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Modelling private land-use decisions affecting forest cover: the effect of land tenure and environmental policy

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Abstract

I use geographic data and discrete choice modelling to investigate private land-use decisions in the context of prominent New Zealand land institutions and environmental policies. Land-use conversions involving gains and losses in planted forests and natural forests are modelled individually. Land under Māori freehold tenure is found to be less likely to be used for pastoral grazing and also less likely to undergo land-use conversion (both to and from a forested use). With respect to environmental policies, results suggest the incentives of the Emissions Trading Scheme did not significantly affect land-use decisions during the sample period of 2008-2016: the carbon reward had little effect on afforestation, and the deforestation liability was largely ineffective at deterring deforestation. On the other hand, the East Coast Forestry Project is found to have increased planted forest area in the district both by encouraging afforestation beyond baseline levels and by discouraging deforestation. Evidence for its effect on regenerating natural forest area is weaker in the data.

JEL codes

Q15, Q23, Q58

Keywords

Land use, forestry, land tenure, environmental policy

Summary haiku

Natural or planted,
Policies and land tenure
Can affect forests.

Table of Contents

1 Introduction

Before humans arrived in New Zealand, native forest covered more than 80 percent of the land (Ministry for the Environment & Stats NZ, 2022). Today, the country's forest cover has shrunk to less than half of its former extent giving way to agricultural, horticultural and urban land uses. Exotic planted forests make up more than a fifth of the area covered by forests today.[1]

The expansion of forest land is considered central to achieving New Zealand's international mitigation commitments. It is expected that between 1.3 and 2.8 million hectares of pasture will need to be converted to forests to achieve the country's emission targets (New Zealand Productivity Commission, 2018). To facilitate a sustainable transition to a low emissions economy, the Government has devoted significant resources aiming to increase tree planting across New Zealand. This is expected to increase the land area occupied by both exotic and indigenous forests.

Identifying marginal land most likely to experience afforestation or deforestation and understanding how previous policy incentives targeting forest land have affected behaviour is therefore as salient as ever. In this paper, I use geographic data derived from New Zealand's Land Use and Carbon Analysis System (LUCAS) to investigate private land-use decisions and the effect of New Zealand land institutions and environmental policies on those decisions. Specifically, I estimate a set of empirical models in order to consider the effect of Māori freehold land tenure, the carbon reward and deforestation liability affecting some forest owners under the New Zealand Emissions Trading Scheme (ETS) and afforestation grant payments offered under the East Coast Forestry Project (ECFP).

I first examine land-use outcomes in cross-sectional data using a discrete choice multinomial logit framework. Next, I estimate binomial logit models for land-use conversions involving gains and losses in planted forest and natural forest areas, respectively. All models include controls for topography, climate, land quality and general spatial location relative to key infrastructure and facilities.

Section 2 specifies the empirical models for both land use and land-use conversion. Section 3 describes the data and summarises variables used in estimation. Results from the cross-sectional land use model are discussed in Section 4, and those from the land-use conversion models are discussed in Section 5. Section 6 offers a summary of main findings and concluding remarks.

[1] https://www.mpi.govt.nz/forestry/new-zealand-forests-forest-industry/about-new-zealands-forests/

2 Modelling approach

Spatially explicit microeconomic analyses of land use are often framed as discrete choice models (Train, 2009). The approach requires location-specific observations of both land use and the various drivers of land-use decisions. It can be used to model land-use choices observed in cross-sectional data (Chomitz & Gray, 1996; Nelson & Hellerstein, 1997; Nelson et al., 2001; Blackman et al., 2008). When data from multiple time periods are available, the approach can also be used to model decisions of land-use conversion explicitly (Bockstael, 1996; Lubowski et al., 2008; Polyakov & Zhang, 2008). This paper incorporates both land use and land-use conversion models.

2.1 Cross-sectional land use

A multinomial logit will be adopted to model the observed choice of land use among eight alternatives at a point in time. It is comparable to the model derived in Timar (2011), with a reduced form specification in which net returns at location *i* from land-use alternative *j*, R_{ij}, can be written as a linear combination of independent variables X_i characterising the location and parameters β_j that vary over the land-use alternatives:

$$R_{ij} = \alpha_j + \beta_j' X_i + \varepsilon_{ij}.$$

The framework is compatible with utility maximisation, and returns do not necessarily have to be monetary in nature. The vector of independent variables will contain terms on institutional and policy settings, geophysical and other attributes of the land as well as variables capturing spatial relationships (such as location relative to key infrastructure). The elements of the parameter vector β_j are to be estimated along with an alternative-specific constant, α_j, associated with each land-use option. The equation also includes an idiosyncratic component, ε_{ij}. This is treated as a random error with an assumed type I extreme value distribution, giving rise to the multinomial logit model.

In the multinomial logit, the predicted probability that the parcel at location *i* will be devoted to land use *j*, P_{ij}, has a closed-form analytic solution:

$$P_{ij} = \frac{e^{\alpha_j + \beta_j' X_i}}{\sum_{k=1}^{K} e^{\alpha_k + \beta_k' X_i}}.$$

This probability enters the log-likelihood function – the maximum likelihood estimates of parameters α_j and β_j are those that make the difference between observed land-use choices and the predicted land-use probabilities of those choices uncorrelated with the explanatory variables (Train, 2009).

2.2 Forest gain and forest loss

Combining data on land-use outcomes over multiple periods, decisions leading to forest cover changes will be analysed separately via a set of four binomial logit models. The four models relate to gains and losses in planted forests and gains and losses in natural forests. This separation allows better focus on factors affecting each type of forest cover change.

The general structure of the binomial logit models closely mirrors that of the multinomial logit introduced in the previous section. However, in the binomial case, the choice set consists of two alternatives only: one alternative is associated with a change in land use and the other alternative is associated with no change from the previous use. Depending on the model, land-use change may represent afforestation or deforestation of planted forests, or regeneration or deforestation of native forests. In each case, the sample contains only observations for which the corresponding type of land-use change is feasible.

Following the reduced form specification of the multinomial logit, net returns associated with a change in land use are specified as linear in the explanatory variables:

$$R_i = \alpha + \beta' X_i + \varepsilon_i,$$

and the probability of a change in land use at location *i* can be expressed as

$$P_i = \frac{e^{\alpha+\beta' X_i}}{1 + e^{\alpha+\beta' X_i}}.$$

Similar to the multinomial case, the estimation of parameters of the binomial logit is by maximum likelihood.

3 Data and variables

Estimation is performed using rasterised data with a cell size of 25 hectares. The sample can be thought of as being drawn by a systematic geographic sampling procedure, whereby a 500 metre by 500 metre rectangular grid is placed over New Zealand and the value of a variable associated with a grid cell is determined by its value recorded at the centroid of the cell. I use a dataset of public conservation areas to constrain the analysis to privately owned land as I consider that incentives for private and public land-use decisions are different. The sampling procedure described above yields 683,870 observations for estimation, representing an area of over 17 million hectares.[2] All datasets used in this paper are identified in Table A1 in the appendix, and Table 2 at the end of Section 3 includes summary statistics for all variables by observed land use.

[2] More precisely, 683,870 is the number of grid cells with complete data in all variables and in a modelled land use in 2016. This comprises the basis for the cross-sectional (multinomial logit) estimation. The number of observations for other data years is similar with minor differences due to transitions into and out of non-modelled land uses.

3.1 Land use

In this paper, I rely on New Zealand's Land Use and Carbon Analysis System (LUCAS) for data on land use. The primary objective of the LUCAS programme is to accurately map four key woody land-use classes: natural forest, pre-1990 planted forest, post-1989 forest and grassland with woody biomass, but it also provides information on various grassland, cropland and other uses (Ministry for the Environment, 2012). The dataset's focus on woody classes is to ensure accurate international reporting of carbon stock changes due to changes in land use across New Zealand, and this makes it appropriate for research on forested land uses. The LUCAS dataset contains land-use maps for 1990, 2008, 2012 and 2016.[3]

LUCAS mapping is principally based on remote sensing data. However, land-use change associated with forestry may be difficult to detect using satellite imagery as it takes time for new planting to become evident. Furthermore, harvest and deforestation may initially look identical. Therefore, the LUCAS dataset also incorporates other afforestation and deforestation related data held by the Ministry for Primary Industries and the Ministry for the Environment (Newsome et al., 2018).

3.1.1 LUCAS land-use data

LUCAS identifies three classes of forest land: natural forest, pre-1990 planted forest and post-1989 forest. The criteria for land-use classification in LUCAS can be complex (Ministry for the Environment, 2012), but for our purposes the key takeaways are the following. Natural forests may contain indigenous or self-sown exotic (wilding) trees as long as they were established before 1990. However, I will show that natural forests are predominantly indigenous. Post-1989 forests may be planted, regenerating indigenous or self-sown exotic. The main criterion for the pre-1990 versus post-1989 classification is not the date of establishment of a particular forest, but whether the land was forest land on 31 December 1989.[4] Following harvest, both pre-1990 and post-1989 forests remain classified as forest if they are replanted. Forest areas that lose vegetation cover due to natural disturbances such as erosion or fire also retain their original classification.

With the exception of the 1990 map, LUCAS further categorises land use into subclasses. In most cases, the subclass of natural forests and pre-1990 planted forests is unknown. However,

[3] The LUCAS date boundaries were dictated by the First and Second Commitment Periods of the Kyoto Protocol. The data have nominal mapping dates of 1 January 1990, 1 January 2008, 31 December 2012 and 31 December 2016.

[4] Consider, for instance, a natural forest that is cleared for pasture at some point after 1990. If a new plantation forest were to be established on this land subsequently, it would be classified as pre-1990 planted forest (as opposed to post-1989 forest) in the LUCAS data.

for post-1989 forests, the subclass identifies whether the forest contains exotic species, wilding trees or regenerating natural species.

