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Changing Rural Land Use In New Zealand 1997 To 2008

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SUMMARY

This paper is a current draft of my Honours research project, and looks into whether changing economic variables have any predictive power on changing rural land use in recent years. To do this I attempt to answer three questions: 1. Do recent commodity prices have any predictive power on land use conversions? 2. Is recently sold land more likely to change use? 3. Does land which is marginal between uses have identifiable characteristics? I present my preliminary findings, which suggest land sales as a good indicator of land use change. Key words: LAND USE, AGRICULTURE, LAND SALES.

INTRODUCTION

Rural land use in New Zealand is an important driver of economic activity, and has clear implications for our environmental performance, such as in the areas of biodiversity, climate change emissions and water quality. Rural land use is always changing, but change occurs slowly (Kerr & Olssen, 2012).

There are clear environmental and economic motivations for research into land use. For New Zealand, our agricultural sector is responsible for roughly half of our current greenhouse gas emissions, and 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, p 37). Land cover and use is also important for biodiversity and the provision of ecosystem services such as soil conservation (Rutledge et al, 2012). 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). The importance and vulnerability of this image has been highlighted recently with the Fonterra botulism scare, and resulting negative media coverage overseas concerning New Zealand's 100% Pure branding. Thus, understanding rural land use in New Zealand is important for understanding New Zealand's economic and environmental performance, and how land use might respond to government policy.

This paper starts with a coverage of some basic theory behind rural land use and rural land use change. It then outlines the econometric models I use to answer my questions, followed by a description of the data. The results section provides an outline of my preliminary results. Finally, I end with a conclusion on my findings to date.

THEORY OF LAND USE

This section covers the basic theory behind land use allocation and conversion.

Land use versus land cover

First, it is useful to make an important clarification - the difference between land cover and land use. In simple terms, land cover is a description of what is on a given piece of land at a given time, whereas land use is the use to which people are putting that land to. Thus, land use describes the economic activity taking place on the land - for example dairy farming or

[1] This research is for the research component of my Honours degree and represents the current state of my draft. As such, it should be treated as a draft. Comments are welcome. The final product is due mid-October.

[2] I would like to acknowledge my supervisor, Dean Hyslop, for the time and thought he has put into this project to date. A huge thanks also to Motu Research for providing me with data and support, particularly to Suzi Kerr.

industrial production. Land cover on the other hand reflects the interaction between economic and ecological processes. Therefore, land cover usually reflects the economic use it is being put towards - for example, the land cover for dairy farming is likely to be pasture. Alternatively, land cover could also reflect a lack of economic use - 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.

I clarify this important distinction between land cover and land use initially as for this project I am conceptually interested in land use. However, the dataset I have is land cover, which I am using as a proxy for land use. This is a limitation, most importantly for pastoral farming as 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. The land cover data is also limited to the extent that land cover does not reflect land use. This is unlikely to be much of an issue, with the exception of abandoned pasture in some parts of the South Island. In certain areas there is not enough seed source for abandoned pasture to be returned to scrub, so the observed cover would be pasture, but the land is not being used (Tímár, 2011). Given the extent of pasture in New Zealand, this issue is unlikely to substantially affect my results.

Therefore, I talk theoretically in terms of land *use*, but use the terms *use* and *cover* interchangeably in the empirical sections.

Bid-rent theory

Land use theory has it roots in the works of David Riccardo and Heinrich von Thünen (in works from 1821 and 1966 respectively). Riccardo 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 (cited by 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 further out will be in agricultural uses - dependent on the value of the agricultural products and their transport costs - and finally land furthest 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.[3] In a uniform region, distance to market will affect farmgate price - the commodity price which the land manger 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 land area. Land quality will affect the level of returns possible from each use. Looking solely at rural land uses, the importance of this dimension for New Zealand land use is clear. For example, 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 & Kerr, 2009). Thus, adding in a land quality dimension complicates the simple, uniform land story above. Furthermore, given agricultural produce and forestry are important exports for New Zealand, the relevant distance to market may be distance to port, or distance to a processing facility.

