Logs or Permits? Forestry Land Use Decisions in an Emissions Trading Scheme

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. New Zealand has a comprehensive emissions trading scheme which includes incentives for farmers to plant permanent exotic forests. We use 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. We find that even if the responsiveness of forestry owners to the carbon price is "low", there is a significant amount of carbon sequestered by forests by 2050. This is because, if foresters decide not to switch to permanent forests in one year, carbon prices and ultimately incentives to convert to permanent forests will be higher in future years.

Keywords

Climate change & greenhouse, Forestry, Computable general equilibrium, Land use & tenure.

1. Introduction

Managed production forests provide both market and non-market benefits. Market benefits come in the form of timber production, where trees are cut down at maturity and sold as pulp, logs, or wood chips. Non-market benefits from mature forests include ecosystem services, natural disaster protection, recreational activities, agricultural productivity improvements, tourism, and carbon sequestration (Hanley, Shogren & White, 2007; and Figueroa & Pasten, 2015). Due to these non-market 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 incorporate the non-market benefits of their forests into their harvesting decisions. This can only be achieved with government intervention.

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 non-market benefits from each rotation. One policy which 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) which currently accounts for approximately 52 percent of New Zealand's domestic emissions (Leining, 2022). Due to changes in 2023, there are rules around forestry in the NZ ETS which will incentivise farmers to plant permanent forests as the price of carbon increases. 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). In comparison, the European Union ETS (EU ETS) covers approximately 40 percent of EU emissions and does not include any incentives for carbon sequestration from forestry (European Commission, 2022). In this paper, we use an economy-wide/computable general equilibrium (CGE) model and a forestry model to estimate the impact of the NZ ETS on the land used for exotic permanent forests. We further investigate how this land use change effects the expected quantity of carbon sequestered, the amount of land harvested, the price of carbon, and economic outcomes.

Other research that 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 & Turner (2012) provided a model to represent the 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, Kahui & Farhat (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 use under the NZ ETS. A limitation of these studies is the low level of carbon prices which they use in their analysis. 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.

Modelling forestry decision-making has often been done from the perspective of the optimal harvest age. An influential model of forestry decision-making is Faustmann's formula (Faustmann, 1849). This formula has since been adapted to: (1) model forestry decisions around the world (Crabbe and Long, 1989; Wilson *et al.,* 1998; and Wang and van Kooten, 2001), (2) represent non-market benefits from standing forests (Hartman, 1976), and (3) account for the risk to profitability from variability in random factors such as climate (Reed, 1984). These studies looked at the decision-making of production forest farmers when they are first planting their trees. Under the NZ ETS, farmers now have an additional trade off to consider: whether to harvest their trees at maturity or keep them in the ground to earn carbon permits. Given the potential profits from permanent forests, rather than calculating the optimal harvest age at the time of planting, we focus on production forest farmers who choose to convert to permanent forests at the time of harvesting.

As summarised by Taheripour *et al*. (2020), several papers have used CGE models to examine changes in land use from one form of agriculture to another. This has included estimating the impact of climate change on agricultural crop production (Costinot, Donaldson & Smith, 2016); modifying constant elasticity of transformation functions to keep total land in a CGE model constant when measuring land use change (Horridge, 2014 and van der Mensbrugghe & Peters, 2016); measuring GHG emissions from land use change driven by crop-based biofuels (Melillo *et al.*, 2009; Hertel *et al.*, 2010; and Timilsina *et al.* 2012); and estimating the impacts of changes in trade on land allocation, productivity, and agricultural yields (Gouel & Laborde, 2018; Sotelo, 2019; and Farrokhi & Pellegrina, 2020). This research is different to other CGE based literature because it focuses on a specific form of land use change within forestry: the switch from production to permanent forests due to a carbon price.

Farmers, like most people, tend to be 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.*, 2011). To represent these characteristics, we use sigmoid functions (also known as S-curves) to model land use change. These curves assume that most farmers will require higher than 'breakeven' carbon prices before they change to permanent forests.

