have the skills to successfully run a new type of farm (Parks 1995); preferences of the land manager may be to keep the land in current use; the land manager may have a status quo bias to keep the land in its current use; and the land manager may be liquidity constrained, thus unable to raise the funds for conversion (Adams and Turner 2012).

The bid-rent theory operates within a market environment; therefore the land manager may choose to sell. In theory, land value will reflect the expected net present value of returns to the land from its best use. A land owner may sell their land in order to retire, or they may sell to maximise their return from the land given their liquidity or human capital constraints. Either way, land sales have the potential to reduce some or all of the barriers to conversion listed above. This is the motivation behind my second research question, through which I test the hypothesis that a recent land sale indicates a land use conversion is more likely.

3. Land use modelling in the literature

This section reviews some of the literature into spatially-explicit land use modelling. This kind of land use modelling can shed light on what drives land use allocation decisions, and what might be driving changes. The land use modelling literature typically deals with land use choices using a revealed preference, discrete and unordered framework. These latter two features of land use modelling arise as there is no natural ordering to the distinctly separate types of land use. Therefore, assuming agents are utility maximising (sometimes framed as profit maximising), land characteristics associated with land use allocation decisions, along with macroeconomic drivers affecting profitability of land uses, can potentially be inferred (Tímár 2011).

Land use modelling may look at two types of uses, or multiple uses. Which approach is the appropriate one depends on the topic of interest. Much of the interest in land use modelling has been looking at conversion of rural land to urban land (eg. Bockstael 1996; Bell and Irwin 2002). There has also been interest in the drivers of tropical deforestation in developing countries (eg. Chomitz and Gray 1996; Nelson *et al.* 2004; Blackman *et al.* 2008). Both of these types of land use modelling can be framed within a binary choice framework, or look at multiple uses.

For the binary choice situation, the most popular model is the binary probit. For the multiple land use situation, the multinomial logit and nested logit models are popular, given their computational tractability (Tímár 2011; Chakir 2009). Some of the limitations of the multinomial logit are discussed in Section 5.

As was covered in the previous section, there are two separate questions regarding land use allocation. First, what are the drivers of land use allocation at a specific point in time? Second, what are the drivers of land use change?

In regards to the first question, taking land use allocations at a snapshot in time is essentially looking at the quality characteristics of the land, including access to markets, and seeing how this affects the profitability of types of land use, and therefore the land use allocation. This approach ignores transition costs, and essentially requires the assumption that the observed land use allocation is optimal, and thus has adjusted to long term economic fundamentals (Tímár 2011). Chakir (2009) uses a static multinomial logit to model how land cover, soil, climate and slope are related to land use in a region of France. Similarly, Tímár (2011) uses a multinomial logit to model New Zealand rural land use, based on land characteristics and ownership. He utilises a cross-section of 2002 land use data for dairy and sheep and beef farms, along with forestry and scrub. This model provides a baseline for calibrating the current version of Motu

Research's land use change model LURNZ, which is also based on the aggregate, non-spatially-explicit gradual land use change model of Kerr and Olssen (2012) (see Anastasiadis *et al.* 2014 for more details about LURNZ). I use some of Tímár's (2011) insights for my modelling, such as his finding that rural land in Māori tenure is less intensively used. I cover more relevant information from Tímár (2011), Kerr and Olssen (2012) and from Todd (2009) (a descriptive paper on rural land use) in the data section.

Chomitz and Gray (1996) estimate a static multinomial logit model to predict probabilities of land use and deforestation around new roads in Belize – essentially combining a static approach to look more at the second question above, regarding drivers of change. Chomitz and Gray (1996) do this by using a single cross-section of observations and estimating the association between distance to market and agricultural land, taking into account the potential endogeneity of road placement using IV methods.

If panel data is available, an alternative approach to look at the drivers of land use change is to look at the probability of a land use transition within a discrete choice framework, given land characteristics, along with observed changes in any relevant socio-economic data (Polyakov and Zhang 2008). Lubowski *et al.* (2008) use cross-sectional variation to estimate transition probabilities between a range of major land uses over mainland USA. They use a nested logit, which is essentially several interacting multinomial logit models (nests), with similar land use types put in the same nests.[2] Bockstael (1996) presents some preliminary results from modelling the likelihood that land transitions into residential use. She uses a binary probit model, several characteristics such as proximity to sewer systems and land slope, and also includes estimates of land value in residential and agricultural uses. She derives these land values herself as an indicator of the expected return of the land in those two types of uses. An alternative approach to modelling development of land is provided by Irwin and Bockstael (2002), who use a hazard model to estimate a rate at which parcels of land convert from non-urban to urban use.

Polyakov and Zhang (2008) use a random parameters logit model (RPL) to estimate the effects of property taxes on land use change in Louisiana, USA. The RPL model is theoretically a more flexible alternative to the multinomial logit as it relaxes the assumption of independence from irrelevant alternatives (discussed in more detail in Section 5). However, Nelson *et al.* (2004) compare multinomial logit, nested logit and RPL approaches and found no advantage to using

[2] In the rest of this paper, I often compare my modelling approach to Lubowski *et al.* (2008). While they use a nested logit and I use a multinomial logit, I argue that, given I model three rural land covers, I am essentially modelling just one nest of land cover types.

the RPL model. Furthermore, Lubowski (2002) argues that the RPL approach is unsuitable for modelling where large datasets are being used.

Li *et al.* (2013) use a similar approach to Lubowski *et al.* (2008) to model land use transitions across mainland China, additionally including spatial autocorrelation between land as a predictor variable. Li *et al.* (2013) note that most studies account for spatial autocorrelation by sub-sampling so there is a minimum distance between observations. They estimate their model for three transitions –1988-1995, 1995-2000 and 2000-2005. They find their models vary significantly in their estimates of coefficients over the different transition periods, which they account for by arguing it is due to significant changes in Chinese land policy over the time period. However, Lubowski *et al.* (2008) also estimate separate models for each of their three transitions, presumably given varying coefficient estimates between the periods, but also because panel data models in this context are difficult or require too many unrealistic assumptions to estimate (Lubowski 2002). Thus, for both Lubowski *et al.* (2008) and Li *et al.* (2013), they use their results to determine the extent to which certain drivers were factors in historical land use change, rather than to forecast future land use change.

Spatially-explicit land use modelling is data intensive, requiring observations of characteristics of large areas of land, potentially including the profitability of types of land use. Studies using spatially-explicit modelling are concentrated in the last couple of decades. Bockstael (1996) expresses frustration at the small number of economic studies at the time taking into account a spatial dimension. Perhaps this is due to the computing requirements associated with the level of data processing inherent in spatial datasets. Furthermore, some variables, such as profitability, often need to be inferred somehow or allocated at a more spatially fine scale (Chakir 2009). Lubowski *et al.* (2008) interact county-level profitability data with a measure of land quality to help achieve a more fine scale resolution. Panel data is also limited in its time dimension, generally to several observations from more recent decades. This makes modelling dependant more on cross-sectional variation and perhaps deficient in its ability to model drivers of change over time (Polyakov and Zhang 2008; Li *et al.* 2013).

It is within this context of the state of land use modelling literature that critiques such as Gibbons and Overman (2012) have been written. They argue that issues with identifying causality in spatial econometrics come from underdeveloped theory and a lack of utilising natural experiments to more robustly infer drivers of change. While it could be argued that there is little or none of this type of data available, Gibbons and Overman (2012) argue that without natural experiments, spatial econometrics becomes "mostly pointless".

There are other alternative ways of modelling land use and land use change. Spatially-explicit land use modelling is often interdisciplinary (Bockstael 1996; Rutledge, Price, and Herzig 2012; Kline *et al.* 2001). Bockstael (1996) points out that ecologists have long seen the spatial dimension of modelling ecological systems as having the same level of importance as the temporal dimension and may have difficulty reconciling the economic concept of equilibrium with natural systems, which many ecologists see as characterised by constant change. Therefore, there is a large scope for alternative approaches to land use modelling, which is beyond the scope of the paper, but worth mentioning. Rutledge, Price and Herzig (2012) suggest a modern approach, based on higher levels of data capabilities from modern computing. Their "atomised" approach features layers of data on spatially arranged atoms of land, allowing more complex systems modelling to be done over space and time. Another alternative approach uses optimising agents, where land use allocations are modelled based on optimal land use, for example from a profitability or ecosystem services perspective. This approach tries to model optimal land use allocations according to certain criteria, rather than be based fully on revealed preferences, such as the multinomial logit approach I am adopting (eg. Herzig 2008; Parker *et al.* 2003). There is also the approach of non-spatially explicit modelling of aggregate land use shares and how they change over time (eg. Stavins and Jaffe 1990; Kerr and Olssen 2012).

In this paper I look at rural land use change in New Zealand, as outlined in the introduction. I am interested in testing the utility of the multinomial logit, estimated using cross-sectional variation, for predicting changes. I outline more about the multinomial logit and its features in the Econometric modelling and Results sections, after describing my data in the next section.

4. Data

In this section I describe my data sources with some descriptive statistics. I first cover the dependent variable – the land cover data – followed by the independent variables. The first of the independent variables are profit and land sales, which are datasets that vary over time. Next, I cover geophysical data and distance, which are important determinants of land productivity and cost of production. Finally, I briefly discuss ownership variables, which indicate publicly owned land and Māori tenure land.

The data used in this project are spatially allocated across a rasterised map of New Zealand.[3] The data are all held, and in some cases produced, by Motu Research. Rasterisation for each map is based on a standardised map of New Zealand, using the software program ArcGIS. Pixel size is 25ha, or 500m by 500m. In the rasterised LCDB3 there are 1,072,805 data points representing New Zealand land. Some of the datasets include pixels along coastlines which are not in the other datasets; I discard pixels where they do not exist across all the maps. Similarly, Stewart Island is excluded from some datasets, so I exclude it from estimation. The value for each pixel is assigned by ArcGIS, which uses the value at the central point of the pixel. My datasets vary at the pixel level unless otherwise noted in the descriptions below.

4.1. Land use

The dependent variable is land cover as a proxy for land use. The data are from the Land Cover Database version three (LCDB3), which is compiled from fine-scale satellite observations for all of New Zealand for 1997, 2002 and 2008. While the LCDB3 cannot distinguish between types of pastoral land use, it does distinguish between scrub, exotic forest and native forest.