Thus, there is an interaction between the distance from markets, the productive potential of the land and the optimal land use.

Utility maximisation

I present the land use decision within a utility maximisation framework. This allows the introduction of extra factors which determine land use decisions, such as amenity value preferences.

Given a discrete choice of J land use types, land manager i's expected return to land use j,

[3] 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.

at time t is:

$$\pi_{ij,t} = p_{ij,t}.q_{j,t}(a,b,k,l) - c_{j,t}(a,b,k,l) \tag{1}$$

where π represents expected profits, $p_{j,t}$ is farmgate price for land manager i, land use j at time t. The production function $q(.)$ depends on various factors, such as production technology (a), land quality (b), capital (k) and labour (l). The cost function, $c(.)$ also depends on these factors.

A land manager is concerned about present value, V, of these profits, which is the sum of their total expected discounted value:

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

where δ is their discount rate.

Finally, there are other factors which affect land use. These reflect the preference of land managers. Land managers may have preferences for certain types of land uses given their family history with the land, amenity value preferences, level of environmental concern and so on. Given land managers may live on their properties, these values could be argued to be more likely to be important than if they do not have a direct connection with the property.

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

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

where ϵ_{ij} 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 equation holds for all other land uses, where $j \neq k$:

$$U_{ij,t} \geq U_{ik,t} \tag{4}$$

For the researcher observing land use choices, this can be thought of in terms of probabilities, given observable variables. Therefore, probability of observing land use j for land parcel i at time t can be represented by:

$$\Pr(V_{ij,t} + \eta_{ij,t} \geq V_{ik,t} + \eta_{ik,t}) \text{ for all } j \neq k \tag{5}$$

where V represents observable characteristics, and η represents unobservable characteristics, which are independently and identically distributed (the preceding equations are developed from Bockstael, 1996 and Tímár, 2011).

This model represents a simple model without conversion costs. Holding all factors constant, land use allocations could be expected to converge to the point where equations (6) and (5) hold for all land parcels. However, land use conversion is costly, and risky, given prices are likely to follow a random walk (Schatzki, 2003).

Land use conversion

Given the costly and risky nature of land use conversion, land use conversions tend to be gradual in practice (Kerr & Olssen, 2012). Thus, land use conversions can be modelled separately to the overall allocation of land uses, decribed in the previous section (Tímár, 2011). Probability of conversion can be thought of by manipulating the previous equations to include conversion costs. Land use 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 when:

$$U_{ij,t} - Z_{ij,t} \geq U_{ik,t} - Z_{ik,t} \text{ for all } j \neq k \tag{6}$$

where $Z_{ij,t}$ is the cost of conversion for land manager i to land use j at time t (Bockstael, 1996 and Tímár, 2011).

While the net present value of conversion may be worthwhile purely on a profitability basis, there are many reasons why a land owner may not convert or may delay conversion. 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; 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 be unable to raise the funds for conversion.

The bid-rent theory does operate within a market environment however, and therefore the land manager may choose to sell. In theory, land value will reflect the net present value of returns the land from its best use. A land owner may sell their land for retirement, 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. Therefore, I also test whether recently sold land is more likely to convert.

ECONOMETRIC MODELLING

To answer the questions outlined earlier I employ two modelling approaches. For the first question, I use a multinomial logit. For the subsequent two questions I use a binary logit model.