LUCAS differentiates between three classes of grassland: grassland with woody biomass, high-producing grassland and low-producing grassland. The LUCAS mapping relies on the New Zealand Land Resource Inventory (NZLRI) database to better define the area of high-and low-producing grassland. Areas tagged as improved pasture in the NZLRI vegetation records were classified as high-producing grassland, and other areas were classified as low-producing grassland in the land-use maps. High- and low-producing grasslands are further classified into grazed dairy, grazed non-dairy and ungrazed subclasses. Nearly all dairy is associated with high-producing grassland and nearly all ungrazed areas are found on low-producing grassland.

The LUCAS land-use maps also identify annual cropland, perennial cropland, wetlands, settlements and other land (that is, land that does not fall into any of the other land-use categories).

Data derived from LUCAS will be used to construct indicators denoting observed land-use outcomes and observed land-use changes (the dependent variables in the multinomial and binary logit models, respectively), and it will be also used to create independent variables characterising treatment under domestic climate policy and native regeneration potential.

3.1.2 Reclassified land use

Although LUCAS facilitates reporting in accordance with international climate accounting rules, its main level of classification does not necessarily represent functional land use well. I will use the 1990 land-use map to help establish what incentives might apply to land under domestic climate change policy (as described shortly), and reclassify the data based on mapped land-use class and subclass for all other years. The reclassified land-use variable intends to characterise land cover and land use as they might be observed on the ground, regardless of the policy treatment of land.

Consequently, rather than being concerned with the date of establishment, forests are classified along the natural versus planted division. The natural forest land use includes the (pre-1990) natural forest class of LUCAS and, for consistency, also the regenerating natural species and wilding trees subclasses within post-1989 LUCAS forests. The planted forest land use consists of pre-1990 planted forests and all remaining post-1989 forests in LUCAS. This grouping also leads to a better-defined choice set for discrete choice modelling considering that the pre-1990 versus post-1989 classification is predetermined and not a choice for the landowner to make.

Grasslands are reclassified into five land uses. Grassland with woody biomass is identical to the LUCAS class of the same description. I define dairy and ungrazed grasslands based on the grazed dairy and ungrazed subclasses in LUCAS. Any remaining grassland is classified into either low-producing non-dairy or high-producing non-dairy subject to its main LUCAS class.

Finally, annual and perennial cropland is grouped into a single cropland use (due to the relatively small number of observations in these classes). Cropland and dairy farming represent the highest-valued uses in the data and have correspondingly strong requirements for high-quality, productive land. The number of observations associated with each modelled land use in 2016 is shown in the first data column of Table 1. The eight alternatives in the table comprise the choice set for the multinomial logit land-use model.

3.1.3 Land-use change indicators

Based on the reclassified land-use variable, I create four indicators representing instances of forest cover gain and forest cover loss observed over time. These will be used as dependent variables in binomial logit estimations of land-use change. Specifically, the four variables relate to afforestation of planted forests (henceforth referred to simply as afforestation), deforestation of planted forests, regeneration of natural forests (henceforth referred to as natural regeneration) and deforestation of natural forests. I identify afforestation and deforestation outcomes through changes in planted forest land use over time, and I identify regeneration and natural deforestation outcomes through changes in natural forest land use over time. The data allow for the creation of these indicators over two time periods of (approximately) the same length: 2008–2012 and 2012–2016; land-use changes observed over the latter period are illustrated in Table 1.

Although for the vast majority of natural forests in any cross-section of the data LUCAS contains no information on species composition, instances of natural regeneration, by definition, involve only post-1989 forests for which such information is available (from the LUCAS subclass field). Therefore, wilding trees will be excluded from the natural regeneration estimations to better reflect regeneration of indigenous forests.

The aforementioned land-use change categories are not mutually exclusive. For example, where the data suggest natural forests were cleared for the establishment of plantation forestry, the cell will be assigned both natural deforestation and afforestation status during the same time period. I also note that it is feasible that some transitions observed in the data are not direct: they may have involved an intermediate, unobserved, land use between observations. However, given the low rate of land-use change, as demonstrated by the figures in Table 1, I expect such instances to be rare.

Table 1. Summary of land use in 2016 and land-use transitions over 2012–2016 (number of observations)

Land use 2016		Total	By previous (2012) land use[1]							
			1	2	3	4	5	6	7	8
1	Forest - Natural	103,482	103,205	18	60	1	185	12	1	0
2	Forest - Planted	80,950	0	80,229	112	15	465	126	3	0
3	Grassland - Woody biomass	29,388	39	73	29,212	11	32	12	9	0
4	Grassland - Ungrazed	16,844	2	21	18	15,067	1,698	35	3	0
5	Grassland - Low prod non-dairy	161,912	20	325	228	748	160,581	10	0	0
6	Grassland - High prod non-dairy	195,380	14	449	113	33	1,794	192,977	0	0
7	Grassland - Dairy	76,980	12	343	37	9	562	7,957	68,060	0
8	Cropland	18,884	1	7	1	0	0	41	0	18,834
Total		683,820	103,293	81,465	29,781	15,884	165,317	201,170	68,076	18,834

[1] The coding of previous land use is identical to that shown for land use 2016.

3.2 Institutional and policy variables

I construct three sets of dichotomous variables to represent features associated with New Zealand land institutions and environmental policy that may affect private land-use decisions.

3.2.1 Land tenure

I use an indicator to identify land under Māori freehold tenure. Māori freehold land, accounting for about 6 percent of New Zealand's total land area, generally has multiple owners and is subject to legal restrictions and protections that do not apply to general land (Kingi, 2008). The ownership of Māori land titles is divided into more than 2 million interests, a number comparable to the interests represented in the other 94 percent of New Zealand's land area, and one that is continuously growing each year (Kingi, 2008). The difficulties faced by Māori freehold landowners in administering their land interests have been recognised by the government as an impediment to the development of the land (Audit Office, 2004). Previous research has also shown that Māori freehold land tends to be underdeveloped even after controlling for land quality and location (Timar, 2011) and less likely to make an active land-cover transition (Cortés Acosta, 2020). To the extent that owners of Māori freehold land express distinctive environmental and cultural preferences through their land-use decisions, the land tenure variable will also control for these differences in preferences (Timar, 2011).

3.2.2 ETS incentives: reward eligibility and deforestation liability

The New Zealand Emissions Trading Scheme (ETS), introduced in 2008 as a part of the country's efforts to meet its Kyoto Protocol obligations, incentivises landowners to establish and manage forests in a way that increases carbon storage. The carbon price in the ETS both provides a reward for afforestation and imposes a cost on deforestation making the New Zealand ETS the only system in the world with symmetrical incentives to encourage afforestation and discourage deforestation (Carver et al., 2022). The reward generally applies to forests established after 1989, and the liability generally applies to forests established before 1990.

To be considered a post-1989 forest for the purposes of ETS eligibility, the land must currently be forest land and meet one of the following conditions:

1) the land was not forest land at the end of 1989
2) the land was forest land at the end of 1989 but was deforested before 2008
3) the land was pre-1990 forest land (see below) that was deforested in or after 2008, and any ETS liability has been paid.

Owners of qualifying forests can apply to register their post-1989 forest land into the ETS to earn carbon rewards, and their participation is voluntary (Te Uru Rākau, 2015).[5]

Forest owners can also face liabilities under the ETS for reductions in carbon stocks. A deforestation liability applies to pre-1990 forest land, defined as land that

1) was forest land at the end of 1989
2) remained forest land by the end of 2007
3) contained mostly exotic forest species at the end of 2007.

In most cases, the participation of pre-1990 forest owners is mandatory if their land is deforested, triggering a deforestation liability.[6] Land that was indigenous forest land at the end of 1989 and remained indigenous forest by the end of 2007 is not considered pre-1990 forest land and does not have ETS obligations (Te Uru Rākau, 2015).

As noted before, forest land in LUCAS is also classified into pre-1990 and post-1989 forests. However, despite the identical labels, the definitions of these classes in LUCAS does not align entirely with those used in the ETS. For example, any forest land that also had forest cover before 1990 would remain classified as pre-1990 forest in LUCAS. As we have seen, this is not necessarily true in the ETS: for example, if the land was deforested by 2008 and then reforested subsequently, the owners of the land would be able register the new forest as post-1989 forest into the ETS and earn carbon rewards (as per the second criterion for post-1989 forest land above). The main reason for this inconsistency is that the LUCAS data is used for international

[5] To reduce administrative costs, the ETS does not attempt to distinguish whether a forest planted after 1989 was additional, so some forest owners could receive windfall gains for forests that are planted independent of the ETS (Carver et al., 2017). By 2017, nearly half of all post-1989 forest land was registered in the ETS (Environmental Protection Authority, 2017).

[6] In recognition of the impact of ETS deforestation rules on land values, owners of pre-1990 forest land were given the option to apply for a one-off allocation of New Zealand Units. An unintended consequence of ETS policy was that it may have increased the deforestation of pre-1990 forests in the years before 2008, the year the policy came into effect, as landowners planned deforestation activity strategically to avoid the liability (Carver et al., 2017).

reporting purposes and conforms to a different, stricter, rule set than the domestic ETS in relation to what may be considered post-1989 forest.