The LCDB3 database was compiled by Landcare New Zealand and released in 2012 (Landcare Research 2013a). The observations were compiled from data recorded over the summers of 1996/97, 2001/02 and 2007/08 (Landcare Research 2013b). Land cover has been categorised into 33 types, which I have aggregate up to the categories of pasture, forestry[4], scrub and other (Landcare Research 2013c). The "other" category includes urban, horticulture, cropland, indigenous forest and (for want of a better term) "unproductive" land (for example the tops of mountains). I exclude all "other" pixels from the data used for estimation.

The LCDB3 overall map accuracy, through random sampling, has been assessed as 96.4 percent for the North Island and 96.6 percent for the South Island. Averaged by category of land cover, the mean accuracy was assessed at 89.8 percent for the North Island and 90.2 percent for the South (Landcare Research 2013d). The data are, however, internally consistent between time periods, as observations for each separate years are cross-checked within the LCDB. Therefore, when a transition between land covers between observations is recorded, it can be assumed that a transition has actually occurred. Furthermore, the 1997 and 2002 observations are likely to be more accurate than the 2008 observations. This is because the older datasets are updated based on the new information from the latest observations. For example, newly planted pine trees look

[3] Rasterisation refers to the process of superimposing a square grid over a map. Each square in the map represents an observation, referred to as a pixel.

[4] I acknowledge that forestry is a land use rather than a land cover, but for simplicity I use the term *forestry* to make it clear that I am using the land cover of exotic forest as a proxy for forestry.

like pasture in the satellite data, but once future observations are recorded of those saplings becoming exotic forest, the older observations are corrected as being exotic forest, rather than pasture. While there is variation in the accuracy of the 33 categories in the LCDB3, there is no obvious pattern which would suggest that one of the aggregated three categories I use for estimation is less accurate than another, though I do not formally test this. Consistent estimation of discrete choice models (such as the multinomial logit) with classical measurement error in the left hand side variable is achieved using maximum likelihood estimation, without additional assumptions or the use of instrumental variables (Hausman 2001).

The LCDB3 highlights how little land cover change there has been in New Zealand between 1997 and 2008. This is consistent with the gradual land use change story from other research in this area (eg. Kerr and Olssen 2012).

Table 1a shows that pasture is the dominant land cover in New Zealand at almost half. Forestry increased its share from 1997 to 2008, while the shares in pasture and scrub decreased. The increase in the other category's share is driven by increasing urban, crop and horticultural land covers.

Table 1b shows that land cover conversions are not all one way between land cover types, but can occur both ways. For example, there is significant movement between forestry and pasture over both transition periods. From 1997 to 2002 the biggest movements appear to be into forestry from pasture and scrub. The 2002 to 2008 transition table still has some (but less) movement into forestry, but shows a marked increase in movement from all land cover types into pasture. When reading the transition tables it is important to remember that the transitions into a type are as expressed a proportion of their original type. Therefore, for the second transition shown in Table 1b, the 0.51 percent shift from pasture to forestry represents a larger land area than the 1.55 percent shift from forestry to pasture, thus pasture is still losing land to forestry overall.

Kerr and Olssen (2012) show that the changes in Table 1a are consistent with long term trends over the last two to three decades. Sheep and beef farming continues to be the major pasture use, although it has declined from above 70 percent of rural land in the mid-1990s, to less than 60 percent by the mid-2000s (noting Table 1a includes all land use, not just rural land use). The upward trends in dairy and forestry land leads to them each accounting for around a 10 percent share of rural land in New Zealand by 2005 according to Kerr and Olssen's (2012) data.

4.2. Profitability

I compile profitability data for two land uses – pastoral farming and forestry. These datasets represent a measure of achievable return from two major New Zealand rural land uses and how they change over the time period of this study. The datasets attempt to take into account the productivity of the land in each pixel under each use, cost of production on the land and price received for production. I assume land managers use recent prices as the best predictor of future prices, as there is some evidence that commodity prices follow a random walk (Schatzki 2003). It is important to note that commodity prices are credibly exogenous for this modelling exercise, as there is little evidence to suggest New Zealand exporters have any global market power (Woods with Coleman 2012). I aggregate the profitability data, which is on an annual basis, by using six year averages, as this represents the longest period of time between LCDB3 observations. Furthermore, averaging profitability data is used in the literature (eg. Lubowski, *et al.* 2008 who use a five year average return). Finally, I use profitability data, as for these land uses it is primarily driven by international commodity prices, while taking into account the productivity of each parcel of land.

I cannot observe whether pasture is being used for dairy or sheep and beef farming. Therefore, I construct a single pastoral farming return, where I assign dairy profitability to all land that could be used for intensive pastoral farming. As dairy returns tend to be much higher than sheep and beef returns, the pastoral profitability dataset is intended to represent the highest potential profitability of any piece of land, if it were in pasture.

I allocate sheep and beef and dairy returns to each pixel based on a map generated by Motu Research of likely MWES farm class for all New Zealand land, excluding areas such as Department of Conservation (DoC) land. The map of potential farm classes is based on 2002 Quotable Value data on type of sheep and beef farms in each area, while ensuring land with low slope is generally classified as high producing farmland (Hendy *et al.* 2009). All land identified as intensive sheep and beef farmland is allocated the appropriate dairy return. Thus, there are a wide range of farm types and profitability levels; I present a box and whisker plot of sample pixel Economic Farm Surplus (EFS)[5] in Figure 1. Given sheep and beef profitability never rises above $300, the median profitability is clearly determined by dairy profitability. The median EFS rises significantly from 1997 to 2002 (from $549 to $880 per hectare), then falls slightly for the 2008

[5] I use EFS for pastoral returns as a measure of the long term profitability of pastoral farms, as it does not count the costs of debt for the farms (Kerr and Zhang 2009). The specific definitions of EFS for the dairy and for the sheep and beef data sources are provided in the proceeding paragraphs.

figures (to $821 per hectare). However, the spread of profitability increases significantly over the three observations (from a range of $738 for 1997 to $1,929 for 2008).

The dairy EFS[6] data are compiled from Ministry of Agriculture and Forestry (MAF)[7] monitor dairy farms. To better understand the dairy EFS component of the pastoral return data, I display dairy EFS by region in Table 1c. MAF monitor farms provide a representative farm balance sheet for farms in each MAF monitor farm region. For areas without a representative farm, I use MAF's national representative farm. The MAF monitor dairy farms grow in size over the time period as the average dairy farm expands. Because there is no monitor farm for Taranaki from 1999 to 2006, I infer profitability using the average difference between Taranaki and the national farm. Therefore, the MAF monitor dairy farms are not an ideal time series to use, but are the best data available to me, and some of the noise in the data is smoothed out by taking six year averages. The correlation between the representative national farm six year average profitability and a six year average of the dairy ANZ commodity price index is 0.99, confirming variations in profitability over time are driven by changing exogenous export prices (ANZ 2014).

The sheep and beef profitability data is compiled from Meat and Wool New Zealand's Economic Service (MWES) sheep and beef farm survey data, a dataset owned by Motu research. This dataset provides annual economic farm surplus (EFS) figures for different classes of sheep and beef farms in different regions (Meat and Wool Economic Service 2009).[8] There are a range of farm types and profitability levels; in Figure 2 I present a box and whisker plot of sample pixel profitability before dairy returns are allocated to areas where intensive pastoral farming is possible. The figure shows how median sheep and beef profitability rises slightly over the three time periods from $63 per hectare in 1997 to $87 per hectare in 2008, but the spread of profitability also increases so that the range of profitability in 2008 includes all values within the range of profitability in 1997. The correlation between the median EFS of my sample data, and the composite meat, sheep and wool ANZ commodity price index is 0.96 (ANZ 2014).

Forestry profitability is from the publicly available Motu dataset created from a variety of sources by Olssen *et al.* (2012). I use their estimates of net present value (NPV) of profits. It takes the net present value in 2008 dollars of expected returns from planting a new piece of

[6] From 2000 EFS is defined by MAF as net cash income plus change in livestock values, minus farm working expenses, minus depreciation, minus wages of management. Prior to 2000 MAF did not report an EFS. Therefore for earlier years I use cash farm surplus less personal drawings, which is the closest measure available to EFS for those years.

[7] MAF has been recently renamed Ministry for Primary Industries (MPI).

[8] MWES defines EFS as farm profit before tax, interest and rent, but after fair managerial salary is paid, including for owner-operated farms.

forestry on a given pixel. Expected returns are based on adaptive expectations simulated using the most recent 12 quarters, for each annual observation. Estimates for returns and costs are based on highly aggregated data, taking into account pixel-level variation in transport costs, and logging costs which vary by slope. Details of how the dataset was constructed are given in their paper (Olssen *et al.* 2012). I take a six year average of their data for each time period.

Figure 3, which displays the mean profitability of land in forestry each year from 1990 to 2008, shows how forestry profitability declines substantially over the time period. From the figure it is clear my 6 year averages will be declining too. The decline is primarily driven by a downward trend in international log prices from the mid-1990s to 2008 (Olssen *et al.* 2012).

4.3. Land sales

This dataset is provided by Quotable Value New Zealand (QVNZ) and records land sales by area of land sold, by type of land, for each meshblock (Quotable Value New Zealand 2009). A meshblock is a fine-scale geographical statistical unit. They vary in size from small urban areas to large rural areas, and may include water bodies in their total area (Statistics New Zealand 2013). Type of land is recorded by QVNZ's judgement of the land's best use, not current use. I use land sale areas for the following types: dairy, exotic forestry, vacant forestry, pastoral, specialist deer and specialist horses. I sum total area of land sold in these categories for the two transition periods 1997 to 2001 and 2002 to 2007. This area is then divided by the total area of the meshblock to get a proportion of land sold for each meshblock. I also have an indicator variable for whether land of the aforementioned types has been sold within that meshblock within the transition period.

Less than half of all meshblocks are accounted for in the rasterised dataset, as many meshblocks (likely all urban) are too small to be recorded. There is a total of 41,384 meshblocks over the country, and the set within the rasterised data totals 19,301. However, given the types of meshblocks which will be excluded from the rasterised dataset, just three observations with land sales from the relevant categories are excluded from the first period data, and two from the second period. Thus the impact of the excluded meshblocks on the data is negligible.