Question 1 - Multinomial logit

The multinomial logit model has been a popular choice for land use choice modelling. It is a discrete, unordered, multi-outcome, latent variable choice model, which produces estimates of the probability of each choice, given observed characteristics. It estimates probabilities for each choice, and ensures total probabilities sum to 1. It estimates separate coefficients for each choice, for all variables except the base variable. A restriction of the multinomial logit is that it exhibits independence from irrelevant alternatives, which is a strong assumption that is unlikely to be applicable in the land use choice situation. However, studies using alternative models without this restriction have often shown little difference when compared with the multinomial logit (Tímár, 2011). The multinomial logit is based on the logistic distribution. It is:

$$\Pr(Y_i = j) = \frac{\exp(\boldsymbol{\beta}'_j \boldsymbol{x}_i)}{\sum_{k=0}^{J} \exp(\boldsymbol{\beta}'_k \boldsymbol{x}_i)} \tag{7}$$

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, $\boldsymbol{x}_i$. Normalising this around the base category of $j = 0$ by setting $\boldsymbol{\beta}_j = 0$ gives the following equations:

$$\begin{aligned} \Pr(Y_i = j) &= \frac{\exp(\boldsymbol{\beta}'_j \boldsymbol{x}_i)}{1 + \sum_{k=1}^{J} \exp(\boldsymbol{\beta}'_k \boldsymbol{x}_i)} \quad \text{for} \quad j = 1, 2, \ldots, J \\ \Pr(Y_i = 0) &= \frac{1}{1 + \sum_{k=1}^{J} \exp(\boldsymbol{\beta}'_k \boldsymbol{x}_i)} \end{aligned} \tag{8}$$

(Green, 1990).

Questions 2 and 3 - Binary logit

I use the binary logit model to estimate transition probabilities for land with various characteristics for questions two and three. This model follows the logistic distribution as with the multinomial logit above. However, it is a binary choice, so estimates the probability of an event occurring or not. The model is as follows:

$$\Pr(Y_i = 1) = \frac{\exp(\boldsymbol{\beta}' \boldsymbol{x}_i)}{1 + \exp(\boldsymbol{\beta}' \boldsymbol{x}_i)} \tag{9}$$

where 1 = conversion, 0 = no conversion. $\boldsymbol{\beta}$ is a vector of coefficients, estimated for the vector of predictor variables, $\boldsymbol{x}$. As this is a latent variable model, the coefficients cannot be directly

Table 1: Land cover proportions, calculated with rasterised data.

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

interpreted except in terms of direction, but rely on other methods to interpret their magnitude (Green, 1990).

DATA

In this section I describe my data sources, with some descriptive statistics. I first cover the dependent variables, the land use data, followed by the independent variables. I cover 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 the project is spatially allocated across a rasterised map of New Zealand.[4] The data is 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 LCDB3 datasets there is a total of 1,072,805 data points representing New Zealand land; the datasets do not match perfectly along coastlines, so some of these points are thrown out where they do not exist across all the maps. The value for each pixel is assigned by the value of the pixel at its central point. My datasets vary at the pixel level, unless otherwise noted in the descriptions below.

Land use

My dependent variables, are land cover as a proxy for land use. They 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, the LCDB3 does distinguish between scrub, exotic forestry and native forest.

The LCDB3 database was compiled by Landcare New Zealand and released in 2012 (Landcare Research, 2013d). 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 aggregated up to the categories of pasture, exotic forestry, scrub and other (Landcare Research, 2013c). The “other” category includes urban, horticulture, cropland, indigenous forest and “unproductive” land (for example the tops of mountains). I exclude all “other” pixels in my 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, 2013a). Therefore there may be some issues with the accuracy of the land cover data.

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 & Olssen, 2012).

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

[4] 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.

Table 2: Transition percentages between land covers, 1997 to 2002, calculated with rasterised data.

		2002 Pasture	Forestry	Scrub	Other
1	**Pasture**	98.63	1.09	0.13	0.14
9	**Forestry**	0.10	99.75	0.11	0.03
9	**Scrub**	0.27	1.03	98.68	0.02
7	**Other**	0.02	0.04	0.01	99.93

Table 3: Transition percentages between land covers, 2002 to 2008, calculated with rasterised data.

