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ORIGINAL ARTICLE

Logs or permits? Forestry land use decisions in an emissions trading scheme

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Abstract

Negative carbon emissions options are required to meet long-term climate goals in many countries. One way to incentivise these options is by paying farmers for carbon sequestered by forests through an emissions trading scheme (ETS). New Zealand has a comprehensive ETS, which includes incentives for farmers to plant permanent exotic forests. This research uses an economy-wide model, a forestry model and land use change functions to measure the expected proportion of farmers with trees at harvesting age that will change land use from production to permanent forests in New Zealand from 2014 to 2050. We also estimate the impacts on carbon sequestration, the carbon price, gross emissions, GDP and welfare. When there is forestry land use change, the results indicate that the responsiveness of land owners to the carbon price has a measured impact on carbon sequestration. For example, under the fastest land use change scenario, carbon sequestration reaches 29.93 Mt CO_2e by 2050 compared to 23.41 Mt CO_2e in the no land use change scenario (a 28% increase). Even under the slowest land use change scenario, carbon sequestration is 25.89 Mt CO_2e by 2050 (an 11% increase compared with no land use change). This is because, if foresters decide not to switch to permanent forests in 1 year, carbon prices and ultimately incentives to convert to permanent forests will be higher in future years.

KEYWORDS

climate change and greenhouse, computable general equilibrium, forestry, land use and tenure

JEL CLASSIFICATION

C68, Q15, Q54, Q58

1 | INTRODUCTION

Mature production forests can provide nonmarket benefits for society including ecosystem services, natural disaster protection, recreational activities, agricultural productivity improvements, tourism and carbon sequestration (Figueroa & Pasten, 2015; Hanley et al., 2007). Due to the value of these nonmarket benefits and the impacts from climate change being felt around the world, the forestry industry has come under increasing scrutiny. Carbon sequestration from forests is a key tool to reduce greenhouse gas (GHG) emissions in the atmosphere (IPCC, 2022). It is therefore important for farmers to have incentives to incorporate the carbon sequestration of their forests into their harvesting decisions.

There are a variety of policies, explored by Englin and Klan (1990), which can incentivise production foresters to change their harvesting behaviour and increase the nonmarket benefits from each rotation. One policy intervention that could encourage farmers to stop harvesting altogether is an emissions trading scheme (ETS) where farmers earn permits for the carbon sequestration of their forests each year (Leining, 2022). One of the most comprehensive ETSs in the world is the New Zealand ETS (NZ ETS). This ETS was recently extended to include sequestration from forests, which incentivises farmers to plant permanent forests as the price of carbon increases (Leining, 2022). Exotic forests currently account for 2.1 million hectares of land in New Zealand, with approximately 1.7 million hectares being used for plantation forests and the remainder being unplanted or used as permanent forests (MPI, 2022a). This accounts for close to 8% of the total available land in New Zealand (MfE & Stats NZ, 2021). Out of the ETSs operating around the world—including those in Canada, China, Japan, the European Union, South Korea, Switzerland, Austria, Indonesia, Montenegro, Germany, Kazakhstan, Mexico and the United States (ICAP, 2022a)—the NZ ETS is the only scheme to include a forestry sector with both surrender obligations and the ability to earn carbon permits (ICAP, 2022b). In this paper, we use an economy-wide/computable general equilibrium (CGE) model and a forestry model to estimate the impact of the forestry rules in the NZ ETS on the land used for exotic permanent forests. We further investigate how this land use change affects the expected quantity of carbon sequestered, the amount of land harvested, the price of carbon and economic outcomes.

Previous research that has analysed the decision-making of foresters in the NZ ETS has focussed on afforestation, deforestation, land productivity and the optimal rotation age. Manley (2022) provided a comprehensive analysis of the impact the carbon price and timber price have on land value and afforestation decisions. He also explored the profitability of forest land under different carbon accounting systems and different carbon prices. Adams and Turner (2012) provided a model to represent the afforestation, deforestation and optimal harvest age decision-making for forestry farmers in New Zealand for carbon prices up to 50 NZD/ tCO_2. They also looked at land use change between other agricultural land uses and forestry with elasticities driving a probability of land use change at each carbon price. As expected, both found that as the carbon price increases, afforestation increases, and deforestation occurs in years where the carbon price is low and expected to increase in future years. Manley (2022) also found, under current NZ ETS rules, the optimal harvest age stays relatively constant even with an increasing carbon price. Hale et al. (2014) projected the changes in the land used for commercial forests as a response to the carbon price. They found that less productive forestry regions are the most efficient land areas to transition to permanent forests when the carbon price increases. Kerr et al. (2012) estimated the expected land use change elasticities between different agricultural land uses. They found a relatively low level of land use change to forestry from agriculture under the NZ ETS. A limitation of these studies is the low level of reactivity of the NZ ETS to forestry land use change, and, in some of the papers, the relatively low carbon price used. By connecting a forestry model with a CGE model, we can explore land use decision-making over a range of carbon prices to 2050 and the impact of those decisions on the economy and the NZ ETS.

To model forestry land use change, we need to represent farmers as risk-averse decision-makers (Binswanger, 1980). There is also a high level of uncertainty for farmers about factors outside their control such as natural disasters as well as unpredictable changes in government policy. In forestry, farmers must make costly decisions years before these uncertainties are resolved (Yousefpour et al., 2012). This is demonstrated by the common use of Faustmann's formula by both researchers and farmers (Crabbe & Long, 1989; Faustmann, 1849; Hartman, 1976; Loehle, 2023; Nakajima et al., 2017; Reed, 1984; Wang & van Kooten, 2001; Wilson et al., 1998). Under the NZ ETS, farmers now have an additional decision to make: whether to harvest their trees at maturity or keep them in the ground to earn carbon permits. This research examines the switch from production to permanent forests incentivised by changes in the carbon price. The choice farmers make will depend on the carbon price in the current year as well as the expected carbon price in future years.