While the LUCAS classification within forest land should not be taken to indicate eligibility for ETS participation, it is nevertheless possible to use it to establish (approximately) what ETS incentives might apply to a plot of land. With this goal in mind, I examine land-use outcomes over multiple LUCAS survey years to assess if the ETS criteria for post-1989 forest land and pre-1990 forest land are met.[7]

I create separate indicator variables for reward eligibility and deforestation liability. As the reward changes opportunity costs for land not yet in forestry use, the value of the reward eligibility indicator is set to one for any land that could meet the post-1989 forest land definition, as laid out in the ETS, if it were afforested (and to zero otherwise). This also applies to pre-1990 forest land that has previously been deforested – I assume any ETS deforestation liability has been settled to satisfy the third condition in the definition of post-1989 forest land. Similarly, the indicator for deforestation liability is set to one for forests meeting the definition of pre-1990 forest land in the ETS (and to zero otherwise). In implementing the third criterion on species composition, I assume all planted pre-1990 forests are mostly exotic and all natural forests are mostly indigenous.[8]

These indicators allow us, in theory, to consider the two incentives provided by the ETS for forestry (discouraging the deforestation of pre-1990 forests and encouraging the planting or replanting of post-1989 forests) individually. The magnitude of the incentive landowners actually face depends on the carbon price and is therefore variable over time. Over the sample period of 2008-2016, the carbon price started out at around $20 but declined sharply in mid-2011; it then stayed under $10 for about four years, getting close to zero during this time, before increasing quickly and approaching $20 again by the end of 2016 (Leining, 2022). The relatively low carbon prices, especially in the second half of the period, combined with uncertainty surrounding future ETS policies may have led to a muted land-use response during this time.

3.2.3 ECFP eligibility

The East Coast Forestry Project (ECFP) was a grant scheme established in 1992 that remained in effect during the length of the sample period. The ECFP provided a grant payment for establishing effective tree cover through planting or encouraging natural reversion to native

[7] As the gap between the relevant LUCAS land-use observations is four years, land-use changes that occur in succession between the data points will be unobserved – this might affect the pre-1990 versus post-1989 classification of some land.
[8] From 2013 offset planting is allowed for owners of pre-1990 forests if they wish to deforest. The forest established to offset the deforestation is classified for ETS purposes as pre-1990. It is not possible to identify offset planting in LUCAS, so I am unable to account for it in the construction of the ETS indicator variables.

bush on eligible erosion-prone land in the Gisborne District. The district has a severe erosion problem with 26 percent of its land susceptible to severe erosion, compared with 8 percent of land nationally (Ministry for Primary Industries, 2014a).

Target land for the scheme included the worst eroding land in the Gisborne District, identified in the New Zealand Land Resource Inventory (NZLRI) as Class 7e18–19, Class 7e21–25 and Class 8e2–9 (Ministry of Agriculture and Forestry, 2007). With certain conditions, an ECFP grant could also be used to control erosion on land adjacent to target land. On the other hand, some land that may have qualified as target land on the basis of NZLRI classification, including areas of indigenous scrub and native forest, was not eligible for an ECFP grant because the existing land cover already provided effective erosion control. In 2007, fifty-year covenants were introduced for forestry, reversion and pole planting in response to instances of deforestation of ECFP grant forests (Ministry of Agriculture and Forestry, 2011). By 2016 over 41,000 hectares have been treated under the ECFP, around two thirds of which was believed to be target land (Gisborne District Council, 2020; Ministry of Agriculture and Forestry, 2011).

Unlike the ETS, the ECFP targeted a geographically limited area within New Zealand. To consider the effect of this policy on land-use change, I decompose its eligibility requirements into separate spatial and land quality components. Thus, I create first an indicator for target region (with its value set to one for land in the Gisborne District and to zero for land elsewhere) and, second, an indicator for target land type (with its value set to one for land, irrespective of location, meeting the aforementioned criteria with respect to NZLRI classification and to zero otherwise).[9] The interaction of these two variables defines land potentially eligible for an ECFP grant. By treating the spatial and land quality eligibility components separately, it becomes possible to isolate the effect of the policy better – for example, by addressing the possibility that land-use outcomes in the Gisborne District would be different even in the absence of the policy due to its high proportion of erosion-prone land.

Because ECFP grants could be used to treat some land adjacent to target land, there may be a spillover of afforestation (and regeneration) outcomes into land not identified as ECFP-eligible using the interaction term. This could cause us to potentially underestimate the effect of the ECFP on afforestation (and regeneration) in the district.[10]

[9] For the afforestation and natural regeneration estimations, ECFP policy criteria on previous land cover are also observed in the creation of the target land type indicator: its value is set to zero for land with any pre-existing forest cover because such land is not eligible for a grant. On the other hand, the context of the cross-sectional and deforestation estimations dictates the exclusion of the previous land cover condition (see Section 5.2). Further, ECFP eligibility rules regarding minimum area are also ignored as there is no way to account for them in the data.

[10] Other afforestation policies, including the Permanent Forest Sink Initiative, the Afforestation Grant Scheme and the Sustainable Land Management (Hill Country Erosion) Programme, were also in effect during part or all of the sample period. I do not account for these policies, and I also do not consider potential interactions between different environmental policies or between land tenure and environmental policies.

3.3 Physical characteristics and spatial relationships

The estimations control for various features of topography, climate and land quality associated with a physical location, and I also include variables to characterise surrounding land use and the cost of access to various markets and facilities.

3.3.1 Physical characteristics

Several variables are sourced from Land Environments New Zealand (LENZ), an environmental classification designed to provide a framework for addressing a range of conservation and resource management issues. These include slope (degrees), mean annual solar radiation (MJ/m2/day), mean annual temperature (degrees Celsius) and annual water deficit (millimetres). Data on elevation (metres) comes from the New Zealand National Digital Elevation Model, an elevation grid generated from 1:50,000 scale topographic data layers by Landcare Research. These variables are expected to affect land-use decisions through their effects on feasibility, productivity and harvest costs.

I also include Land Use Capability (LUC) rating from the New Zealand Land Resource Inventory (NZLRI), a national database of physical land resource information (Newsome et al., 2008). LUC class characterises the ability of land to sustain agricultural production, based on a combination of several physical and other factors (some of which are also controlled for individually). It provides an ordinal measure of land quality, with limitations to use increasing from class 1 to class 8: classes 1–4 are generally suitable for a wide range of land uses including arable and pastoral farming; classes 5–7 have serious limitations for arable production but can be suitable for pasture or forestry; class 8 is considered unsuitable for productive land uses. As this broader grouping corresponds well to the level of detail available for land use, I adopt it by creating three indicators for LUC classes 1–4, classes 5–7 and class 8.

In addition to the use of LUC class category as an explanatory variable, information on the LUC subclass modifier and the LUC unit identifier is retained – these enable the identification of target land for the ECFP, as described in the previous section.

3.3.2 Spatial relationships

For each grid cell in the data, I create variables measuring distances to four types of destinations and one variable capturing surrounding land use. For accuracy, these calculations are based on the original maps in vector data format, and they are performed via Python scripts implemented in ArcGIS 10.6 and QGIS 3.20.[11]

[11] The choice of GIS software was dictated by convenience and toolset availability for specific tasks. Considering the number of grid cells for which computations need to be performed, the variables discussed in this section are computationally expensive to create with a combined execution time of over three weeks.

The distance variables, all measured in kilometres, proxy for the accessibility and remoteness of the plot. They are based on a road centrelines dataset from the Land Information New Zealand (LINZ) Topo250 map series whose features represent formed all-weather routes suitable for the passage of any vehicle. First, I determine the Euclidean distance to the nearest road from the centroid of each grid cell. Next, I compute road distances to the nearest (in terms of road distance) urban area, wood processing facility and shipping port, respectively. Road distances are measured from the point representing the nearest road feature to a grid cell, as identified in the first step, and can be very different to straight-line distances due to the topography of New Zealand.

Distance to the nearest town is intended to capture the cost of access to local factor markets and any other amenities associated with population centres (von Thünen, 1966). In generating this variable, I make use of a point layer for New Zealand populated places and focus on features representing major urban areas, secondary urban areas and minor urban areas. Together, these include all towns with a population of at least 1,000.[12]

Distances to the nearest wood mill and nearest port are based on a geographic dataset of wood processing facilities and ports with log export infrastructure provided by Scion. Most New Zealand forestry products are exported, so distances to both types of facilities may affect log transportation costs and hence the profitability of plantation forestry.[13] At the same time, most New Zealand agricultural products are also exported, so distances to ports may also factor into decisions for competing land uses.

Lastly, I create a variable for the percentage of natural forest cover within a circle of a 1-kilometre radius around each grid cell (for each year represented in the LUCAS data). As this variable is designed to capture native regeneration potential, its lagged value will be used in estimations: all else equal, a higher initial natural forest cover is expected to be correlated with the availability of nearby seed sources and thereby with the probability of regeneration in the current period. However, recall that the natural forest category in LUCAS includes self-sown exotics in addition to indigenous species. The potential presence of exotics such as wilding conifers in the natural forests category introduces some noise into my measure of native regeneration potential. A comparison of LUCAS with the New Zealand Land Cover Database

[12] Using points rather than polygons for towns simplifies distance calculations but may introduce measurement error, especially for large urban areas that are not well represented by a point. This concern is mitigated by the fact that some suburbs of larger cities are included individually in the dataset.

[13] It would be reasonable to expect that wood processing facilities are established near significant plantation forestry areas, so facility locations could be affected by land use, and vice versa, leading to endogeneity in a cross-sectional model of land-use choice. I am unable to test this empirically as the wood mills dataset represents a single point in time. However, endogeneity is not an issue in modelling land-use change: a landowner considering afforestation, for instance, could be expected to take the set of existing facilities as given.