		2008 Pasture	Forestry	Scrub	Other
2	**Pasture**	98.98	0.51	0.16	0.35
0	**Forestry**	1.55	98.12	0.25	0.08
0	**Scrub**	0.95	0.63	98.33	0.09
2	**Other**	0.06	0.04	0.02	99.86

Tables 2 and 3 show 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 a proportion of their original type. Therefore, in table 3, 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, p 10), show that the trends in table 1 are long term trends, continuing for roughly 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. The upward trends in dairy and forestry see them account for around 10 percent of rural land in New Zealand by 2005 according to Kerr and Olssen's (2012, p 10) data.

Profitability

I compile profitability data for three land uses - dairy, sheep and beef farming and forestry. These datasets represent a measure of achievable return from three 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).

Although I cannot observe whether pasture is in dairy or sheep and beef, I use profits for both, rather than a composite of the two. This is because I expect dairy profitability and sheep and beef profitability to act on land use in two different ways. From trends over the last few decades, as mentioned in the previous section, the proportion of rural land in dairy is increasing, while the proportion of rural land in sheep and beef is decreasing. Therefore, while it is impossible to observe whether sheep and beef is converting to dairy, it is likely that land converting from pasture to forestry is being converted from sheep and beef, and land converting from forestry to pasture is likely to be converting to dairy. Therefore, the two profitability measures may affect pasture cover versus other types of cover in an observable way.

I aggregate the data, which is on an annual basis, by using six year averages, as this represents the longest period of time between LCDB3 observations.

The dairy data is compiled from Ministry of Agriculture and Forestry (MAF) monitor dairy farms.[5] 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 data starts in the 1991/92 season, as this is when MAF monitor dairy farms began to be aggregated using the current regional system. Therefore the 1997 data in the dairy series is an average from 1992 to 1996, so is a five year average.

I interact dairy profitability with a slope index in order to allocate dairy profitability figures spatially, based on an indicator of suitability of the land for dairy. Todd and Kerr (2009, p 14) document how flat land in New Zealand is far more likely to have dairy on it than sloped land, and almost no dairy is on land with a slope greater than 10 degrees. Thus, my slope index S for observation i is calculated as follows:

$$S_i = \begin{cases} 10 - s_i & \text{when } s_i \leq 10 \\ 0 & \text{when } s_i > 10 \end{cases} \tag{10}$$

where s_i is the slope of observation i in degrees.

My sheep and beef 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).[6] I allocate these 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 DoC land. The map of potential farm classes is based on 2002 Quotable Values 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).

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 forestry on a given pixel. Expected returns are based on recent data I use the dataset which has been smoothed over 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.

Unfortunately I am unable to provide many descriptive statistics on profitability data at this point in the project. This will be remedied in the final version of the project. Olssen et al (2012) do document how their dataset changes over time. It shows a decline in expected returns from forestry over each time step in my study. They put this trend down to declining log prices from the mid-1990s to the end of the data period (Olssen et al, 2012, p 19).

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 geographic statistical unit, which 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 QVNZs judgement of the lands best use, not current use. I take land sales areas recorded 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 for whether land of the aforementioned types has been sold within that meshblock for 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

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

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

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; this figure is 10 times the meshblock area for the second period. These two figures highlight that there are likely some inaccuracies in QVNZs data, as even accounting for double counting the former figure implies the entire meshblock was sold approximately once a month over the five year period. Therefore I allow the maximum value of the proportion dataset to be 100 percent. The issue of double counting is mitigated if land cover change is even more likely follow multiple sales, and is unlikely to be a major issue given how infrequently rural land is sold.

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.

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 CCAV, slope of land and distance to ports and supermarkets.

The CCAV dataset, held by Motu 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. Todd and Kerr (2009) document how land quality and slope affect the land managers choice between dairy, sheep and beef, forestry and scrub. Highest quality land (including productive capacity and slope) can be expected to be in dairy, followed by sheep and beef, 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 (Todd & Kerr, 2009, pp 14-15).