We use sigmoid functions (also known as S-curves) to represent this forestry decision appropriately. Sigmoid functions have been used to represent the adoption of new technologies in agriculture (Beal & Bohlen, 1956; Beal & Rogers, 1960; Coleman et al., 1955; Kuehne et al., 2017; Llewellyn & Brown, 2020; Rogers, 2003; Swamila et al., 2020). This approach has the benefit of characterising heterogeneous decision-makers with segments of adopters that require different carbon prices to change production practices. The sigmoid functions also account for uncertainties felt by farmers surrounding climate change policy and embody long-run decisions around a short-run carbon price. To our knowledge, this is the first time S-curves have been used to represent land use change in a CGE model, and also the first CGE analysis to consider land use change caused by ETS incentives for permanent forests. The sigmoid functions allow us to avoid the land accounting issues, which come from using other CGE land use change techniques, whilst suitably representing forestry land use decision-making.[1]

This paper has four further sections. Section 2 provides an overview of the NZ ETS. Section 3 describes the methods used for our analysis. Section 4 presents and discusses the results. Section 5 offers a discussion and some concluding remarks.

2 | THE NEW ZEALAND ETS

The NZ ETS operates through the generation and trading of carbon permits, which are limited by the government to meet emissions targets each year. As of 2022, this ETS included 52% of New Zealand's gross emissions (biogenic methane emissions from agriculture, which accounts for approximately 48% of New Zealand's gross emissions, are scheduled to be included in an external pricing system by 2025; MfE & MPI, 2022). Carbon permits can be acquired in the NZ ETS by receiving them from the government for free, purchasing them from other participants, purchasing them at auction, receiving them from sequestration activities or purchasing them from external offset mechanisms (Leining, 2022).

The NZ ETS was introduced in 2008 to help New Zealand meet its 2050 emissions target (Leining, 2022). Since its introduction, there have been several amendments to the structure and scope of the NZ ETS. A notable milestone in New Zealand climate policy was the Climate Change Response Amendment Act, more commonly known as the Zero Carbon Act, which was passed in 2019. This act set a new GHG emissions target for New Zealand, specifying that biogenic methane must be reduced by at least 10% below 2017 levels by 2035 and 24%–27% below these levels by 2050, and all other GHGs must be at net zero by 2050 (PCO, 2019). The

[1] See Taheripour et al. (2020) for a review of land use change in CGE models.

act noted that the ETS is New Zealand's most important policy tool to achieve these targets. The most recent amendment to the NZ ETS was the Climate Change Response (Emissions Trading Reform) Amendment Act, passed in 2020. This act detailed changes in the structure of the ETS, including the future pricing of biogenic methane from agriculture and changes in forestry rules and accounting (PCO, 2020).

Forestry within the NZ ETS applies only to trees afforested after 1989 (Leining, 2022). Trees planted before 1990 cannot claim permits from carbon sequestration but do face emissions liability for deforestation. Since 2023, post-1989 foresters can claim permits as either permanent or production (also known as 'standard') forests. Previously, only production forests could claim permits. Permits can be earned using either the stock change or the 'averaging' accounting approach. The stock change approach measures the creation and surrender of permits based on the change in carbon sequestration from a forest each year and is used for permanent forests. A condition of permanent forests claiming permits is they cannot change their land use for 50 years. The 'averaging' approach, which is used by production forests, measures the change in carbon sequestration each year in the first rotation of the forests up until an 'average' age. The 'average' age is calculated as the long-run level of carbon sequestration achieved by production forests if they continue to be harvested and replanted. After the 'average' age, forest owners will no longer surrender or claim permits. The government has pledged to revisit forestry in 2025 to try and increase incentives for native forests to be planted (MPI, 2022b). It is unclear what these policy changes will be, so we model forestry land use change based on the NZ ETS policies, which have already been passed.

Native forest land use decision-making is not included in this research due to the lack of data available for private native forest landowners. Exotic forests, especially pine, also have a higher rate of carbon sequestration per hectare than native forests (PCO, 2008), so planting of native forests is largely carried out for noneconomic reasons.

3 | METHODOLOGY

This paper combines a CGE model with a forestry model to estimate the impacts of land use change from exotic production forest to permanent forest at harvesting age from 2014 to 2050 in New Zealand.

In our approach, a CGE model augmented to include permanent and production forests provides a representation of the New Zealand economy and estimates the carbon price in each period. A forestry model estimates the sequestration from forestry based on the amount of land used for production and permanent forests. To connect the two models, we include a land use decision-making module for farmers, using sigmoid functions, which operates when the carbon price becomes high enough for the value of permanent forests to be greater than the value of production forests. At harvesting age, farmers can choose to either cut the trees down as planned or leave them unfelled and generate permits for the NZ ETS. This decision is a function of the carbon price from the year before, as calculated in the CGE model, and provides land use estimates for the forestry model to calculate carbon sequestration. Outputs from the forestry model also determine the amount of production and permanent forest land in the CGE model in the next year. Figure 1 illustrates how the models and functions are connected to each other.

