The impact of carbon and water cycles on farm economics in a changing climate

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Abstract

We examine the empirical impact of carbon and water cycles on farm economic performance in Aotearoa New Zealand. We do so by linking a unique longitudinal dataset of farms' financial and agricultural activities with outputs from the Biome-BGC model that simulates the storage and flows of water, carbon, and nitrogen between ecosystems and the atmosphere across ecosystems. The interlinked dynamics of carbon-water cycles over time and across space are observed via changes in pasture dry matter, exotic forest net ecosystem productivity, and soil moisture water deficit. We estimate separate econometric models for different farm systems, including dairy, sheep and beef and forestry farms.

On a dataset of 387,009 annual observations from 95,532 farms over the period 2003-2022, we establish a statistically and economically significant relationship of carbon and water cycles on economic outcomes of pastoral farms. Specifically, higher photosynthetic carbon uptake, proxied by higher pasture dry matters, increase farm profitability through substantially increased revenues as compared to intermediate costs. This effect is less statistically significant but more economically meaningful for sheep and beef farms as compared to dairy farms due to their less intensive input systems. In contrast, reduced surface water availability, indicated by increased soil moisture deficit, has a negative effect on profitability. This impact is weaker for sheep and beef farms due to the delayed economic response to drought which materializes only after three years. We also find little evidence of the contemporary effect of carbon-water cycle on forestry farm economics, most probably due to long harvest cycle and the design of carbon accounting methods.

JEL Classification

Q51; Q54

Keywords

Nature related risk • Climate finance • Water cycle • Carbon cycle • Farm economics

Data Statement

Access to the data used in this study was provided by Stats New Zealand under conditions designed to give effect to the security and confidentiality provisions of the Data and Statistics Act 2022. The results presented in this study are the work of the author, not Stats New Zealand or individual data suppliers. These results are not official statistics. They have been created for research purposes from the Longitude Business Database (LBD) which is carefully managed by Stats New Zealand. For more information about the IDI please visit https://www.stats.govt.New Zealand/integrated-data. The results are based in parts from the Agriculture Production Survey and Tax filed financial account (IR10) from LBD database. Any discussion of data limitations or weaknesses is in the context of using the LDB for statistical purposes and is not related to the data's ability to support Inland Revenue's core operational requirements.

Declaration of Generative AI and AI-assisted Technologies

During the preparation of this work, the author(s) used ChatGPT to assist with writing codes, proofreading and identifying minor typographical and grammatical errors. All content was subsequently reviewed and edited by the author(s), who take full responsibility for the final version of the published article.

1. Introduction

This study explores how Aotearoa New Zealand's farm economics are influenced by the interlinked dynamics of the water and carbon cycles. Our overarching question is: *To what extent do spatio-temporal variations in water and carbon cycles impact farm economic outcomes across different land use?* This question worths investigation for several reasons, most notably due to the dominant role of farming industries in New Zealand's nature-based economy. In New Zealand, food and fibre contributes to 11% of its annual GDP but 80% of its total exported good. Rural land use is dominated by pastoral farming and harvest forestry, in addition to horticulture and biodiversity conservation. Unlike other developed countries, the country maintains an exceptionally low level of agriculture subsidy, which means farmers are directly exposed to global market signals. Furthermore, New Zealand Emissions Trading Scheme is the only carbon price scheme in the world that is designed to cover the entire forestry sector and to allow a 100% offset of fossil fuel emissions through forestry carbon sequestration. This context provides a unique setting to investigate how nature-based ecosystem services, such as carbon and water, influence farm-level economic outcomes without distorts from government intervention. In the present context of increasing pressure from climate change and nature loss, exploring the impact of water and carbon cycles on farm economics is highly relevant to land management and land-use change decisions in New Zealand.

Given the dominance of farming industries, land-use change in New Zealand has historical been, and continues to be, largely driven by economic considerations. Starting in the 1990s, the country experienced a dairy boom driven by low land prices and rising global dairy prices, leading to a shift from sheep and beef farming to irrigated dairy farming on large scales. Between 1990 and 2022, the national dairy herd more than doubled from 2.4 million to 5.9 million, while the sheep population halved to 24.4 million in the same period (MfE & Stats New Zealand, 2024). Although this trend has stabilised in the recent years, dairy farms have continued to intensify their farming practices via higher stocking rates and increased uses of fertilizers, irrigations, and supplementary feed. As dairy herds grow, they put increasing pressures on the natural environment, including blue water losses from irrigated pasture, nitrogen leakage into waterways, and rising greenhouse gas emissions including methane from enteric fermentation in ruminant livestock and nitrous oxide from urine, dung, and nitrogen fertilisers (Leahy et al., 2019; Cameron and Peer 2025).

Concurrently, rising carbon prices and the inclusion of forestry as a carbon sink under the NZ ETS have driven widespread conversion of pastoral farms into forestry (Polyakov et al., 2024). On annual basis between 2019 and 2022, it is estimated that around 55,000 hectare is converted from sheep and beef farms to forestry farms for the dual purpose of harvest wood and carbon storage (Beef + Lamb

New Zealand, 2023a).[1] While plantation forestry is often perceived as more environmentally friendly than pastoral farms, the long-term implications of large-scale afforestation, particularly monoculture exotic carbon forests, have not been fully considered. Concerns have been raised that pine carbon forestry are locking up productive farmlands, competing for downstream water resources, contributing to biodiversity loss, while subsiding fossil fuel emissions which will eventually lead to an even higher hidden carbon cost (ref). Alternative solutions have been advocated, including restricting farm-to-forest conversion or pricing agricultural emissions, which are still in the discussion stages.

These anecdotal evidence showcases that rural land-use decisions, at its core, are an economic optimization problem, with the goal to achieve the maximum dollar value from a fixed area of land. Like many other economic decisions, short-term thinking is inscribed in this decision-making process, with priorities placed on short-term cash flows rather than long-term sustainability (Carney, 2015). Environmental outcomes are typically treated as constraints or trade-offs rather than being integrated into economic outcomes, reflecting a "marriage of inconvenience" between economics and the environment (Upton, 2024). This perspective is rooted in the implicit assumption that farms' access to nature and its ecosystem services, including the water and carbon cycles, will remain free and unlimited over the long term. As a result, some land-use decisions while bring additional economic values may deplete the water resources or contribute to the unbalanced carbon cycles. Managing these sometimes-conflicting interests will only become more challenging in the future with climate change. To reconcile these interests, it is important to understand the implications of the water and carbon cycles on the economic performance of different land use.

Meanwhile, a paradigm shift that reconceptualise the nature-society-economy relationship is emerging in global market, and particularly that of economic and financial practitioners. This perspective views that a society's economy is embedded in nature, recognizing that while it cannot exist without nature, it also impacts nature and its underpinning prosperity (Dasgupta, 2021). This view contrasts with neoclassical economic models that often overlook nature's role or traditional metrics, like GDP, measures growth via dollar output but fails to account for the broader notion of inclusive wealth, including natural capital. Past finite growth is often achieved by depleting the natural resources, and the price we pay for nature, such as water and carbon cycles, is far less than its true value. This is beginning to shift with the growing realisation that nature-related risk may pose a major source of economic and financial risks. This risk is intertwined with climate change and may pose the greater risk to financial stability and the broader economy. Efforts like the 2022 Kunming-Montreal Global Biodiversity Framework that aim to halt and reverse the loss of nature by 2030, and the 2023 Taskforce on Nature-related Financial Disclosures framework that set the global standard for reporting on nature and biodiversity by corporate and financial institutions is driving this reconceptualization. The

[1] See Appendix S1 for the role of agriculture and forestry sector in New Zealand carbon emission profile and the change in New Zealand Emission Unit prices over time.

mainstreaming of nature-related considerations in economic decision-making will have a direct implication for agricultural farms that rely on a sustained flow of ecosystem services to operate. This is particularly relevant to New Zealand given its direct exposure to the global trades and its intensified pastoral farming practices which are both heavily reliant on, and placing increasing pressures, on the interlinked water and carbon cycles.

Against this backdrop, our empirical study seeks to quantify the “observed” impact of the water and carbon cycle on farm economics, in other words, the shadow prices of these ecosystem services in dollar terms. To do so, we exploit a unique dataset - the long-standing and large-scale Agricultural Production Statistics (APS) survey - conducted by Statistics New Zealand to collect official statistics on agricultural and forestry production over time. We combine this dataset with biophysical outputs from the BiomeBGC model, a widely used ecosystem process model that estimates fluxes and storage of *energy, water*, *carbon*, and *nitrogen* for the *vegetation* and *soil* components of terrestrial ecosystems across different land uses. The BiomeBGC model originated from the United States but has undergone extensive calibration and validation to better represent New Zealand pastoral farm and forestry systems in the past decade, including improved representation of water cycle, soil hydrology, and the simulation of managed crop and pasture systems (Keller et al., 2014). The model generate a suite of biophysical outputs, among which the most relevant carbon-water cycle indicators for our analysis are: pasture dry matter (DM) - derived from the amount of carbon available for plant growth and is a proxy for feed availability on pastoral farms; net ecosystem productivity (NEP) - derived from the total amount of organic carbon accumulated in an ecosystem over a specific period and is an indicator of forestry’s (annual) carbon sequestration; soil moisture deficit (SMD) - derived from daily rainfall minus potential evapotranspiration in the pasture plant root zone and capture surface water shortage or drought periods.

Employing longitudinal data for 387,009 distinct farms during the period 2003-2022, we document a statistically and economically significant relationship of the carbon and water cycles on the profitability of pastoral farms. Specifically, pastoral farms operated on land parcels with higher pasture dry matter and lower soil moisture deficit tend to have better taxable profit per hectare, holding other things equal. We find that the magnitude of pasture dry matter effect is relatively more pronounced for sheep and beef farms’ farm profit since most of their food is supplied by grazed pasture as compared to dairy farms that rely heavily on supplemental feeds. In contrast, the marginal effect of surface water shortage seems to have a contemporary effect on dairy profit but not on sheep and beef farms. This implies that dairy profit is very sensitive to short-term water availability due to higher daily water demand among dairy cows, but for meat production (e.g., lambs or cattle), the water shortage effect can only manifest over years. Our results withstand accounting for bilateral differences in farm economic and operational scales, geographical/agroclimatic characteristics, farm diverse land-use activities, spatial spillover effects from neighbouring farms of similar land use, as well as unobserved farm management practices captured by fixed effect models. A placebo test show that the effect of water-and carbon-cycles either reduce or totally disappear after fertiliser and irrigation practices are accounted for. The core findings also remain intact when we control for abnormal economic downturns such as the global financial crisis 2008-2009, the severe drought that affect the entire North Island and the west coast of the South Island in 2012-2013, as well as the financial Covid period within 2019-2020.

We propose several explanations for the established relationship among the carbon and water cycles affect farm profitability, and we examine a range of economic outcomes, including total output, intermediate expenses, and short-term debt, as proxies for these mechanisms. Our results suggest that reduced pastoral profitability associated with surface water shortages is most likely driven by a sharp decline in total output, and to a lesser extent, a reduction in intermediate expenses per hectare. Conversely, increased pastoral profitability associated with higher vegetation and soil carbon sequestration, proxied by greater pasture dry matter, appears to be linked to higher output and lower intermediate costs, although these relationships are not statistically significant. This pattern is more evident among dairy farms and less so for sheep and beef farms. These findings demonstrate that while the water and carbon cycles are intimately connected, their economic spillover effects vary across agricultural land uses.

As for forestry farms, we hypothesize that with their carbon sequestration directly monetarised via NZ ETS carbon credit units (NZUs) and water-carbon cycles indirectly monetarised via growing harvested wood, they tend to have higher profitability that are associated with higher carbon sequestration and lower soil moisture. Contrary to our expectations, we find almost null impact of carbon sequestration or surface soil moisture deficit on forest farm profitability. Similar findings are observed when we examine other economic outcomes such as revenue, expenses, and debts. While initially counterintuitive, we propose several explanations for these null findings. First, our forestry dataset may include a mix of production forests and carbon forests, and in the case of purely production forests, there is no revenue stream from carbon credits. Second, carbon credits are allocated based on standardized, modelled carbon exchange in advance of actual harvest or physical carbon uptake, with no variation due to climate and soil conditions (Sedjo & Sohngen, 2012). The designation of carbon accounting methods in NZ ETS allows forestry farmers can earn carbon credits either as tree grows (*carbon-stock change*) or as the forest grows up to a pre-determined average level (*average-accounting*). The actual timing of carbon uptake (reflected in annual net primary productivity) does not always coincide with annual profitability as revenue from carbon credit sales is only realized upon sale.[2] Further, the Biome-BGC model has not been optimised for New Zealand's exotic forestry systems due to the lack of suitable eddy covariance data. This model–data mismatch may also contribute to the null results observed.

[22] Carbon sequestration potential is closely linked to its above-ground, below-ground biomass and type of vegetation. Typically, the carbon sequestration rate follows a logistic growth curve, with exponential growth in the first few years and stabilisation after the ecosystem reaches maturity (typically +23 years of native forest, +16 years for pines, +12 years for exotic hardwood, +22 year for exotic softwood, +50 years of agriculture, and +20 years of wetlands).

The null results related to surface soil moisture deficit on forestry farms can be explained in a similar manner. Unlike pastoral farms which are direct extractors of water resources and consumers of blue water (e.g., surface water and groundwater), plantation forestry relies on green water (e.g., rainfall) for their water demand. Forestry, especially indigenous species, can enhance net groundwater recharge or groundwater volumes. However, planted exotic forests are increasingly seen as a competitor for water resources by downstream users, as past work (Mourot et al., 2021; Mourot et al., 2022) highlighted that exotic forests generally have higher evapotranspiration rates and have deeper root systems that can access moisture from deeper soil layers. In both cases, however, forestry farms do not rely on surface water or irrigation (indicated by surface and shallow subsurface soil moisture deficit). Second, forestry farms have a long average harvest age that can span through several decades. The long-term nature of rotations therefore weakens any direct, short-term link between carbon uptake, water availability and net income in the economic models.