Table 2. Variables used in the empirical analysis: mean value by land use (2016)

Variable	Forest - Natural	Forest - Planted	Grassland - Woody biomass	Grassland - Ungrazed	Grassland - Low prod non-dairy	Grassland - High prod non-dairy	Grassland - Dairy	Cropland
Indicator variables[1]								
Māori freehold tenure	0.2096	0.0873	0.0918	0.0452	0.0326	0.0383	0.0260	0.0272
ETS reward eligibility	0.0259	0.3062	0.9939	0.9988	0.9978	0.9981	0.9954	0.9997
ETS deforestation liability	0.0008	0.6934	0.0054	0.0036	0.0033	0.0037	0.0076	0.0004
ECFP target region	0.0678	0.0923	0.0576	0.0091	0.0533	0.0231	0.0004	0.0342
ECFP target land type	0.0002	0.0004	0.1410	0.3329	0.1453	0.0009	0.0022	0.0009
ECFP eligible (target region & land type)	0.0001	0.0002	0.0092	0.0015	0.0057	0.0002	0.0000	0.0000
LUC class 1-4	0.0760	0.1919	0.1953	0.1519	0.0445	0.6584	0.8188	0.9520
LUC class 5-7	0.7876	0.7937	0.7217	0.6807	0.8889	0.3411	0.1792	0.0472
LUC class 8	0.1364	0.0144	0.0831	0.1675	0.0666	0.0005	0.0020	0.0008
Continuous variables								
Slope (degrees)	16.6178	10.5777	13.7456	14.3749	14.5079	4.5551	1.8997	0.7355
Elevation (m)	373.6026	315.3466	375.4093	807.6431	587.1660	206.9531	129.5308	112.7426
Solar radiation ($MJ/m^2/day$)	14.4186	14.3877	14.0838	13.8498	13.7860	13.9469	14.1467	14.1545
Temperature (C)	11.5445	11.6616	10.8453	8.0066	9.2207	11.6411	12.2954	11.8486
Water deficit (mm)	16.8968	29.7735	46.7213	37.5604	53.4304	65.4348	49.4960	134.1673
Natural forest cover in area (%)	65.0952	11.9424	13.9419	6.7996	7.2915	5.5184	3.7175	1.0258
Distance to nearest road (km)	2.5485	0.7889	1.8958	3.2946	2.4672	0.5939	0.4512	0.3663
Road distance to nearest wood mill (km)	47.6931	34.6316	45.2502	56.1563	58.0100	30.8194	26.1171	22.6549
Road distance to nearest port (km)	122.8523	103.9385	127.5473	154.7838	131.3028	100.3460	92.9521	69.3517
Road distance to nearest town (km)	43.8921	35.0691	40.7132	50.7189	49.8041	28.3734	19.9430	17.1559
Observations	103,482	80,952	29,389	16,852	161,926	195,394	76,991	18,884

[1] For dichotomous indicator variables, the base category is supressed. For LUC class, the values correspond to the sample proportion of each category.

(LCDB), a database with more detailed information on species composition, indicates that in 2008, a year for which both LUCAS and LCDB data are available, around 96 percent of LUCAS natural forests were classified as an indigenous type in the LCDB.[14] The proportion rises to over 99 percent if the cross-tabulation is performed only for areas classified as forests in both datasets. This suggests that natural forests are predominantly indigenous, and the noise resulting from not being able to separate different species will be minimal.

4 Results: cross-sectional land use

Estimation results for the land-use choice model based on the most recent (2016) cross-section of land-use data are presented in Table 3. Multinomial logit parameter estimates may not reflect the sign of the associated marginal effects, so to facilitate a more intuitive interpretation, I also include the estimated average marginal effects in Table 4. The discussion of results will be framed primarily in terms of these marginal effects, although it will become apparent that characterising the effect of any variable using a single average value does not always do justice to the complex patterns that can emerge in a non-linear model such as the multinomial logit.

The model excludes variables on ETS incentives as these would not be meaningful in the cross-sectional context. Consider, for instance, reward eligibility. Of all land uses in the 2016 map, the natural forest and planted forest classes have (by a significant margin) the lowest proportion of land potentially eligible for an ETS reward. This happens not because the reward discourages forest uses, but because policy treatment is determined on the basis of previous land use: land with pre-existing forest cover is not eligible for ETS enrolment.[15] An analogous argument applies to deforestation liability.

Results in Table 4 indicate that, after accounting for other influences, Māori freehold land tenure is associated with a decreased probability of grazed pastoral land uses and an increased probability of forested, ungrazed grassland and cropland uses. These marginal effects generally support previous research findings on the relationship between land tenure and land use in New Zealand (Timar, 2011; Cortés Acosta, 2020).

[14] The comparison is performed using rasterised data and, consistent with the context of regeneration potential, also includes land under public ownership.
[15] For a more detailed discussion of ETS eligibility rules, see Section 3.2.2.

Table 3. Parameter estimates for the multinomial logit land-use choice model

	Forest - Natural	Forest - Planted	Grassland - Woody biomass	Grassland - Ungrazed (base)	Grassland - Low prod non-dairy	Grassland - High prod non-dairy	Grassland - Dairy	Cropland
Land tenure								
Māori freehold	0.2852***	0.1340***	0.4654***	0	-0.2027***	-0.1818***	-0.6057***	0.1850***
	(0.0452)	(0.0445)	(0.0474)		(0.0440)	(0.0450)	(0.0508)	(0.0680)
ECFP eligibility								
Target region	0.8419***	0.8060***	1.0779***	0	1.4910***	0.6172***	-2.7798***	1.6066***
	(0.0949)	(0.0927)	(0.0961)		(0.0918)	(0.0933)	(0.2030)	(0.1088)
Target land type	0.4380***	-0.3380***	0.3800***	0	-0.4585***	-1.3269***	1.3441***	1.8084***
	(0.0378)	(0.0398)	(0.0371)		(0.0263)	(0.0887)	(0.1015)	(0.2734)
Eligible (target region & land type)	0.0696	1.2459***	-0.2928	0	0.1103	-0.7532***	-14.4900	-16.5717
	(0.2274)	(0.2243)	(0.2321)		(0.2233)	(0.2867)	(763.4062)	(1.4e+03)
LUC class								
Class 1-4	0.0263	0.3927***	-0.0507	0	-1.5613***	3.9513***	3.5484***	4.2689***
	(0.0538)	(0.0567)	(0.0528)		(0.0427)	(0.1144)	(0.1114)	(0.2883)
Class 5-7	-0.0775*	0.5866***	-0.2886***	0	0.2635***	2.8564***	2.2449***	2.0516***
	(0.0426)	(0.0487)	(0.0414)		(0.0301)	(0.1111)	(0.1079)	(0.2878)
Class 8 (base)	0	0	0	0	0	0	0	0
Slope	0.0555***	0.0188***	0.0583***	0	0.0302***	-0.0576***	-0.1986***	-0.3104***
	(0.0013)	(0.0013)	(0.0014)		(0.0011)	(0.0013)	(0.0020)	(0.0053)
Elevation	-0.0009***	-0.0017***	-0.0024***	0	0.0009***	-0.0000	-0.0049***	-0.0041***
	(0.0001)	(0.0001)	(0.0001)		(0.0001)	(0.0001)	(0.0001)	(0.0002)
Solar radiation	-0.7778***	-0.0197	-0.5097***	0	-1.0650***	-1.2548***	-0.4677***	0.1652***
	(0.0281)	(0.0262)	(0.0288)		(0.0250)	(0.0264)	(0.0286)	(0.0349)
Temperature	0.6794***	0.3172***	0.3516***	0	0.4660***	0.9085***	0.5774***	0.2442***
	(0.0197)	(0.0188)	(0.0205)		(0.0183)	(0.0189)	(0.0200)	(0.0243)
Water deficit	-0.0016***	-0.0090***	-0.0004**	0	0.0044***	0.0002	-0.0103***	0.0064***
	(0.0002)	(0.0002)	(0.0002)		(0.0002)	(0.0002)	(0.0002)	(0.0002)
Natural forest cover in area	0.0747***	0.0041***	0.0117***	0	0.0001	-0.0066***	-0.0252***	-0.0303***
	(0.0007)	(0.0007)	(0.0007)		(0.0007)	(0.0007)	(0.0009)	(0.0022)

Distance to nearest road	0.0215***	-0.3657***	0.0503***	0	0.0177***	-0.2022***	-0.2141***	-0.3703***
	(0.0042)	(0.0061)	(0.0042)		(0.0034)	(0.0058)	(0.0098)	(0.0226)
Road distance to nearest wood mill	0.0042***	-0.0021***	0.0055***	0	0.0135***	0.0028***	0.0107***	0.0075***
	(0.0004)	(0.0004)	(0.0004)		(0.0003)	(0.0004)	(0.0005)	(0.0007)
Road distance to nearest port	-0.0060***	-0.0059***	-0.0019***	0	-0.0045***	-0.0077***	-0.0082***	-0.0159***
	(0.0002)	(0.0002)	(0.0002)		(0.0002)	(0.0002)	(0.0002)	(0.0003)
Road distance to nearest town	-0.0056***	-0.0024***	-0.0056***	0	-0.0021***	-0.0079***	-0.0213***	-0.0291***
	(0.0004)	(0.0003)	(0.0004)		(0.0003)	(0.0004)	(0.0005)	(0.0008)
Constant	4.0957***	0.4419**	4.9242***	0	11.6649***	9.0455***	3.5639***	-3.9349***
	(0.2381)	(0.2206)	(0.2385)		(0.2021)	(0.2384)	(0.2524)	(0.4023)
Observations	683,870							
Pseudo R-squared	0.386							

Stars denote statistical significance: * p<0.1, ** p<0.05, *** p<0.01.