We focus on land use change from production to permanent forests as there are strict rules within the NZ ETS, which make it difficult for permanent forestry farmers to change their land use (PCO, 2020). This decision only applies to forests about to be harvested as this is the youngest age a forest can be before production foresters can start earning money from permanent forests. We represent the decision to change land use based on the expected carbon price in 2050 and the carbon price from the year before. This is carried out under the assumption

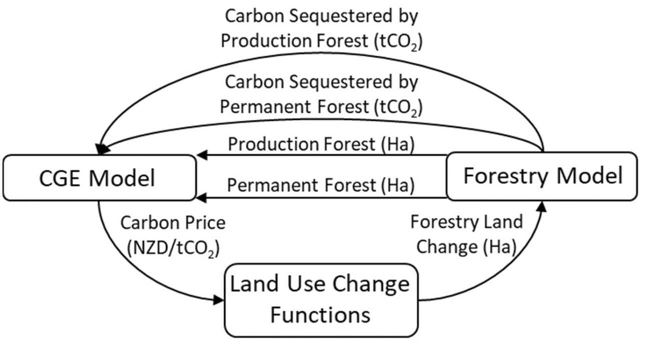

FIGURE 1 How the CGE model, forestry model and land use change functions are connected via outputs.

that, as detailed in Section 3.4, farmers do not have perfect information on the ETS and the carbon price and will make decisions on the long-run profitability of permanent forests using, among other intelligence, historical price information. This assumption is based on the papers by Yousefpour et al. (2012) and MPI (2019) who specify that farmers are particularly uncertain about climate change and climate change policies and will act differently compared with other land use decisions.

For the remainder of this section, the analysis is split into (1) an overview of the CGE model, (2) an overview of the forestry model, (3) a description of 'breakeven' carbon prices (used in the land use change model), and (4) a description of our land use change model.

3.1 | The CGE model: Climate PoLicy ANalysis (C-PLAN)

The CGE model used for this analysis is an augmented version of the C-PLAN model (Winchester & White, 2022), a global, recursive dynamic model built for the New Zealand Climate Change Commission (CCC). The C-PLAN model provides a representation of the New Zealand economy including climate change mitigation policies such as the NZ ETS. The model is solved annually from 2014 to 2050 and uses information from Version 10 of the Global Trade Analysis Project (GTAP) database (Aguiar et al., 2019; Chepeliev, 2020) and the New Zealand Government to supplement the benchmark data and calibrate the baseline. It is coded using the Mathematical Programming Subsystem for General Equilibrium (MPSGE) (Rutherford, 1999) a subsystem of the General Algebraic Modelling System (GAMS) (GAMS, 2021). We use the C-PLAN model to provide inputs to the forestry model and estimate the impacts of forestry land use change on the New Zealand economy. The land use change between production and permanent forests for this analysis is modelled outside the C-PLAN model, with updated amounts of land in permanent and production forests provided as exogenous inputs into the C-PLAN model each year. The model is packaged with a baseline scenario and three policy scenarios. In the baseline scenario, the carbon price is imposed as an exogenous carbon tax. Details on each scenario and more information on the model are available in Winchester & White (2022).

Our analysis uses the C-PLAN model policy scenario 'Transition Pathway 1' (TP1). This scenario models the NZ ETS (which includes all GHGs except biogenic methane) and a carbon pricing policy for biogenic methane emissions. The ETS in the model specifies targets for net emissions (other than biogenic methane) that are tightened over time so that they fall from 40.08 Mt CO_2e in 2022 to zero Mt CO_2e by 2050. The targets for each year are achieved by setting caps for gross GHG emissions (other than biogenic methane) accounting for the (exogenous) amount of emissions sequestered by forests in that year. In the policy scenario, carbon prices are determined endogenously by the supply and demand for emissions permits. The supply of permits is set exogenously each year according to the emissions cap in that period. Demand for permits reflects producers' operating decisions and is influenced by, for each sector, substitution possibilities between inputs, the availability of new technologies and the level of output. The carbon pricing policy for biogenic methane limits methane emissions to 24% below the 2017 level in 2050. There are also green technologies available in this scenario, which include electric vehicles, bioheat, electric heat, geothermal electricity with carbon capture and storage and methane-reducing technologies.

In the original version of the C-PLAN model, there is a single forestry sector that includes both production and permanent forests, with the hectares of land used and the carbon sequestered by forests exogenously determined using external estimates. In this research, the total land used for exotic forestry is still exogenously determined using estimates from the CCC (1.81 million hectares in 2014 up to 2.82 million hectares in 2050). However, the land used for permanent and production forests as well as the carbon sequestered and carbon permits produced by forestry are now endogenously determined in the modelling framework. These components are included in the C-PLAN model using two additional production activities. One production activity produces ETS permits from production forests (in their first rotation) and the other produces ETS permits from permanent forests. Both production activities use inputs of forestry land. The model also continues to represent a conventional production forestry sector that produces forestry products.

The value (and quantity) of land use in the new forest production activities is estimated from the value of land used in the original (conventional) forest production activity. The land inputs for the original production activity now represent rent paid on all production forest land not producing carbon permits. Accordingly, the value of land used as an input in the two new forest production activities represents the land used by permanent forests and the land used by first rotation production forests producing carbon permits, respectively. Both these values are calculated using the CCC's estimate of the total land used for forestry and projections of the area of forest land in each production activity. These value estimates are updated each year to reflect changes in land use due to changes in the carbon price. The carbon permits produced by production and permanent forests are based on the estimated carbon sequestration rates by these types of forestry and are also updated each year due to the differences in estimated carbon sequestration from each forest age group and the changing quantity of land in each of those age groups.