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 concluding remarks.

2. The New Zealand Emissions Trading Scheme

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 percent of New Zealand's gross emissions (biogenic methane emissions from agriculture, which accounts for approximately 48 percent 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. One of the most notable changes was the delinking from the international Kyoto Market in 2015, since then it has been a domestic only ETS. Another change has come from 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 percent below 2017 levels by 2035 and 24-27 percent below these levels by 2050, and all other GHGs must be at net zero by 2050 (PCO, 2019). The 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 to the structure of the ETS, including the future pricing of biogenic methane from agriculture and changes to 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. Permits can be earnt 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.

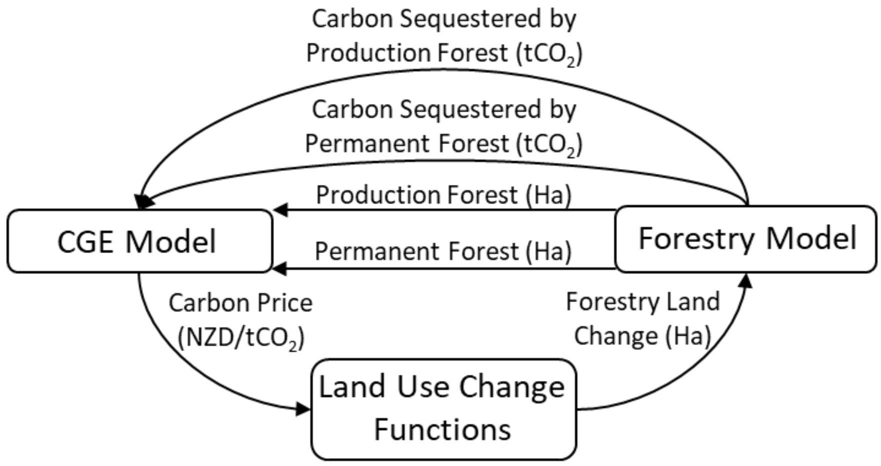
Native forest land use decision-making is not included in this research due to the lack of data available for private native forest landowners. Exotic forests, especially pine, also have a higher rate of carbon sequestration per hectare compared to native forests (PCO, 2008), so planting of native forests is largely done for non-economic 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 model 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 to leave them unfelled and generate permits for the NZ ETS. This decision uses 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.

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



We focus on the land use decision 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 carbon price from the year before. This is done under the assumption that, as detailed in Section 3.4, farmers do not have perfect information and will make decisions on the profitability of permanent forests over a short period of time.

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, and (4) a description of our land use change model.

3.1 The CGE model: C-PLAN

The CGE model used for this analysis is an augmented version of the Climate PoLicy ANalysis (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, 1995) a subsystem of the General Algebraic Modeling 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 of 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. Details on each scenario and more information on the model is 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. The carbon pricing policy for biogenic methane limits methane emissions to 24 percent 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 forestry is still exogenously determined using estimates from the CCC. 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 value of land inputs used in the original production activity represents 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 values are calculated using the CCC 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. The carbon permits need to be updated 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 ENZ

The Energy and Emissions in New Zealand (ENZ) model was built for the CCC to provide policy advice for the government (CCC, 2021). A section 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. 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. Permanent forest carbon sequestration is calculated using the stock change approach. The model assumes, in all years, that 6.1 percent of exotic trees planted are permanent forest, with the rest being production forest. 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 include this code in 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 affects total carbon sequestration and feed that information into the C-PLAN model.

3.3 The 'Breakeven' Carbon Price

The change in land use between permanent and production forests modelled in this paper assumes a harvest age of 28 years, based on the average age of harvest for radiata pine from 2017 to 2021, as it is the most planted species of exotic tree in New Zealand (MPI, 2021). 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 hectares in size that use the government provided carbon look up tables for their permit calculations and for forests larger than 100 hectares in size which have unique carbon look up tables created for their permit 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) and the site index (the height of the dominant tree at a predefined age) which measure productivity based on the change in tree biomass over time (Kimberley *et al.*, 2005). 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 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) 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 hectares in size.