Overall, this study proposes and establishes empirically that New Zealand pastoral farms economics are heavily influenced by the water and carbon cycles. As previewed earlier, we find empirical support for this proposition in pooled panel and fixed effect regression analyses. These findings contribute to the growing literature on the economic and financial implications of climate change and nature degradation and lay empirical foundations for emerging climate and nature stress testing framework. In particular, it addresses a key empirical gap concerning how carbon and water cycles jointly affect farms profitability. This is important since terrestrial carbon and water cycles are inherently connected through plant-mediated exchanges between the biosphere and the atmosphere across multiple spatial and temporal scales (Friedlingstein, 2015; Gentine et al., 2019). Yet, despite this fundamental coupling, research and resource management efforts often treat water and carbon in isolation. Much of the existing literature remains narrowly focused on single-resource dynamics, overlooking the complex synergies and trade-offs between water availability, greenhouse gas mitigation strategies, food production, and farm-level economic performance. Managing for only one outcome risks generating unintended consequences in other areas due to their deeply interlinked nature. Therefore, this study highlights the need for integrated, holistic approaches that recognise the dual roles of carbon and water especially in a changing climate.

The rest of this paper proceeds as follow. Section 2 provide more backgrounds on Aotearoa New Zealand farming sector and their impact of water and carbon on farms economics. Section 3 and Section 4 describes data and empirical strategies to derive the impact of water and carbon cycle on different land use types. Section 5 summarise the main findings. Section 6 document robustness test. Section 7 concludes.

2. Background

2.1. The roles of agriculture farming in Aotearoa New Zealand nature-based economy

Rural land use in Aotearoa New Zealand encompasses a wide range of purposes, dominated by pastoral farming but also forestry, horticulture and environmental/biodiversity conservation. With the significant role of primary industries in New Zealand's economy, economic returns are a strong driver of land use transitions. Food and fibre contribute to 10.5% of the national GDP and account for 80% of total exported goods and 13.1% of the national labour force (MPI, 2023). The sector comprises 47,250 farms covering 44% of the country's land (8.2 Mha for sheep and beef farms, 2.2 Mha for dairy farms, and 1.8 Mha for forestry farms). Pastoral agriculture is dominant, and herd size (particularly dairy) has continued to grow in recent years. As of 2023, New Zealand has 3.7 million beef cattle, 5.9 million dairy cattle and 24.4 million sheep (Stats New Zealand, 2023).

New Zealand agriculture subsidy policy is globally unique, as it maintains a very low level of government subsidies compared to other developed countries. A 2016 estimate found that government subsidies make up less than 1% of New Zealand farmers' income as compared to 16% among OECD countries (MPI, 2019). Agricultural subsidies, introduced in the 1970s to combat foreign exchange shortfall from increased oil costs and collapsed commodity prices, underwent major reforms in the 1980s due to unsustainable high costs while making the sector inefficient and uncompetitive on the international market (MPI, 2017). Nowadays, the only form of direct agricultural subsidies is for erosion control and income hardship for natural hazards (e.g., flood and drought). Indirect subsidies are limited to "green shoes" options to cover government expenditure on biosecurity, research and development, and natural disasters. This policy means that farmers' behaviours are more responsive to market signals and that the interrelationships between water, carbon cycle, and farm economics are less likely to be distorted by agricultural subsidies (Timar & Apatov, 2020).

Farm-level land-use decisions involve complex trade-offs between economic returns, water resources, and the carbon cycle. Dairy farms generate the highest economic value but can deplete water resources, lower groundwater recharge, and contribute significantly to biological GHG emissions while reducing soil carbon sequestration. However, over-irrigation in agriculture can increase carbon emissions by releasing GHGs from waterlogged soils and degrading organic matter. Sheep and beef farms produce lower economic returns, rely less on water, and contribute fewer carbon emissions. Forestry historically, in contrast, supports groundwater recharge by reducing surface runoff and enhancing infiltration. Forests also act as carbon sinks, absorbing CO_2 and storing it in biomass and soils. Land management strategies that protect or expand forests can enhance carbon sequestration, mitigate climate change impacts, and generate economic values. Climate change amplified this problem by reducing water availability and increase dry matter.

In practice, New Zealand farms' environmental impacts are closely tied to land-use. Beef and sheep farms typically have lower environmental impact, as they are stocked at much lower rates and are rarely fertilized or irrigated. Additionally, most of their food is supplied by grazed pasture, only requiring small amounts of forage crops grown on-farm to overcome occasional pasture shortages in summer or winter. Dairy farms, meanwhile, have very high stocking rates and require substantially more inputs such as fertilizers, irrigation, and supplementary feed. As dairy herds grow, so do the associated environmental pressures, such as nitrate leakage into groundwater, leading to declining water quality and sometimes rendering it undrinkable (Joy et al., 2022). A national limit of nitrogen concentration of 1 mg/L in water was introduced in 2021 to address this problem but faced pushbacks, as economic modelling projected potential losses of $6 million in annual GDP and a 5.2% drop in exports (MPI, 2021).

Against this background, forestry often serves a dual purpose of carbon storage and economic return from wood production (PCE, 2025). There is currently 10.1 Mha of forest in New Zealand; roughly 80% of this is native forest, and the other 20% is exotic (PCE, 2025). 1.8 Mha of the total is devoted to the forestry industry, which is almost exclusively exotic plantation forest (predominantly Pinus radiata). New Zealand has committed to be carbon neutral by 2050 and heavily relies on afforestation to offset its carbon emissions. Government incentives for tree planting such as the 2008 New Zealand Emissions Trading Scheme (NZ ETS) and the One Billion Trees Programme (MPI, 2025) as well as high market carbon prices have resulted in an increase in afforestation in New Zealand in recent decades (PCE, 2025). This has mostly been accomplished with exotic plantation forest because of their rapid growth rates in New Zealand's temperate, maritime climate, with the additional benefits that they can eventually be harvested for profit.

The NZ ETS is the only carbon price scheme in the world that is designed to cover the entire forestry sector and to allow a 100% offset of fossil fuel emissions with forestry (Leining & Kerr, 2018).[3] This is different from other carbon pricing systems that only allow forestry offsets on a case-by-case basis. The New Zealand ETS uses 1 January 1990 as a baseline to define the deforestation and afforestation boundary: (1) pre-1990 forest land is not eligible for carbon credits but may incur penalties if deforested, and (2) post-1990 forest land may be eligible to earn carbon credits, but these units must be surrendered when harvested. After removing the price cap on carbon units in 2019, the subsequent increases in carbon price resulted in around 55,000 ha per year being converted from sheep and beef farms to forestry between 2019-2022 (Beef + Lamb New Zealand, 2023a).

The long-term implications of large-scale afforestation with exotic species have not been fully considered. Planted exotic forests are increasingly seen as a competitor for water resources by downstream users. Past work (Mourot et al., 2021; Mourot et al., 2022) highlighted that exotic forests generally consume more water than other vegetation types and tend to reduce available water downstream, but they can also improve soil and water quality, provide cooling boundary layers, and provide erosion control. However, planting monocultures on New Zealand steep slopes combined with

[3] According to Liao et al (2024), "the original NZ ETS aspired to include all sectors and all GHGs and should have had the most extensive sectoral coverage by far among all the ETSs in the world. As of December 2019, just over 50% of NZ GHGs emissions are covered by surrender obligations in the NZ ETS".

poor management practices can result in severe damage caused by debris flow during extreme rainfall events. These events are becoming more frequent due to climate change. For example, Cyclone Gabrielle hit New Zealand North Island on 14 February 2023 with extreme heavy rainfall, particularly on the East Coast and the Gisborne region, causing sediment and forestry slash to be washed downstream and resulting in loss of life and damage to infrastructure, private property and natural ecosystems (Ministerial Inquiry into Land Uses in Tairawhiti and Wairoa, May 2023).

Land-use conversion also happens within pasture farming. The dairy boom started in the 1990s due to low land prices and rising global dairy prices, leading to a shift from sheep and beef farming to irrigated dairy farming on large scales. Between 1990-2022, the national dairy herd more than doubled from 2.4 million to 5.9 million, while the sheep population declined from 57.9 million to 24.4 million in the same period. In the last decade, these trends have stabilized (MfE & Stats New Zealand, 2024). However, the New Zealand dairy industry continues to intensify with higher stocking rates and increased use of fertilizer and irrigation.

Pasture farming is a major consumer of freshwater. Cameron and Peer (2025) found that the dairy sector accounts for approximately 20% of the consumptive water use in the country, with 90% of water sourced from surface water and >90% of dairy water use driven by irrigation. On-farm water use guidelines for dairy farms suggests an average daily demand of 70 L/cow/day for milking cows and 45 L/cow/day per day for dry stock, but the water footprint of dairy farming can vary markedly from this estimate (Higham, 2017). Meanwhile, beef and sheep farms generally use less water, as the average daily demand for mature animals is about 30 L/cattle/day and 3L/sheep/day (Horizon Council, 2022). Zonderland-Thomassen et al. (2014) found that New Zealand blue water losses from grazing systems is low compared to global benchmark (0.37 L/kg meat for beef and 0.26 L/kg meat for sheep). However, blue water losses due to evapotranspiration from irrigated pasture continue to be the greatest contributor to water shortages despite a relatively small area of irrigated farmland.

In addition to their pressure on water resources, New Zealand pasture farms are also generally net GHG emitters. Approximately half of New Zealand total GHG emissions come from agriculture, including methane (CH4) from enteric fermentation in ruminant livestock and nitrous oxide (N2O) emissions from urine, dung, and nitrogen fertilisers (Leahy et al., 2019). Since agricultural emissions are not priced, interventions to reduce biogenic GHGs are optional. These solutions can include changing farming practices such as reducing stocking rates, improving productivity per animal, or reducing the frequency of milking. Additionally, farms may partially offset their emissions through carbon sequestration in soils (although its net effect on New Zealand remains uncertain) and planting a portion of the farm with trees and woody shrubs (Whitehead et al., 2024). However, a 2021 survey of New Zealand farmers found that reducing GHG emissions is secondary compared to other environmental goals such as managing biosecurity, improving the health of waterways, and reducing soil erosion (Landcare Research, 2021). Notably, a US study found that even when soil carbon sequestration is encouraged via carbon offset credits, farmers still consider this only as an add-on to their already-implemented sustainable practices due to the burdensome and unpredictable nature of these credits (Barbato & Strong, 2023).

2.2. The impact of water -carbon cycle on farm economics

While farms have substantial environmental footprints, the reverse is also true- the environment significantly shapes farm economics. Given the farming industry's reliance on water availability and the water cycle, droughts can pose significant impacts on farms' economics performance.

The economic impact of droughts and climate change-induced drought risk in the agricultural sector is a well-documented topic (Pourzand, 2023; Pourzand et al., 2020; Timar & Apatov, 2020). The consequences of droughts are multi-faceted, but fundamentally water limitation constrains plant growth and leads to shortage of pasture feed and reduced output. Farmers may adopt various strategies to mitigate these effects and protect their profits, such as purchase supplementary feed, reduce herd size, lower inputs per cattle - though this could lead to reduced outputs, and cut or delay spending. Also, the impact of droughts can be mitigated by timely weather forecasts or favourable market conditions. A widespread drop in agricultural production can drive up the commodity prices as was the case with the 2013 NZ nation-wide drought. In the aftermath of this drought, export milk prices increased in 2014 as NZ is the market maker in the global dairy market (Pourzand et al., 2020).

Droughts can pose significant impacts on economic performance of New Zealand agricultural farms due to their reliance on the water cycle. The impacts of droughts are multi-dimensional, but fundamentally they constraint plant growth and result in a shortage of livestock feed and lead to reduced output. However, farmers can adopt various strategies to mitigate the effects of droughts on outputs and consequently their profits. For instance, they can purchase additional feed or reduce their herd size by selling off cattle to maintain their short-term cash flows. Alternatively, they may lower inputs per cattle - though this could lead to reduced outputs – and cut operational expenses or delay spending to compensate for such losses. However, the impact of water shortage can be alleviated with timely weather outlooks or favourable commodity prices. In certain cases, a widespread reduction in production can end up increasing the commodity prices. For example, while the 2013 drought have severe and costly impacts on New Zealand's agricultural production, the milk prices increased in 2014 as New Zealand is the market maker in this global market (Kamber et al., 2013).

It is important to note that farmers of different land use can respond differently to droughts. Dairy farms typically have greater cash flow situations and greater access to banks – so they can afford costly drought response to maintain outputs. They are also less likely to reduce operational costs due to higher input systems and higher production costs. Existing research on the impacts of droughts on farms' economics (Timar et al, 2020; Pourzand 2023; Kendon et al., 2021) find conflicting results. Bell et al. (2021) finds a positive link between soil moisture and farm profits, with low soil moisture (more droughts) having an intermediate impact on dairy farm profits but lagged effects on sheep and beef farms. Pourzand (2023); Pourzand et al. (2020), however, observe that droughts can have an associated positive impact on gross income and profit, particularly in major dairy farm regions (e.g., Waikato and Taranaki) where drought causes an increase in milk price, meanwhile, sheep/beef farms' gross income and profit were negatively affected by droughts across most farming regions.

Timar and Apatov (2020) find that increasing drought leads to lower gross output and intermediate expenditure in dairy farms, along with rising current debt and declining taxable profit per hectare. For sheep and beef farms, droughts were associated with reduced output and intermediate costs but no impact on debt or profit. For forestry plantations, extreme or recurrent drought events can lead to stress on forests and affect their overall health and growth rate, thus leading to slower generation of wood logs or NZUs. Further, a climate stress testing for agriculture lending (RBNZ, 2023) shows that a one-year drought could leads to 8 percent in dairy loan defaults and 7 percent in sheep and beef defaults as compared to the baseline case, and the two-year drought could lead to doubling that of the one-year drought. A common theme across these analyses is the use of soil moisture deficit or potential evapotranspiration deficit as a proxy for droughts (Porteous & Mullan, 2013). This indicator accounts for surface water (e.g., rainfall and potential evaporation) and plant water capacity, but excludes below-ground water sources and irrigation.