3.2 | The forestry model: Energy and Emissions in New Zealand (ENZ)

The forestry model for this research comes from the ENZ model. This model was built for the CCC to provide policy advice for the government (CCC, 2021). A component of this model estimates the land used for different types of forestry, the emissions from afforestation and deforestation, as well as the carbon sequestered by exotic permanent and production forests. It estimates, without land use change at harvesting age, that 0.55 million hectares in 2014 and 0.83 million hectares of exotic forest in 2050 will be generating carbon permits in the NZ ETS. The carbon sequestered by production forests is calculated using the ‘averaging’ accounting approach. The ‘average’ age of production forests in the ENZ model is 23 years and remains constant.[2] Carbon sequestration by permanent forests is calculated using the stock change approach. Based on advice from the CCC and the New Zealand Ministry for Primary Industries, the model assumes, in all years, that 6.1% of exotic trees planted per year are permanent forest, with the rest being production forest. This 6.1% accounts for 210 of 3435 ha of exotic trees planted in 2014, and 2537 of 41,595 ha planted in 2050. In our analysis, the total amount of forest land is exogenous, and we only consider the allocation of this land between production and

[2]This is an assumption made by the CCC and to remain consistent with the government baseline, we have maintained it in our analysis.

permanent forests. Focussing on the decision to convert production forests into permanent forests at harvesting age is supported by the research by Kerr et al. (2012), which found that the change in land use from other types of agriculture into forestry as incentivised by the carbon price is negligible. Additionally, if any land use change occurs between production and permanent forests at afforestation, it will not affect the creation of carbon permits for 23 years due to the crossover between stocktake and averaging accounting. The ENZ model estimates the carbon dioxide sequestered by forests per hectare at each age and multiplies this by the hectares of forest at each age to calculate total carbon sequestration. This calculation only includes forests planted after 1989 to avoid double counting emissions and carbon sequestration from the pre-1990 Kyoto Protocol baseline.

We convert the exotic forestry component of the ENZ model from Excel to GAMS and add this code to the C-PLAN model. This includes the amount of post-1989 forest land at each age group, the carbon dioxide emissions sequestered per hectare and emissions sequestered in each year. We use this module to determine how land use changes in forestry affect total carbon sequestration and feed that information into the C-PLAN model.

3.3 | The 'breakeven' carbon price

All exotic forestry is treated the same in this analysis, with each tree assumed to have the same harvesting age, level of carbon sequestration and productivity. Carbon sequestration and productivity are based on the average levels for exotic trees in New Zealand as calculated by the ENZ model, and the harvesting age is assumed to be the average age of harvest for radiata pine. This is due to the limitations of the ENZ model, which does not have the functionality to look at different regions and different species of trees as well as the fact that radiata pine is the most abundantly planted species of exotic tree in New Zealand (MPI, 2021). Therefore, the change in land use between permanent and production forests modelled in this paper occurs at a harvest age of 28 years, based on the average age of harvest for radiata pine from 2017 to 2021 (MPI, 2021). We assume that this age of harvest does not change with the carbon price, based on the modelling by Manley (2022), who found that under averaging accounting, the age of harvest for production forests is not expected to change significantly.

In our model, farmers will only switch to a permanent forest when the carbon price increases to a level where permanent forests are more valuable than production forests. To calculate when this occurs, we use the 'breakeven' carbon prices estimated by Manley (2022). He used a forestry model to calculate the carbon price in New Zealand where the expected value of land in production forests is the same as permanent forests. This price is determined separately for forests less than 100 ha in size (that use the government-provided carbon look-up tables for their carbon sequestration calculations) and for forests larger than 100 ha in size (which have unique carbon look-up tables created for their carbon sequestration calculations). For these two forest sizes, Manley (2022) separated the forests into three levels of site productivity: 'low', 'medium' and 'high'. These productivity levels are based on the 300 index (the volume of stem growth for 300 trees at a predefined age) (Kimberley et al., 2005) and the site index (the height of the dominant tree at a predefined age) (Husch et al., 1982), which measure the productivity based on the change in tree biomass over time. Within these levels of site productivity, Manley (2022) further estimated three separate prices for different degrees of harvesting difficulty. This means the report estimated breakeven carbon prices, in New Zealand dollars (NZD) per tonne of carbon dioxide (tCO_2), for 18 (two farm sizes, three types of site productivity and three types of harvesting difficulty) different types of forest land in New Zealand.

Manley (2022) further estimated area-weighted site index and 300 index values for New Zealand across 12 regions. He also provided examples of typical 300 index and site index values for 'low', 'medium' and 'high' productivity sites. The 12 regions described by Manley (2022)

TABLE 1 Carbon prices where the expected value of land is the same for production and permanent forests and the proportion of land in each farm size–productivity bucket.

Productivity	Breakeven CO_2 Price (NZD/tCO_2)	Proportion of total harvested land (%)
Small forests (less than 100 ha)		
Low	102.33	5.3
Medium	100.33	4.4
High	106.67	9.5
Large forests (greater than 100 ha)		
Low	72.33	14.5
Medium	76.00	16.4
High	82.33	49.9

Source: Authors' calculations based on information from Manley (2022) and MPI (2021).

are similar to the aggregation used in MPI (2021), which estimated the total land used for production forests in New Zealand in 2021. Using the examples of site productivity from Manley (2022) as mid-points for each productivity level and the proportion of land in each of the 12 regions, as estimated by MPI (2021), we calculate the proportion of total production forest land at each site productivity level in New Zealand. From the information provided in MPI (2021), we also estimate the proportion of land for each productivity level that was below or above 100 ha in size. As seen in Table 1, approximately 19.2% of forest land in New Zealand is classified as small forests and 80.8% is classified as large forests.

Harvesting difficulty is challenging to determine for each region as there is a high level of heterogeneity in the harvesting costs for each site (West, 2019). There is also not a reliable data source, which estimates harvesting difficulty in the same regions used by Manley (2022). As a result, we average the 'breakeven' carbon price for each level of site productivity across harvesting difficulty. This means we use six 'breakeven' carbon prices (Table 1) compared with the 18 calculated by Manley (2022).