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 6 'breakeven' carbon prices (see Table 1) compared to the 18 calculated by Manley (2022).

The baseline used in the C-PLAN and ENZ models assumes there is a 35 NZD/tCO_2 carbon price in the years the NZ ETS is active (Winchester & White, 2022; and CCC, 2021). 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.

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 Harvested Land
	Small Forests (Less than 100 ha)	
Low	102.33	0.053
Medium	100.33	0.044
High	106.67	0.095
	Large Forests (Greater than 100 ha)	
Low	72.33	0.145
Medium	76	0.164
High	82.33	0.499

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

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 a sigmoid function (also known as an S-Curve). The use of S-Curves to describe farming decisions was pioneered by Beal & Bohlen (1956), Beal & Rogers (1960) and Coleman *et al*. (1955). 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, 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.* (2011), 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 climate change and climate change policies. There is also scepticism regarding the longevity of government policies by farmers which leads 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 colleagues 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 (non-adopters) (Beal & Bohlen, 1956).

The sigmoid function used in this analysis determines the proportion of forest land that changes from production to permanent forests. This function includes 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/tCO2, the 2050 (and highest) carbon price in the TP1 scenario estimated by Winchester & White (2022).[1] This is used under the assumption that foresters have access to this information (available on the CCC's web site) and will internalise this as the expected high price.

[1] 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.

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

$$\sigma_{lyt} = \frac{1}{(1 + e^{-0.05(p_{t-1} - \hat{p}_{ly})})^{a}} \quad (1)$$

where σ_{lyt} 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; p_{t-1} is the carbon price estimated by the C-PLAN model at time $t-1$; $\hat{p}_{ly}$ 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.

The maximum amount of land that can change from production to permanent forests each year is based on the estimated hectares of land expected to be harvested, as estimated by the ENZ model. The amount of land that changes from production to permanent forests is a function of the maximum amount of land that can change uses and a series of sigmoid function calculations (one for each productivity-farm size category). In each year, there are six S-Curves operating, each using one 'breakeven' carbon price as its starting point, with the proportion of harvest land applying to each S-Curve described in Table 1. Equation 2 shows how the results from each of the six curves are added together to get the total proportion of harvest land changing use.

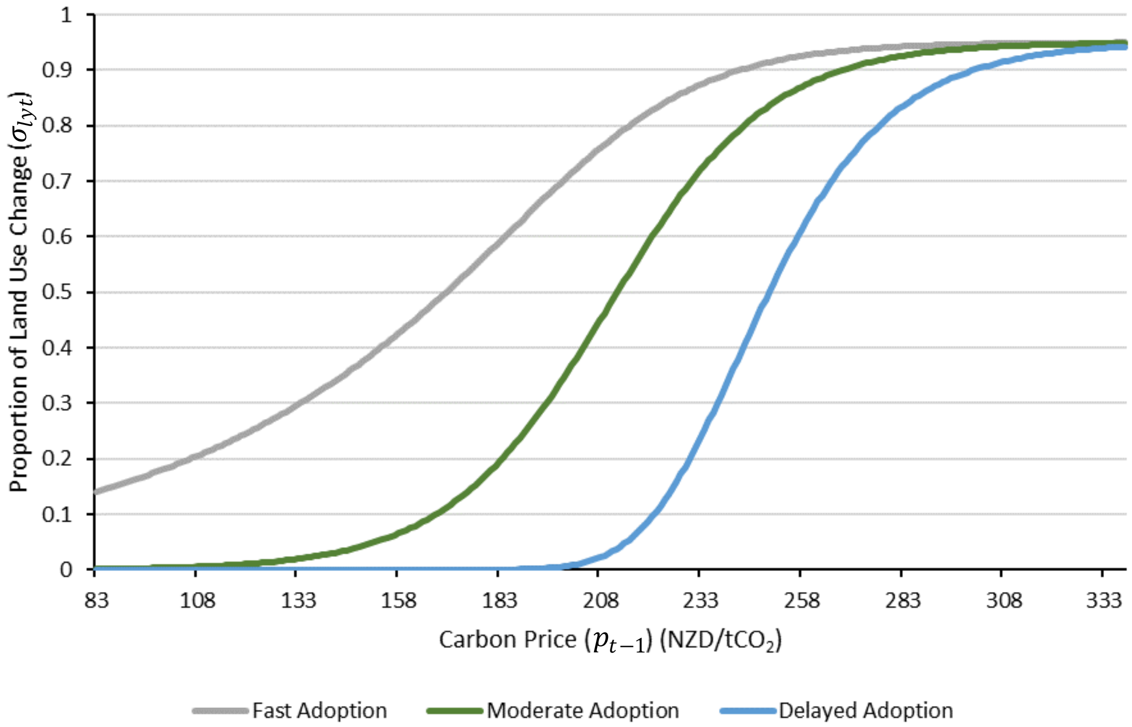
$$\varphi_t = 0.95 \sum_{l} \sum_{y} \beta_{ly} \sigma_{lyt} \quad (2)$$