Table 4. Average marginal effects from the multinomial logit land-use choice model

	Forest - Natural	Forest - Planted	Grassland - Woody biomass	Grassland - Ungrazed	Grassland - Low prod non-dairy	Grassland - High prod non-dairy	Grassland - Dairy	Cropland
Land tenure								
Māori freehold	0.0152***	0.0210***	0.0261***	0.0019*	-0.0292***	-0.0102***	-0.0357***	0.0108***
	(0.0010)	(0.0016)	(0.0014)	(0.0010)	(0.0018)	(0.0024)	(0.0016)	(0.0014)
ECFP eligibility								
Target region	-0.0073***	0.0004	0.0033**	-0.0170***	0.0871***	0.0001	-0.1093***	0.0427***
	(0.0013)	(0.0018)	(0.0013)	(0.0007)	(0.0021)	(0.0031)	(0.0009)	(0.0025)
Target land type	0.0334***	-0.0121***	0.0254***	0.0064***	-0.0413***	-0.2179***	0.1548***	0.0514***
	(0.0018)	(0.0027)	(0.0018)	(0.0007)	(0.0021)	(0.0058)	(0.0137)	(0.0131)
Eligible (target region & land type)[1]	0.0007	0.2661***	-0.0033	-0.0038*	-0.0019	0.0282**	-0.1631***	-0.1229***
	(0.0040)	(0.0093)	(0.0048)	(0.0023)	(0.0058)	(0.0132)	(0.0140)	(0.0135)
LUC class								
Class 1-4	-0.0395***	-0.0838***	-0.0461***	0.0055***	-0.3227***	0.3628***	0.0964***	0.0274***
	(0.0026)	(0.0050)	(0.0032)	(0.0015)	(0.0046)	(0.0040)	(0.0031)	(0.0013)
Class 5-7	-0.0431***	-0.0341***	-0.0627***	-0.0131***	-0.0936***	0.1921***	0.0499***	0.0047***
	(0.0023)	(0.0049)	(0.0029)	(0.0010)	(0.0045)	(0.0039)	(0.0031)	(0.0013)
Class 8 (base)	0	0	0	0	0	0	0	0
Slope	0.0027***	0.0036***	0.0025***	-0.0002***	0.0038***	0.0028***	-0.0104***	-0.0047***
	(0.0000)	(0.0001)	(0.0000)	(0.0000)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Elevation	-0.0000***	-0.0001***	-0.0001***	0.0000	0.0002***	0.0004***	-0.0003***	-0.0001***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Solar radiation	-0.0032***	0.0824***	0.0119***	0.0196***	-0.0502***	-0.1193***	0.0352***	0.0236***
	(0.0007)	(0.0009)	(0.0006)	(0.0005)	(0.0011)	(0.0014)	(0.0010)	(0.0005)
Temperature	0.0081***	-0.0285***	-0.0084***	-0.0113***	-0.0058***	0.0685***	-0.0115***	-0.0109***
	(0.0004)	(0.0006)	(0.0004)	(0.0004)	(0.0008)	(0.0009)	(0.0006)	(0.0003)
Water deficit	-0.0000	-0.0008***	0.0000**	-0.0000***	0.0008***	0.0006***	-0.0008***	0.0002***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Natural forest cover in area	0.0035***	-0.0002***	0.0001***	-0.0001***	-0.0010***	-0.0004***	-0.0016***	-0.0004***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0001)	(0.0000)	(0.0000)
Distance to nearest road	0.0076***	-0.0249***	0.0065***	0.0014***	0.0179***	-0.0045***	-0.0003	-0.0037***
	(0.0001)	(0.0005)	(0.0001)	(0.0001)	(0.0003)	(0.0008)	(0.0007)	(0.0005)

Road distance to nearest wood mill	-0.0001***	-0.0008***	-0.0000**	-0.0002***	0.0012***	-0.0007***	0.0006***	0.0000***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Road distance to nearest port	-0.0000***	0.0000	0.0002***	0.0001***	0.0001***	-0.0001***	-0.0000***	-0.0002***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Road distance to nearest town	-0.0000***	0.0004***	-0.0000	0.0001***	0.0004***	0.0005***	-0.0009***	-0.0004***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)

Stars denote statistical significance: * p<0.1, ** p<0.05, *** p<0.01.

[1] For the interaction term capturing ECFP eligibility, the effects shown represent contrasts of predictive margins.

Statistical significance aside, some of the marginal effects in Table 4 are relatively small in absolute value and might not seem economically significant. For example, the positive marginal effect of Māori freehold tenure on cropland use suggests that land under Māori freehold tenure is, on average, around 1 percentage point more likely to be cultivated as cropland than land under general freehold tenure. In assessing these results, however, one must bear in mind that the estimated marginal effect varies by observation due to the non-linearity of the multinomial logit, and that the average marginal effect represents a mean taken over the entire sample. (Moreover, it is expressed in percentage points which may apply to a low baseline percentage.) With respect to the average marginal effect of Māori freehold tenure on cropland use above, this implies that the calculation also includes land on which cropland use would be extremely unlikely due to low land quality, high slope or remoteness. For some observations or within more focused subsamples, the marginal effect can therefore be significantly larger. [16]

The ECFP target region indicator is a dummy variable identifying the Gisborne District, so parameters associated with it control for differences in land use outcomes not explained by other variables (compared to areas outside the district). The parameters associated with the target land type indicator have an analogous interpretation, controlling for, in this case, differences in outcomes between target land type and other land. Considering that the land targeted by the ECFP tends to be highly erosion prone, the positive marginal effects for dairy and cropland may seem counterintuitive. However, I do not attribute economic significance to these results because other related physical land attributes such as LUC class and slope are included individually as independent variables (and have marginal effects of the expected sign).

The land area eligible for an ECFP grant is identified by the interaction of the target region and target land type variables. In considering the effect of ECFP eligibility on land use, entries for the interaction term in Table 4 represent a comparison of predictive margins using all permutations of the target region and target land type indicators (computed by specifying contrast operators on both factors in Stata). The value of 0.266 for planted forest use indicates that the effect of being target land type is associated, on average, with a 26.6 percentage point greater probability for plantation forestry in the target region than outside the target region. This finding is consistent with the policy having led to an increase in planted forest area in the district. The corresponding effect for natural forest land use is small and not statistically significant.

[16] The marginal effect of Māori freehold tenure on cropland probability is around 0.07 for the average cropland (that is, for land with characteristics equal to the mean across all cropland). This is around seven times larger than the corresponding average marginal effect shown in Table 4. Similarly, the marginal effect of Māori freehold tenure on dairy probability is -0.10 for the average dairy land – nearly three times larger than the corresponding average marginal effect in Table 4.

For the most part, the estimated average marginal effects of other variables are consistent with our understanding of how those variables affect land use. It is evident from the results that cropland and dairy land have the strongest requirements for high quality, productive land with good access to infrastructure: higher land quality (as manifested in a lower LUC classification), lower slope, lower elevation, higher solar radiation and greater proximity to towns and ports all significantly increase the probability of both dairy and cropland use.

For continuous variables, the average marginal effect can sometimes mask more complex patterns. In Table 4, slope has a positive marginal effect associated with high-producing non-dairy grassland, suggesting (surprisingly) that higher slope increases the probability of this land use. Further investigation reveals that the estimated marginal effect is negative for slopes over 5 degrees but positive when evaluated at lower values.[17] The marginal effect thus decomposed is more consistent with prior expectations: initial increases in slope raise the likelihood of high-producing non-dairy grassland use (flat or nearly flat land tends to be suitable for dairy farming and cropland cultivation making other uses less likely), but further increases beyond gentle to moderate slopes make high-producing grassland use less likely (such land is better suited to low-producing grassland or forest uses).

The average marginal effects for natural and planted forests show that forests tend to be located on lower quality, higher sloping land. Additional analysis shows that, as was the case for high-producing non-dairy grassland, the marginal effect of slope for planted forest use is positive at lower values and negative at higher values of slope. In this case, the direction of the estimated effect changes around 30 degrees meaning that a further increase in slope beyond this level decreases the probability that plantation forestry will be established. For natural forests, the marginal effect remains positive throughout the entire range of slope values. The results in Table 4 also suggest that natural forests are more likely to be found in areas not easily accessed by road and in areas with previously high natural forest coverage.[18] Planted forests, on the other hand, tend to be located closer to roading infrastructure and wood mills but farther from towns.

5 Results: forest gain and forest loss

As a reminder, four types of land-use change involving transitions to and from forest cover are considered: afforestation, deforestation of planted forests, natural regeneration, and

[17] Land with slope under 2 degrees comprises about a third of all land in the sample, so the positive coefficient enters the average with a higher weight leading to the positive overall effect.
[18] Because of the slow rate of land-use change, particularly for natural forests, the positive effect associated with previous natural forest cover essentially just reflects the spatial clustering of the land use in a cross-sectional estimation. In Section 5.3, I will examine the effect of previous natural forest cover on natural regeneration specifically.

deforestation of natural forests. I estimate separate logit models for each type of transition, and each sample is defined such that it consists only of observations where the transition in question is feasible. For instance, planted forests are excluded from the afforestation estimations. Conversely, the estimations for deforestation of planted forests contain only observations that started out as planted forests. The estimations are performed on pooled land-use change data for the periods 2008-2012 and 2012-2016.

Results relate to three model specifications for each of the four transition types. The specifications differ with respect to the types of variables included in the estimation. The first model only includes variables characterising geophysical and climatic conditions and the general spatial location of observations. The second model focuses instead on policy and institutional variables. Finally, the third model contains the complete set of explanatory variables. All three models control for time period and geographic region via a full set of indicator variables. These capture the overall effect on land-use transitions of all factors (whether observed or unobserved) that vary systematically over time and regions, respectively.[19] The afforestation and regeneration estimations also include indicators for initial land use.