Since agricultural emissions have not been priced by the NZ government, the primary way the carbon cycle impacts farm economics is through *carbon sequestration* and *food and wood production*. Carbon sequestration is the process of capturing and storing CO_2 in vegetation and soils via photosynthesis. For *forestry* plantations, carbon sequestration is directly monetarised via NZ ETS. Forestry farmers can enter NZ ETS as *standard forest* (harvest + ETS) or *permanent forest* (ETS only). For standard forests, two accounting methods can be used: Under *carbon stock-change,* participants can earn NZUs as trees grow and surrender NZUs upon harvesting or deforestation, while for *averaging accounting*, participants can receive NZUs as the forest grows up to a pre-determined average level and will face no liabilities at harvest if forest is replanted (Acosta et al., 2020). Of these, the *carbon stock-change* imposes higher financial risk due to uncertainty in future carbon price. Meanwhile, permanent carbon forestry is a more attractive option due to a combination of significantly lower up-front costs and a longer period of carbon revenues (Manley, 2023). Native forests earn substantially less carbon credits than exotic plantation forest since they grow more slowly. In 2024, a policy change was proposed to avoid exotic forests permanently locking up productive land by (a) excluding exotic forests from the NZ ETS and (b) temporarily restricting land-to-forestry conversions on productive land but has not been implemented yet (as of June 2025).

New Zealand pastoral farms are generally perceived as a net contributor to the carbon cycle. At least half of New Zealand's greenhouse gas emission profiles come from agriculture, primarily methane from livestock digestive systems and nitrogen emissions from urine, dung and nitrogen fertilisers. As aforementioned, farms biological GHG emissions are not currently priced, but pastoral farms can enter earn from carbon sequestration by registering to the NZ ETS if the forested area is at least 1 ha, the land area covered by tree canopy is at least 30%, and trees reach at least 5 m in height at maturity. While soil carbon sequestration is not yet recognised for NZUs as an income stream, it can lead to co-benefits such as improved soil quality and ecosystem functions or services, improving water and nutrient retention capacity, reducing erosion risk and non-point source pollution, and reduced reliance on synthetic inputs. Higher soil organic carbon also means higher dry matter (food supply) available for grazing animals. Previous analyses have shown a strong correlation between modelled DM and total national milk solids production, with an R^2 of 0.86 over a 5-year period (2006–2012) and a moderate correlation ($R^2 = 0.46$) over a 15-year period (Keller et al., 2014). All together, they contribute to improved farm economic outcomes in long term (Lal et al., 2015).

Offsetting biological GHG emissions can indirectly benefit pastoral farm economics. Fleming et al. (2019) finds that NZ farms with higher productivity tend to have lower emissions and higher profits, and thus a combination of lower stocking rates and higher animal productivity appears to offer an effective, cost-neutral mitigation strategy. Similarly, Flaten et al. (2019) find a statistically significant relationship between higher profitability and lower GHG emissions among Norway farms. Reisinger et al. (2017) examined a range of options to reduce biological GHG emissions on-farm and find that these solutions come with varied profitability implications. For dairy farms, options such as once-a-day milking (as opposed to multiple times per day) or reducing stock rates can be cost-neutral or even increase profitability, but on-farm forestry may reduce profits. For sheep and beef farms, mitigation options are more limited with on-farm forestry being the primary option, yet its associated cost is less than that of dairy farms.

The Reserve Bank of New Zealand's 2023 climate stress testing revealed important insights into the agricultural lending's exposure to agricultural emissions pricing (RBNZ,2023). The analysis showed that an emissions price of NZ$15 per tonne would increase product prices by approximately NZ$0.15 per kgMS for dairy, NZ$0.20 per kgCEW for beef, and NZ$0.30 per kgCEW for sheep. At this $15 carbon price level, it is sufficient to meet the 10% emissions reduction target by 2030 but the impact on farm profitability was relatively limited. Across participating banks, there was only a marginal increase in the share of dairy and sheep and beef loan exposures deemed unprofitable. However, under a NZ$50 per tonne, a price that aligns more closely with the NGFS Delayed Transition scenario for 2050, the proportion of unprofitable loans rose significantly. Specifically, 14% of dairy farm exposures and 44% of sheep and beef exposures were projected to become unprofitable, compared to baseline levels of 6% and 15%, respectively.

International studies have also pointed to a clear water-carbon-economic interrelationship in agricultural sectors. Berazneva et al. (2019) assess the relationship between soil carbon sequestration and farm economics in context of smallholder maize farmers in Kenya. They find that when using a "climate-smart" agricultural practice that combines mineral fertilizers with organic resources, it is possible to boost maize yields while increasing or maintaining soil carbon stocks. This is translated to a shadow price of soil carbon ranged from \$95 to \$168 per Mg of carbon depending on the discount rate applied. Jackson et al. (2005) documents the trade-off between water and carbon in global biological carbon sequestration, where monoculture plantations, while maximise carbon sequestration and centre in climate policy, have considerable impact on surface water availability and degrade soil quality. Chisholm (2010) consider the economic implication of this trade-off in South Africa forestry farms and find that afforestation appears viable to the forestry industry under current water tariffs and current carbon accounting legislation but would appear unviable if the forestry industry were to pay the true cost of water used by the plantations. Tang et al. (2019) look at the mixed crop-livestock farming in China and find that the optimised agricultural farms move towards cropping-dominated farming and crop-livestock farmers may reduce their on-farm GHG emission by 16% to 33% with marginal abatement costs not higher than AU\$20/t CO_2e and AU\$30/t CO_2e, respectively. Using farm-level data from Italian farms, (Coderoni & Vanino, 2022) find that a higher carbon productivity indicator, defined as the amount of agricultural gross production value per unit of GHG emissions, is positively associated with higher farm net value added. Importantly, this relationship is non-linear and varies across farm types, suggesting that the economic benefits of improving carbon efficiency depend on the structure and characteristics of the farm.

Moving beyond agricultural sector, there have been several other studies aiming at understanding the economic impact of water-carbon cycle. WWF (2023) find a high cost of the cheap water, where the total use value of freshwater is approximately to 58 trillion USD or 60% of global GDP, and agriculture stands out as the largest water user and account for 70% of global extracted water. Of which, direct use via industry, agriculture and municipalities, hydropower, recreation, inland transportation and freshwater fisheries only contributes 7.5 trillion USD, but indirect use, via environmental regulation, biodiversity, and extreme event protection, is 50 trillion annually or 7 times more value than direct use. Dolan et al. (2021) employ a coupled global hydrologic-economic model with basin-level resolution to calculate the loss of economic surplus due to water basis, and find that dependent on scenario assumptions, major basins can experience strong negative or positive economic impacts due to global trade dynamics and market adaptation. UNEP FI (2023) introduced a drought stress testing for major financial institutions around the world to incorporate droughts in their credit mortgage portfolios. The implementation of this tool on a Brazil portfolio, for instance, show that 65%-70% of companies credit rating will be downgraded in a drought scenario and drought will increase portfolio loss by 1.5x and 2x.

Meanwhile, the economic values of carbon sequestration and emissions are a well-documented topics in climate mitigation studies. Unlike water, carbon is already a commodity, and several proxies can be applied for carbon costs. This includes the "social cost of carbon" (the monetary damages caused by an incremental tonne of greenhouse gases emissions, encompassing environmental and social costs used to inform climate policy), the "marginal abatement of carbon" (the monetary cost of reducing an incremental tonne of emissions to meet a particular emissions target at least cost to society), and "market price" (carbon tax or carbon price on the emission trading schemes) (Rennert et al., 2022). Currently, the "market price" of carbon emissions remains relatively insufficient. The carbon market, although expanding, only covers ~24% of global GHG emissions via 75 pricing instruments (carbon tax and ETS). Only seven pricing instruments, covering <1% of emissions, reached the minimum price levels consistent with the 2oC pathway (US$63-127 per tCO2e) (World Bank, 2024). It is critical to understand this gap and choose an appropriate value proxy when accounting for the economic benefits of the carbon-cycle.

3. Data and empirical specification

3.1. The Baseline Model

To examine the direction and mechanisms through which water and carbon cycles influence farm profitability, we adopt a flexible reduced-form econometric framework and estimate the following panel data model for each land use type (dairy, sheep and beef and forestry farms):

$$Y_{imt} = \alpha + \boldsymbol{\beta_1 Carbon_{mt}} + \boldsymbol{\beta_2 Water_{mt}} + \tau Control_{it} + \varphi Region_k + \sigma Year_t + \varepsilon_{it} \quad (1)$$

Where: Y_{imt} is a proxy for farm profitability for farm *i* operate on a land mesh-block *m* at the fiscal year end *t*. $Carbon_{mt}$ is one of the carbon indicators that represents the pastoral dry matter and forestry net primary productivity. $Water_{mt}$ is the surface soil moisture deficit. $Control_{it}$ denotes a set of geographical/agroclimatic/price/farm characteristics covariates; $Region_k$ is a vector of regional dummies for other unobserved time-invariant characteristics at regional-level such as regional policies and industry bodies; $\sigma Year_t$ is a vector of year fixed effect to control for unobserved industry-wide shocks, such as supply chain disruption and COVID-19 and εit is an unobserved county-specific disturbance term. $\boldsymbol{\beta_1}$ **and** $\boldsymbol{\beta_2}$ captures the marginal effect of carbon- and water-cycle on farm profit, respectively. A description of key variable definitions is captured in Appendix Table 1.

3.2. Data

Farm-level agriculture activities and financial data

We rely on a unique dataset of farm's Agricultural Production Statistics (APS) survey, retrieved from Statistics New Zealand's Longitudinal Business Database, to explore information on agricultural production on farms and forests. APS is a long-standing and large-scale survey programme conducted by MPI and STATS New Zealand aiming at collecting official statistics on agricultural and forestry production. APS is produced annually including a full census every five years, and a survey with a stratified sample size that aims at out of the three farming enterprises conducted in intervening years.

The survey population includes all businesses included in the Statistics New Zealand's Business Register as having agricultural activity, thus mainly include businesses classified in agriculture, and forestry sector (exclude native forest) but also parts of other sectors (e.g., scientific research, education, non-residential properties, and conservation parks) that are partly involved in farming. Respondents include businesses primarily operate in agricultural and forestry activities (excluding native forest) as well as those from other sectors. The APS collects a wide range of information, such as farm location, land details, livestock herd-size, land-use activities, farm management practices such as fertiliser use and irrigation practices, forestry practices such as cubic meter of wood production or harvested exotic forest area awaiting restocking. Some survey questions related to planted exotic production forests was discontinued over time and is included in the National Exotic Forest Description survey.

For this study, we restrict our analysis to a ten-year period from 2003 to 2022. This period is long enough to capture inter-annual variation in farm practices and outcomes, while short enough to avoid major structural changes in data collection or infrastructure and land-use policies. Four census years are included in this sample, namely 2007, 2012, 2017 and 2022. Our starting point is all farms whose primary activities are in pastoral agriculture and forestry following in the Australian and New Zealand Standard Industrial Classification ANZSIC 6-digit codes. Specifically, sheep and beef farms include codes 0141 (sheep farming), 0142 (beef cattle farming), 0143 (beef cattle feedlots), and 0144 (mixed sheep–beef farming). Forestry farms include 0301 (forestry) and 0302 (logging), encompassing both permanent and production carbon forests. It should be noted that while farms are classified by primary activity, many engage in mixed land use, including combinations of pasture, horticulture, and forestry. Since farms are geo-identified with Stats NZ mesh-blocks (e.g., the smallest geographic unit that represents around 30-60 dwellings or 60-120 residents), and multiple farms can form a farming enterprise that spans across several farms and several mesh-blocks – we restrict our sample to farming enterprise located within one mesh-block only. However, similar to Timar and Apatov (2020), we keep farms whose meshblock changes over time, as we are unable to see whether these changes reflect genuine changes in locations, administrative change or purely data errors[4]. In the dairy sector, such changes are likely influenced by *Moving Day* on 1 June, the start of winter, when an estimated 5,000 farming families relocate to new farms to begin new sharemilking contracts. Finally, we restrict our sample to farms with at least one hectare of total land use.

We then link the APS survey with the IR10 dataset, also from the Statistics New Zealand's Longitudinal Business Database using the farm enterprise ID. This dataset collects all financial statement return of all enterprise in New Zealand, with a vast majority of businesses using 31 March, 31 May, and 30 June. We employ taxable profit per hectare as our main indicator of farm profitability as it allows comparison across land-use and accounts for heterogenous in farm scales. For channel

[4] See Appendix S2 for a breakdown of farms associated with multiple meshblocks.

analysis, we use a range of additional economic outcomes to understand the transmission from water-carbon cycles to farms economics. This includes gross outputs (e.g., total income minus stock adjustment), intermediate expenses (e.g., total purchase expenses minus depreciation and interest expenses and covering fertilisers, supplemental feeds, and irrigation costs) and current loans (e.g., the amount of loans outstanding that are repayable within one year). Respectively, these three indicators represent the revenue, cost and liability side and signifies how farms respond to changes in water-carbon cycles. All economic outcomes are adjusted to real term using the Consumer Price Index (CPI), expressed in NZ dollars as of December 2024. Dollar values are normalised using hectare of land areas and all extreme values are winsorised on under 1st or above 99th percentile.

Carbon and Water Cycle

Annual average outputs from the Biome-BGC model are used as proxies for the spatial and temporal dynamics of carbon flows between ecosystems and the atmosphere across different land uses (see **Fig 1**). Carbon fluxes and storage in grasslands and exotic and indigenous forests were modelled with the Biome-BGCMuSo v6.1 model (Hidy et al., 2022; Hidy et al., 2016)). The BGCMuSo model is a terrestrial ecosystem process model that simulates the biological and physical processes controlling fluxes of carbon, nitrogen (N) and water in vegetation and soil in terrestrial ecosystems. It was originally developed for North American forests (Running & Coughlan, 1988; Running & Gower, 1991; Thornton et al., 2002; Thornton et al., 2005) but has undergone significant development in the past decade to include multiple soil layers, improved representation of the water cycle, and the simulation of managed crop and pasture systems. We previously adapted the original Biome-BGC model to New Zealand pasture systems (Keller et al., 2014). The BGCMuSo model represents a significant advance on previous versions. Among the improvements include the addition of management modules for grasslands, croplands and forest (such as harvesting, mowing, grazing, etc), a multi-layer soil module (as opposed to just one layer), soft-stem carbon and nitrogen pools, and implementation of plant senescence (Hidy et al., 2016). Soil hydrology has also been significantly improved (Hidy et al., 2022).