where φ_t is the total land use change which occurs at time t, and β_{ly} is the proportion of harvest land impacted at each 'breakeven' carbon price based on land size *l* and productivity level *y*. The total proportion of harvested land changing use is multiplied by 0.95 to represent the small proportion (five percent) of land holders who will never change their land use to permanent forest regardless of how high the carbon price is.[2]

To give a diverse representation of land use change, we provide results from three separate S-Curve parametrizations by specifying alternative values for the a parameter in equation (1). These parameterizations are labelled: (1) Fast adoption (a = 0.3), (2) Moderate adoption (a = 1); and (3) Delayed adoption (a = 5). The shape of the three curves which determines the proportion of eligible forest land in a given year that is converted to permanent forest is illustrated in Figure 2.

[2] We scale the aggregated S-curves by 0.95 based on research by Boscolo, Snook & Quevedo (2009), which found that the average adoption rates by farmers in Bolivia are 88 percent, 96 percent and 93 percent for, respectively, sustainable forestry management practices which have clear regulations, are easy to enforce, and have clear and measurable changes on the farm.

Figure 2: The shape of the three S-Curves in the land use change model.



4. Results

This section reports results for the TP1 simulation for four alternative land use scenarios: the (exogenous) land use scenario used by Winchester & White (2022), labelled no S-curve, and one for the each of the S-curves described in Section 3. For each scenario, we report the carbon price, GDP, welfare, land used for permanent forests, and gross emissions (excluding biogenic methane) from 2014 to 2050.