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

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 for its conservation value. I have datasets for these two types of ownership in 2002 and 2003 respectively (Department of Conservation, 2005 and Landcare Research, 2008). Therefore I exclude land under DoC ownership, and include Māori tenure land in 2002 as an indicator variable.

RESULTS

In this section I present the preliminary results from my multinomial and binary logit modelling.

My modelling strategy for both models is as follows. I estimate the models with a sample of the first period dataset, excluding the “other” category. Although Lubowski et al (2008) do not find issues with auto-spatial correlation in their study, I use a sample in order to prevent auto-spatial correlation from affecting my estimates. I regularly sample the pixels in the full grid so that no two pixels are closer than two pixels apart, ensure no pixels are adjacent, as suggested

Table 4: Estimated marginal effects, coefficients and their significance for pasture (1) and forestry (2).

Coefficient	**Marg effect**	**Coefficient**	**Std error**	**t-value**	**Signif**
1:(intercept)	0.4152485	4.3266e+00	1.6647e-01	25.9899	***
2:(intercept)	0.9534355	5.5395e+00	2.0464e-01	27.0695	***
1:ccav	0.009119772	9.5021e-02	3.5133e-03	27.0462	***
2:ccav	0.005220757	3.0333e-02	4.2214e-03	7.1855	***
1:slope	-0.003619862	-3.7716e-02	1.9810e-03	-19.0387	***
2:slope	-0.008275067	-4.8079e-02	2.9974e-03	-16.0400	***
1:dists	4.981076e-07	5.1899e-06	2.0486e-07	25.3335	***
2:dists	1.894214e-07	1.1005e-06	3.1658e-07	3.4763	***
1:distp	-2.916984e-07	-3.0393e-06	1.2393e-07	-24.5249	***
2:distp	-6.237979e-07	-3.6243e-06	1.5121e-07	-23.9687	***
1:maori	-0.1470477	-1.5321e+00	5.1069e-02	-30.0009	***
2:maori	-0.09286814	-5.3957e-01	5.8886e-02	-9.1630	***
1:defsslope	2.232401e-05	2.3260e-04	9.1432e-06	25.4395	***
2:defsslope	1.455287e-05	8.4553e-05	1.1725e-05	7.2114	***
1:defs	-0.0002942518	-3.0659e-03	2.1807e-04	-14.0594	***
2:defs	-0.001241603	-7.2138e-03	2.7617e-04	-26.1213	***
1:sefs	-6.371067e-05	-6.6382e-04	2.7429e-04	-2.4201	*
2:sefs	-9.169247e-05	-5.3274e-04	3.7492e-04	-1.4209	
1:fp	-1.30467e-05	-1.3594e-04	7.5392e-06	-18.0307	***
2:fp	3.604468e-06	2.0942e-05	9.5225e-06	2.1992	*

Signif. codes: *** 0.001; ** 0.01; * 0.05; . 0.1
Log-Likelihood: -55768
Likelihood ratio test : chisq = 12831 (p.value $\leq$ 2.22e-16)

by Lubowski et al (2008). Where pixels have no data (for example, because they are in the "other" category) I exclude them. Using the estimated model, I then predict future periods and compare them with observed values. I use the same sample of my dataset, corresponding to the same pixels, for all estimations and comparisons.

The multinomial logit model estimates are presented first. The predictions for this model are somewhat unsuccessful; I discuss possible reasons why. The binary logit model is more successful. I then discuss possible next steps in the project.

Question 1 - multinomial logit

I use a multinomial logit model to model the effects of recent change in profitability of dairy, sheep beef and forestry on the change in their share of land use.

Estimated coefficients:

The estimated coefficients are presented in table 4. I estimate them using the mlogit package in the R software program. The marginal effects are estimated as suggested in the mlogit package documentation (Croissant, 2012 - see p 19, for alternative specific variables). I use scrub as the base category, therefore the table presented shows the coefficients for pasture (1) and forestry (2), relative to scrub.