Of the 19,301 meshblocks in the full rasterised dataset, 4,764 recorded sales in the relevant categories between 1997 and 2001 (24.7 percent), and 5,141 meshblocks had relevant sales between 2002 and 2007 (26.6 percent). I cannot tell whether a piece of land has been sold more than once within the transition periods, therefore any land sold twice within the transition periods will be double counted. The mean proportion of land sold for 1997 to 2001 is 4.7 percent, with that figure being 5.4 percent for the latter period. The maximum area sold for the first period is 56 times the meshblock area and 10 times the meshblock area for the second period. These two figures highlight that there are likely some inaccuracies in QVNZ's data, as the former figure implies the total land area of the meshblock was sold approximately once a month over the five year period. Therefore, I censor the proportion dataset at a maximum value of 100 percent. The issue of double counting is mitigated if land cover change is even more likely following multiple sales, and is unlikely to be a major issue given how infrequently rural land is sold on average. Of the meshblocks in the rasterised dataset, the smallest is 0.6ha, the largest is 1,033,000ha, the lower quartile is 12.4ha, the upper quartile is 884.4ha and the median size is 109.5ha.

4.4. Geophysical data and distance

Geophysical factors are important determinants of land productivity, suitability to various types of use, and cost of production. Distance to ports and population centres are also important for cost of transport and availability and therefore cost of labour. These factors may affect different types of land use differently. For example, logs are costly to transport to ports and dairy can be labour intensive. While some of these factors are included in the profitability measures, they are not included consistently, and are major determinants of land use type. Therefore, as separate variables, I include average stock carrying capacity (CCAV), slope of land and distance to ports and supermarkets.

The CCAV dataset, held by Motu Research and compiled by Landcare Research, is a measure of the carrying capacity of rural land in New Zealand and is therefore a measure of land quality for production. It is measured in ewe stock units per hectare, which is a convertible unit for other types of stock. The data were collected from 1970 to 1984 and it is the best currently available dataset of New Zealand land carrying capacity. The main restriction with the data being old is that carrying capacity in stock units is now higher than the 1970s due to advances in farming techniques, but the data still provides a reasonable measure of relative carrying capacity of land.[9] Todd and Kerr (2009) document how land quality and slope affect land managers' choices between dairy, sheep and beef, forestry and scrub. Highest quality land (including highest productive capacity and a low slope) can be expected to be in dairy, followed by sheep and beef and forestry, with lowest quality in scrub. There is little dairy on land with more than a 10 degree slope, with 85 percent of dairy farms being found on what is effectively flat land. Extensive sheep and beef is found on hilly terrain, whereas intensive sheep and beef is on flatter land

[9] Information from Motu Research's internal data documentation.

(Todd and Kerr 2009). The distance datasets, held by Motu Research, are calculated using the distance of each pixel to ports and supermarkets around the country.

4.5. Ownership

Tímár (2011) finds that land in Māori tenure is used less intensively than other privately owned land. Furthermore, Department of Conservation (DoC) land is publicly owned land, managed primarily for its conservation value. I have datasets for these two types of ownership in 2002 and 2003 respectively (Department of Conservation 2005; Landcare Research 2008). Therefore, I exclude land under DoC ownership and include Māori tenure land in 2002 as an indicator variable.

5. Econometric modelling

This section describes the multinomial logit model, its features and how I apply them given my data. I start by outlining the bridge between the theory explained in Section 2 and the empirical models used here. I then describe the multinomial logit model. Finally, I cover some potential modelling issues and how I deal with them.

5.1. Multinomial logit

In this subsection I derive the multinomial logit from the land use theory outlined in Section 2. Next I describe how this model is used to predict land cover shares of pasture, forestry and scrub, given varying profitability over time and space. I then describe how I apply the multinomial logit to modelling land use transitions. Finally I describe some of the characteristics and limitations of the multinomial logit.

In regards to land cover shares, Section 2.3 on land use choice theory, ends with Equation (4), that land managers will choose their optimal land use by choosing land use j, so that:

$$\boldsymbol{U_{ij,t}} \geq \boldsymbol{U_{ik,t}} \quad \text{for all } \boldsymbol{j} \neq \boldsymbol{k} \tag{4}$$

where $j, k \in \{\text{pasture, forestry, scrub}\}$ in this project.

Empirically, the expression of land use choice can be thought of probabilistically, using observed land characteristics to estimate the probability of a given pixel of land being in a given land use. This can be done by setting $\boldsymbol{U_{ij,t}} = \boldsymbol{\beta'}_{\boldsymbol{j}}\boldsymbol{x_{i,t}} + \boldsymbol{\eta_{ij,t}}$. Here, $\boldsymbol{x}$ represents a vector of observable land characteristics for each pixel, and $\boldsymbol{\eta}$ represents unobservable characteristics for each pixel and how they impact the utility for each land use type. The observable characteristics $\boldsymbol{x}$ are assumed to affect the probability of being in land use j linearly, according to the coefficient weights represented by the vector $\boldsymbol{\beta}$, where each land use j has a unique $\boldsymbol{\beta_j}$.

Therefore, probability of observing land use j for land pixel i at time t can be represented by:

$$\Pr\left(\boldsymbol{\beta'}_j \boldsymbol{x}_{i,t} + \boldsymbol{\eta}_{ij,t} > \boldsymbol{\beta'}_k \boldsymbol{x}_{i,t} + \boldsymbol{\eta}_{ik,t}\right) \text{ for all } \boldsymbol{j} \neq \boldsymbol{k} \tag{6}$$

From Equation (6) it follows that:

$$\Pr\left(\boldsymbol{\eta}_{ij,t} - \boldsymbol{\eta}_{ik,t} < \boldsymbol{\beta'}_j \boldsymbol{x}_{i,t} - \boldsymbol{\beta'}_k \boldsymbol{x}_{i,t}\right) \text{ for all } \boldsymbol{j} \neq \boldsymbol{k} \tag{7}$$

The functional form of this probability term is dependent on the distribution of the error term $\boldsymbol{\eta}$. By assuming the error terms are independent and identically distributed according to the type I extreme value distribution, the functional form of the probability becomes a multinomial logit (McFadden 1973; Tímár 2011).

The multinomial logit model is as follows:

$$\Pr(\boldsymbol{Y_i} = \boldsymbol{j}) = \frac{\exp(\boldsymbol{\beta'}_j \boldsymbol{x_i})}{\sum_{\boldsymbol{k=0}}^{\boldsymbol{J}} \exp(\boldsymbol{\beta'}_k \boldsymbol{x_i})} \tag{8}$$

where $\boldsymbol{\beta}_j$ is a vector of coefficients unique to land use type j, estimated for the vector of predictor variables for each observation i, $\boldsymbol{x}_i$.[10] In estimating $\boldsymbol{\beta_j}$, it is useful for the purpose of identification to normalise the coefficients around a base category of land use $j = 0$ by setting $\boldsymbol{\beta}_0 = 0$. In this paper, the base land cover $j = 0$ is scrub, and the other two land covers can be thought of as $j = 1$ being pasture and $j = 2$ being forestry. This set up gives:

$$\begin{aligned} \Pr(\boldsymbol{Y_i} = \boldsymbol{j}) &= \frac{\exp(\boldsymbol{\beta'}_j \boldsymbol{x_i})}{\boldsymbol{1} + \sum_{\boldsymbol{k=1}}^{2} \exp(\boldsymbol{\beta'}_k \boldsymbol{x_i})} \quad \text{for } \boldsymbol{j} = \boldsymbol{1}, \boldsymbol{2} \\ \Pr(Y_i = 0) &= \frac{1}{1 + \sum_{k=1}^{2} \exp(\boldsymbol{\beta'}_k \boldsymbol{x}_i)} \end{aligned} \tag{9}$$

(Greene 1990). Once estimated, the multinomial logit can be used to predict the probabilities of each pixel of land being in each land cover j. The mean of these probabilities over all pixels can be interpreted as total predicted land share for each land cover (Train 2009; Croissant 2012).

I also apply the multinomial logit to model land use transitions in a similar manner to Lubowski *et al.* (2008) and Li *et al.* (2013). To do this I estimate three separate models

[10] While I assume utility maximisation to derive the multinomial logit model, this is not necessary. At its heart, the multinomial logit is a probability model, where probabilities are predicted from a vector of characteristics. Therefore, the multinomial logit is consistent with utility maximisation, but does not have to assume utility maximisation (Train 2009).

corresponding to transitions from pasture, forestry and scrub. These models are estimated by selecting subsets of the data. For example, to model the transition from pasture for 1997 to 2002, I select the land in pasture in 1997, and the choice variables are transition into pasture, forestry or scrub in 2002.

Moving from the theory in Section 2.4 to deriving the multinomial logit in Equation (9) follows as above, replacing the starting Equation (4) with Equation (5):

$$\boldsymbol{U}_{\boldsymbol{ij},\boldsymbol{t}} - \boldsymbol{Z}_{\boldsymbol{ij},\boldsymbol{t}} \geq \boldsymbol{U}_{\boldsymbol{ik},\boldsymbol{t}} - \boldsymbol{Z}_{\boldsymbol{ik},\boldsymbol{t}} \quad \text{for all } \boldsymbol{j} \neq \boldsymbol{k} \tag{5}$$

As noted above, the mean predicted probabilities by the multinomial logit can be read as aggregate shares. In this case, the mean predicted transition probabilities can be interpreted as total predicted land use transitions for each type of transition.

Also similar to Lubowski *et al.* (2008) and Li *et al.* (2013), I use socio-economic variables (profitability and land sales in this case), along with land quality variables as the observable characteristics, $\boldsymbol{x}_i$, to model the probability of a land cover transition. This is a common approach in the literature given the difficultly of observing land conversion costs. Lubowski *et al.* (2008) argue conversion costs are proxied in their study by their intercept term (which varies by initial use) and their measure of land quality. They also include profitability, and interact profitability with their land quality variable. I include similar variables in this study, testing a range of model specifications.