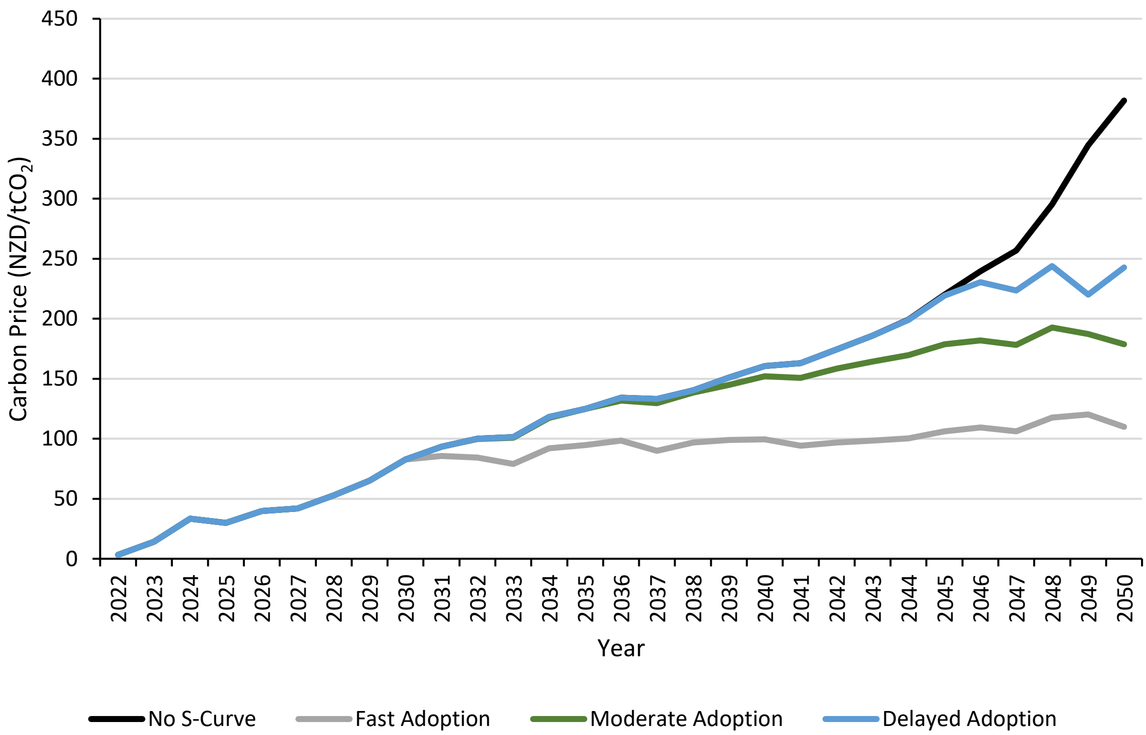
Table 2 presents a summary of results in 2015, 2035, and 2050 for the no S-Curve and three S-Curve scenarios. The table shows that, in all the S-Curve scenarios, the carbon price decreases, gross GHG emissions increase, forestry removals increase, and land used for permanent forests increase compared to the no S-Curve scenario (where forestry land use change is exogenous). These results are further demonstrated in Figures 3 to 7. Table 2 also shows that, compared to the no S-Curve scenario, land use change to permanent forests increases welfare and increases GDP. This is due to the increase in the gross GHG emissions cap caused by the additional carbon permits produced by permanent forests.

Table 2: Summary results for 2015, 2035 and 2050.

	2015	2035				2050			
		No S-Curve	Fast Adoption	Moderate Adoption	Delayed Adoption	No S-Curve	Fast Adoption	Moderate Adoption	Delayed Adoption
CO_2 Price, NZD/tCO_2	-	124.96	94.71	124.88	124.96	381.84	109.86	178.77	242.66
Gross GHG Emissions*, Mt CO_2e	45.45	35.74	36.93	35.78	35.74	23.41	29.93	27.19	25.89
Forestry Removals, Mt CO_2e	13.20	13.07	14.26	13.11	13.07	23.41	29.93	27.19	25.89
Total Permanent Forest Land, 000s ha	34.84	62.99	92.78	64.06	62.99	96.89	277.20	193.91	158.76
Welfare, billions 2014 NZD	120.72	190.09	190.15	190.10	190.09	245.59	245.95	245.88	245.83
GDP, billions NZD	251.99	395.22	395.42	395.23	395.22	508.72	509.78	509.52	509.40