It is important to note that the estimates are based on the spatial variation in 1997; I then use this spatial variation to predict total shares in the next subsection. The profit data is the data which varies between years, and the coefficients on this data are not all in the direction that would be expected. For example, dairy economic farm surplus (defs) is strongly negative for both pasture (1) and forestry (2). The only spatial variation in this dataset is regional, however the strength of these coefficients causes issues, as discussed in the next section.

Total shares:

Table 5: Actual and predicted land cover change as a percent of 1997 to 2002 of sample pixels. Predicted land cover for 1997 is excluded as the multinomial logit ensures the predicted matches actual for the estimation year.

Land cover	**1997**	**2002**	**Pred 2002**	**Δ**	**Pred Δ**
Pasture	77.91	76.93	76.53	-0.98	-1.38
Forestry	11.34	12.41	2.16	1.07	-9.18
Scrub	10.75	10.66	21.31	-0.09	10.56
Total	100.00	100.00	100.00	0.00	0.00

Table 6: Actual and predicted land cover change 2002 to 2008 of sample pixels.

Land cover	**2002**	**Pred 2002**	**2008**	**Pred 2008**	**Δ**	**Pred Δ**
Pasture	76.93	76.53	76.76	71.51	-0.17	-5.02
Forestry	12.41	2.16	12.69	1.20	0.28	-0.96
Scrub	10.66	21.31	10.55	27.29	-0.11	5.98
Total	100.00	100.00	100.00	100.00	0.00	0.00

Tables 5 and 6 show the predicted and observed shares for the model for 2002 and 2008. While pasture prediction performs reasonably well, especially for 2002, forestry predictions are far too low, and forestry land is allocated instead to scrub. Therefore, there is an issue with the profitability data and its ability to predict the overall shares of land covers, particularly forestry.

To test what is causing the issue, I produce the predictions for 2002 keeping forestry profitability at 1997 levels, and then test the predictions keeping just dairy profitability at 1997 levels. The results of these basic tests suggest dairy profitability is driving the poor predictions of the model. While the coefficients on dairy profitability, interacted with the slope index (defsslope) are positive as expected, this result appears to be outweighed by the negative coefficients on the regional dairy profitability variables (defs).

Keeping forestry profitability at 1997 levels leads to the predicted 2002 share of 73.7 percent pasture, and 2.6 percent forestry. Therefore little changes in terms of prediction accuracy. However, when dairy profitability is kept at 1997 levels, pasture is predicted to have a 80.9 percent share in 2002, and forestry a 9.6 percent share. Clearly dairy prices are driving the large change in forestry share.

Therefore, there is an issue with the profitability data. Either it is a poor predictor of land use share, the data is flawed, the modelling approach is flawed, or a combination of the above. I find in the next section that, while my binary logit modelling is more promising, profitability data detracts from my results. At the end of this results section I discuss potential remedies for the profitability data issues.

Questions 2 and 3 - binary logit

This section presents the preliminary results of the land cover transition modelling. The initial estimates appear to show strong support for land sales in the area as a predictor for land cover change. There is still work to be done to interpret the estimates in terms of question 3.

The first model presented models all transitions. The second model looks at pasture to forestry transitions, estimated both without and with change in profitability data. In all cases land sales are a good predictor of land use change; however, profitability data seems to detract more from the modelling than it adds.

All transitions:

I estimate a binary logit model on the sample data selection, for the 1997 to 2002 transition period. I include all land quality variables, and the Maori tenure dummy, but exclude change in profitability data. I exclude profitability data as it is difficult to see the coherency of including it for all transitions, as some transitions will be from pasture to forestry, while at

Table 7: Transition coefficients for all transitions in the sample data for 1997 to 2002, with profitability data excluded.