The multinomial logit model has a number of characteristics worth covering to help understand my results. It is a discrete, unordered, multi-outcome, latent variable choice model. It predicts probabilities for each choice and ensures total probabilities sum to 1.

A key characteristic of latent variable choice models is that the estimated coefficients $\widehat{\boldsymbol{\beta}}_j$ are not directly interpretable. Further complicating issues for the multinomial logit is that the signs of the coefficients are not directly interpretable either, except for the highest and lowest coefficient (including the coefficients on scrub, $\boldsymbol{\beta}_0 = 0$). Given I am modelling three land use choices, this means that the marginal effects of two of the coefficients are interpretable in terms of their sign, but the middle coefficient is ambiguous as to its marginal effect.[11] The intuition for this can be understood by considering $\boldsymbol{\beta}_0$. All the coefficients for scrub ($\boldsymbol{\beta}_0$) are set to 0, but clearly it is unlikely that any of the marginal effects of the predictor variables are actually 0. For example, if forestry profitability rises, it might be expected that more scrub will be converted to

[11] If the highest coefficient is $\beta_o = 0$, then the marginal effect of β_0 is positive; if β_0 is the lowest coefficient, its effect is therefore negative.

forestry, meaning a negative marginal effect of forestry profitability on the probability of scrub on a given piece of land.

In particular, the marginal effects of the characteristics for individual i on probability of being in (or transitioning to) land cover j, are given by the following equation:

$$\frac{\partial \boldsymbol{P_{ij}}}{\partial \boldsymbol{x_i}} = \boldsymbol{P_{ij}}(\boldsymbol{\beta_j} - \sum_{k=0}^{2} \boldsymbol{P_{ik}} \boldsymbol{\beta_k}) \qquad (10)$$

where $P_{ij} = \Pr(Y_i = j)$. From this it is clear that the sign of the marginal effect of the $\boldsymbol{x_i}$ are actually given by $(\boldsymbol{\beta_j} - \sum_{k=0}^{2} \boldsymbol{P_{ik}} \boldsymbol{\beta_k})$, which is the coefficients minus a weighted average of the coefficients for all the alternatives. The weights for each of the coefficients for land use k are $\boldsymbol{P_{ik}}$. This explains why the sign of the highest and lowest coefficients on each predictor variable, for each land use, can be directly interpreted (Croissant 2012; Train 2009). Note too that the marginal effects differ for each individual i, given the observed $\boldsymbol{x_i}$ for that individual (as these effects give the values for the $\boldsymbol{P_{ij}}$). Therefore, when calculating the marginal effects of the predictor variables in the Results section, I calculate the means of the marginal effects across the sample.

A restriction of the multinomial logit is that it exhibits independence from irrelevant alternatives, a characteristic which must be assumed as part of a more extensive derivation than presented here. This restriction essentially means that the relative probability of choosing one land use over another is unaffected by the existence of a third alternative (McFadden 1973; Train 2009). Tímár (2011) argues this is a strong assumption that is unlikely to be applicable in the land use choice situation in reality. This is because it does not hold when more than two of the choices are close substitutes (McFadden 1973). However, Tímár (2011) also argues that empirically this restriction has been shown to have little impact on the final results in studies that compare the multinomial logit to alternative models without this restriction (eg. Nelson *et al.* 2004). Given my project looks at just three land covers, this restriction of the multinomial logit is unlikely to have much of an effect on the findings.

The multinomial logit is estimated using the maximum likelihood method. I use the R software package *mlogit* to estimate the coefficients, their marginal effects and produce predictions from the estimated models (Croissant 2012).

I follow Lubowski *et al.* (2008) and estimate the multinomial logit model using cross-sectional variation in the data. This strategy is based off the assumption that land managers' responses to spatial variation in profitability, controlling for land quality, can be used to predict how land use will respond to macroeconomic-driven changes in profitability over time. In order to test the utility of this modelling exercise for predicting future land use shares, I estimate a multinomial logit using cross-sectional data from 2002, and predict land cover shares for 1997 and 2008. For the transition modelling, I estimate the models from the 1997 to 2002 transition period and test how well they predict the land cover transitions from 2002 to 2008.

5.2. Modelling issues

Tímár (2011) outlines some issues to consider when undertaking spatial modelling, in particular spatial autocorrelation and endogeneity. I cover them briefly here and discuss how they apply to this paper and how I have taken them into account.

5.2.1. Spatial autocorrelation

Spatial autocorrelation is conceptually inherent in any spatially-explicit land use modelling. Spatial randomness requires that the location of an observation may be altered, keeping all other characteristics of that observation the same, without affecting its likely land use. Clearly this is an assumption which is unlikely to hold in reality. Within the land use context, an example would be that land on the same property would likely be mostly under the same use, and if the land use changed, the whole property would change to the same use. Many properties will likely span more than one pixel. Furthermore, similar types of land use are likely to cluster together. Spatial autocorrelation leads to inefficient estimation of coefficients and inaccurate standard errors and thus statistical significance (Tímár 2011).

In order to compensate for spatial autocorrelation, the most common measure that can be used with large datasets is systematic sub-sampling to increase the distance between observations. Other methods are not computationally possible with large datasets. This method is designed to reduce the level of autocorrelation between the data. Lubowski *et al.* (2008) and Tímár (2011) compare their results between models estimated with their sub-sampled data and their full data sets, and find little difference in their results. Tímár (2011) outlines other studies with similar findings. Li *et al.* (2013) use a new technique to utilise spatial autocorrelation in their modelling as another predictor variable of land use. For simplicity, and given spatial autocorrelation is theoretically a problem, I follow much of the literature and estimate the models using a sub-sample of the original data. I systematically take every seventh observation, starting in the top left of the full gridded map. This sampling design ensures no observations have less than one pixel between them diagonally, leaving at least a 1.1km distance between observations and usually more. It is beyond the scope of this project to compare the sub-sampled estimations with a full dataset.

5.2.2. Endogeneity

Tímár (2011) also identifies a potential endogeneity issue with spatial modelling concerning the location of processing facilities. Access to processing facilities lowers farm gate prices, therefore the location of processing facilities is not independent of optimal land use in the area. Tímár (2011) concludes there is no satisfactory way to control for endogeneity, as he argues instrumental variable methods are likely to create more problems than they solve within a non-linear context. He therefore estimates models with and without processing facilities. I do not use data on processing facilities. This could be a limitation in terms of the profitability data, but it is also a limitation to include processing facilities. By including distance to supermarkets and ports I control for transport costs to some extent, using variables much less likely to have endogeneity issues.

The other variable I include which has potential for endogeneity is the land sales data, which I use as a predictor variable for land use transition. Given the theory outlined in Section 2.4, it would be incorrect to say that a sale of land causes land use change. There are reasons to believe that a land sale increases the chance of land use change, for example by relaxing credit constraints affecting the previous owner's ability to convert. But this does not imply causation; the land use is converting not because of the sale, but because it is optimal to convert. The sale is just enabling the conversion to happen, which was limited by the credit constraint of the owner previously. Therefore, I interpret coefficient estimates on the land sales variables carefully, seeing them as a demonstration of correlation rather than causation.

6. Results

In this section I describe the results of this modelling exercise and their implications. First, I look at the land cover share multinomial logit model estimates, building up the model specifications from fewer to more explanatory variables. I present the coefficient estimates from the 2002 cross-section and analyse the ability of the multinomial logit to predict future land cover shares. I then discuss the implications of the land cover share multinomial logit modelling for my first question on the ability of profitability data to predict land use change. In the second part of the section I estimate three transition multinomial logit models for 1997 to 2002, using four combinations of predictor variables. These transition models separately estimate the likelihood of transitions from pasture, from forestry and from scrub. I use these estimates to predict transitions for 2002 to 2008. These results are interpreted in terms of my first and second questions on profitability and the impact of recent land sales on land use change. I conclude with a discussion of the two modelling approaches and how they contribute to an understanding of my third question, regarding the identification of marginal rural land in New Zealand.

6.1. Modelling land cover shares using the multinomial logit

In this subsection I discuss my spatially explicit modelling results for aggregate land cover shares and their implications for using profitability as a predictor of future land use change.

6.1.1. Fitting the model

I present coefficient estimates from four model specifications, estimated from the 2002 cross-section of my data, in Table 2a. In this subsection I discuss the coefficient estimates sequentially from the Model 1 specification, ending with Model 3. First though, it is important to note some features of multinomial logit models.

As outlined in the previous section, the multinomial logit model requires a base land cover type, for which all coefficients are set to 0. Therefore, the coefficient estimates presented in Table 2a are for pasture and forestry only and these can be considered as relative to the base category, scrub. Also mentioned in the previous section, the coefficients are not directly interpretable as they represent an underlying latent model, which is an input into the multinomial logit model to calculate the probability of each land cover for each pixel. The direction of the estimated coefficients is not directly interpretable either, except for the highest and lowest coefficient estimates (remembering the coefficients for scrub are all set to 0).

I turn now to the results presented in Table 2a. In Model 1 I include just the profitability variables, to test the relationship between land cover and the profitability variables alone. These results show the relationships are in line with what should be expected – pasture profitability is positively related to pasture and forestry profitability is positively related to forestry land. Scrub has a negative relationship with pastoral profitability and an ambiguous relationship with forestry profitability (based solely on reading the coefficients). Pasture has an ambiguous relationship with forestry profitability and forestry a negative relationship with pastoral profitability. It is important to note that the forestry profitability dataset I use takes into account the fertility of the land and harvest costs associated with terrain and distance to port. On the other hand, the pastoral profitability takes into account average profitability for aggregate types of land by region, but does not take into account the carrying capacity and terrain of the land at as fine a scale as the forestry profitability dataset. Thus, it is important to introduce other control variables, including ones that may affect the costs of land use conversions.

For Model 2 the profitability variables are removed and land quality controls are added – CCAV, slope, distance to supermarket, distance to port and Māori tenure. This model is similar to the variables included in Tímár's (2011) modelling of New Zealand rural land use, though I use CCAV instead of his two land quality variables. The estimates are generally in line with Tímár (2011) and Todd and Kerr (2009), though a more direct comparison is not possible as he breaks pasture down into dairy and sheep and beef. In Model 3 profitability and land quality controls are all included, with the marginal effects of the variables presented in Table 2b. The coefficient estimates of the variables do not change greatly, except for pasture profitability. This variable becomes insignificant in its effects on pasture and less significant for forestry. Therefore, the land quality variables do a better job at explaining the cross-sectional variation in land cover than the pastoral profitability variables. This is reflective of the relatively imprecise, regional nature of the pasture profitability data, as noted earlier. Forestry profitability on the other hand is estimated at a pixel level by Olssen *et al.* (2012) using similar land quality variables to what I include. Therefore, forestry profitability remains an important predictor of forestry (and pastoral) land on the inclusion of land quality variables.