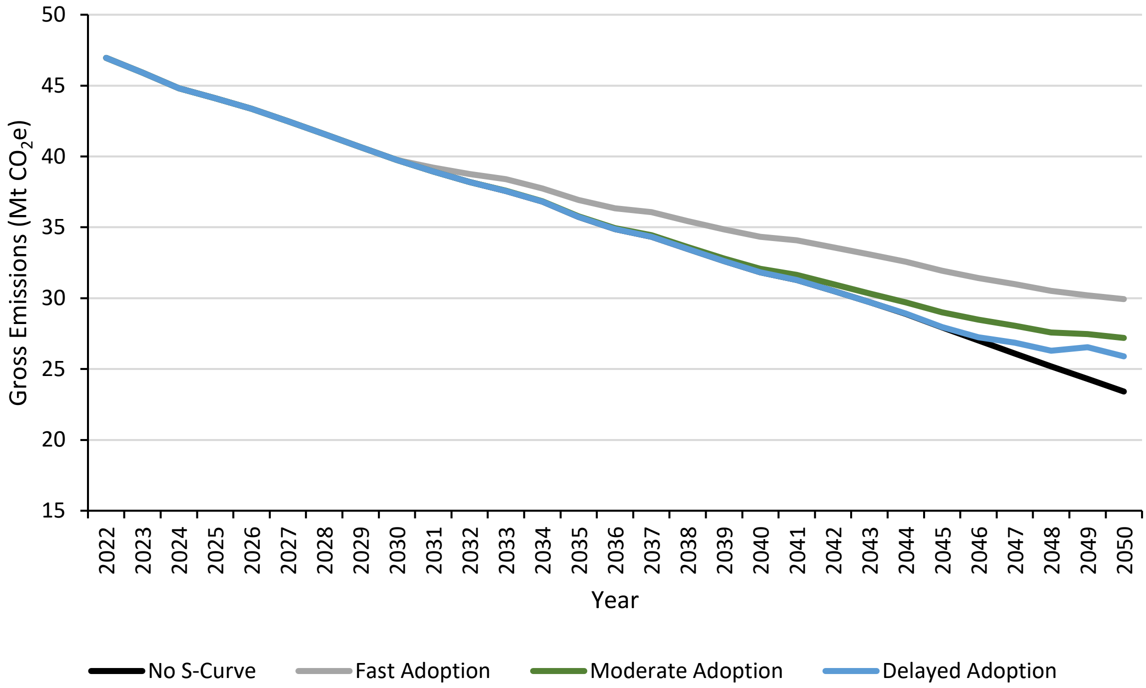
*: this measure is excluding biogenic methane emissions.

Figure 3: The carbon price from 2022 to 2050 in each scenario.



In the S-Curve scenarios, the carbon price drives changes in forestry land use. As the carbon price increases, land changes use from production to permanent forests and carbon sequestration increases. Consequently, there are more carbon permits produced in the economy and, relative to the no S-Curve scenario, the carbon price decreases. When there is no S-curve, the carbon price reaches a maximum of 381.84 NZD/tCO_2, as seen in Figure 3. In the fast adoption scenario, the carbon price reaches a maximum of 109.86 NZD/tCO_2; in the moderate adoption scenario it reaches 178.77 NZD/tCO_2; and in the delayed adoption scenario it reaches 242.66 NZD/tCO_2. This shows that a quicker uptake in permanent forests, as seen in the fast adoption scenario and the moderate adoption scenario, causes a lower carbon price than would be expected under no harvest age land use change.

Figure 4: Gross GHG emissions (excluding biogenic methane) from 2022 to 2050 in each scenario.



Gross emissions (excluding biogenic methane), displayed in Figure 4, increase above the no S-Curve 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. By 2050, gross emissions in the fast adoption scenario are 1.28 times greater than the no S-Curve scenario, 1.16 times greater in the moderate adoption scenario, and 1.11 times greater in the delayed adoption scenario. In every scenario, net emissions (excluding biogenic methane) reach zero by 2050. Land use change to permanent forests has an impact on the gross emissions under the NZ ETS as the increased number of permits and the lower carbon price allows other sectors in the economy to emit more and stay within the emissions cap. The increase in permits comes from the additional carbon sequestration from exotic trees. The gap in gross emissions between the scenarios starts to close by 2050. This is driven by, relative to the fast adoption scenario, higher carbon prices in later years in the moderate and delayed adoption scenarios which creates greater incentives for more permanent forests.

Figure 5: Total land used for permanent forests from 2014 to 2050 in each scenario.