The Biome-BGC model was run on a daily time step at a 0.05^{o} grid resolution (~5.6 km x 4.2 km) for all of New Zealand. Climate inputs include daily minimum and maximum air temperature, precipitation, vapour pressure deficit, and solar radiation, using the downscaled Coupled Model Intercomparison Project Phase 6 (CMIP6) outputs. Site-specific soil information (texture, pH, and rooting depth) comes from the Fundamental Soil Layers database (Manaaki Whenua – Landcare Research, 2010), which has been re-gridded to match the climate input data. For pastoral farms, eighteen eco-physiological model parameters for two types of New Zealand pasture systems (“dairy” and “sheep/beef”) were calibrated using eddy covariance data from five sites across New Zealand, with an additional five sites available for validation (Villalobos et al., 2023). All sites had at least one full year of data available, and most had three years or more. The parameters were optimized to produce the best match between observed and modelled weekly mean net primary productivity (NEP), gross primary production (GPP), Ecosystem Respiration (Re), evapotranspiration (ET), and 10 cm soil moisture content (SMC) using the PEST software package (Doherty, 2015). To represent exotic forests (pine plantation forests), we used the built-in evergreen needleleaf forest biome, but these biome parameters were not optimized for New Zealand due to the lack of suitable eddy covariance data. Instead, default parameters were used. A full description of the calibration methodology and results is the subject of a forthcoming paper (Keller et al., in prep).

For carbon-cycle, dry matter yield (DM), measured in kilograms of dry matter per hectare per year (kg DM/ha/year), is used as a proxy for pastoral farms as it reflects the spatial variations in pasture growth or grass available as food for grazing animals. DM yield is converted from net primary production or the amount of carbon retained in an ecosystem via the ratio of above-ground to below-ground allocation by the inverse of the new fine root. As for forestry farms, we rely solely on net ecosystem production (NEP) from evergreen broadleaf forest, in grams of carbon per square meter per year (gC/m²/year), as a proxy for potential carbon sink from vegetation and soils from exotic forests. indicates farm-level carbon sequestration (but does not include the biological GHG emissions from cattle and sheep). It should be noted that net ecosystem production and carbon sequestration are not necessarily equivalent as the latter term implies a longer-term sink while the modelled NEP is a transient term. Further, in international application of Biome-BGC for managed forests, wood production amount can also be simulated based on the tree growth rates, however this module has not been available in New Zealand context. We hypothesize that higher DM yield will lead to higher profit for pastoral farms while higher NEP may lead to higher profits for forestry farms. DM yield is transformed using natural logarithm to remove the effect of extreme values, while NEP (which can be negative that indicates emission source) is winsorised by 1^{st} – 99^{th} percentile.

For water-cycle, we employ soil moisture potential evapotranspiration deficit (PED), measured in topsoil to 90 cm depth and in mm/month and represents the amount of rain needed to bring the soil moisture content back to field capacity. Soil PED is modelled in Biome-BGC model a 1km grid resolution for the period 2013-2022 as a function daily weather (temperature, precipitation), land covers, and soil texture and is the difference between field capacity and soil water content of that day. A soil PED value of 0 means that the soil is fully saturated, while a soil PED value that is closer to field capacity mean that the soil is very dry. Soil PED is effectively served as a surface water availability indicator and is a universal value across pastoral and forestry farms.

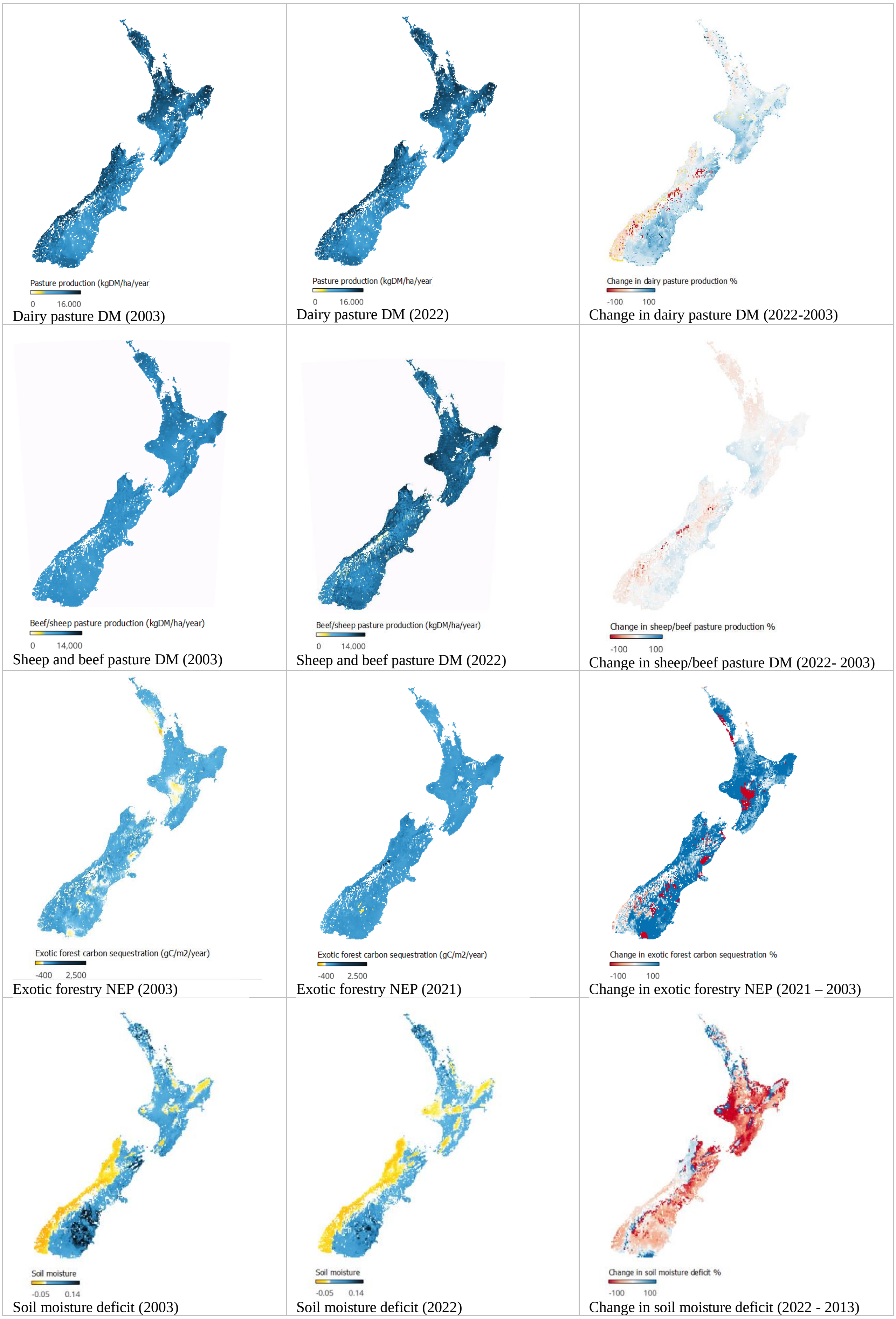


Figure 1 The spatiotemporal variation in water-carbon-cycle across New Zealand. Estimates from the BGCMuSo-Biome model. Panel (a) shows pasture dry matter (DM) production for dairy farm systems; panel (b) shows pasture DM for sheep and beef systems; panel (c) presents net ecosystem production (NEP) from evergreen broadleaf forests; and panel (d) depicts soil moisture deficit. Each panel displays annual averages for the beginning and ending year and the difference

For robustness test, we also explore outputs from a set of national groundwater models, including the GNS national groundwater recharge model at 1 km grid resolution (Westerhoff, White, & Rawlinson, 2018) and the GNS national water table model at 200 m grid resolution (Westerhoff, White, & Miguez-Macho, 2018). The first model provides the *total groundwater rainfall recharge,* measured in mm/month, simulates the total amount of rainwater that can be infiltrate into the subsurface and replenish groundwater resource, but the caveat is that it does not represent *net* groundwater availability.

The second model provides groundwater table depth, measured in meter below the ground (*mbg*), which provides an estimated table depth in main alluvial aquifers. A limitation is that these models only capture historical records of total groundwater recharge in the first half of sample (2003-2013) and a steady-state groundwater table (snapshot as of 2018), therefore limits in capturing temporal changes in groundwater availability over the sample period.

Control Variables

To alleviate plausible concerns about omitted variable bias, we augment the baseline model with several attributes that represent geographic/agroclimatic condition, farm characteristics, and global market signals. It is plausible that other than carbon-water other characteristics of the land parcels where farm is located help shape the farm economics outcomes, including land-use capability, soil particle size, distance to nearest town, elevation above the sea level. Therefore, the inclusion of these geographic/agroclimatic conditions can help rules out the possibility that our findings are exclusively driven by these potential confounding factors. In addition, rural industry bodies (e.g., DairyNZ, Beef+Lamb NZ) play a crucial role for primary industries in New Zealand, as they are known to advocate for knowledge and technology sharing, policy, research and community support. Therefore, we also control for this community effect by calculating the share of neighbour farms that are also operate in the same primary land-use (Timar, 2022); Timar and Apatov (2020). Farm economic scales such as land size and herd size (dairy cow, meat cow, and sheep) are controlled to rule out the size effect, in addition, the fraction of land dedicated for non-primary land-use activities is also taken into consideration. Finally, we also incorporate regional dummies in the regression to account for unobserved (time-invariant) heterogeneity across New Zealand regions, and a range of commodity price relevant to the primary activity of farms (e.g., FAO global dairy price index, IMF global lamb and beef price indices, the FRED lumber and wood product price index, and the NZU spot price index) (Bell et al., 2021; Pourzand, 2023; Pourzand et al., 2020).

4. Main Result

4.1. Data Description

The New Zealand national farm dataset includes 387,009 annual observations from 95,532 distinct farms over a 20-year period (2003-2022). This includes 245,322 annual observations from sheep and beef farms, 107,583 from dairy farms, and 34,104 from forestry farms: or 57,369 distinct sheep and beef farms, 29,520 distinct dairy farms, and 8,643 distinct forestry farms. **Fig.2** depicts the number of farms across their primary land-use activities over time. As expected, we observe peaks in the census years and dips in between, especially in the global financial crisis period 2008-2009 and the Covid period 2019-2020. There is a noticeable sharp decline in the number of farms, particularly sheep and beef farms, in the 2012 census year. This number rebounds by 2017, followed by a slight decrease again in 2022. This pattern may be due to our sample restriction process, where we include only farming enterprises located within a single meshblock and those that report their total hectares of land use. However, it may also reflect variation in survey response rates or an organic decline in farm numbers. A cross check with Statistics New Zealand report confirms that the nationwide APS response rate was 80% in 2007, 84% in 2012, 84% in 2017, and drop to 73% in 2022. At the same time, there is a steady national decline in farm numbers by 33% from 2002 to 2022 (from 70,336 in 2002 to 58,068 in 2012 to 47,250 by 2022) (Stats NZ, 2023). This decline likely reflects aging farmers existing the business, difficulties in generational turnover, land use conversion, and further a broader trend of farm business consolidation (Landcare Research, 2021).

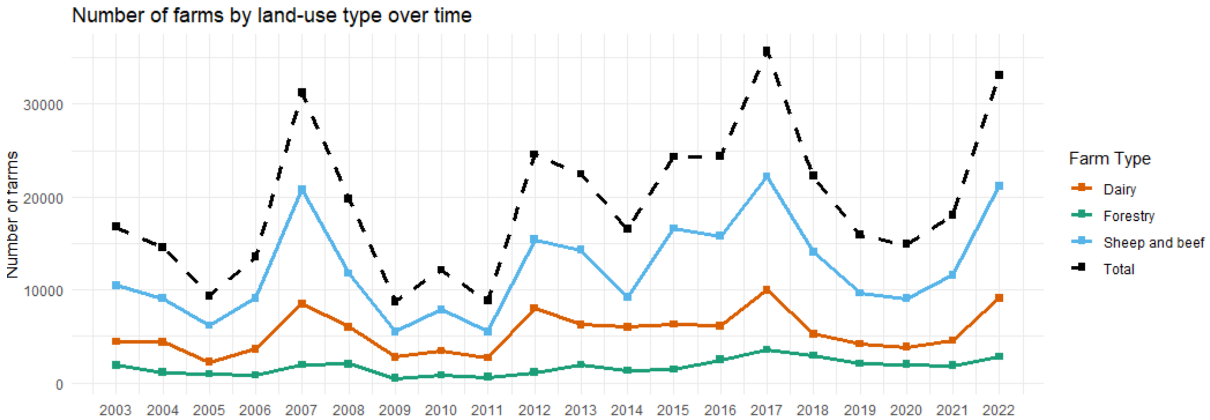


Figure 2 Number of farms by land-use type over time in the national dataset. This figure depicts the number of farms responded to the Agriculture Production Survey over time. Farm type is characterised based on primary land-use activities using ANZSIC 6-digit codes.