In terms of the quality variables themselves, pasture is on land with a higher carrying capacity than forestry (CCAV) and slope affects pasture negatively, whereas forestry is more likely on sloped land and scrub even more likely on sloped land. Distance to supermarket is a variable included as a proxy for distance to population centres and thus as a measure of the accessibility of labour, processing facilities and other amenities. Table 2b shows that forestry is more likely to be close to population centres than pasture, though this variable has a very minor effect. Tímár's (2011) modelling suggests that for pasture this result is largely driven by the dominant pastoral land use, sheep and beef, as close proximity to a population centre is important for dairying. The signs of the marginal effects for distance to port are reversed, but the effects are even smaller. For Māori tenure land, the results of Model 3 are roughly consistent with Tímár (2011) – pasture is less likely on Māori land, whereas forestry is more likely and scrub more likely still.

6.1.2. Profitability as a predictor of aggregate land cover shares

The first question this paper seeks to address is whether recent commodity prices (which are the main driver of profitability) can be used as a predictor of land use change. In this subsection I use the Models 1 and 3 in Table 2 to predict the land cover shares in different periods to address both this question and how the modelling approach performs.

Table 3 presents the land cover share predictions from Models 1 and 3 using four different datasets to estimate the models. The predictions can be compared to observed land cover shares, shown in the top left hand corner of the table. In the first three columns I show the predictions of the two models, estimated using the 1997 cross-sectional data. The next three columns show the same exercise, but this time using Models 1 and 3 estimated from 2002 data (as in Table 2). In the next three columns the 1997 and 2002 data have been pooled to estimate the models. Finally, all three cross-sections are pooled to produce the final three columns of the table.

The first feature of Table 3 to note is that the multinomial logit will always predict the land cover shares correctly within sample. Therefore, the predictions are all correct for 2002 when the 2002 data has been used to estimate the models. I do not show the predictions for Model 2 as this model is estimated using exclusively time invariant data, so the model has no predictive ability outside of the year it has been estimated from. The predictions for the 1997 and 2002 pooled data will be correct for the 1997 and 2002 combined means, but not necessarily correct for the specific predictions for 1997 and 2002 separately. Therefore, it is the out of sample predictions which are important. Given the predictions from the fully pooled sample (1997, 2002 and 2008) are all within sample, these predictions are not directly comparable to the out of sample predictions in Table 3. Furthermore, the assumption that there are no correlated errors over time is required for all coefficient estimates from pooled data to be believed (Train 2009). I will discuss this assumption further at the end of this subsection (and conclude that it is not a good assumption, but I include the pooled data to demonstrate how the model predicts within sample for more than one year).

Both of the models do a very poor job at predicting land shares, even within sample for the pooled data. Clearly the cross-sectional variation in land cover as it relates to profitability at a given point in time cannot tell us anything about land cover share changes over time, using the multinomial logit in the way I have used it here. There appear to be two main reasons for this.

First, in the cross-sectional data, pastoral profitability is positively related to pasture, as expected, and forestry profitability is positively related to forestry, also as expected. However, pastoral profitability rises on average from 1997 to 2008 (Figure 1) and forestry profitability falls overall from 1997 to 2008 (Figure 3), but pasture land cover declines, whereas forestry land cover increases over the same period. Clearly, on this data there is a disjoint between recent commodity prices and aggregate land cover transitions.

Second, there is a high level of persistence in land cover over time. Estimating the models using cross-sectional variation causes out of sample predictions to show much more movement between land covers than actually occurs.

One solution for accounting for the high level of persistence in land cover is to include a lagged dependent variable in the model. However, including this variable requires the assumption that the error terms are independent over time (Train 2009). Lubowski (2002) argues that this assumption is unlikely to hold in reality, as with land use modelling there are likely to be unobserved variables in the error term which are serially correlated. If the assumption does not hold, coefficient estimates will be biased (presumably positively) and inconsistent for the lagged variables (Train 2009). I experimented with models which included the lagged dependent variable and their out of sample predictions improved markedly as expected (and were marginally better than the transition multinomial logits I discuss in the next subsection). However, their coefficient estimates are not reliable given the unrealistic assumption required, therefore I do not present the models here. This is a potential area for future work though, sorting out how to get reliable estimates for a multinomial logit with a lagged dependent variable in this context.

6.2. Modelling land cover transitions using the multinomial logit

In this section I discuss the results of modelling the land cover transitions directly. To do this, I estimate separate multinomial logit models for each starting land use. Therefore, I discuss the results from the four model specifications I estimate for each initial land use for the 1997 to 2002 transition period. Next, I discuss how well these models predict the transitions from 2002 to 2008 and how these results address the three questions set out at the start of this paper.

6.2.1. Fitting the models

The first transition type I model is the transitions from pasture, from 1997 to 2002, presented in Table 4. Table 4a holds the estimated coefficients for the four models. Model 1a, in the first two columns, is a simple model with just the profitability variables. Transitions from pasture to pasture is the base category, therefore the coefficients presented are for transitions to forestry and to scrub. The profitability variables included are the same as for the 2002 land share model discussed above – so they are six year averages of the years 1996 to 2001 inclusive. Therefore, transitions are modelled as potentially responding to future prices, as well as recent prices, given it is impossible to tell when a transition occurs within the period of 1997 to 2002. Again, it is the cross-sectional variation in recent profitability that is being used to determine in what way land cover is likely to transition.

The signs of the coefficients on the profitability variables are reasonable. Pastoral profitability is positively associated with pasture. The coefficient on forestry profitability is negative in its marginal effects for pasture, but ambiguous for forestry. However, calculating the mean marginal effects for each variable confirms this variable is behaving as expected too (with the similar coefficients on forestry in Model 4a, Table 4b shows the most positive marginal effect of forestry profitability is on forestry at 0.0045, and the marginal effect for scrub is small at 0.0007).

The next variables added in to Model 2a are the land sales variables. Adding these variables into the model does not have much of an effect on the profitability coefficients, as should be expected. Interpreting these coefficient estimates carefully, there is a positive association between land sales and transitions to forestry and a negative (but not statistically significant) association between transitions from scrub to pasture.

Model 3a adds in the land quality control and Māori tenure variables and removes land sales. The results here are generally in line with the qualitative results from the land cover share modelling. Pasture profitability loses its statistical significance once the land quality variables are added, but forestry profitability remains a good predictor of transitions to forestry.

Model 4a includes all the variables, and again the inclusion of the land sales variables makes little difference to coefficient estimates of the other variables. The mean marginal effects of Model 4a are given in Table 4b.

The land sales variables show similar results to Model 2a. Both a sale in a meshblock and the proportion of land sales within the meshblock are associated with a transition from pasture to forestry, whereas it does not seem to be associated with a transition from pasture to scrub. This association occurs even though the land sales variables are an imprecise measure, given they are at the meshblock rather than the pixel level. Given forestry tends to be on large blocks of land, it is perhaps unsurprising that a sale of a large amount of pasture land within a meshblock to convert to forestry land may lead to the meshblock that land is in having a higher proportion of it sold than other meshblocks. The land quality variables show similar qualitative results to the land share modelling. As for Māori tenure, this model provides a finer scale result that shows that Māori tenure land is unlikely to convert from pasture to forestry at a greater rate than other land, but is marginally more likely to convert from pasture to scrub.

Table 5 is basically the same as Table 4, but this time the transitions are from forestry. Overall it is clear that not many of the variables show any level of statistical significance in any of the models. The sample size is 10,351 for these models, which is significantly smaller than the

71,126 sample size for the transitions from pasture modelling. However, it is still a large sample size. As shown in Table 1b though, the vast majority of forestry land stays in forestry from 1997 to 2002. This means that out of the sample, only 5 pixels transition from forestry to pasture, and only 9 pixels transition to scrub. This lack of transitions also means the distance variables have to be excluded to allow the models to be estimated; hence the Models 3b and 4b are different from Models 3a and 4a. Therefore, little information can be garnered from these models, except that transitions from forestry are rare over this time period, and therefore extremely difficult to predict. There are significantly more transitions out of forestry from the 2002 to 2008 period, so modelling this period may give more information but may not help explain why there are so few transitions out of forestry from 1997 to 2002. Table 6 displays the results for transitions from scrub. There are more transitions – 40 to pasture and 156 to forestry out of 9,818 – but the numbers are not large, and still many variables' coefficient estimates do not show statistical significance. In general, the results that are significant are that profitability is positively associated with land transitioning to a productive use, CCAV is positively associated with pasture, and slope and distance to supermarket are negatively associated with forestry transitions. Māori tenure, though not significant at the 10 percent level, is still negatively associated with moving from scrub to forestry or pasture as expected.

6.2.2. Profitability, land sales and transitions

Modelling the land cover transitions provides useful evidence around the three questions that this paper seeks to address. In terms of the first question regarding profitability, along with assessing the ability of this type of modelling to predict future transitions, Table 7 presents the predictions for 2002 to 2008 transitions from the models estimated from the 1997 to 2002 transitions.

Overall, the models for transitions from pasture perform reasonably well. They consistently predict that transitions to forestry fall from the first transition period to the second, and that transitions to scrub remain rare. They do however consistently over-predict the transitions to forestry and under-predict the transitions to scrub. These predictions are based solely off the change in profitability between periods, the change in meshblock land sales for Models 2a and 4a, and a minor change in which pixels have the initial land cover of pasture.

For the initial land uses of forestry and scrub, the models perform poorly. From forestry, the predicted transitions are similar to the level of transitions from 1997 to 2002. This would be from the lack of transitions in 1997 to 2002 and therefore the very low marginal effects of all variables estimated by the models. Clearly something changes between 1997 and 2002, and 2002 and 2008 for forestry. While there are more transitions from scrub, it suffers from a similar problem to forestry, namely that the models predict similar levels of transitions for 2002 to 2008 as in 1997 to 2002, but the patterns of transitions are quite different. Therefore, these models appear to show that recent profitability is a predictor of transitions from pasture, but not from forestry or scrub.