Coefficient	**Estimate**	**Std error**	**z-value**	**Signif**
(Intercept)	-5.169e+00	1.161e-01	-44.524	***
ccav	-2.605e-03	7.673e-03	-0.339	
slope	6.228e-02	3.971e-03	15.684	***
dists	-7.801e-06	7.443e-07	-10.482	***
distp	1.227e-06	2.029e-07	6.048	***
maori	2.932e-01	1.576e-01	1.861	.
salesprop	6.860e-01	2.356e-01	2.912	**
salesind	3.435e-01	7.532e-02	4.561	***

Signif. codes: *** 0.001; ** 0.01; * 0.05; . 0.1.

Table 8: Transition coefficients for all 1997 to 2002 sample data transitions from pasture to forestry, with profitability data excluded.

Coefficient	**Estimate**	**Std error**	**z-value**	**Signif**
(Intercept)	-5.458e+00	1.403e-01	-38.897	***
ccav	-1.039e-03	9.238e-03	-0.112	
slope	8.345e-02	4.798e-03	17.394	***
dists	-9.734e-06	9.359e-07	-10.401	***
distp	1.456e-06	2.522e-07	5.773	***
maori	4.352e-01	2.314e-01	1.881	.
salesprop	7.947e-01	2.613e-01	3.041	**
salesind	4.336e-01	9.174e-02	4.726	***

Signif. codes: *** 0.001; ** 0.01; * 0.05; . 0.1.

the same time other transitions will be from forestry to pasture and it is unclear how change in profitability data fits within that context.

The coefficient estimates are presented in table 7. Given the nature of binary logit models, these represent coefficients on latent values and therefore cannot be interpreted directly, except for their direction. All variables have some statistical significance, except CCAV. Importantly, both the proportion of sales in the land parcel's meshblock over the five year transition period of 1997 to 2002 (salesprop) and the indicator of a sale (salesind) have positive and statistically significant values. I interpret the results more in the following sections.

Although the sample size is $n = 91295$ variables, as land cover transitions are rare, only 1151 observations experience a transition over the period. This may help explain the low z-values, along with the somewhat inexact measure of meshblock sales data.

Pasture to forestry:

I take one transition type, pasture to forestry, to help test the findings around land sales from the more general model, and also to include profitability data. While the land sales data results seem to hold, profitability data, *prima facie*, seems to detract from the model rather than increase its predictive power.

Again I estimate the model using the 1997 to 2002 transition period. The coefficients and their significance are presented in tables 8 and 9. The results have a high level of statistical significance overall given the nature of the data, and that the sample size is now reduced to $n = 71025$, with just 840 transitions.

I look at the predictive power of the models next, and then interpret the marginal effects of land sales in the area on transition likelihood.

Predictive power:

I estimate the transition probabilities for all three models presented from 1997 to 2002 data. I

Table 9: Transition coefficients for all 1997 to 2002 sample data transitions from pasture to forestry, including change in profitability.

Coefficient	**Estimate**	**Std error**	**z-value**	**Signif**
(Intercept)	-6.656e+00	2.941e-01	-22.632	***
ccav	-5.909e-02	1.083e-02	-5.456	***
slope	1.700e-02	7.258e-03	2.343	*
dists	-9.288e-06	9.671e-07	-9.604	***
distp	1.866e-06	3.000e-07	6.219	***
maori	-4.912e-02	2.331e-01	-0.211	
salesprop	8.765e-01	2.802e-01	3.128	**
salesind	2.979e-01	9.294e-02	3.205	**
cdefsslope	-5.300e-04	4.680e-05	-11.326	***
cdefs	1.826e-03	3.360e-04	5.436	***
csefs	-4.417e-03	1.442e-03	-3.064	**
cfp	-1.601e-03	1.132e-04	-14.134	***

Signif. codes: *** 0.001; ** 0.01; * 0.05; . 0.1.

Table 10: Predicted proportions of transitions for 2002 to 2008 sample data, predicted from 1997 to 2002 estimated model.

Model	**Actual %**	**Predicted %**
All transitions	1.02	1.30
P-F no profitability	0.53	1.22
P-F with profitability	0.53	1.98

test how well they predict total number of transitions within the sample pixels for the 2002 to 2008 period. The results are shown in table 10.