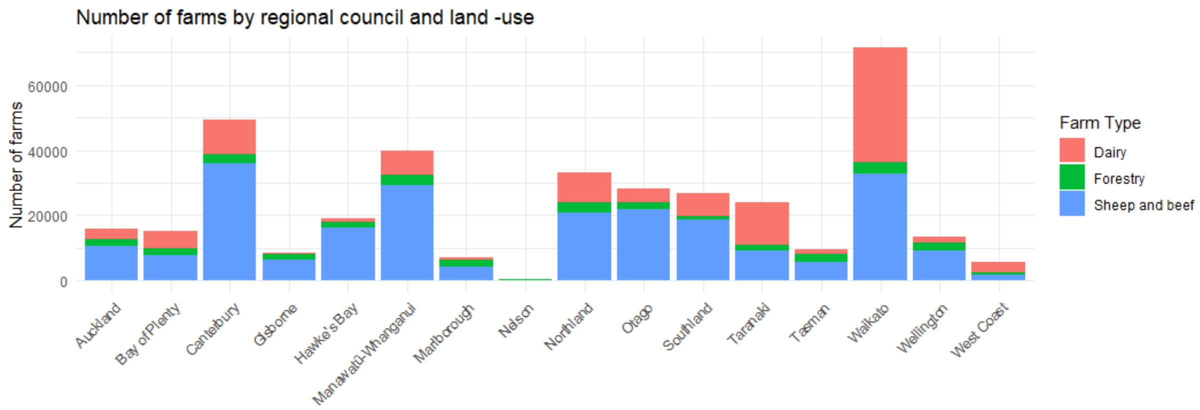
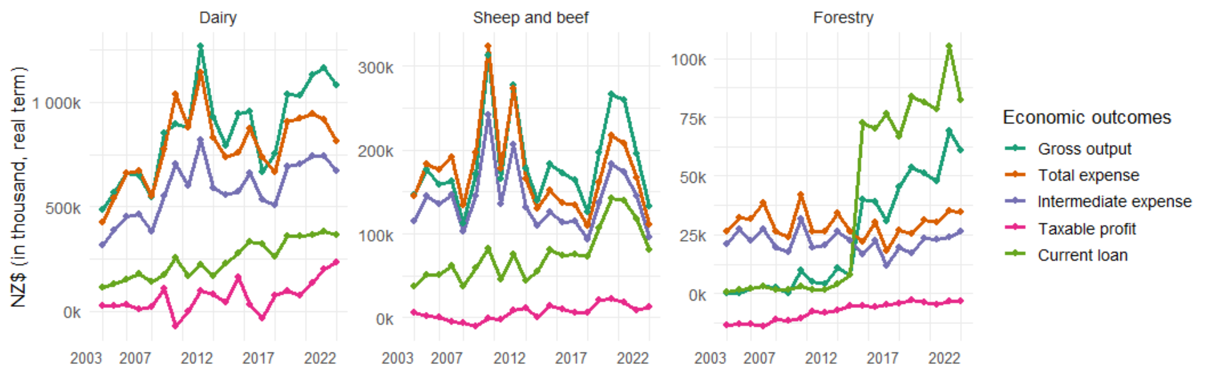
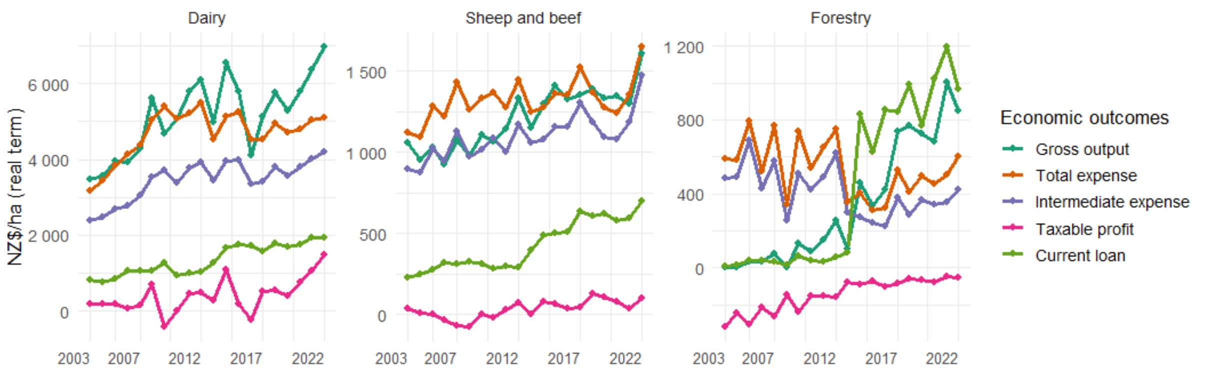


Figure 3 Number of farms by land-use type by region. This figure depicts the number of farms responded to the Agriculture Production Survey by sixteen regions. New Zealand is divided into sixteen regions for local government purposes. Farm type is characterised based on primary land-use activities using ANZSIC 6-digit codes. Farms are geolocated to their regions based on their Stats New Zealand mesh-block IDs.



(a) Farm median economic outcomes in original values



(b) Farm median economic outcomes normalised by land use hectare

(c) Relevant commodity price over time

Figure 4 **Farm economics over time.** This figure depicts the median farm economic outcome over time by different land-use types. Panel (a) shows the absolute economic values per farm, while panel (b) presents these outcomes normalized by total land area in hectares for the ease of comparison across farm size. Additionally, panel (c) provides data on the number of farms with available financial statements (IR10), alongside a depiction of relevant commodity prices over time. All dollar values are presented in real terms, adjusted to December 2023 dollars using the Consumer Price Index (CPI).

Fig. 3 depicts the distribution of farms across regions. From this figure, we find that New Zealand's agricultural farm landscape is diverse with farming activities vary significant across regions due to geographic and agroclimatic condition. Sheep and beef farms dominate the national landscape, particularly in the South Island- most notably in Canterbury, Otago, and Southland- as well as in parts of the North Island, such as Manawatu–Whanganui and Northland. In contrast, dairy farming is a major agricultural activity primarily concentrated in the North Island, especially in Waikato and Taranaki, and to a lesser extent in Canterbury in the South Island. Plantation forestry farms are distributed across both islands, reflecting broader land-use diversification.[5]

Fig. 4 illustrates the changes in median economic outcomes for farms across different land-use types. Panel (a) shows that dairy farms, due to several years of strong profits, tend to operate at a significantly larger economic scale than sheep/beef and forestry farms. The median dairy farm generates between NZ$632,000 and NZ$1,500,000 in gross output, equivalent to approximately NZ$3,500 to NZ$7,000 per hectare. In contrast, the median sheep and beef farm operates at a smaller scale, with gross output ranging from NZ$111,000 to NZ$312,000, or around NZ$900 to NZ$1,600 per hectare. Forestry farms exhibit considerable variation over time, with median gross output ranging from as low as NZ$250 to as high as NZ$68,900, or NZ$3 to NZ$1,000 per hectare.

Panel (b) shows an overall upward trend in farm profit after adjusting for land use area. There is, however, substantial year-to-year fluctuation in farm profit, and this appears to be largely driven by fluctuations in revenue sides as compared to relatively stable total and intermediate expenses that closely track one another. Dairy farms continue to be the most profitable land-use type as compared to sheep/beef and forestry farms and also appear to be more highly leveraged with higher levels of current loans. Notably, there seems to be a structural shift in the financial outcomes and loan levels of forestry farms after 2014. While the exact cause is unclear, this shift may be linked to reforms in the New Zealand Emissions Trading Scheme (NZ ETS), including the Climate Change Response (Unit Restriction) Amendment Act in 2014 and the formal delinking from the international Kyoto market in mid-2015 to establish more effective emission pricing scheme. In anticipation of delinking, NZ ETS participants began stockpiling (or "banking") NZUs for future use while meeting most of their current surrender obligations with cheaper international Kyoto units. This could drive up demands for NZUs held by forestry farms and lead to an increase in carbon revenues.

Panel (c) illustrates the evolution of commodity prices over time. Dairy prices exhibit significant volatility, fluctuating by a factor of two to three, which appears to be a key driver of changes in gross output for dairy farms. In contrast, sheep and beef farms show a mixed pattern: while global beef prices have trended upward, global lamb prices have declined over the study period. For forestry farms, a sharp rise in lumber and wood prices, combined with a gradual increase in the price of New Zealand Units (NZUs), appears to have supported improvements in farm profitability. These price movements likely contributed to the shift in forestry farm profitability, with median profits turning positive in the second half of the study period.

[5] Appendix S3 depicts the spatial distribution of these land-use activities using the Land Use and Carbon Analysis System (LUCAS) map using a snapshot of December 2020. Appendix S4 depicts the number of farms across land-use types within each region, where a consistent downward trend in farm counts continues to be observed at regional level.

4.2. Summary Statistics

Table 1 contains summary statistics of key variables[6]. As previewed earlier, this table confirms that dairy, sheep and beef, and forestry farms operate under distinct economic and operational conditions. The median dairy farm operates on a land size of 160 ha with 334 cows, generating NZ$5,238 per hectare in gross output and NZ$423 in taxable profit while spending NZ$3,524 in intermediate expense and borrowing NZ$1,359 in current loans. The median sheep and beef farm has a smaller land area (120 ha) and a herd size of 48 beef cows and 121 sheep, but they manage significantly larger operations at the upper end (around 5675 hectares, 1537 beef cattle, and 1,000 dairy cattle and 13,200 sheep at the 99th percentile). Sheep and beef farms tend to operate at a smaller economic scale compared to dairy farms, with a median gross output of NZ$1,265 per ha, intermediate expenses of NZ$1,144 per ha, taxable profit of NZ$29 per ha, and current loans of NZ$442 per ha. Forestry farms tend to be smaller in land size (51 ha) and generate negative profit (-NZ$106 per ha) with smaller gross output scale (NZ$289 per ha), yet on the upper end, they are as comparable as dairy farm in term of economic scale and profit. Forestry farms exhibit the most variation in term of their operation/ economic scales (signified by a high standard deviation in land use and economic outcomes).

Levente (2020) finds that geographical and agroclimatic conditions are among the key factors that influence land-use decisions. The trends depicted in Table 1 largely support this finding although some differences emerge to some certain extent. Dairy farms tend to occupy land with closer proximity to town, land with smaller soil particle, higher land-use capability, flatter terrain and in areas with more neighbouring dairy farms. Sheep and beef farms, by contrast, typically operate on land further from town, land with bigger soil particle and with moderate land-use capability, in areas with steeper slopes. However, neighbourhood effects are less pronounced for sheep and beef farms: Dairy farms are more frequently located in mesh-blocks with a higher proportion of surrounding dairy activity (13%) compared to sheep and beef farms (1%) and forestry farms (0%). In contrast, sheep and beef farms tend to be in mesh-blocks where only 22% of land is used for the same purpose, compared to 25% for dairy farms and 19% for forestry farms. Plantation forests usually located on the remote areas with large soil particle, steeper slopes, lower-quality land and are more commonly found in regions with higher forest cover (both native and plantation forest), suggesting a strong neighbourhood effect (38%).

We also find that dairy farms tend to be more recently established (with younger farm age), whereas forestry farms are generally older and more likely to self-identify as Māori-owned businesses. However, this Māori ownership indicator is only available for approximately 2% of farms, which limits the reliability of this comparison. Farms often engage in multiple land uses alongside their primary activity, such as growing crops or establishing forestry plantations on pastoral farms or retaining areas of bush or scrub land that are not actively exploited. In terms of farm inputs, the average farm,

[6] Appendix S5 shows variables' definition and data sources.

Table 1 Summary statistics

In accordance with Statistics New Zealand's confidentiality rules, all observation counts are randomly rounded to the nearest 3, and summary statistics are suppressed when based on fewer than 6 observations. Soil moisture data is measured monthly to a depth of 0–90 cm; we use the annual average of monthly soil moisture deficit. Rainfall recharge data is originally provided as monthly values from 2000 to 2014; we use the annual total over that period. Forestry data (e.g., harvested volume, harvested area, new planting) is only available for years prior to 2019. Fertiliser data is available from 2011 onward. Irrigation data is available only for selected years: 2007, 2012, 2014, 2017, and 2018. Financial data is available only for specific time periods, depending on IR filing records.

Stats	Number of observations			Median			1st Percentile			99th Percentile			Standard Deviation		
Land use Type	**Dairy**	**SnB**	**Forestry**	**Dairy**	**SnB**	**Forestry**	**Dairy**	**SnB**	**Forestry**	**Dairy**	**SnB**	**Forestry**	**Dairy**	**SnB**	**Forestry**
Operational scale															
Total land use (ha)	107,583	245,322	34,104	160	120	51	4	2	2	1,173	5,675	3,221	298	1,718	1,114
Beef (lsu)	103,038	242,244	32,157	0	48	0	0	0	0	439	1,537	239	101	371	81
Dairy (lsu)	107,094	230,241	31,596	334	0	0	0	0	0	2,259	1,000	90	479	249	45
Sheep (lsu)	100,947	238,515	32,034	0	121	0	0	0	0	1,564	13,200	1,585	426	2,982	556
Harvested wood (m^3)	85,926	193,800	25,362	0	0	0	0	0	0	172	1,000	30,199	1,809	1,673	20,254
Economics outcome per ha															
Taxable profit per hectare (NZ$/ha)	80,967	182,895	23,250	423	29	-106	-5,640	-10,981	-10,981	11,450	19,956	19,956	2,608	3,412	4,022
Gross output per hectare (NZ$/ha)	81,573	184,200	19,881	5,238	1,265	289	-995	-869	-471	53,816	68,988	68,988	8,483	9,656	10,549
Intermediate expense per hectare	81,768	185,085	23,478	3,524	1,144	405	17	15	2	34,489	41,765	41,765	5,355	5,960	5,735
Current loan per hectare (NZ$/ha)	80,775	174,168	20,175	1,359	442	248	0	0	0	67,692	115,469	115,469	12,822	17,016	18,524
Farm characteristics															
Farm age (year)	106,920	245,013	34,056	13.0	16.0	17.0	0.0	0.0	0.0	36.0	37.0	44.0	10.0	10.2	10.0
Māori business indicator (yes/no)	3,189	5,445	906	0	0	1	0	0	0	1	1	1	0	0	0
Farm spatial characteristics															
Distance to town (km)	103,554	232,395	32,004	9.1	11.6	11.8	0.4	0.4	0.3	50.7	54.0	54.7	10.6	12.9	12.8
Mean soil class (1-8)	103,548	232,380	32,004	3.0	4.0	4.0	0.0	0.0	0.0	8.0	8.0	8.0	2.1	2.2	2.5
Mean slope (1-8)	95,001	212,403	27,678	1.0	3.0	4.0	1.0	1.0	1.0	7.0	7.0	7.0	1.8	2.0	2.0
% neighbour land for dairy	107,583	245,322	34,104	13%	1%	0%	0%	0%	0%	50%	38%	29%	11%	9%	6%
% neighbour land for sheep/beef	107,583	245,319	34,104	25%	22%	19%	0%	0%	0%	67%	57%	50%	14%	12%	12%
% neighbour land for forestry	107,583	245,322	34,104	18%	26%	38%	0%	0%	0%	66%	72%	80%	18%	20%	23%
Land use on farm															
Grassland/ tussock land (%)	107,583	245,322	34,104	94%	90%	0%	14%	0%	0%	100%	100%	100%	15%	20%	26%
Forestry land (%)	107,583	245,322	34,104	0%	0%	81%	0%	0%	0%	19%	25%	100%	4%	6%	35%
Horticulture land (%)	107,583	245,322	34,104	0%	0%	0%	0%	0%	0%	46%	62%	45%	9%	11%	8%
Bush/ scrub land (%)	107,583	245,322	34,104	0%	0%	0%	0%	0%	0%	46%	67%	96%	9%	14%	22%
Farm management practice															
Fraction of irrigation total (%)	49,377	104,649	15,231	0%	0%	0%	0%	0%	0%	100%	96%	31%	27%	16%	8%
Fertiliser use (tonne) nitrogen (K)	69,597	150,921	21,615	0.0	0.0	0.0	0.0	0.0	0.0	237.2	45.5	0.8	2,278.7	951.2	308.1
Fertiliser use (tonne) phosphorus (P)	69,252	151,155	21,627	0.0	0.0	0.0	0.0	0.0	0.0	122.8	90.0	1.0	2,164.5	1,419.2	302.1
Fertiliser use (tonne) sulphur (S)	69,135	150,606	21,600	0.0	0.0	0.0	0.0	0.0	0.0	85.0	52.0	0.5	3,906.9	2,195.2	359.1
Water cycle															
Monthly soil moisture deficit (0-90cm)	100,203	223,548	29,394	0.026	0.033	0.030	-0.026	-0.018	-0.026	0.090	0.103	0.101	0.023	0.024	0.024
Total water recharge (mm/year)	56,793	120,669	14,205	297	267	324	3	0	0	1,841	1,417	1,751	376	288	325
Groundwater table depth (mbg)	103,551	232,383	32,007	6.09	15.14	20.24	0.00	0.04	0.00	65.39	76.36	78.88	12.61	16.71	20.68
Carbon cycle															
Dry matter (kg DM/ha/year)	101,703	228,138	30,573	12,477	10,102	na	7,279	6,805	na	15,436	12,033	na	1,846	1,224	na
Net NEP ($gC/m^2/year$)	102,237	229,161	30,684	136	32	84	-106	-122	-220	285	154	322	87	58	106

regardless of whether it is a dairy, sheep and beef, or forestry farm, does not typically use irrigation or fertiliser. However, on the upper scale, dairy farms tend to apply inputs such as irrigation water, nitrogen, phosphorus, and sulphur than other land uses. In contrast, sheep and beef farms generally have a lower environmental footprint, as their primary feed source is grazed pasture. Forestry farms, meanwhile, typically do not rely on irrigation or fertilisers at all.