In terms of the second question regarding land sales, Table 7 seems to indicate that including land sales within the meshblock does not improve the predictive ability of the models. However, Models 2a and 4a in Table 4 do indicate that there is a positive association between land sales within a meshblock and transitions from pasture to forestry.

The third question posed at the start of this paper concerns whether land which is marginal between uses has identifiable characteristics. Modelling the transitions does provide some useful descriptive data regarding this question, though so too does modelling land shares. Therefore, I address this question in the next section.

6.3. Comparing the models

The multinomial logit has been a popular choice for spatially explicit land use modelling and is usually applied in one of two ways – to model land use statically, or to model land use transitions. In this study I use both approaches and find some of their strengths and weaknesses, and also find how they complement each other.

For the land share modelling, Models 1 and 3 are estimated in a static manner from a cross-section of 2002 data, and estimate how profitability and land quality characteristics are spatially related. However, this method of land use modelling cannot be used to predict land cover shares in different periods as it is missing the vital element of consistently estimated coefficients for lagged land cover, which I am unable to incorporate satisfactorily in this study. The static modelling approach does however show how land cover is spatially related to the quality and profitability of that land in different land uses, at a given point in time.

Therefore, modelling the transitions by initial land cover plays an important role in understanding how land cover evolves over time in a consistently estimated framework. However, it suffers when there are few transitions from certain land covers and may not provide any useful information other than transitions from a given land cover are rare and therefore hard to predict, as is the case for transitions from forestry.

6.3.1. Marginal land

Both modelling approaches employed in this paper provide useful information about land which is marginal between uses, and thus the third question this study aims to address. The transitions modelling provides the most direct information about this – for example, that land with a lower CCAV is more likely to transition from pasture to forestry. Furthermore, it shows that land was unlikely to transition out of forestry between 1997 and 2002. This, however, is not necessarily useful information if we know or predict that a certain amount of forestry land will transition into pasture and scrub, but we want to get a better idea of what type of land that will be. If we are predicting an aggregate transition from forestry to pasture, Table 2 would guess that that would be land with a higher CCAV and lower slope. Indeed, it could be argued that Table 4 shows evidence that if land in pasture with a low CCAV and high slope is likely to transition to forestry, perhaps the reverse is true if land is transitioning from forestry. A quick comparison between Tables 4 and 6 would support this argument – for example, land with a low CCAV is more likely to transition from pasture to scrub (Table 4); land with a higher CCAV is more likely to transition from scrub to pasture (Table 6). Therefore, these models can provide useful information about marginal land, which increase the evidence around what type of land is likely to transition when aggregate land use transitions are predicted in New Zealand, given a predicted aggregate transition from a model such as that employed by Kerr and Olssen (2012). The multinomial logit model is useful in this sense, as any parcel of land can thus be assigned a specific transition probability.

6.3.2. Stability of estimates over time

In this paper I assess the utility of using the multinomial logit to predict out of sample land cover shares or transitions. While the static multinomial logit model gives a useful description of the cross-sectional relationship between land cover and profitability and land quality variables at a given point of time, it has no utility in predicting land cover shares in any other periods. The transition multinomial logit models hold more promise, particularly in this case, transitions out of pasture.

Therefore, I test the stability of my transition model coefficient estimates more formally. To do this, I test the transition models 4a for pasture and scrub, and 4b for forestry. I pool the data from the 1997 to 2002 transitions and the 2002 to 2008 transitions, and add a time dummy for the 2002 to 2008 transitions. For all initial land uses – pasture, forestry and scrub – this time dummy is highly statistically significant. I then interact this time dummy with all the variables and estimate the models again with the time dummy, the variables from models 4a/b, and the time dummy interactions. I then test the joint significance of the time dummy interaction coefficients for the three initial land uses.

For all initial land uses, using the Wald, Lagrange multiplier or the likelihood ratio tests, the time dummy interaction coefficients are highly statistically significant. For the Wald test, the Chi-squared value is 75.4 for pasture, 69.7 for forestry and 48.6 for scrub. This is strong evidence that the relationships between the variables and transitions are not stable over time.

Lubowski *et al.* (2008) and Li *et al.* (2013) model transitions, and do not find the estimates stable over time. Li *et al.* (2013) in particular compare their models from the different transition periods in their study, along with a panel data model, and conclude the relationships are not stable over time, in this case due to regularly changing policy regimes around land use in China. Lubowski *et al.* (2008) and Li *et al.* (2013) thus use models for each transition period to draw conclusions about historical land use change, rather than project future land use change. My results also suggest that extreme caution must be taken when trying to extrapolate past estimates to future probabilities of land cover change. The multinomial logit model (in both static and transition settings) does not seem to perform well at predicting aggregate shares of land cover, or land cover transitions out of sample. It does, however, seem to provide useful information about what land is likely to transition when transitions do occur, and this appears to be where its utility lies.

7. Conclusion

This project provides evidence around the three questions I set out to answer. Concerning the first question, I find recent profitability data (and therefore commodity prices) have little predictive power in terms of aggregate rural land use change in New Zealand, using the multinomial logit modelling approach. The only moderately successful predictions from the models are predicting the land use transitions out of pasture and into forestry or scrub from 1997 to 2002. For the second question, I find that land sales are positively associated with land use transitions from pasture into forestry. This finding suggests that the sale of land breaks down barriers to conversion, most likely in this case the capital constraints (both human and financial) on converting from pasture to forestry. However, this is an area for future research to determine why exactly this association holds. In regards to the third question, I find that the two multinomial logit modelling approaches I utilise both provide useful descriptive information about land that has been marginal between uses in recent years. For example, pasture with a higher slope and lower carrying capacity is more likely to transition to forestry compared with flat pasture.

The multinomial logit model is popular for spatially explicit land use modelling, and this modelling exercise has shown some of the utility of the multinomial logit and some of its drawbacks. This study suggests that the multinomial logit is not a good model to use for predicting future land use transitions. However, given a predicted aggregate land use change, the multinomial logit may help identify what land is most likely to transition between land uses.

Thus, this modelling exercise provides useful information for the questions set out at the start of this paper, but other modelling is needed on longer time series data to supplement this work if reasonable predictions for future land use shares are to be produced. As data and computing power improves, so too do the prospects of modelling land use and land use change, including for producing more accurate means of predicting future land use transitions. I allude to some of these prospects briefly in Section 3. There is plenty of scope for more data and better models to help simulate changes and drivers of change over time. An important gap in current understanding is how to model land use in a spatially-explicit way from land use change over time without relying solely on cross-sectional variation to estimate its parameters. This would help improve our understanding of how land use change evolves over time, and therefore be able model long run changes to land use due to changing economic circumstances, and perhaps land use transitions due to major policy changes, such as a gradually increasing carbon price. No doubt panel data models provide an important means of doing this as availability of data, computing power and modelling techniques improve. The reliable incorporation of lagged land cover in the static multinomial logit would also potentially help in this regard. Furthermore, modelling natural experiments and how they affect land use would contribute greatly to the field if they can be found, as suggested by Gibbons and Overman (2012). There is still much work that could be done to better understand and model the important economic relationships between macroeconomic drivers and rural land use change.

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9. Figures

Figure 1: Box plot of pasture 6 year average profitability in sample pixels.

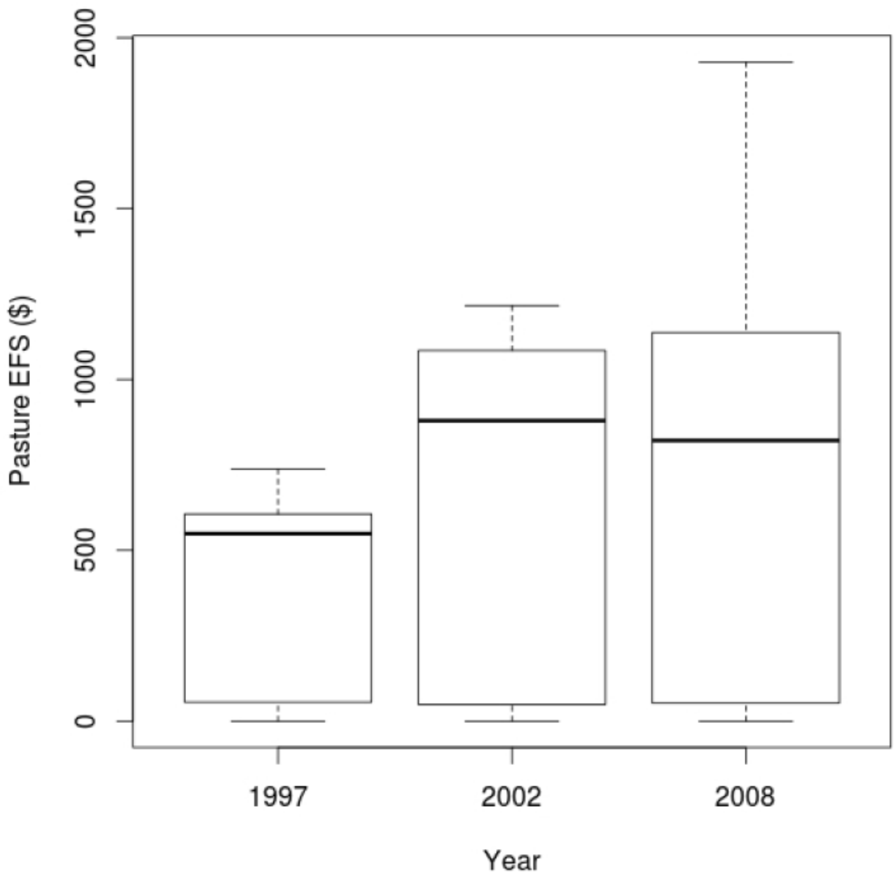


Figure 2: Box plot of sheep and beef 6 year average profitability in sample pixels.