Table 10 show that in all three models, numbers of transitions are over-predicted. The closest model to the actual proportion of transitions is the all transitions model. The pasture to forestry (P-F) model with no profitability data predicts the proportion of transitions more accurately than the model with profitability.

Marginal effect of sales:

This section presents the marginal effects of sales as estimated in the three models. The striking finding is that all three models have relatively close estimates.

Table 11 displays the marginal effects of sales within a meshblock on the probability a piece of land within that meshblock changes cover. These figures show the level of increased percentage likelihood that a pixel changes cover, given sales within the pixel's meshblock. They are evaluated at their 1997 to 2002 means for all other predictors.

Thus, under the first model, an average pixel in a meshblock with sales will have a 0.33 higher percentage point chance of land use conversion than an average pixel in a meshblock without land use sales. This is significant given the total proportion of pixels in the sample with a transition between 1997 and 2002 is just 1.26 percent. Also under the first model, the results say that a 1 percent rise in the proportion of the meshblock sold, given there has been a sale in that meshblock, leads to a 0.0083 percentage point increase in the chance that an average

Table 11: Marginal percentage point effect of sales from the three estimated models, evaluated at the 1997 to 2002 means of the other predictors.

Model	**Sales indicator**	**1% rise in sales proportion**
All transitions	0.333	0.0083
P-F no profitability	0.199	0.0073
P-F with profitability	0.384	0.0092

pixel in that meshblock is sold. This is evaluated at the average proportion of meshblock sales, which is 7.97 percent[7] in the 1997 to 2002 transition period.

The precision of this modelling is hampered by the fact that it is impossible to tell whether the pixels themselves were sold or not over the transition periods. However, these results look strong enough to suggest that recent sales are a good predictor of land use transition. Thus, the association between transition and sales likely goes the other way; that is, the pixels which transitioned in meshblocks with land sales are more likely to be the pixels which were sold within that meshblock.

Next steps

This project is not yet complete, therefore the results are provisional and there are more specifications of the models to try and more testing of the results to be done.

Profitability data is clearly an issue, especially the data for dairy. While it is unlikely I can get different data for this, there are some other specifications to try. Potentially I could include just the dairy interacted with slope variable, and exclude the regional dairy profitability data. I could also try squaring the slope index, as (Todd & Kerr, 2009, p 14) figures suggest that the number of dairy farms decays exponentially from a zero degree slope, to higher slopes. I could also try different ways of averaging the profitability data. Perhaps my modelling approach, using spatial variation, is flawed. However, given land use changes gradually, perhaps it cannot be expected that land use responds measurably to recent changes in profitability, at least not without more fine-scale data.

The binary logit modelling shows much more promise. I will test other specifications of the model to see if the result holds. I intend also to feed in any other specifications of the profitability data to see if that improves its predictive power. I could also look at whether there are other ways to model transitions, so that more than one type of transition can be included in the same model.

CONCLUSION

So far this project has shown promising results that could indicate that a recent land sale is a good predictor of land use change. This has implications for the theory behind land use change; it indicates that barriers to and costs of land use change for a current land manager may be reduced when the land is sold. I have suggested that these factors could include liquidity constraints and the human capital of the current land manager. Furthermore, new land managers will have different preferences around amenity values and risk. In terms of amenity values, a new land manager is less likely to have a historical connection with the land and the area, and therefore may be less resistant to change.

There is still work to do in the project to see whether profitability has any utility in predicting land use change, given the datasets available. There is also work to be done to see if there are any other identifiable characteristics of land that is marginal between uses. However, the result at this stage that land sales is a good predictor of land use change is an important one, given how gradual and rare rural land use change is.

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[7] This figure is significantly higher than the numbers reported in the DATA section as the sample data used here excludes the "other" category, while the numbers in the DATA section include "other" land.

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