5.1 Afforestation

Parameter estimates and standard errors (in parentheses) from the three model specifications for exotic afforestation are presented in Table 5. For each specification the sample consists of private land not in planted forest use at beginning of the period – sample size and afforestation frequency are shown near the bottom of the table.

Estimates from model 1 indicate that exotic afforestation is most likely on class 5-7 land. Generally, such land is considered suitable for forestry but not suitable for intensive agricultural production. Afforestation probability is positively related to slope and mean annual temperature, and negatively related to solar radiation and water deficit. Lower slope and higher solar radiation tend to make land more suitable for higher-valued uses, so the estimated relationships for these variables are in line with prior expectations. Using similar data, West et al. (2020) also find that a higher water deficit decreases the probability of afforestation.

[19] As the coefficients of region indicators control for inter-regional differences in the average levels of all other explanatory variables (save for the time period indicator), the effects of those variables are estimated from intra-regional variation.

Table 5. Logit parameter estimates for afforestation

	(1)	(2)	(3)
Land tenure			
Māori freehold		-0.4763***	-0.5032***
		(0.0820)	(0.0849)
ETS incentive			
Reward eligibility		0.0847	0.1275
		(0.7673)	(0.6687)
ECFP eligibility			
Target region		1.3657***	2.0862***
		(0.1514)	(0.1905)
Target land type		-1.7079***	-1.5182***
		(0.1699)	(0.1839)
Eligible (target region & land type)		3.1065***	2.8201***
		(0.1984)	(0.2108)
LUC class			
Class 1-4	0.4115**		-0.0302
	(0.2011)		(0.2096)
Class 5-7	1.3111***		0.8304***
	(0.1819)		(0.1911)
Class 8 (base)	0		0
Slope	0.0314***		0.0336***
	(0.0030)		(0.0030)
Elevation	-0.0000		0.0004
	(0.0005)		(0.0005)
Solar radiation	-0.5160***		-0.5278***
	(0.0923)		(0.0924)
Temperature	0.2665***		0.2971***
	(0.0845)		(0.0852)
Water deficit	-0.0070***		-0.0068***
	(0.0005)		(0.0005)
Natural forest cover in area	0.0004		0.0013
	(0.0012)		(0.0012)
Distance to nearest road	-0.0765***		-0.0619***
	(0.0140)		(0.0141)
Road distance to nearest wood mill	-0.0013		-0.0005
	(0.0010)		(0.0011)
Road distance to nearest port	0.0049***		0.0052***
	(0.0006)		(0.0006)
Road distance to nearest town	-0.0020**		-0.0035***
	(0.0008)		(0.0009)
Previous land use			
Forest - Natural	-3.7997***	-3.0961***	-3.7449***
	(0.2300)	(0.7783)	(0.6827)
Grassland - Woody biomass	0.4874***	0.9393***	0.4507***
	(0.1422)	(0.1392)	(0.1422)
Grassland - Ungrazed (base)	0	0	0
Grassland - Low prod non-dairy	0.2952**	0.7367***	0.2256*
	(0.1351)	(0.1327)	(0.1351)
Grassland - High prod non-dairy	-0.7779***	-0.8654***	-0.8134***
	(0.1433)	(0.1384)	(0.1431)
Grassland - Dairy	-3.8595***	-4.3935***	-3.8960***
	(0.4331)	(0.4297)	(0.4331)
Cropland	-3.5745***	-4.4759***	-3.5733***
	(1.0116)	(1.0086)	(1.0116)

Time period			
2008-2012 (base)	0	0	0
2012-2016	-1.0353***	-1.0289***	-1.0331***
	(0.0435)	(0.0434)	(0.0435)
Region[1]	included	included	included
Constant	-3.4128***	-5.9333***	-3.3756**
	(1.1258)	(0.7904)	(1.3110)
Observations	1,203,492	1,214,824	1,203,492
Observations with afforestation	2,776	2,781	2,776
Pseudo R-squared	0.174	0.160	0.181

Stars denote statistical significance: * p<0.1, ** p<0.05, *** p<0.01.

[1] Region indicators are included in the estimation but supressed in the results table.

Remoteness, in the sense of being located farther away from roads and towns, decreases the probability of afforestation, conceivably reflecting constraints associated with infrastructure and labour availability. The estimates of the proxy variables for log transportation costs do not have the expected negative sign. Distance to the nearest wood mill does not seem to significantly affect afforestation decisions, while distance to ports has a significant positive effect on afforestation. As the 13 ports with log export infrastructure are located in some of New Zealand's largest cities, it is possible the estimated relationship reflects a tendency for new plantings not to be established near large population centres. It is also possible that distance to port matters more to competing agricultural land uses which also tend to be export oriented. These findings are also largely consistent with those of West et al. (2020). Finally, natural forest cover in the area does not significantly affect afforestation in my results.

Previous land use affects afforestation decisions in expected ways. Existing natural forest cover, high productivity pastoral uses (both non-dairy and dairy) and cropland use all decrease the probability of afforestation relative to the base category of ungrazed pasture. These findings reflect high conversion costs from natural forest cover (including clearing costs and potentially legal protection in some cases) and high opportunity costs for the pastoral and cropping land uses due to their profitability. Including indicators for previous land use is also necessary for the estimation of parameters associated with policy variables. For instance, not controlling for previous land use could bias the estimate of the effect of ETS eligibility upward: areas with natural forest cover tend to be ETS ineligible (as most of them already had forest cover in 1990), but, *ceteris paribus*, these areas are also less likely to be planted with exotics due to the aforementioned costs associated with the clearing of original cover.

Turning to model 2 which focuses on policy and institutional variables, the negative parameter estimate on Māori freehold suggests that Māori freehold land tenure makes afforestation less likely. This result is consistent with the findings of previous empirical research based on similar data (Dorner & Hyslop, 2014; Cortés Acosta, 2020).

In contrast to the analysis of West et al. (2020) who find that landowners are influenced by the potential revenue from the ETS, the ETS eligibility variable is not significant in my results suggesting that eligibility did not affect afforestation decisions during the study period. Some differences in methodology may contribute to the conflicting findings. First, West et al. (2020) define afforestation as any forest gain between 2012 and 2016, whereas in this paper I attempt to separate exotic afforestation from natural regeneration and make use of land-use changes pooled over a longer time period.[20] Second, I constrain my analysis to privately owned land because I consider private and public land-use decisions as fundamentally different. West et al. (2020), on the other hand, include public land in their study and control for protected areas (primarily Department of Conservation land under public ownership) via the inclusion of a dummy variable.

It is worthwhile at this point to review the identification of the ETS eligibility effect in the model. The sample does not cover pre-ETS times, so it is not possible to observe how the policy may have affected land-use decisions over time. Rather, we must rely on cross-sectional variation to compare (controlling for other variables) afforestation outcomes on the basis of ETS eligibility. However, as ETS eligibility is determined by previous land use, the low rate of land-use change poses a problem by limiting the variation in outcomes: nearly all land classified as ETS ineligible is under natural forest cover, and only 32 of these ineligible observations undergo afforestation in the sample. Due to this sparsity of data, it is difficult to estimate the effect of ETS eligibility with precision.

Estimation challenges notwithstanding, it is not inconceivable that rewarding carbon sequestration in the ETS indeed had limited impact on afforestation decisions during the time period modelled. Carbon prices were close to zero for much of the second half of the sample period, and there also existed considerable policy uncertainty (Leining, 2022; Karpas & Kerr, 2011). Other research has also concluded that the ETS motivated minimal new forest planting in the early years of the scheme (Ministry of Agriculture and Forestry, 2011; Manley, 2016; Ministry for the Environment, 2016).

As in the multinomial logit, in estimating the effect of ECFP eligibility on afforestation, I decompose the variable into two indicators: one for target region (to represent the geographic area in which the policy was implemented) and one for target land type (to designate land that meets eligibility requirements for land type, ignoring location). To facilitate the interpretation of results, both main effects and an interaction of these indicators are included in the estimation.

[20] My estimate of the ETS reward eligibility effect is positive in the natural regeneration equations, potentially reconciling my findings with those of West et al. (2020).

By explicitly estimating an effect for comparable land in regions not actually targeted by the policy, the possibility that target land type would be more likely to experience afforestation even without policy intervention can be addressed. The parameter estimate for ECFP eligibility, the interaction term, is positive and significant, suggesting that the grant payments provided by the East Coast Forestry Project led to an increase in afforestation activity beyond baseline levels.

Estimation results from model 3, the full model, are consistent with those discussed above. Finally, the indicator for the 2012-2016 time period has a significant negative parameter estimate in all three models, and this corresponds to overall changes in the level of afforestation activity as new planting fell to one third its previous level during this time.

5.2 Deforestation of planted forests

Logit parameter estimates for deforestation of planted forests are presented in Table 6. There are two minor differences in the set of explanatory variables used compared to Table 5 – both of them a logical consequence of the fact that the deforestation samples consist entirely of land in planted forest use initially. First, previous land use is not included as a control variable in these equations. Second, previous land use is also ignored in the construction of the ECFP eligibility indicator variable. The policy-relevant question in this context is whether forests that were established via the ECFP are more or less likely to be deforested than similar forests elsewhere. In the absence of data on ECFP grant forest locations, I assign ECFP eligible status to all forested land that may have qualified for an ECFP grant in the past based on NZLRI classification (this might include some land that had never been cleared and was therefore not eligible for a grant payment). Including the main and interaction terms from the decomposition of ECFP eligibility allows us to tease out the effect of past potential eligibility on deforestation outcomes.

Parameter estimates from model 1 are generally in line with expectations in that deforestation tends to happen on relatively higher quality land on which agricultural production is also feasible. Nearly all coefficients on geophysical and climate variables are, as expected, of the opposite sign compared to the afforestation estimations.