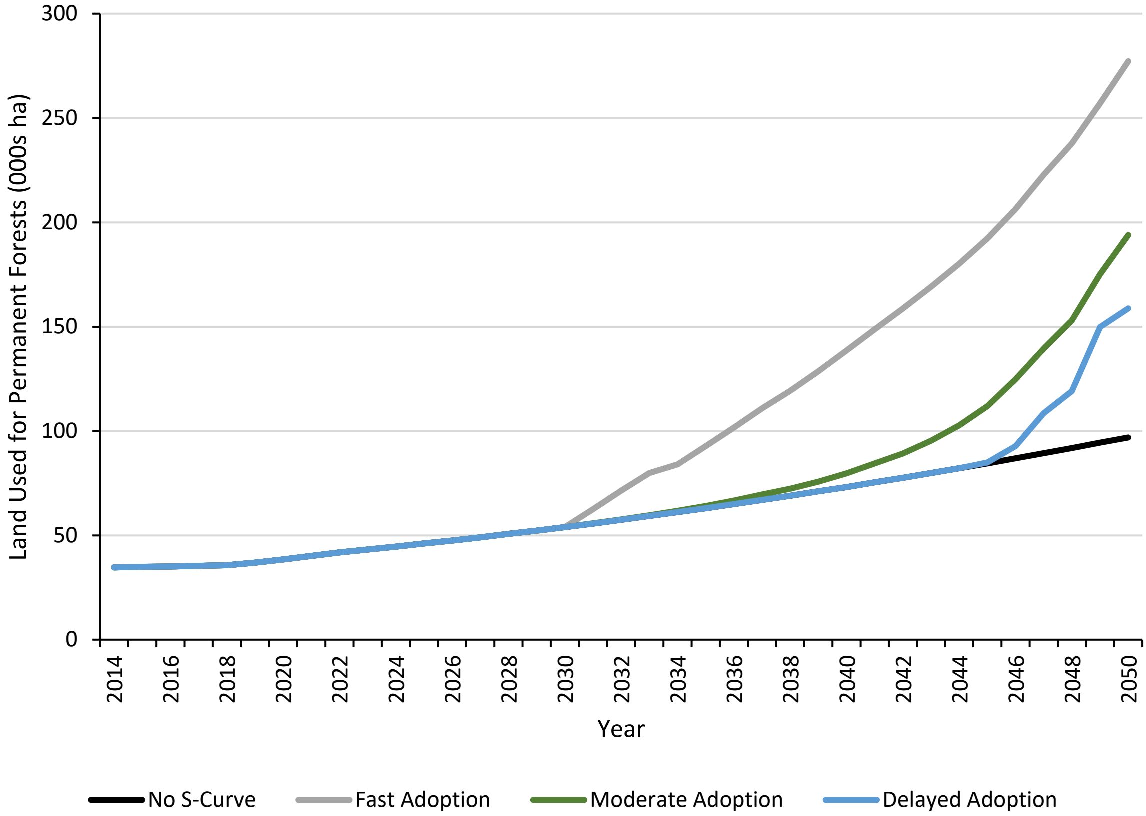
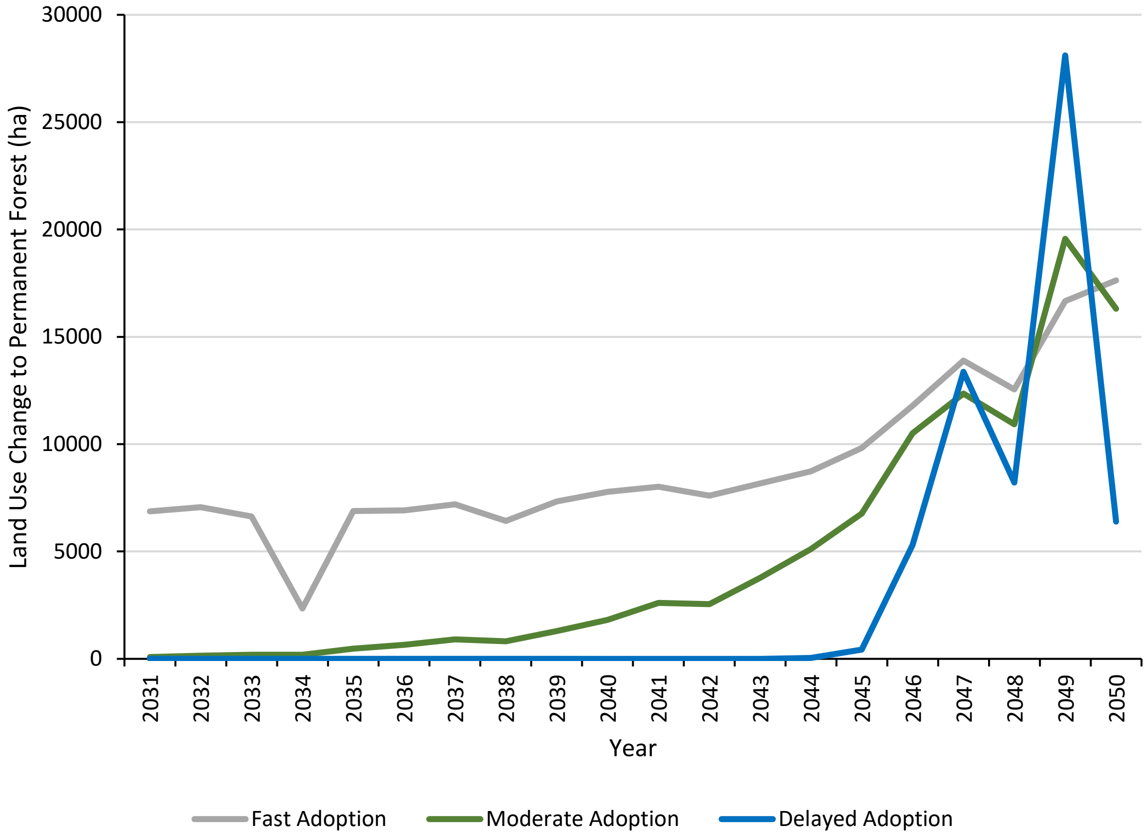