The baseline used in the C-PLAN and ENZ models assumes that there is a 35 NZD/tCO_2 carbon price in the years the NZ ETS is active (CCC, 2021; Winchester & White, 2022). To avoid double counting any land use change estimated in these models, we add 35 NZD to the 'breakeven' carbon prices averaged from Manley (2022). The prices we use and the proportion of forest land at harvest age in each farm size–productivity 'bucket' are shown in Table 1.

3.4 | Land use change

To represent land use change from harvest age production forest to permanent forest once the carbon price is above the 'breakeven' price, we use sigmoid functions (also known as S-curves). The use of S-curves to describe farming decisions was pioneered by Coleman et al. (1955), Beal and Bohlen (1956), Beal and Rogers (1960) and Rogers (2003) and continues to be used in more recent studies such as Kuehne et al. (2017), Swamila et al. (2020) and Llewellyn and Brown (2020). In using this function, we represent the switch to permanent forests as a similar process to the adoption of new technologies by farmers.

In other models, which use Faustmann's formula (Crabbe & Long, 1989; Hartman, 1976; Loehle, 2023; Nakajima et al., 2017; Reed, 1984; Wang & van Kooten, 2001; Wilson et al., 1998), forestry owners tend to be represented as rational decision-makers with full information. In reality, this is not the case and quite often each forestry owner makes decisions using different information and assumptions to their neighbours. As explained by Yousefpour et al. (2012), there is general knowledge within the industry on how to react to productivity risks using silvicultural methods but there are differences in how forestry owners react to the risks related to climate change. There is also scepticism regarding climate change-related policies by farmers in New Zealand (MPI, 2019), which will contribute to a slow adoption of technologies related to policy changes.

An S-curve can represent the heterogeneity in attitudes to switching to permanent forest at different carbon prices. This includes: (1) the small number of forest owners that are quick to make land use changes with the view of making more profit in the long term (innovators/ early adopters); (2) the forest owners who take more time to make land use decisions but when profits for permanent forests are high enough they will make the change (early majority); (3) forest owners that wait until most of their peers in the industry have made the switch to permanent forests before they also change their land use (majority); and (4) the forest owners who are unlikely to change regardless of the carbon price (nonadopters) (Beal & Bohlen, 1956; Rogers, 2003).

The sigmoid functions used in this analysis determine the proportion of forest land that changes from production to permanent forests at harvesting age. Each carbon price above the 'breakeven' price corresponds to a probability of land use change. The S-curve functions include the carbon price from the previous period and the difference between an estimated 'high' carbon price (the maximum expected carbon price in 2050) and the breakeven carbon price. The estimated high carbon price is 337.79 NZD/tCO_2, the 2050 (and highest) carbon price in the TP1 scenario estimated by Winchester and White (2022).[3] This is used under the assumption that foresters have access to this information (available on the CCC's website) and will internalise this as the expected high price.

Equation (1) shows the structure of the sigmoid function used in our analysis.

$$\sigma_{lyt+1} = \frac{0.95}{\left(1 + e^{-0.05\left(p_t - \hat{p}_{ly}\right)}\right)^a} \tag{1}$$

where σ_{lyt+1} is the proportion of production forest land at harvesting age changing from production to permanent forests at forest size l (small or large), productivity level y (low, medium or high) and time $t+1$; p_t is the carbon price estimated by the C-PLAN model at time t; $\hat{p}_{ly}$ is the mid-point between the high carbon price calculated by the C-PLAN model (337.79 NZD/tCO_2) and the breakeven carbon price for forest size l and productivity level y; and a is a parameter that controls the shape of the curve/responsiveness of land owners to increases in the carbon price. The total proportion of harvest land changing use is multiplied by 0.95 to represent the small proportion (5%) of landholders who will never change their land use to permanent forest regardless of the carbon price.[4]

The maximum amount of land that can change from production to permanent forests each year is based on the hectares of land expected to be harvested, as estimated by the ENZ model (between 42,087 and 72,327 ha each year). The amount of land that changes from production to permanent forests is a function of the maximum amount of land that can change use and a series of sigmoid function calculations (one for each productivity–farm size category). In each year, there are potentially six S-curves operating, each using a different 'breakeven' carbon

[3]The 2050 carbon price with no forestry land use change calculated in this study differs from what is reported by Winchester and White (2022) due to an update in the projected carbon sequestration from forestry in the ENZ model.

[4]We scale the aggregated S-curves by 0.95 based on research by Boscolo et al. (2009) and Flett et al. (2004). Boscolo et al. (2009) found that the average adoption rates by farmers in Bolivia are 88%, 96% and 93% for, respectively, sustainable forestry management practices, which have clear regulations, are easy to enforce and have clear and measurable changes on the farm. Flett et al. (2004) found similar new technology adoption rates for New Zealand farmers, but they did not explicitly consider sustainable forestry.

TABLE 2 Hectares of harvest land available for change in each S-curve in 2022, 2035 and 2050.

Forest land characteristics (breakeven carbon price NZD/tCO$_2$)	Area of land available for change (ha)		
	2022	2035	2050
Small forests low productivity (102.33)	3156	2727	3833
Small forests medium Productivity (100.33)	2620	2264	3182
Small forests high productivity (106.67)	5657	4889	6871
Large forests low productivity (72.33)	8634	7461	10,487
Large forests medium productivity (76.00)	9766	8439	11,862
Large forests high productivity (82.33)	29,714	25,678	36,091
Total	59,548	51,458	72,327

Note: Due to rounding, the total harvest area may not equal the sum of the individual S-curve harvest areas.

price as its starting point, with the proportion of harvest land applying to each S-curve described in Table 2.