Negative parameter estimates for distance to wood mills and ports indicate that deforestation is more likely to occur closer to these facilities. Following the reasoning in the discussion of afforestation results, it is possible that the estimated relationship for distance to the nearest port picks up higher deforestation rates near large population centres, possibly due to increased pressure from alternative land uses.

Table 6. Logit parameter estimates for deforestation

	(1)	(2)	(3)
Land tenure			
Māori freehold		-0.9714***	-0.6028***
		(0.1064)	(0.1091)
ETS incentive			
Deforestation liability		0.3156***	0.0629
		(0.0483)	(0.0508)
ECFP eligibility			
Target region		-0.4992**	0.2172
		(0.2089)	(0.2402)
Target land type		-0.0104	0.9278***
		(0.1342)	(0.1691)
Eligible (target region & land type)		-0.9605*	-1.6706***
		(0.4996)	(0.5114)
LUC class			
Class 1-4	0.2304		0.7408***
	(0.1651)		(0.2005)
Class 5-7	-0.3779**		0.1408
	(0.1637)		(0.1992)
Class 8 (base)	0		0
Slope	-0.0854***		-0.0883***
	(0.0045)		(0.0045)
Elevation	-0.0014***		-0.0013**
	(0.0005)		(0.0005)
Solar radiation	0.7635***		0.6796***
	(0.1045)		(0.1055)
Temperature	-0.0909		-0.0567
	(0.0907)		(0.0916)
Water deficit	0.0027***		0.0028***
	(0.0006)		(0.0006)
Natural forest cover in area	0.0028*		0.0033**
	(0.0016)		(0.0016)
Distance to nearest road	0.0234		0.0288
	(0.0248)		(0.0243)
Road distance to nearest wood mill	-0.0091***		-0.0088***
	(0.0014)		(0.0014)
Road distance to nearest port	-0.0048***		-0.0042***
	(0.0007)		(0.0007)
Road distance to nearest town	0.0013		0.0013
	(0.0017)		(0.0017)
Time period			
2008-2012 (base)	0	0	0
2012-2016	-0.1602***	-0.1881***	-0.1590***
	(0.0390)	(0.0384)	(0.0391)
Region[1]	included	included	included
Constant	-13.5709***	-5.2736***	-13.4206***
	(1.2665)	(0.1185)	(1.2663)
Observations	162,465	163,542	162,465
Observations with deforestation	2,807	2,831	2,807
Pseudo R-squared	0.139	0.076	0.142

Stars denote statistical significance: * p<0.1, ** p<0.05, *** p<0.01.

[1] Region indicators are included in the estimation but supressed in the results table.

Results from models 2 and 3 containing policy and institutional variables indicate that, in addition to being less likely to undergo afforestation, land under Māori freehold tenure is also less likely to be deforested if it already has planted forest cover.

Being subject to an ETS liability increases the probability of deforestation according to the results of model 2, although the estimate becomes statistically not significant in the full model. At best, the deforestation liability appears ineffective at deterring deforestation, at worst, it appears counterproductive. Following the reasoning set forth in the discussion of the ETS afforestation reward in the previous section, low carbon prices may also have caused the liability to be a weak deterrent of deforestation during the period under study. Moreover, if the carbon price was expected to rise, it may also have led to strategic deforestation decisions while it was possible to do so at a low cost (potentially leading to a seemingly counterintuitive positive effect).

Also recall that the estimated effect is relative to the base category of planted forest land to which a deforestation liability does not apply. Essentially, that base category is composed of post-1989 forests, and this has implications for the age composition of trees. Most planted forests in New Zealand are harvested when trees reach 26-30 years of age, and deforestation (change to a non-forestry use) typically happens after the harvest of mature trees. The vast majority of post-1989 forests have not reached harvestable age in the sample simply because not enough time has passed since 1990. Consequently, forests not subject to the deforestation liability are unlikely to undergo deforestation as they tend to contain immature trees. In a model, such as the present one, where identification is based on comparing outcomes across forests on the basis of whether a liability applies, this difference in age composition could also cause the ETS deforestation liability to seem counterproductive or inefficient in discouraging deforestation.

Regarding ECFP eligibility, I find that forests on land that may have qualified for a grant in the past are, on average, less likely to be deforested, as shown by the significant negative estimate on the eligibility (interaction) term. This is what would be expected if the covenants for planting under the ECFP were successful at discouraging the deforestation of grant forests.

5.3 Natural regeneration

Table 7 contains results for the three model specifications for natural regeneration. Recall that samples for these estimations exclude regenerating natural forests known to contain wilding trees in order to better characterise indigenous regeneration. At least 77 percent of regeneration in the estimation samples involves regenerating natural species – for the remaining

23 percent the tree species is listed as unknown in the data. Key results from the three different specifications are generally consistent, so unless otherwise noted, the discussion refers to the full model in column (3) of the table.

In terms of land quality attributes, belonging to LUC class 5-7 has the largest (positive) effect on the probability of natural regeneration. Higher slope, higher elevation, higher solar radiation, higher temperature and lower water deficit are also positively associated with regeneration probability.

Plots are more likely to experience regeneration near towns, but farther from wood mills and ports. This pattern of estimates for locational parameters would be consistent with regeneration of natural forests being allowed (or encouraged) in the relative proximity of populated places, especially in areas without existing plantation forestry infrastructure. Such a pattern could reflect the balance between amenity values provided by natural forests and the profitability of plantation forestry.

As expected, the percentage of natural forest cover in the vicinity of the plot has a strong positive effect on regeneration probability. Existing natural forest cover nearby could signal the general suitability of the area for natural forest growth, the availability of natural seed sources for regeneration and preferences of other landowners in the area.

Regarding the previous land use of the regenerating plot, grasslands with woody biomass and (surprisingly) planted forests are the most likely uses to give rise to new natural forests; dairy grasslands and high-producing non-dairy grasslands are the least likely to do so – the effect is inestimable for cropland.

Results from the models including policy and institutional variables suggest that, similar to afforestation, regeneration is also less likely on Māori freehold land.

ETS eligibility, or the potential to earn carbon rewards from forest growth, is estimated to increase the likelihood of natural regeneration. This is consistent with what one would expect to happen given economic incentives, but it stands in contrast with the no-effect finding in the afforestation equations. Given the relatively low number of positive regeneration outcomes across the ETS eligibility categories, the estimate of this effect is subject to similar caveats around data availability as that in the afforestation equations. It is also possible that the effects of other afforestation schemes could be attributed to the ETS in my results. For example, the Permanent Forest Sink Initiative (PFSI) was active during the sample period, had similar eligibility criteria to the ETS and a significant fraction of forests established under it were indigenous (Ministry of Agriculture and Forestry, 2011).

Table 7. Logit parameter estimates for natural regeneration (excluding wilding trees)

	(1)	(2)	(3)
Land tenure			
Māori freehold		-0.3014	-0.7437***
		(0.2205)	(0.2273)
ETS incentive			
Reward eligibility		1.8646***	1.7282***
		(0.2596)	(0.2575)
ECFP eligibility			
Target region		1.1852***	3.0655***
		(0.4167)	(0.5278)
Target land type		0.4221**	0.2822
		(0.2031)	(0.2510)
Eligible (target region & land type)		0.8299**	0.6697
		(0.4006)	(0.4265)
LUC class			
Class 1-4	0.7334*		0.8921**
	(0.3935)		(0.4105)
Class 5-7	1.0597***		1.1971***
	(0.3127)		(0.3302)
Class 8 (base)	0		0
Slope	0.0393***		0.0361***
	(0.0074)		(0.0074)
Elevation	0.0063***		0.0065***
	(0.0012)		(0.0012)
Solar radiation	0.6649***		0.7173***
	(0.2511)		(0.2516)
Temperature	1.2074***		1.2316***
	(0.2066)		(0.2086)
Water deficit	-0.0091***		-0.0095***
	(0.0019)		(0.0020)
Natural forest cover in area	0.0254***		0.0266***
	(0.0022)		(0.0023)
Distance to nearest road	-0.0321		-0.0380
	(0.0247)		(0.0253)
Road distance to nearest wood mill	0.0149***		0.0143***
	(0.0022)		(0.0023)
Road distance to nearest port	0.0053***		0.0058***
	(0.0015)		(0.0015)
Road distance to nearest town	-0.0061**		-0.0062**
	(0.0024)		(0.0025)
Previous land use			
Forest - Planted	0.4642	1.6667***	1.2183***
	(0.4356)	(0.4335)	(0.4407)
Grassland - Woody biomass	1.7089***	2.2113***	1.7449***
	(0.4285)	(0.4210)	(0.4294)
Grassland - Ungrazed (base)	0	0	0
Grassland - Low prod non-dairy	0.6735	1.0976***	0.7033*
	(0.4263)	(0.4208)	(0.4273)
Grassland - High prod non-dairy	-1.0585**	-1.4949***	-1.0559**
	(0.4896)	(0.4784)	(0.4905)
Grassland - Dairy	-2.2967***	-3.0698***	-2.2734***
	(0.8363)	(0.8222)	(0.8365)
Cropland	0	0	0

Time period			
2008-2012 (base)	0	0	0
2012-2016	-0.4243***	-0.4309***	-0.4227***
	(0.1017)	(0.1012)	(0.1018)
Region[1]	included	included	included
Constant	-40.1749***	-10.9318***	-43.1059***
	(4.0734)	(0.6143)	(4.1054)
Observations	1,028,046	1,037,699	1,028,046
Observations with natural regeneration	408	411	408
Pseudo R-squared	0.220	0.166	0.231

Stars denote statistical significance: * p<0.1, ** p<0.05, *** p<0.01.

[1] Region indicators are included in the estimation but supressed in the results table.