Figure 5 shows the total land used by permanent forests under the different land use change S-Curves. As expected, there is more permanent forest land in the fast adoption scenario than in other scenarios. However, even when there is a relatively low rate of land use change, as seen in the moderate and delayed adoption scenarios, there is still 1.64 to 2 times more land used for permanent forests compared to the no S-Curve scenario by 2050.

Figure 6: Land use change from production to permanent forests each year from 2031 to 2050 in the S-Curve scenarios.



While 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, as illustrated in Figure 6. In the moderate and delayed adoption scenarios, it takes a relatively higher carbon price for land use change to occur. This means the moderate and delayed adoption scenarios have a higher carbon price across all years compared to the fast adoption scenario. The carbon price in these scenarios increases to a point where the yearly increase in permanent forest land begins to increase above the fast adoption scenario. This relatively high level of land use change then significantly reduces the carbon price in future years which causes some volatility in the hectares of land changing use from 2046 to 2050 in both slower adoption scenarios. This result demonstrates that over the long run, 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. Conclusions

The core climate change policy tool in New Zealand is the 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 production forests to permanent forests when trees are at harvest age. We represent this choice using three S-Curve scenarios, with the assumption that the decision to switch from production to permanent forests is similar to the adoption of new technology. 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 considered land use change from production to permanent forest motivated by the ability to earn carbon permits by sequestering carbon rather than harvesting timber. This is done under the assumption that farmers do not have perfect carbon price forecasting information and will make decisions on the profitability of permanent forests in short periods of time.

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 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 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. 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-Curve 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 pine tends to be harvested in New Zealand (MPI, 2021)**.** It is likely that land will change use at all forest ages, which impacts the amount of carbon sequestration. Future studies could expand on this research by adding in a 'trust component' to the S-Curves and using a more accurate harvest 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 done by specifying additional S-Curves or using an existing approach to represent land-use change in CGE models.

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