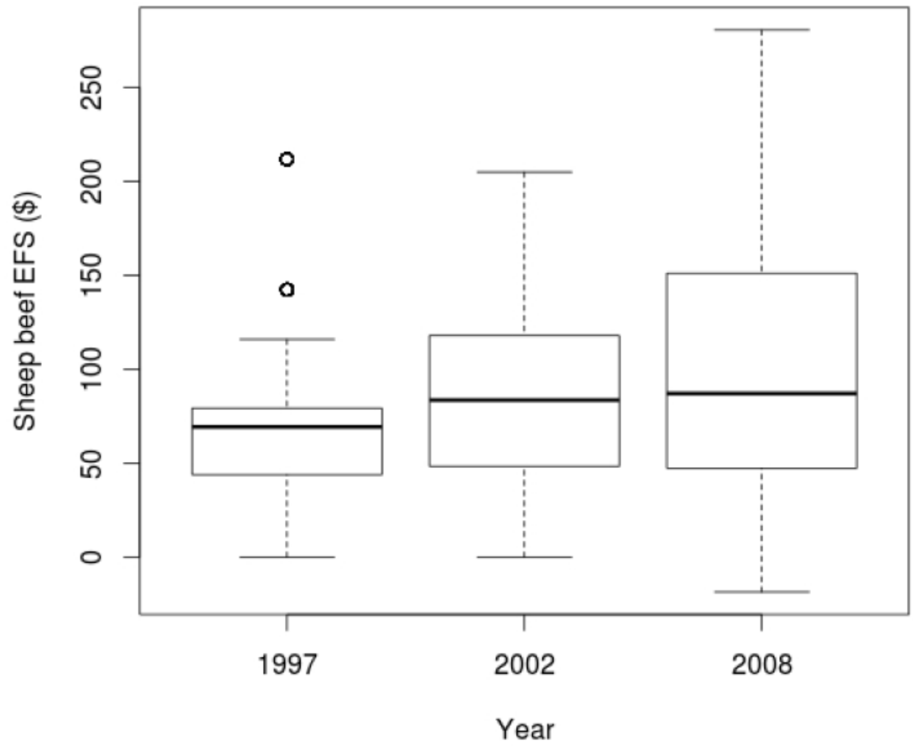
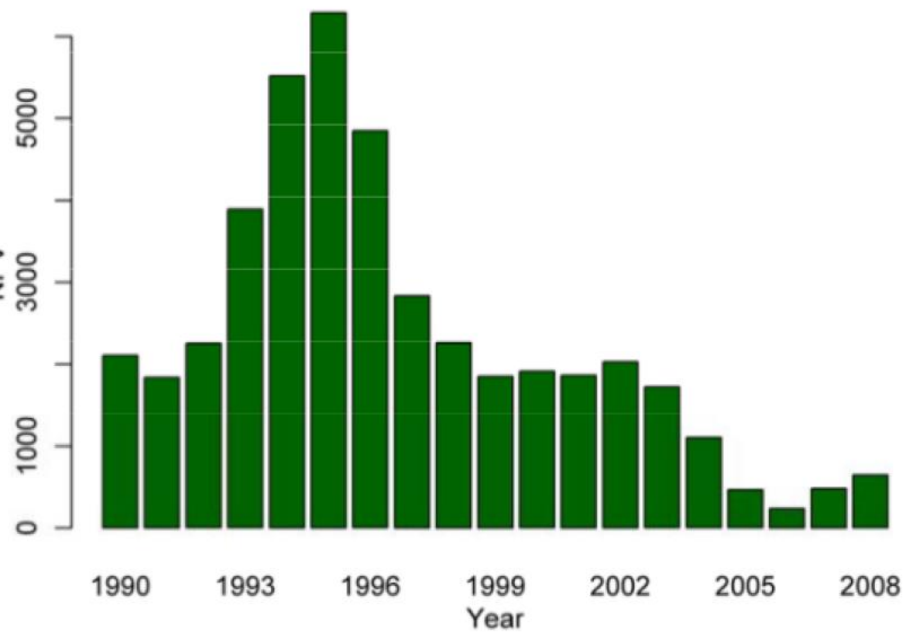


Figure 3: Forestry profitability change over time on land in forestry (Olssen et al., 2012, pg 19).



10. Tables

Table 1: Descriptive statistics.

(a) Total land cover in each year.

Land cover	% 1997	% 2002	% 2008	Δ 1997 to 2008
Pasture	49.44	48.80	48.54	-0.90
Forestry	7.08	7.72	7.90	0.82
Scrub	9.89	9.84	9.78	-0.11
Other	33.59	33.64	33.78	0.19

(b) Transition percentages between land covers.

	End year			
Start year	Pasture	Forestry	Scrub	Other
1997	**2002**			
Pasture	98.63	1.09	0.13	0.14
Forestry	0.10	99.75	0.11	0.03
Scrub	0.27	1.03	98.68	0.02
Other	0.02	0.04	0.01	99.93
2002	**2008**			
Pasture	98.98	0.51	0.16	0.35
Forestry	1.55	98.12	0.25	0.08
Scrub	0.95	0.63	98.33	0.09
Other	0.06	0.04	0.02	99.86

(c) Dairy profitability per hectare, six year averages.

Region	1997	2002	2008
Northland	$394	$575	$762
Waikato-Bay of Plenty	$578	$880	$821
Taranaki	$706	$1,085	$1,084
Lower North Island	$644	$906	$914
Canterbury	$738	$1,251	$1,929
Southland	$549	$1,211	$1,466
National*	$606	$916	$1,138

*National is a MAF weighted average of the regions.

Table 2: Land share multinomial logit model estimated from 2002 data.

(a) Coefficient estimates for Models 1-3.

Variable	Model 1 Pasture	Model 1 Forestry	Model 2 Pasture	Model 2 Forestry	Model 3 Pasture	Model 3 Forestry
Intercept	1.579 ***	-0.605 ***	2.703 ***	0.739 ***	2.860 ***	0.749 ***
	(0.020)	(0.030)	(0.037)	(0.047)	(0.049)	(0.057)
Pasture EFS/ha	0.806 ***	0.506 ***			-0.034	-0.074 *
$1,000s	(0.022)	(0.029)			(0.027)	(0.034)
Forestry profit/ha	-0.027 ***	0.187 ***			-0.169 ***	0.082 ***
$1,000s	(0.006)	(0.008)			(0.008)	(0.010)
CCAV			0.746 ***	0.454 ***	1.053 ***	0.352 ***
10 ewe stock			(0.030)	(0.036)	(0.034)	(0.040)
Slope			-0.819 ***	-0.452 ***	-0.785 ***	-0.513 ***
10 degrees			(0.015)	(0.019)	(0.015)	(0.019)
Dist to supermarket			0.056 ***	-0.020 ***	0.049 ***	-0.017 ***
10,000 kms			(0.002)	(0.003)	(0.002)	(0.003)
Dist to port			-0.023 ***	-0.005 ***	-0.020 ***	-0.007 ***
10,000 kms			(0.001)	(0.001)	(0.001)	(0.001)
Māori tenure			-1.817 ***	-0.624 ***	-1.614 ***	-0.692 ***
			(0.049)	(0.056)	(0.051)	(0.057)
n		91,295		91,295		91,295
Log-likelihood		-62,459		-58,967		-58,188
Likelihood ratio index		0.022		0.077		0.089

Coefficient; (Standard Error). Signif. codes: *** 0.001; ** 0.01; * 0.05; · 0.1

(b) Marginal effects of Model 3.

Variable	Pasture	Forestry	Scrub
Pasture EFS/ha	0.0012	-0.0047	0.0035
$1,000s			
Forestry profit/ha	-0.0344	0.0239	0.0106
$1,000s			
CCAV	0.1369	-0.0577	-0.0791
10 ewe stock			
Slope	-0.0795	0.0166	0.0629
10 degrees			
Dist to supermarket	0.0094	-0.0062	-0.0032
- 10,000 kms			
Dist to port	-0.0026	0.0011	0.0015
- 10,000 kms			
Māori tenure	-0.1961	0.0724	0.1236

Mean marginal effects across the sample, expressed as proportions.

Table 3: Predicted multinomial land share percentages for sample pixels using different years for estimation for Models 1 and 3.

Data used for estimation		**1997**			**2002**			**1997 & 2002**			**1997, 2002 & 2008**		
Prediction year		1997	2002	2008	1997	2002	2008	1997	2002	2008	1997	2002	2008
Land cover													
Observed	Pasture	77.91	76.93	76.76									
	Forestry	11.34	12.41	12.69									
	Scrub	10.75	10.66	10.55									
Model 1	Pasture	77.91	82.69	85.74	71.30	76.93	81.08	75.42	79.41	82.30	74.24	77.49	79.87
	Forestry	11.34	8.37	6.07	16.72	12.41	8.85	13.19	10.57	8.21	14.35	12.10	9.99
	Scrub	10.75	8.93	8.19	11.98	10.66	10.07	11.39	10.02	9.49	11.41	10.42	10.14
Model 3	Pasture	77.91	81.53	85.22	71.61	76.93	82.13	75.79	79.04	82.60	74.40	77.11	80.09
	Forestry	11.34	8.76	6.38	16.40	12.41	8.81	12.99	10.76	8.45	14.03	12.18	10.23
	Scrub	10.75	9.72	8.41	11.99	10.66	9.06	11.22	10.20	8.95	11.56	10.72	9.68

Table 4: Multinomial logit transitions from pasture, 1997 to 2002.

(a) Coefficient estimates for Models 1a-4a.