Finally, in relation to our main variables of interest, we find that dairy farms generally operate on land capable of producing approximately 12,477 kg DM/ha/year of pasture dry matter. In contrast, sheep and beef farms typically operate on land with around 20% less pasture productivity (10,102 kg DM/ha/year). In terms of net primary production (NPP), forestry farms average around 84 gC/m²/year, while dairy farms exhibit significantly higher values at 136 gC/m²/year, and sheep and beef farms average around 32 gC/m²/year. Dairy farms also tend to be located in areas with lower soil moisture deficits (at 26 mm/month) compared to sheep and beef (at 33 mm/month) or forestry farms (at 30 mm/month), indicating less water stress. Additionally, they are more often situated in areas with a shallower groundwater table closer to the ground (6 meter below ground), which may enhance irrigation efficiency, as compared to sheep and beef farms (15 m) or forestry farms (20 m). However, when it comes to total groundwater recharge, forestry farms appear to occupy lands with higher recharge rates (324 mm/year), likely due to deeper root systems and lower water abstraction.

4.3. Base Model Estimates

Table 2 presents the base model estimate of Eq. (1). The specification from column 1 involves a naïve regression of dairy farms' taxable profit per hectare on the carbon indicator, pasture dry matter, using pool OLS regression without controlling for any cofounding factors. In column 2, the variable of interest is replaced with the water indicator, soil moisture deficit, still in a naïve regression setting. All the main control variables, including region dummies and year dummies are incorporated in the full specification in column 3. We then re-estimate the full specification in Eq. (1) using fixed-effect (FE) estimator. All reported standard errors are clustered at the farm level to account for within-farm correlations and heteroskedasticity, ensuring that our inference is robust and not biased by underestimated standard errors or inflated Type I error rates.

For the difference between column 3 and column 4, it is important to noted that the pool OLS regression rely on the assumption of strict exogeneity, that is, all *explanatory variables* must be uncorrelated with the idiosyncratic error term (ε_{imt}) across all time periods. When this condition holds, the estimated coefficients of water and carbon indicators can be interpreted as unbiased and consistent measures of the causal relationships of interest. In practice, it is nearly impossible to identify and include all potential confounding characteristics in the regression models, including both observed characteristics and unobserved characteristics.

The fixed effect estimator (FE) helps reduce omitted variable bias by controlling for unobserved, time-invariant heterogeneity across farms such as farm management styles, business and supply chain model, or technology (as long as they remain constant over time). In panel data setting, this moves us closer to causal inference relative to pooled OLS, especially if other biases are alleviated (such as omitted variable bias due to unobserved heterogeneity across time, measurement error bias, and simultaneity bias). However, it should be noted that FE estimates are identified solely from within-farm variation over time. As a result, any explanatory variables that do not vary within farms (for instance, a long-term water table) over the study period cannot be estimated. Further, measurement biases can be amplified in FE models as the demeaning process using farm fixed effects may eliminate much of the true variation while leaving noises intact.

Accordingly, both pasture dry matter and soil moisture deficits enter the regressions for the dairy farm subset with coefficients that are sign-consistent with expectations and are mostly statistically significant. This lends support to the hypothesized association between the dual impact of water-carbon indicator on farm profit across New Zealand. The FE estimates in column 4 in Table 1 suggests that a 1% increase in dairy pasture dry matter is associated with a NZ$5.6 per hectare increase in farm profit, while a 1 mm/month (or 0.001 m/month) increase in annual averages of monthly soil moisture deficit corresponds to a NZ$4.87 (equal to 4,868 * 0.001m/month) per hectare reduction in farm profit, holding other things equal. To put these estimates into perspective, the median dairy farm currently earns approximately NZ$423 in taxable profit per hectare, with an average pasture dry matter of 12,477 kg DM/ha/year and an average monthly soil moisture deficit of 0.023 m/month (refer to Table 1). Therefore, a 1% increase in pasture dry matter would be associated with 1.3% increase in taxable profit, while a 1% increase in soil moisture deficit (or 0.26 mm/month) would reduce profit by NZ$1.26 per ha, equivalent to a 0.29% decrease in profit. Taken together, the beneficial effect of increased pasture growth on farm profits appears to dominate the adverse impact of drought conditions.

On the subset of dairy farms, the estimated coefficient on soil moisture deficit retains its sign and statistical precision when several observed control variables are included in the regression, either individually or jointly. Similarly, the coefficient on pasture dry matter remains positive across all model specifications, although its statistical significance diminishes under pooled OLS, where time-varying farm-level heterogeneity is not controlled for. A post-estimation test on the joint significance of water–carbon cycle variables further confirms their combined influence on farm profitability, with a Wald chi-square statistic of 126.09 ($p < 0.01$). Moreover, a Hausman specification test supports the choice of the fixed effects estimator over the random effects model, indicating that unobserved farm-specific heterogeneity is correlated with the covariates.

Column 5 to 8 repeats these specifications on the subset of sheep and beef farms. Here similar to dairy farms, we observe a statistically significant impact of pasture dry matter on farm profitability across all models, although the strength of this significance is marginal (remaining significant only at the 10% level). Taking the most restrictive model in column 8, a 1% increase in pasture dry matter is associated with a NZ$1.8 per hectare increase in farm profit. Although the absolute profit gain is smaller than that observed for dairy farms (NZ$5.6 per hectare), the relative economic impact is more substantial when considering the lower baseline profitability of sheep and beef farms. With a taxable profit of NZ$29 per hectare for a median sheep and beef farm, a 1% increase in pasture dry matter represents a 6.2% increase in profit for sheep and beef farms, compared to only 1.3% for dairy farms. This suggests that changes in dry matter production is more economically significant to sheep and beef farms due to their less intensive input systems, while dairy farms can have supplemental feed, fertiliser, or irrigation to cope during these times.

Meanwhile, the water-related indicator, soil moisture deficit, shows a statistically significant effect in the naïve model; however, the magnitude and significance of this effect gradually reduces once we control for the carbon-related indicator (pasture dry matter), other confounding factors (column 7), as well as farm fixed effects (column 8). Again, the negative impact of droughts seems to be dominant by positive effect of pasture growth. The joint significance of water–carbon cycle variables on farm profitability continue to be confirmed by a Wald chi-square statistic of 10.64 ($p < 0.01$), and the suitability of a FE estimator continue to be confirmed by the Hausman identification test. However, the overall model goodness of fit for sheep and beef farms seem to be relatively low, as the adjusted R^2 is only 2.1% as compared to the subset of dairy farms. This may be due to the lagged nature of drought impacts on meat production, where the economic effects materialize only after several consecutive years of limited inputs, such as reduced feed availability or stock numbers.

For forestry farms, the FE estimator appear less suitable for this subset. This is indicated by an insignificant Hausman test result on the null hypothesis that the preferred model is random effects vs. the alternative the fixed effects. In addition, the FE model (column 12) yields lower adjusted R^2 as compared to OLS model (column 11) for forestry farms. It is worth noting that the forestry farm subset is limited to the period 2010–2018 due to of data availability in NZU price and harvest wood volume data (m^3). A further limitation is the heterogeneity within the forestry category, as the data do not distinguish between native and plantation forests, which may have substantially different economic characteristics.

Across all specifications, there is no statistically significant effect of net primary production (or *transient carbon capture*) on taxable profit (see column 9,11,12). While surprising, several factors may

Table 2 Baseline estimates of the impact of carbon-water cycle on farm profitability

This table presents estimates of the effect of carbon-water on farm-level taxable profit per hectare. Controls include geographical/agroclimatic attributes, farm characteristics, land use and farm practice, and time fixed effect, region and farm fixed effects (in a FE model). For each variable, we report the point estimates and the standard errors (in parentheses). Heteroscedasticity robust standard errors clustered at farm-level are reported in parentheses. A Hausman specification test is conducted to assess the difference between the fixed effects (FE) and random effects (RE) estimators. If significant, the test rejects the null hypothesis that individual effects are uncorrelated with the explanatory variables, indicating that the FE specification is consistent for this model. For brevity, constant terms, regional fixed effects, and year fixed effects are estimated but not reported. Number of observations and adjusted R^2 are reported for all specifications. Especially for FE model, we also report Intraclass correlation coefficient which describes how much of the variation in the outcome variable is due to differences across farms, as opposed to changes over time within each farm. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Sample	Dairy farms				Sheep and beef farms				Forestry farms			
Model Name	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Estimation Model	Base OLS	Base OLS	Full OLS	Full FE	Base OLS	Base OLS	Full OLS	Full FE	Base OLS	Base OLS	Full OLS	Full FE
Carbon-Water Cycle												
Dry Matter (log)	796.1***		76.74	560.1***	241.8***		189.5**	194.9*				
	(70.95)		(79.99)	(112.2)	(66.45)		(87.08)	(106.6)				
NEP (gCm2)									-0.0809		-0.733	-0.709
									(0.277)		(0.504)	(0.531)
Soil Moisture Deficit		-6439.7***	-2920.0***	-4868.9***		-6154.8***	-980.1*	-841.8		-8097.4***	-7557.3***	-6038.7
		(478.2)	(644.3)	(896.8)		(386.0)	(570.2)	(620.5)		(1411.1)	(2771.4)	(3702.3)
Control Variables												
Total land use (log)			-484.6***	-943.0***			37.47**	-322.0***			-67.60	0.972
			(34.49)	(76.70)			(15.53)	(35.54)			(50.00)	(184.8)
Dairy cow (log)			192.8***	43.60								
			(23.65)	(29.30)								
Beef cow (log)							-27.09***	-15.43*				
							(6.374)	(7.991)				
Sheep (log)							0.763	-5.803				
							(4.964)	(8.045)				
Distance to town (log)			1.845	4.020			3.064***	2.967			9.988*	-11.61
			(1.178)	(5.472)			(0.925)	(3.233)			(5.438)	(14.38)
Slope class (1-8)			-2.623	-27.30			-19.41*	-30.59			-74.79	82.48
			(9.924)	(29.86)			(11.30)	(22.25)			(58.83)	(123.5)
Soil class (1-8)			-35.59***	27.67			12.34	48.13*			44.58	-79.20
			(10.06)	(31.61)			(12.90)	(25.27)			(54.28)	(117.6)
% similar neighbour land use			683.6***	712.9***			164.4	-299.5			-73.24	-1208.7*
			(125.7)	(257.2)			(158.2)	(210.6)			(333.2)	(733.6)
Farm age (year)			18.09***	313.9			21.54***	156.2***			38.48***	72.53
			(1.819)	(267.5)			(1.305)	(37.39)			(7.803)	(405.5)
Māori indicator*			604.0*	21.09			-272.6**	-257.1***			-197.9	4949.6**

			(323.8)	(209.4)			(149.1)	(61.65)			(646.7)	(988.5)
Horticulture land (%)			-457.5**	-188.5			326.3*	-335.5**			1626.5	2022.4**
			(197.3)	(271.6)			(150.3)	(158.9)			(1214.4)	(846.8)
Forestry land (%)			-58.71	1210.8*			137.1	300.5				
			(428.9)	(651.2)			(279.5)	(320.2)				
Grassland (%)											-230.4	-99.06
											(212.6)	(419.9)
Harvested wood (m3) (log)											170.5***	158.5***
											(25.97)	(32.83)
Dairy price (log)			1538.7***	-3755.4								
			(59.38)	(5033.6)								
Beef price (log)							-9292.0***	-3218.1***				
							(1055.8)	(726.5)				
Lamb price (log)							-867.8***	-6204.0***				
							(131.1)	(886.8)				
Wood price (log)											2139.1***	1306.9
											(701.9)	(10729.3)
NZU price (log)											865.1	1011.5
											(555.3)	(1699.1)
Number of observations	69,285	68,730	*62,712*	*62,712*	*158,615*	*155,315*	*136,001*	136,002	*19,002*	*19,914*	*8,196*	*8,196*
Adjusted R^2	0.3%	0.4%	*13.8%*	*20.5%*	*0.0%*	*0.0%*	*1.7%*	1.9%	*0.0%*	*0.3%*	*4.6%*	*3.4%*
Intraclass correlation	*NA*	*NA*	*NA*	*0.829*	*NA*	*NA*	*NA*	0.771	*NA*	*NA*	*NA*	*0.738*
Hausman Test χ2 statistics				*892.84****				*54.24****				*24.95*
Likelihood ratio test χ2				*126.09****				*10.64****				*7.51***
IDENTIFICATION												
Control for regional fixed effect	No	No	Yes	Yes	No	No	Yes	Yes	No	No	Yes	Yes
Control for year fixed effect	No	No	Yes	Yes	No	No	Yes	Yes	No	No	Yes	Yes
Control for farm fixed effect	Yes	Yes	No	Yes	Yes	Yes	No	Yes	Yes	Yes	No	Yes

explain this result. First, the longer harvest cycles in forestry means that the increase in transient NEP or wood growth has little influence on farm profitability from wood production and carbon credits. Second, the timing of carbon uptake is decoupled from when income from NZU sales is realized due to the set-up of NZ ETS. Third, the Biome-BGC model has not been specifically calibrated to NZ's native forest, which may hamper the model accuracy. The long-term nature of forestry rotations and strategic carbon trading behaviour therefore weakens any direct, short-term link between carbon uptake and net income in the models. Regarding soil moisture deficit, its negative and significant effect on forestry farm profit observed in the pooled OLS model disappears in the FE model. This leaves the effect of soil moisture deficits on forestry profitability *inconclusive*. Nevertheless, the joint significance of water–carbon cycle variables on forestry farm profitability is supported by a Wald chi-square statistic of 10.64 ($p < 0.05$).