Equation (2) shows how the results from each of the six curves are added together to get the total area of harvest land changing use.

$$\varphi_{t+1} = \sum_{l} \sum_{y} \beta_{ly} \sigma_{lyt+1} \tag{2}$$

where φ_{t+1} is the total hectares of land use change at time $t+1$, and β_{ly} is the total hectares of harvest land available at each 'breakeven' carbon price based on land size l and productivity level y. Table 2 shows the area of land at harvest age (β_{ly}) available to change use under each breakeven carbon price in the model in 2022, 2035 and 2050.

To give a diverse representation of land use change, we consider a scenario with no endogenous land use change from production to permanent forests, and three separate S-curve parametrisations by specifying alternative values for the a parameter in Equation (1). These scenarios are labelled: (1) no land use change, (2) fast adoption ($a=0.3$), (3) moderate adoption ($a=1$) and (4) delayed adoption ($a=5$). As the total amount of forest land is exogenous in all scenarios, the area of harvest land available for land use change does not change between these adoption scenarios. The shape of the fast, moderate and delayed adoption land use change curves that determine the proportion of eligible forest land that is converted to permanent forest in a given year is illustrated in Figure 2.

Table 3 provides an overview of forestry decisions in our modelling framework. As an ETS first operates in 2022 and forestry decisions are based on the carbon price from the previous year, endogenous land use change begins 2023. The table shows how the models are linked and how decisions in 1 year affect outcomes in subsequent years.

4 | RESULTS

This section reports results for the TP1 simulation for four alternative land use scenarios: the (exogenous) land use scenario used by Winchester and White (2022), labelled no land use change, as well as the three S-curve scenarios: delayed adoption, moderate adoption and fast adoption. For each scenario, we report the carbon price, GDP, welfare, land used for permanent forests, output from the production forest sector and gross emissions (excluding biogenic methane) from 2014 to 2050.

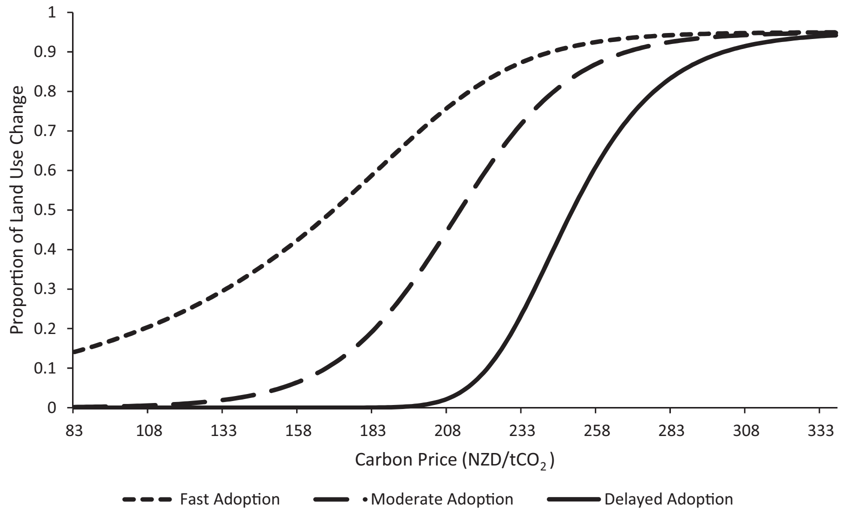

FIGURE 2 Shape of the three S-curves in the land use change model.

TABLE 3 Overview of forestry decisions in the modelling system.

Step	Action
1	If $t = 2022$: Simulate the C-PLAN model to estimate the carbon price in year t (p_t). If $t > 2022$: Go to Step 2
2	Use p_t in Equation (1) to calculate the proportion of production forest land at harvesting age that changes from production to permanent forest for the six forest size–land productivity categories (σ_{lyt+1})
3	Use σ_{lyt+1} values in Equation (2) to calculate the total amount of land that changes from production to permanent forests at $t+1$ (φ_{t+1})
4	Use φ_{t+1} to update the total amount of permanent forest land in the ENZ model
5	Simulate the forestry component of the ENZ model to calculate land used for production and permanent forests, and CO_2 emissions sequestered by production and permanent forests
6	Use the CO_2 sequestration estimates from the ENZ model to calculate the cap on gross emissions required to meet the ETS cap on net emissions in year $t+1$
7	Simulate the C-PLAN model with land use estimates from Step (5) and the gross emissions cap from Step (6) to estimate the carbon price in year $t+1$. Go to Step (2) to calculate forest land use and sequestration for year $t+2$

Table 4 presents a summary of results in 2015, 2035 and 2050 for the no land use change and three S-curve scenarios. The table shows that, in all the S-curve scenarios, the carbon price decreases, gross GHG emissions increase, forestry removals increase and land used for permanent forests increase compared with the no land use change scenario (where forestry land use change is exogenous). Land use change begins to occur in the fast and moderate adoption scenarios by 2031, and for the delayed adoption scenario, this does not occur until 2043. Table 4 also shows that, compared with the no land use change scenario, land use change to permanent forests increases welfare and increases GDP by 2050. This is due to the increase in the gross GHG emissions cap caused by the additional carbon permits produced by permanent forests. The increase in land for permanent forests in the S-curve scenarios decreases output from the production forestry sector.

TABLE 4 Summary results for 2015, 2035 and 2050.