Variable	Model 1a To Forestry	Model 1a To Scrub	Model 2a To Forestry	Model 2a To Scrub	Model 3a To Forestry	Model 3a To Scrub	Model 4a To Forestry	Model 4a To Scrub
Intercept	-5.370 ***	-7.785 ***	-5.545 ***	-7.731 ***	-5.830 ***	-9.469 ***	-6.094 ***	-9.538 ***
	(0.103)	(0.318)	(0.113)	(0.330)	(0.164)	(0.540)	(0.734)	(0.555)
Pasture EFS/ha	-0.959 ***	-1.349 ***	-1.040 ***	-1.324 ***	-0.263 ·	-0.001	-0.276 ·	-0.007
\$1,000s	(0.127)	(0.369)	(0.128)	(0.371)	(0.141)	(0.420)	(0.142)	(0.421)
Forestry profit/ha	0.310 ***	0.396 ***	0.298 ***	0.400 ***	0.396 ***	0.489 ***	0.390 ***	0.487 ***
\$1,000s	(0.019)	(0.057)	(0.019)	(0.057)	(0.022)	(0.067)	(0.022)	(0.067)
Sales dummy			0.277 **	-0.063			0.275 **	0.088
sale in meshblock			(0.091)	(0.250)			(0.093)	(0.254)
Sales proportion			0.631 *	-0.458			0.974 ***	0.240
of meshblock			(0.287)	(1.054)			(0.278)	(0.980)
CCAV					-0.762 ***	-0.830 **	-0.819 ***	-0.845 **
10 ewe stock					(0.101)	(0.288)	(0.102)	(0.290)
Slope					0.703 ***	0.944 ***	0.704 ***	0.944 ***
10 degrees					(0.050)	(0.139)	(0.050)	(0.140)
Dist to supermarket					-0.086 ***	-0.091 ***	-0.082 ***	-0.090 ***
10,000 kms					(0.010)	(0.024)	(0.010)	(0.024)
Dist to port					0.008 **	0.033 ***	0.009 ***	0.034 ***
10,000 kms					(0.003)	(0.007)	(0.003)	(0.007)
Māori tenure					-0.282	1.132 ***	-0.139	1.175 ***
					(0.232)	(0.333)	(0.233)	(0.343)
n		71,126		71,126		71,126		71,126
Log-likelihood		-5,115.5		-5,102.5		-4,881.1		-4,863.2
Likelihood ratio index		0.039		0.042		0.083		0.087

Coefficient; (Standard Error). Signif. codes: *** 0.001; ** 0.01; * 0.05; · 0.1

(b) Marginal effects of Model 4a.

Variable	To Pasture	To Forestry	To Scrub
Pasture EFS/ha \$1,000s	0.0032	-0.0032	0.0000
Forestry profit/ha \$1,000s	-0.0051	0.0045	0.0007
Sales dummy sale in meshblock	-0.0033	0.0032	0.0001
Sales proportion of meshblock	-0.0115	0.0112	0.0003
CCAV 10 ewe stock	0.0011	-0.0009	-0.0001
Slope 10 degrees	-0.0009	0.0008	0.0001
Dist to supermarket - 10,000 kms	0.0011	-0.0009	-0.0001
Dist to port - 10,000 kms	-0.0002	0.0001	0.0000
Māori tenure	-0.0000	-0.0017	0.0017

Mean marginal effects across the sample, expressed as proportions.

Table 5: Transitions from forestry, 1997 to 2002.

(a) Coefficient estimates for Models 1a-4b.

Variable	Model 1a To Pasture	Model 1a To Scrub	Model 2a To Pasture	Model 2a To Scrub	Model 3b To Pasture	Model 3b To Scrub	Model 4b To Pasture	Model 4b To Scrub
Intercept	-5.484 ***	-6.329 ***	-6.175 ***	-6.520 ***	-4.366 ***	-6.133 ***	-5.015 ***	-6.148 ***
	(0.784)	(1.011)	(1.242)	(1.137)	(1.083)	(1.212)	(1.439)	(1.329)
Pasture EFS/ha	-1.805	-2.141	-1.974	-2.027	-2.235	-1.968	-2.555	-1.931
$1,000s	(1.590)	(1.333)	(1.590)	(1.326)	(1.634)	(1.358)	(1.671)	(1.350)
Forestry profit/ha	-0.430 *	-0.015	-0.403 *	0.020	-0.328	0.020	-0.297	0.048
$1,000s	(0.189)	(0.203)	(0.196)	(0.211)	(0.201)	(0.216)	(0.206)	(0.227)
Sales dummy			0.704	1.848 *			0.742	1.826 *
sale in meshblock			(1.184)	(0.799)			(1.184)	(0.805)
Sales proportion			2.078	-96.491 ·			2.224	-94.023 ·
of meshblock			(2.494)	(57.644)			(2.463)	(56.453)
CCAV					-0.863	-0.685	-0.875	-0.532
10 ewe stock					(1.126)	(0.839)	(1.141)	(0.804)
Slope					-0.927	0.024	-0.991	0.057
10 degrees					(0.768)	(0.455)	(0.775)	(0.455)
Māori tenure					-14.025	0.644	-13.770	0.622
					(2524.2)	(1.078)	(2,476.6)	(1.091)
n		10,351		10,351		10,351		10,351
Log-likelihood		-111.51		-105.26		-109.85		-103.65
Likelihood ratio index		0.035		0.089		0.050		0.103

Coefficient; (Standard Error). Signif. codes: *** 0.001; ** 0.01; * 0.05; · 0.1

(b) Marginal effects of Model 4b.

Variable	To Forestry	To Pasture	To Scrub
Pasture EFS/ha	0.0029	-0.0012	-0.0017
$1,000s			
Forestry profit/ha	0.0001	-0.0001	0.0000
$1,000s			
Sales dummy	-0.0019	0.0004	0.0016
sale in meshblock			
Sales proportion	0.0803	0.0011	-0.0815
of meshblock			
CCAV	0.0009	-0.0004	-0.0005
10 ewe stock			
Slope	0.0004	-0.0005	0.0000
10 degrees			
Māori tenure	0.0061	-0.0066	0.0005

Mean marginal effects across the sample, expressed as proportions.

Table 6: Transitions from scrub, 1997 to 2002.

(a) Coefficient estimates for Models 1a-4a.

	Model 1a		**Model 2a**		**Model 3a**		**Model 4a**	
Variable	To Pasture	To Forestry	To Pasture	To Forestry	To Pasture	To Forestry	To Pasture	To Forestry
Intercept	-6.134 ***	-5.033 ***	-6.313 ***	-5.070 ***	-6.788 ***	-3.458 ***	-6.975 ***	-3.423 ***
	(0.457)	(0.239)	(0.113)	(0.330)	(0.713)	(0.341)	(0.754)	(0.353)
Pasture EFS/ha	0.944 ·	1.210 ***	0.790	1.172 ***	0.988	0.681 *	0.883	0.678 *
$1,000s	(0.557)	(0.289)	(0.569)	(0.294)	(0.629)	(0.313)	(0.635)	(0.315)
Forestry profit/ha	0.084	0.122 **	0.082	0.121 **	0.002	0.124 **	0.005	0.125 **
$1,000s	(0.074)	(0.039)	(0.075)	(0.039)	(0.082)	(0.042)	(0.082)	(0.042)
Sales dummy			0.540	0.133			0.449	-0.004
sale in meshblock			(0.384)	(0.190)			(0.394)	(0.194)
Sales proportion			-1.615	-0.426			-1.787	-0.512
of meshblock			(1.964)	(0.890)			(2.068)	(0.936)
CCAV					1.163 **	-0.193	1.165 **	-0.180
10 ewe stock					(0.044)	(0.022)	(0.447)	(0.217)
Slope					-0.118	-0.364 **	-0.109	-0.363 **
10 degrees					(0.223)	(0.111)	(0.224)	(0.111)
Dist to supermarket					0.012	-0.092 ***	0.014	-0.092***
10,000 kms					(0.023)	(0.024)	(0.023)	(0.024)
Dist to port					0.013	-0.008	0.013	-0.008
10,000 kms					(0.010)	(0.006)	(0.010)	(0.006)
Māori tenure					-0.886	-0.432	-0.836	-0.450
					(0.740)	(0.339)	(0.745)	(0.342)
n		9,818		9,818		9,818		9,818
Log-likelihood		-1,045.2		-1,043.9		-1,011.2		-1,010.2
Likelihood ratio index		0.014		0.015		0.046		0.047

Coefficient; (Standard Error). Signif. codes: *** 0.001; ** 0.01; * 0.05; · 0.1

(b) Marginal effects of Model 4a.

Variable	**To Scrub**	**To Pasture**	**To Forestry**
Pasture EFS/ha	-0.0140	0.0035	0.0104
$1,000s			
Forestry profit/ha	-0.0019	0.0000	0.0019
$1,000s			
Sales dummy	-0.0017	0.0018	-0.0001
sale in meshblock			
Sales proportion	0.0150	-0.0072	-0.0078
of meshblock			
CCAV	-0.0018	0.0047	-0.0029
10 ewe stock			
Slope	0.0060	-0.0004	-0.0056
10 degrees			
Dist to supermarket	0.0014	0.0001	-0.0014
- 10,000 kms			
Dist to port	0.0001	0.0001	-0.0001
- 10,000 kms			
Māori tenure	0.0103	-0.0033	-0.0069

Mean marginal effects across the sample, expressed as proportions.

Table 7: Predicted percentage of transitions of sample pixels for the models estimated with 1997 to 2002 data.

	Transition from					
	Pasture		Forestry		Scrub	
	1997-2002	2002-2008	1997-2002	2002-2008	1997-2002	2002-2008
Observed						
To Pasture	98.68	99.32	0.05	1.63	0.41	1.43
To Forestry	1.18	0.53	99.86	98.07	1.59	1.02
To Scrub	0.14	0.14	0.09	0.30	98.00	97.55
Model 1a						
To Pasture	98.68	99.31	0.05	0.07	0.41	0.45
To Forestry	1.18	0.63	99.86	99.86	1.59	1.77
To Scrub	0.14	0.06	0.09	0.08	98.00	97.78
Model 2a						
To Pasture	99.68	99.30	0.05	0.07	0.41	0.42
To Forestry	1.18	0.64	99.86	99.88	1.59	1.75
To Scrub	0.14	0.06	0.09	0.05	98.00	97.83
Model 3a						
To Pasture	99.68	99.31			0.41	0.50
To Forestry	1.18	0.62			1.59	1.56
To Scrub	0.14	0.07			98.00	97.94
Model 3b						
To Pasture			0.05	0.06		
To Forestry			99.86	99.87		
To Scrub			0.09	0.07		
Model 4a						
To Pasture	99.68	99.29			0.41	0.48
To Forestry	1.18	0.65			1.59	1.54
To Scrub	0.14	0.07			98.00	97.98
Model 4b						
To Pasture			0.05	0.06		
To Forestry			99.68	99.89		
To Scrub			0.09	0.05		

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