Taken together, these findings suggest that the results for forestry farms should be interpreted with caution, given data limitations, model uncertainties, and the characteristics of forestry as a long-term land use.

5. Robustness Test

5.1. Channel analysis

The base models in Table 2 document the empirical impact of the water–carbon cycle on farm profitability. To further investigate the channels through which these biophysical indicators affect profit, we examine their associations with other components of the farm financial statements. Table 3 presents the results of this extended analysis, where we re-estimate the full specification of Eq. (1) but use alternative outcome variables including gross output, intermediate expense and current loan, all normalised using the farmland area in hectare.

In panel (a), we find that the positive impact of pastoral dry matter production on dairy farms' taxable profit operates through two main channels: a substantial increase in gross output (total revenue minus stock adjustment) and a smaller, yet notable, rise in intermediate expenses (including spending on supplemental feed, irrigation, repairs and maintenance, contractor payments, and other operating costs). While the positive association between pastoral dry matter and revenue aligns with expectations, the increase in intermediate expenses is somewhat surprising, as one might expect reduced spending on supplemental feed or fertilizers. However, this can be explained by the fact that more intensive pasture production often involves greater expenditures on repairs, machinery use, fencing, and more variable costs due to a larger herd size per hectare or higher milking frequency. In contrast, the negative effect of soil moisture deficit on profit primarily manifests through a decline in gross output per hectare.

In panel (b), for sheep and beef farms, the marginal impact of pastoral dry matter production on taxable profit appears limited across all dimensions such as output or intermediate expenses or current loans. Similarly, the negative impacts of soil moisture deficit on gross output, intermediate expenses, or current loans are statistically insignificant within this subset. This may be again due to the lagged nature of water-carbon effects on meat production. Panel (c) presents results for forestry farms, where no significant relationships between the studied variables and profitability are observed.

Table 3 The impact of water-carbon cycles on farms' other economic outcomes

This table presents estimates of the effect of carbon-water on farm-level alterative economic outcomes. Controls include geographical/agroclimatic attributes, farm characteristics, land use and farm practice, and time fixed effect, region and farm fixed effects. To conserve space, we report the point estimates and the standard errors (in parentheses) of the main variables of interest only. Heteroscedasticity robust standard errors clustered at farm-level are reported in parentheses. Number of observations and adjusted R^2 are reported for all specifications. Especially for FE model, we also report Intraclass correlation coefficient which describes how much of the variation in the outcome variable is due to differences across farms, as opposed to changes over time within each farm. * p<0.1, ** p<0.05, *** p<0.01.

Dependent Variable	Taxable profit per hectare	Output per hectare	Intermediate expense per hectare	Current loan per hectare
Estimation Model	Full FE	Full FE	Full FE	Full FE
Panel (a) Dairy farms				
Dry Matter (log)	560.1***	721.4**	351.1*	268.3
	(112.2)	(299.1)	(181.8)	(480.0)
Soil Moisture Deficit (mm/month)	-4868.9***	-4355.7*	-984.9	1845.8
	(896.8)	(2287.9)	(1409.7)	(3731.4)
Number of observations	*62,712*	*63,204*	*63,294*	*62,661*
Adjusted R^2	*20.5%*	*39.8%*	*40.6%*	*11.7%*
Intraclass correlation coefficient	*0.829*	*0.879*	*0.843*	*0.699*
Panel (b) Sheep and beef farms				
Dry Matter (log)	194.9*	-246.3	-102.01	-537.8
	(106.5)	(270.2)	(170.33)	(370.0)
Soil Moisture Deficit (mm/month)	-841.8	-540.2	-119.8	-4241.5
	(620.46)	(1519.8)	(879.8)	(2750.3)
Number of observations	*136,001*	*137,047*	*137,516*	*151,182*
Adjusted R^2	*2.1%*	*27.8%*	*36.7%*	*14.2%*
Intraclass correlation coefficient	*0.771*	*0.984*	*0.919*	*0.939*
Panel (c) Forestry farms				
NEP (gC/m²/year)	-0.709	0.455	0.709	0.0368
	(0.531)	(1.157)	(0.470)	(1.976)
Soil Moisture Deficit (mm/month)	-6038.7	-14115.7	-4857.2	-8988.1
	(3702.3)	(8735.6)	(3546.5)	(18716.1)
Number of observations	*8,196*	*6,693*	*8,301*	*6,891*
Adjusted R^2	*3.4%*	*10.3%*	*16.3%*	*8.9%*
Intraclass correlation coefficient	*0.738*	*0.843*	*0.895*	*0.803*

5.2. Control for fertiliser and irrigation

One could argue that the observed dual impact of water and carbon cycles on farm profits for dairy farms, and to a lesser extent, for sheep and beef farms, discussed in Section 4.3 may be confounded by intensified farm management practices, particularly the use of fertilisation and irrigation. In **Table 4**, we gradually account for fertiliser application and irrigation as a control variable as part of our effort to address this concern.

Table 4 Inclusion of fertiliser and irrigation on the impact of water-carbon cycles on pastoral farm profitability.

This table presents estimates of the effect of carbon-water on farm-level profit in a test where we include irrigation and fertiliser activities. Controls include geographical/agroclimatic attributes, farm characteristics, land use and farm practice, and time fixed effect, region and farm fixed effects. To conserve space, we report the point estimates and the standard errors (in parentheses) of the main variables of interest only. Heteroscedasticity robust standard errors clustered at farm-level are reported in parentheses. Number of observations and adjusted R^2 are reported for all specifications. Especially for FE model, we also report Intraclass correlation coefficient which describes how much of the variation in the outcome variable is due to differences across farms, as opposed to changes over time within each farm. * p<0.1, ** p<0.05, *** p<0.01.

Sample	Dairy farms			Sheep and beef farms		
Column	(1)	(2)	(3)	(4)	(5)	(6)
Estimation Model	Full FE	Full FE	Full FE	Full FE	Full FE	Full FE
Identification Strategy	Base model	With fertiliser	With fertiliser + irrigation	Base model	With fertiliser	With fertiliser + irrigation
Carbon-Water Cycle						
Dry Matter (log)	560.1***	948.5***	1108.9***	194.9*	313.8**	276.4
	(112.2)	(160.8)	(224.6)	(106.6)	(150.2)	(209.7)
NEP (gCm^2)						
Soil Moisture Deficit (mm)	-4868.9***	-5669.0***	-2454.1	-841.8	-1054.9	-836.6
	(896.8)	(1177.8)	(1621.1)	(620.5)	(731.2)	(1065.7)
Farm Practice						
Fertiliser - nitrogen (log)		22.43**	2.738		5.536	-1.366
		(10.83)	(14.51)		(10.05)	(15.16)
Fertiliser -phosphorus (log)		-22.65	-18.50		-7.422	12.14
		(15.78)	(21.28)		(8.792)	(16.26)
Fertiliser -potassium (log)		-31.12*	-19.57		12.89	11.63
		(17.16)	(23.22)		(11.05)	(16.08)
Fertiliser -sulphur (log)		35.25**	33.94		-0.102	-25.50*
		(16.89)	(26.14)		(8.742)	(14.32)
% of irrigation land			-119.6			251.4
			(131.8)			(205.3)
Number of observations	*62,712*	*43,005*	*25,359*	*136,001*	*91,643*	*51,963*
Adjusted R^2	*20.5%*	*22.2%*	*17.2%*	*2.0%*	*2.4%*	*3.1%*
Intraclass correlation	*0.829*	*0.935*	*0.988*	*0.793*	*0.856*	*0.792*

Our findings show that the amounts of fertilisers applied, particularly nitrogen (N) and sulphur (S), are strongly and positively associated with dairy farm profitability, but potassium (K) has a marginally significant and negative impact (see column 2). Furthermore, the effects of water- and carbon-related indicators remain statistically significant even after controlling for fertiliser use. This suggests that the observed relationships are not solely driven by input intensification. Notably, the effect of pastoral dry matter production on taxable profit remains robust and nearly doubles in magnitude (refer to column 2 – a repeat of the full FE model in Table 2). This indicates that its economic impact is partially masked when fertiliser inputs are omitted. Similarly, soil moisture deficit continues to show a significant negative association with profit when fertilisers are included in the model.

In column (3), we present an even more restricted model specification when we account for irrigation practices by including the proportion of irrigated land at the farm level. In this specification, the effect of soil moisture deficit becomes statistically insignificant, while the effect of pastoral dry matter remains strong and significant. This shift likely reflects the role of irrigation as a direct response to water scarcity, and once irrigation is accounted for, it absorbs much of the explanatory power that soil moisture deficit previously held. In contrast, dry matter continues to maintain its strong association with profitability. A caveat of this approach is that the irrigation data are only available for approximately for some of the years, as some annual surveys do not include this information.

Similarly, for sheep and beef farms, we find that the effect of dry matter strengthens after controlling for fertiliser use (column 5), with sulphur (S) showing a marginally negative association with farm profitability. In contrast, the contemporary soil moisture deficit does not seem to affect sheep and beef farm profits with or without fertiliser and irrigation controls.

5.3. Regional and time-specific effect

In **Fig. 4**, we test the regional-and year-specific impact of water and carbon cycle to farm profit. To do so, we re-estimate the full specification of Eq. (1) using the interaction terms between the water-carbon indicators (e.g., soil moisture deficit, pastoral dry matter, carbon sequestration) with a categorical variable (e.g., region dummies or year dummies) (see Eq. (2a) and (2b), respectively). This approach allows the estimated effects of these indicators to vary across regions and enables a direct comparison of regional differences within a single regression framework. It also ensures greater statistical efficiency and consistency than estimating separate models for each region, while allowing formal testing of whether regional effects are significantly different. Alternatively, we estimate separate regressions for each regional subset to explore local dynamics. While this approach captures regional variability more directly, it may suffer from smaller sample sizes, limiting statistical power and complicating cross-region comparisons. [7]

$$Y_{imt} = \alpha + \sum \boldsymbol{\beta_{1k} Carbon_{mt}} * Region_k \; + \; \sum \boldsymbol{\beta_{2k} Water_{mt}} * Region_k \qquad (2a)$$
$$+ \tau Control_{it} \; + \varphi Region_k + \sigma Year_t \; + \; \varepsilon_{it}$$

$$Y_{imt} = \alpha + \sum \boldsymbol{\beta_{1t} Carbon_{mt}} * Year_t \; + \; \sum \boldsymbol{\beta_{2t} Water_{mt}} * Year_t \qquad (2b)$$
$$+ \tau Control_{it} \; + \; + \varphi Region_k + \sigma Year_t \; + \; \varepsilon_{it}$$

Panel (a) presents the estimated regional- effect of carbon-water indicators across farm types. With the subset of dairy farms, we find that the general positive impact of dry matters on farm profit seems to be driven by Taranaki, Waikato, Bay of Plenty, among the largest dairy centres of New Zealand while soil moisture deficit has a statistically significant regional-specific effect on Waikato,

[7] These findings largely align with those from the national interaction model and are available upon request.