Finally, eligibility for the ECFP is found to increase the probability of regeneration suggesting that grant payments for reversion under the programme increased reversion rates beyond what would have been expected in the absence of the policy. However, the effect is not statistically significant in the full model.

5.4 Deforestation of natural forests

The final type of land-use change affecting forest cover is the deforestation of natural forests. Estimation results corresponding to this transition are included in Table 8. However, their interpretation is not straightforward because of uncertainty around the precise nature of the land-use changes identified by the dependent variable.

The estimation sample is comprised of grid cells that start out in natural forest use. Natural forests are made up of indigenous or self-sown exotic trees – while it was possible to exclude wilding trees from the natural regeneration estimations, it is not possible to remove them here because they are not necessarily identified in the data if established prior to 1990. Further, as noted in Section 3.1.1, loss of forest cover associated with natural causes such as erosion, disease or fire is not shown as forest loss in LUCAS. Instances of natural forest cover loss should thus reflect human activity (or data errors). Because indigenous forests, even those on private land, are protected in New Zealand, the logical conclusion is that the activity has to be associated with the removal of wilding trees (unless one is willing to assume illegal clearing which I consider improbable).[21]

[21] Under the Forests Act 1949, native timber can only be taken from forests sustainably, in a way that maintains forest cover and ecological balance.

Table 8. Logit parameter estimates for natural deforestation

	(1)	(2)	(3)
Land tenure			
Māori freehold		-0.8372***	-0.5345***
		(0.1944)	(0.1979)
ECFP eligibility			
Target region		-0.5521	0.4592
		(0.4251)	(0.5011)
Target land type		-2.3077***	-1.5262***
		(0.3225)	(0.4012)
Eligible (target region & land type)		1.5527	1.1746
		(1.1170)	(1.1265)
LUC class			
Class 1-4	1.5015***		0.4260
	(0.3977)		(0.4669)
Class 5-7	1.2607***		0.1975
	(0.3690)		(0.4435)
Class 8 (base)	0		0
Slope	-0.0255***		-0.0226***
	(0.0080)		(0.0080)
Elevation	-0.0020*		-0.0017
	(0.0012)		(0.0012)
Solar radiation	0.1445		0.1790
	(0.2183)		(0.2196)
Temperature	-0.1615		-0.1307
	(0.2112)		(0.2118)
Water deficit	-0.0000		-0.0001
	(0.0019)		(0.0019)
Natural forest cover in area	-0.0144***		-0.0136***
	(0.0020)		(0.0020)
Distance to nearest road	-0.0086		-0.0012
	(0.0252)		(0.0251)
Road distance to nearest wood mill	0.0022		0.0033
	(0.0021)		(0.0021)
Road distance to nearest port	0.0042***		0.0041***
	(0.0013)		(0.0013)
Road distance to nearest town	-0.0114***		-0.0117***
	(0.0028)		(0.0028)
Time period			
2008-2012 (base)	0	0	0
2012-2016	-1.1914***	-1.1951***	-1.1909***
	(0.1163)	(0.1161)	(0.1163)
Region[1]	included	included	included
Constant	-6.2800**	-6.0095***	-6.2272**
	(2.7322)	(0.1920)	(2.7463)
Observations	205,413	207,223	205,413
Observations with natural deforestation	415	417	415
Pseudo R-squared	0.113	0.092	0.117

Stars denote statistical significance: * p<0.1, ** p<0.05, *** p<0.01.

[1] Region indicators are included in the estimation but supressed in the results table.

The spread of wilding trees affects large areas of New Zealand. During the study period, estimates by the Department of Conservation indicated that up to 1.7 million hectares were affected, of which around 85,000 hectares were densely populated by wilding conifers (Ministry for Primary Industries, 2014b). Despite control efforts, wilding trees continued to infest tens of thousands of hectares each year (Ministry for Primary Industries, 2014b). A significant proportion of these areas is likely to involve public land (and is therefore excluded from the sample), but private land is also affected. In fact, most of the wilding removals by Marlborough, Canterbury and Southland Councils in the mid-2000s were claimed to be on private farmland (Ledgard, 2009).

The estimation data represent approximately 10,000 hectares of natural forest loss over a period of 8 years. It is not inconceivable that most of this could represent wilding tree control considering the statistics on affected land areas in the previous paragraph. However, I am unable to ascertain if and to what extent other factors might contribute to natural forest loss identified in the sample.

With these caveats in mind, presuming that the parameter estimates in Table 8 relate to the control of wilding trees, the results are generally plausible. They suggest that the removal of wilding trees is less likely on land under Māori freehold tenure, on erosion-prone land (land similar to that targeted by the ECFP) and on steeper land. On steep, erosion-prone sections, the private benefits derived from erosion control may outweigh the private costs associated with wilding trees. Wilding tree control is also less likely in areas with a higher percentage of pre-existing natural forest cover and farther away from population centres. The ETS deforestation liability does not apply to natural forests, so an ETS policy effect is not estimable in this context.

6 Conclusion

In this paper, I estimate discrete choice models of land use and land-use conversion to investigate private land-use decisions and the effect of New Zealand land institutions and environmental policies on those decisions. The models of land-use conversion focus on changes in forest cover examining four types of land-use change individually: afforestation, deforestation of planted forests, natural regeneration and deforestation of natural forests. All models control for features of topography, climate, land quality and various dimensions of accessibility thought to be important determinants of land-use decisions.

Although the natural forest land cover class in the LUCAS data includes forests made up of either indigenous or self-established exotic trees, it is possible to exclude the latter from the model of natural regeneration. Therefore, the results of that estimation could reasonably be interpreted in the context of regenerating indigenous forests. However, selection by tree species is not possible when considering the deforestation of natural forests. Given the protected status of indigenous forests in New Zealand, instances of deforestation of natural forests identified in the data likely represent the removal of wilding trees.

Results from the cross-sectional model suggest that Māori freehold land tenure is associated with a decreased probability of grazed pastoral land uses and an increased probability of forested, ungrazed grassland and cropland uses. Underscoring previous research findings, land under Māori freehold tenure is less likely to undergo land-use change than general freehold land in all four models of land-use conversion.

In terms of environmental policies, I first consider the impact of the twin incentives provided under the New Zealand Emission Trading Scheme to forest owners: the carbon reward and the deforestation liability. My results suggest the reward had little effect on afforestation, and the liability was ineffective at deterring deforestation during the 2008 to 2016 period. This is plausible given prevailing carbon prices and policy uncertainty at the time, and other analyses (though not all) have also reached a similar conclusion. On the other hand, the carbon reward appears successful in having increased native regeneration, although it is possible that this result reflects the impact of other environmental programmes.

An important (and perhaps underappreciated) caveat is that the ETS incentives are difficult to assess using available geographic land-use data because the policy is relatively recent, uniform across the country and its treatment of land is determined by past land use – all these features limit the availability of an acceptable control group for estimation.

The second environmental policy considered in this paper is the East Coast Forestry Project, an afforestation grant scheme that targeted highly erodible land in the Gisborne District. As this is a regional programme directed at land with specific attributes, estimating its effect is feasible in cross-sectional data as well. In combination, estimation results from the two modelling approaches suggest the ECFP has increased planted forest area in the district both by encouraging afforestation beyond baseline levels and by discouraging deforestation. Evidence for its effect on regenerating natural forest area is weaker.

Results for the influence of physical factors on land use and on land-use conversion are generally consistent with expectations and previous research. On average, both afforestation and natural regeneration tend to happen on higher sloping, LUC class 5-7 land. Generally, such land is considered suitable for forestry but not suitable for intensive agricultural production. In contrast, deforestation is more likely on lower sloping, higher quality land better suited to agricultural production. In terms of previous land use, grasslands with woody biomass and low producing grasslands are most likely to be converted to planted forest use. Grasslands with woody biomass, low producing grasslands and areas previously under planted forest use are relatively more likely to undergo natural regeneration. Proximity to roading infrastructure has a strong positive effect on afforestation, and pre-existing natural forest cover in the area is found to have a strong effect on regeneration probability. All else equal, both afforestation and natural regeneration are more likely near populated places.

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Appendix

Table A1. Datasets used to construct all dependent and explanatory variables

Dataset name	Source
LUCAS NZ Land Use Map 1990 2008 2012 2016 v008	https://data.mfe.govt.nz/layer/52375-lucas-nz-land-use-map-1990-2008-2012-2016-v008/
DOC Public Conservation Areas	https://koordinates.com/layer/754-doc-public-conservation-areas/
Māori Land Spatial Dataset	http://www2.justice.govt.nz/website-documents/mlc/MLC_2017_05-Shapefile.zip
LENZ - Slope	https://lris.scinfo.org.nz/layer/48081-lenz-slope/
LENZ - Annual water deficit	https://lris.scinfo.org.nz/layer/48097-lenz-annual-water-deficit/
LENZ - Mean annual solar radiation	https://lris.scinfo.org.nz/layer/48095-lenz-mean-annual-solar-radiation/
LENZ - Mean annual temperature	https://lris.scinfo.org.nz/layer/48094-lenz-mean-annual-temperature/
NZDEM - Elevation (North Island)	https://lris.scinfo.org.nz/layer/48131-nzdem-north-island-25-metre/
NZDEM - Elevation (South Island)	https://lris.scinfo.org.nz/layer/48127-nzdem-south-island-25-metre/
NZ Road Centrelines	https://data.linz.govt.nz/layer/50184-nz-road-centrelines-topo-1250k/
NZ Populated Places	https://koordinates.com/layer/3657-nz-populated-places-points/
Wood processing mills and ports	Scion (private data)
Regional Council boundaries	https://datafinder.stats.govt.nz/layer/106667-regional-council-2022-clipped-generalised/