	2015	2035				2050			
		No land use change	Delayed adoption	Moderate adoption	Fast adoption	No land use change	Delayed adoption	Moderate adoption	Fast adoption
CO_2 price, NZD/tCO_2	3.37	124.96	124.96	124.88	94.71	381.84	242.66	178.77	109.86
Gross GHG emissions[a], Mt CO_2e	45.45	35.74	35.74	35.78	36.93	23.41	25.89	27.19	29.93
Forestry removals, Mt CO_2e	13.20	13.07	13.07	13.11	14.26	23.41	25.89	27.19	29.93
Total permanent forest land, 000s ha	34.84	62.99	62.99	64.06	92.78	96.89	158.76	193.91	277.20
Production forestry output, billions 2017 NZD	3.84	5.51	5.51	5.51	5.42	6.34	6.16	6.05	5.79
Welfare, billions 2014 NZD	120.72	190.09	190.09	190.10	190.15	245.59	245.83	245.88	245.95
GDP, billions 2017 NZD	251.99	395.22	395.22	395.23	395.42	508.72	509.40	509.52	509.78

[a]This measure is excluding biogenic methane emissions.

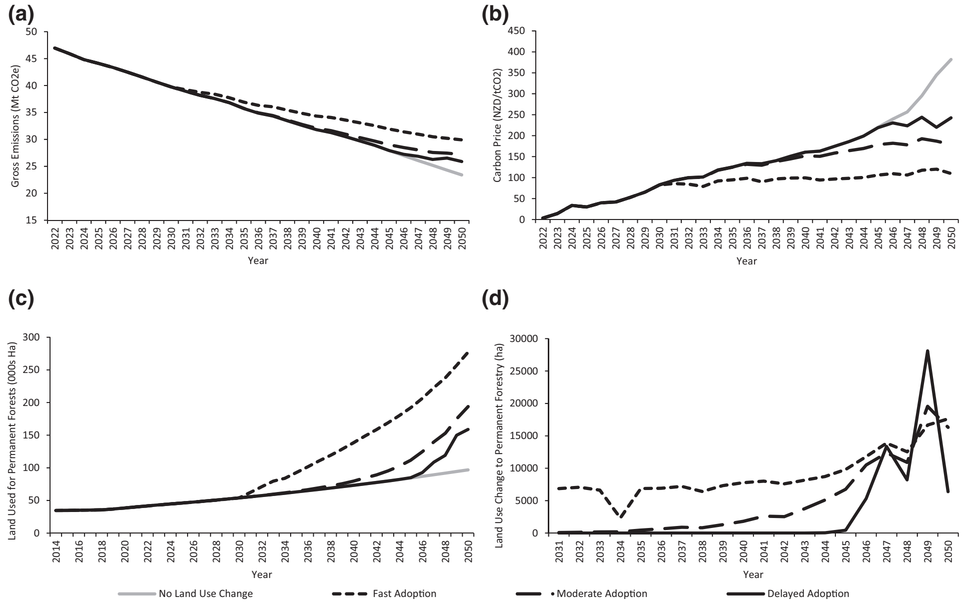

FIGURE 3 (a) Carbon price from 2022 to 2050 in each scenario. (b) Gross GHG emissions (excluding biogenic methane) from 2022 to 2050 in each scenario. (c) Total land used for permanent forests from 2014 to 2050 in each scenario. (d) Land use change from production to permanent forests each year from 2031 to 2050 in the S-curve scenarios.

Results for each year are reported in Figure 3a–d. In the S-curve scenarios, the carbon price (Figure 3a) drives changes in forestry land use. As the carbon price increases, land changes use from production to permanent forests and carbon sequestration increases. Consequently, relative to the no land use change scenario, this allows for higher gross emissions within the NZ ETS cap (Figure 3b) and ultimately results in lower carbon prices. Gross emissions increase above the no land use change scenario in the fast adoption scenario and the moderate adoption scenario by 2031, and they do the same for the delayed adoption scenario in 2043. In all scenarios, net emissions are the same and (excluding biogenic methane) reach zero by 2050.

As more land use change occurs in the fast adoption scenario than in the moderate and delayed adoption scenarios (Figure 3c), carbon prices are relatively high in the slower adoption scenarios. Specifically, when there is no land use change, the carbon price reaches 381.84 NZD/tCO_2 in 2050. In the delayed adoption scenario, the 2050 carbon price is 242.66 NZD/tCO_2; in the moderate adoption scenario, it is 178.77 NZD/tCO_2; and in the fast adoption scenario, it is 109.86 NZD/tCO_2. This means that if farmers delay their land use change to permanent forests, there will be higher carbon prices in future years that increase incentives to switch to permanent forests in those years.

The impact of delayed action on future land use change is illustrated in Figure 3d, which shows the annual changes from production to permanent forest land. Whilst the total amount of land in permanent forests is highest in the fast adoption scenario, the yearly amount of land converted to permanent forest is sometimes higher in other scenarios in later years. For example, in 2049, 16,662 ha of land are converted to permanent forests in the fast adoption scenario, and the corresponding numbers in the moderate and slow adoption scenarios are, respectively, 19,566 and 28,109. These relatively high levels of land use change then reduce carbon prices in future years (Figure 3a), which causes some volatility in the amount of land changing use from 2046 to 2050 in all scenarios.

As delayed action increases incentives to convert to permanent forests in future, there will be significant land use change in all scenarios by 2050 (Figure 3c). For example, even in the moderate and delayed adoption scenarios, there is 1.64 to two times more land used for permanent forests than the no land use change scenario by 2050. This delayed action effect also means that gross emissions start to converge across scenarios in later years (Figure 3b). In 2050, gross emissions in the fast adoption scenario are 1.28 times greater than the no land use change scenario, 1.16 times greater in the moderate adoption scenario and 1.11 times greater in the delayed adoption scenario. Due to land use change only occurring at harvesting age in this modelling, the total amount of land in permanent forests is only a small proportion of total exotic forest land in all scenarios. For example, in the fast adoption scenario, only 0.28 of 2.82 million hectares of exotic forests will be permanent forests in 2050.

Overall, our results illustrate that over the longer periods, short-run decisions by foresters have little impact on land use change to permanent forests in this model. If foresters decide not to switch to permanent forests in the current year, the carbon price will increase, and they will be incentivised to make the change in a later year.

5 | DISCUSSION AND CONCLUSION

The core climate change policy tool in New Zealand is the NZ ETS (PCO, 2019). With the current rules around forestry, there are incentives for forestry owners to switch to permanent forests. We focus on land use change from exotic production forests to permanent forests when trees are at harvest age. We represent this choice using three S-curve scenarios. To estimate this land use change and the impacts from it, we simulated a modelling system that included an economy-wide model, a forestry model and land use change functions.

Our analysis considers land use change from production to permanent forest motivated by the ability to earn carbon permits rather than harvesting timber. To represent this change, we use S-curves. This is carried out under the assumption that farmers do not have perfect carbon price forecasting information and will make decisions on the profitability of permanent forests as if it is the adoption of a new technology. Our approach is based on the scepticism regarding climate change (Yousefpour et al., 2012) and climate change-related policies (MPI, 2019) by farmers, which will contribute to a slow adoption of new forms of land use related to policy changes. This is comparable with the methodology used by Adams and Turner (2012), who used transition probabilities to show that a higher carbon price leads to an increase in afforestation and carbon sequestration from forestry, but that optimal land use change is limited by uncertainty around the future carbon price. Manley (2022) reached similar conclusions regarding afforestation, although with a different methodology. Our analysis supports the results of these papers and has the additional robustness of an annually updating carbon price based on the change in carbon sequestration every year.

We found that when forestry owners respond to the carbon price, there is a noticeable increase in the amount of carbon sequestered and with more carbon permits produced in the NZ ETS, other sectors can emit more and stay within the emissions cap. Ultimately, this lowers the economic costs of meeting New Zealand's long-term climate goals.

We also found that feedback from the land use change to the carbon price means that the responsiveness of forest owners to the carbon price (as measured by the S-curves) has a relatively modest long-run impact. That is, a small response in the current year leads to a higher carbon price in future years, which incentivises more conversion to permanent forests, and ultimately offsets some of the small response in previous years. This is a consequence of the emissions cap imposed as part of the NZ ETS, with an increase in permanent forests (and their carbon sequestration) decreasing carbon prices in future years.

This suggests that if foresters are able to earn ETS permits for sequestering carbon, the long-run amounts of permanent forests and carbon sequestered are relatively insensitive to the responsiveness of farmers. To ensure foresters respond to the carbon price, the New Zealand Government should put resources into encouraging farmers to understand the potential benefits of including permanent forests in the ETS. These benefits include the potential additional profit foresters can make from being included in the NZ ETS and nonmarket benefits including the increased carbon sequestration from the trees and the benefits to soil and water quality they can provide (New Zealand Forest Service, 2021). The treatment of permanent forests in the NZ ETS should serve as a blueprint for other regions to incentivise forestry carbon sequestration.

A limitation of our approach is that we assume that foresters' trust in the longevity of the ETS is constant. As the NZ ETS is around for longer, there should be an expectation that farmer's trust of the policy and its potential benefits will increase. This means that the shape of the S-curves could change over time, and the switch to permanent forests could be higher than what is estimated here. Another limitation is the expectation that all land use change occurs at the age of 28, the age when radiata pine tends to be harvested in New Zealand (MPI, 2021). It is likely that land will change use at other mature forest ages, which impacts the amount of potential carbon sequestration (i.e. if a production forester changes land use at a harvesting age of 25, this will be included as three additional years of carbon permit production relative to our analysis). There may also be changes in forestry inputs (e.g. a preharvesting age decision to switch from production to permanent forests may result in less trimming for the affected trees). Also, this paper is potentially restricted in its analysis because it models all exotic forests as if it is radiata pine and excludes indigenous forests. Other species of trees in New Zealand, especially native trees, may not have as high a potential for ETS profitability but they do provide a host of other nonmarket benefits such as improvements in biodiversity, increased habitats for native species and increased cultural significance compared with what can be provided by radiata pine (New Zealand Forest Service, 2021).

Future studies could expand on this research by adding in a ‘trust component’ to the S-curves, including an analysis where species other than radiata pine are represented, and using a less rigid land use change age projection to estimate the changes in carbon permits produced over time. This work could also be augmented by including land use change between agricultural uses in the CGE model. This could be carried out by specifying additional S-curves or using an existing approach to represent land use change in CGE models.

Finally, policy-driven forestry incentives in New Zealand have been introduced in the past, including the One Billion Trees Program (New Zealand Forest Service, 2021). This project had the aim of helping meet the government's goal of planting 1 billion trees around New Zealand by 2028 through funding grants for planting native and exotic trees between 2018 and 2021. It incentivised 42 million trees to be planted around New Zealand, 80% of which were native species and 20% were exotic. The difference between this policy and the inclusion of forestry permits in the NZ ETS is the One Billion Trees Program was more focussed on increasing the incentives for native trees to be planted rather than trees with high levels of carbon sequestration. This provides an interesting dilemma for the government: whether to value the higher levels of carbon sequestration from exotic trees over the additional co-benefits and ecosystem service values from native forests. To increase incentives for native forests in New Zealand, the government would have to introduce a policy outside the NZ ETS.

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DATA AVAILABILITY STATEMENT

The data analysed in this study are available as part of the Global Trade Analysis Project (GTAP) Database and the Energy and Emissions in New Zealand model. To gain access to the GTAP data, users need to purchase a GTAP license. To gain access to the Energy and Emissions in New Zealand model and data, users need to sign license agreements with the Climate Change Commission available here: https://www.climatecommission.govt.nz/our-work/advice-to-government-topic/inaia-tonu-nei-a-low-emissions-future-for-aotearoa/modelling.

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