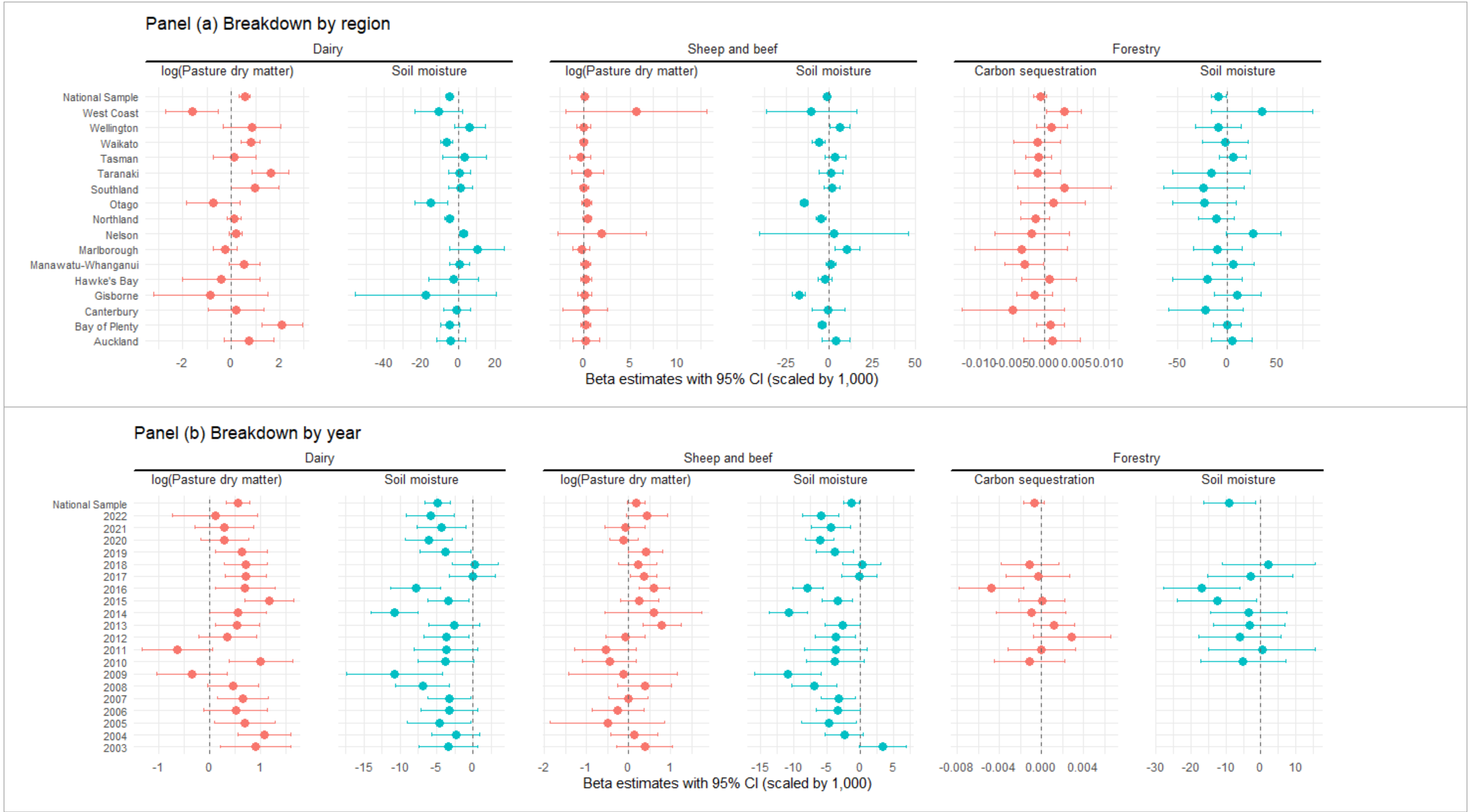


Figure 5 The temporal and spatial variation in water-carbon effects on farm profitability. This figure presents the point estimates (β coefficients) and 95% confidence intervals (±2 standard deviations) for the effects of carbon and water on farm-level profit, varying across regions (panel a) and over time (panel b). Within each panel, results are grouped into farms with primary land use types (Dairy, Sheep and Beef, Forestry). These represent the interaction terms Carbon × Region and Water × Region from Eq. 2a and 2b, respectively. Estimates are derived from FE models that control for geographical and agroclimatic attributes, farm characteristics, land use and management practices, as well as time, region, and farm fixed effects. Underlying figures are presented in Appendix Tables S7 and S8.

Northland and Otago. For sheep and beef farms, the positive impact of pasture production seems to be mostly significant in Northland region, while the adverse impact of soil moisture deficit is found across Bay of Plenty, Otago, Northland, and Waikato regions. For forestry farms, much of the regional-specific impacts are insignificant, aligned with the main results.

Panel (b) presents the estimated year-specific effects of carbon–water indicators. For the subset of dairy farms, higher levels of pastoral dry matter are consistently associated with increased farm profits across years, with the strongest effects observed in 2004, 2010, and 2015. A visual inspection shows that these effects often occur during years when dairy farms record lower profits and economic outcomes. Correlation analysis supports this interpretation, suggesting that the carbon-effect is amplified under adverse conditions where higher pasture growth may help buffer dairy profits during more challenging years. Meanwhile soil moisture deficits have the largest negative impacts on farm profits in 2009, 2014, and 2016. Of which, 2009 and 2016 is the years marked by poor conditions, but 2014 comes with higher profits.

For the subset of sheep and beef, the effect of pasture dry mater on these farms' profit can only be observed in a few years, including 2013, 2016, and 2019. The yearly-specific effects of soil moisture deficits, however, follow essentially the same patterns with those of dairy farms. These findings highlight the varying sensitivity of farm profitability to carbon and water availability across time particularly under market and weather stress. These visual inspection and correlation analyses are presented in Appendix Table S9. Additional analyses where we remove the adverse years in our sample size (including the global financial crisis 2008-2009, the North Island drought 2013, the Covid years 2019-2020) confirms ,

5.4. Testing for lagged effect, non-linearity, and interaction terms of water-carbon cycles

To ensure our results are not distorted by model misspecification, we tested for both lagged effects and non-linear relationships in the carbon–water variables. Lagged effects were examined by gradually introducing from one- to four-year lags of pasture dry matters, NEP, and soil moisture deficit variables into the FE models. This allows us to test whether past values of carbon uptake or water stress have delayed impacts on farm profitability.

To explore potential non-linearities we included squared terms of NPP and SMD to capture diminishing or amplifying marginal effects. We also tested for interaction terms between carbon and water variables to assess whether their combined effect differs from the sum of individual effects. The significance and direction of these terms were assessed to determine whether linear assumptions hold or if more complex functional forms are appropriate.

Table 5 Testing for lagged effect of water-carbon cycle on farm profitability.

This table presents estimates of the lagged effect of carbon-water on farm-level profit. Controls include geographical/agroclimatic attributes, farm characteristics, land use and farm practice, and time fixed effect, region and farm fixed effects. To conserve space, we report the point estimates and the standard errors (in parentheses) of the main variables of interest only. Heteroscedasticity robust standard errors clustered at farm-level are reported in parentheses. * p<0.1, ** p<0.05, *** p<0.01.

Sample	Dairy farms				Sheep and beef farms				Forestry farms			
Column	(1)	(2)	(3)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Estimation Model	Full FE	Full FE	Full FE	Full FE	Full FE	Full FE	Full FE	Full FE	Full FE	Full FE	Full FE	Full FE
Dry Matter (log), t	560.1***	503.6***	437.7*	606.8*	194.9*	350.0***	353.1**	554.8***				
	(112.2)	(174.5)	(228.8)	(320.7)	(106.6)	(122.4)	(157.8)	(204.4)				
Dry Matter (log), t-1		653.3***	817.1***	873.1**		196.3**	353.4***	491.5***				
		(199.5)	(243.0)	(360.9)		(99.30)	(130.8)	(169.9)				
Dry Matter (log), t-2			-43.51	157.7			139.0	60.25				
			(169.9)	(277.7)			(106.0)	(135.8)				
Dry Matter (log), t-3				70.67				-178.1				
				(243.9)				(112.9)				
NEP, t									-0.709	-2.072**	-2.339	-0.972
									(0.531)	(0.936)	(1.519)	(2.093)
NEP, t-2										-0.239	0.279	1.115
										(0.764)	(1.227)	(1.595)
NEP, t-2											1.103	1.111
											(1.178)	(2.045)
NEP, t-3												0.145
												(1.696)
Soil Moisture Deficit, t	-4868.9***	-6583.7***	-7139.6***	-8039.6***	-841.8	-534.6	-598.3	39.03	-6038.7	-12867.9*	-14281.9	-4702.0
	(896.8)	(1255.0)	(1583.2)	(1884.3)	(620.5)	(647.2)	(731.0)	(792.0)	(3702.3)	(7053.2)	(9420.4)	(14057.5)
Soil Moisture Deficit, t-1		1555.9	3304.3**	4766.2**		36.88	-61.40	926.5		-3835.2	-5635.3	4416.6
		(1194.1)	(1510.4)	(1911.2)		(631.2)	(725.7)	(830.4)		(6143.7)	(9221.1)	(16661.8)
Soil Moisture Deficit, t-2			-815.1	-1869.3			-1881.0***	-1659.4**			-6154.0	-9617.0
			(1437.3)	(1848.2)			(710.4)	(791.0)			(7556.1)	(10098.6)
Soil Moisture Deficit, t-3				-2409.3				276.9				16306.4
				(1593.4)				(671.6)				(14748.4)
Number of observations	*62,712*	*35,235*	*23,406*	*16,422*	*136,002*	*80,064*	*54,078*	*39,069*	*8,196*	*4,455*	*2,406*	*1,362*
Adjusted R^2	*20.5%*	*24.4%*	*26.1%*	*26.4%*	*1.9%*	*2.4%*	*2.5%*	*2.9%*	*3.4%*	*4.0%*	*3.7%*	*2.0%*
Intraclass correlation coefficient	*0.829*	*0.653*	*0.704*	*0.768*	*0.771*	*0.841*	*0.855*	*0.878*	*0.738*	*0.789*	*0.709*	*0.571*
Degree of freedom	*46*	*44*	*43*	*38*	*47*	*46*	*46*	*47*	*22*	*20*	*22*	*25*
AIC	*1,083,916*	*603,111*	*398,632*	*278,001*	*2,420,339*	*1,386,485*	*924,651*	*658,445*	*148,369*	*80,290*	*43,453*	*24,787*
BIC	*1,084,332*	*603,484*	*398,978*	*278,294*	*2,420,801*	*1,386,913*	*925,060*	*658,848*	*148,523*	*80,418*	*43,581*	*24,917*

Table 5 presents the first set of results examining the lagged effects. The findings confirm that both the water and carbon cycles exhibit significant lagged impacts on dairy farms and sheep and beef farms. In relation to the carbon cycle, the effect of pasture dry matter persists for up to two years, as indicated by the statistically significant coefficients at both lagged (t–1) and current (t) time periods across both land-use categories. This is particularly evident for sheep and beef farms, where the inclusion of lagged values for pasture dry matter reveals a much larger and more significant impact on farms profit.

In contrast, the lagged effects of soil moisture deficit differ between farm types. For dairy farms, a significant positive lagged effect from the previous year (t–1) is observed, suggesting that drought conditions in the prior year are associated with higher income in the current year. This result may reflect the dominant market role of dairy farms in New Zealand, which allows them to influence milk prices, especially during periods of supply shock. For sheep and beef farms, however, the lagged effect of soil moisture deficit emerges only at a two-year lag (t–2), with no discernible effects at t or t–1. These findings are further supported by lower values of the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) in the lagged models, indicating improved model fit.

Table 6 presents the second set of results. For dairy farms, we find significant non-linear effects of both carbon and water cycle indicators on profits supported by F-values of joint-significant tests (16.25 and 12.86), respectively (column 2). The relationship between pasture dry matter and profit is U-shaped indicated by the estimated coefficients of -3,275 (linear term) and 212 (squared term), with a turning point at log(dry matter) ≈ 7.7 (≈ 2,248 kg DM/ha/year). Below this threshold, more pasture dry matter reduces profit, beyond it profit increases likely due to improved productivity. As real-world values of dairy pasture DM is in the range of from 7,279 to 15,436 kg (see table 1, 1^{st} to 99^{th} percentile), the combined effect is most likely positive. In contrast, the effect of soil moisture deficit follows an inverted U-shape, with a turning point at SMD ≈ –0.06 mm/month. Again, this turning point lies outside the observed range (see Table 1), profits generally decline as soil moisture deficit increases. No significant interaction effects between water and carbon cycle indicators are found (column 3), suggesting that their impacts on profit operate independently rather than synergistically.

For the subset of sheep and beef farms, there is a significant non-linear effect of pasture dry matter on profits, but no such relationship is observed for soil moisture deficit, as indicated by F-values of 2.65 and 1.66, respectively. The estimated coefficients for pasture dry matter on sheep and beef farms are -833.4 (linear term) and 60.17 (squared term), continues to indicate a U-shaped relationship with the turning point at approximately 1,020 kg DM/ha/year (log ≈ 6.92). We also find so significant interaction effects between water and carbon cycle indicators for this subset of sheep and beef farms (column 6).

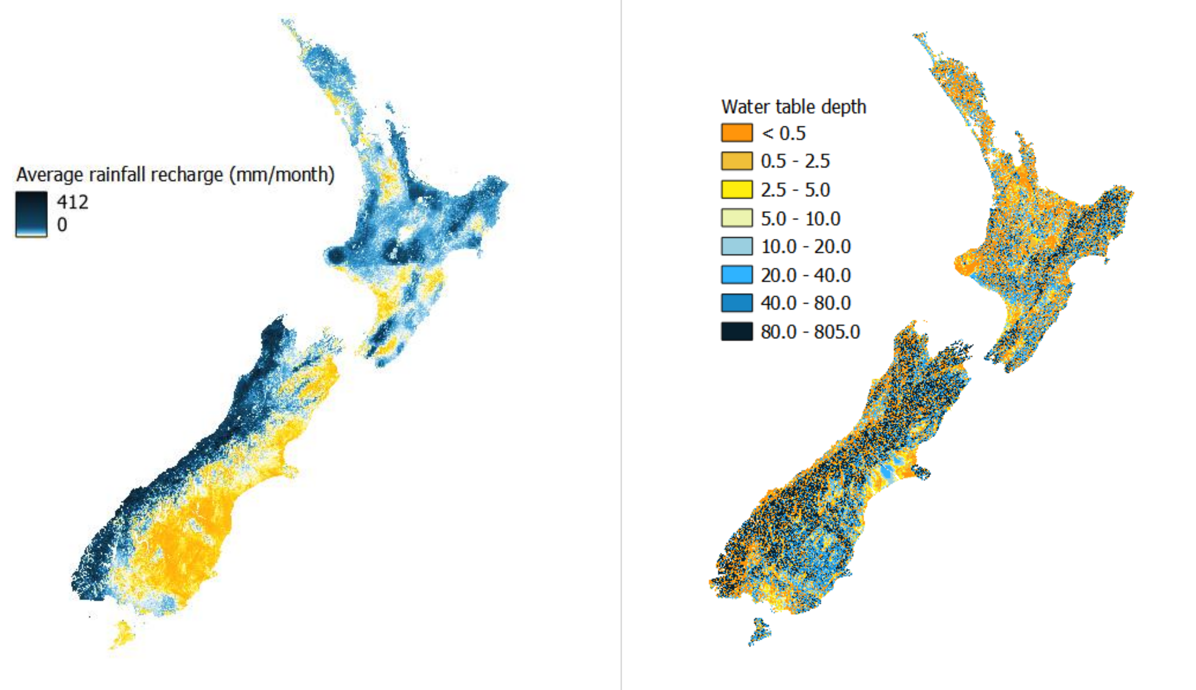
Table 6 Testing for non-linearity and interaction effect of water-carbon cycle on farm profitability.

This table presents estimates of the non-linearity and interaction effect of carbon-water on farm-level profit. Controls include geographical/agroclimatic attributes, farm characteristics, land use and farm practice, and time fixed effect, region and farm fixed effects. To conserve space, we report the point estimates and the standard errors (in parentheses) of the main variables of interest only. Heteroscedasticity robust standard errors clustered at farm-level are reported in parentheses. * p<0.1, ** p<0.05, *** p<0.01.

Sample	Dairy farms			Sheep and beef farms			Forestry farms		
Column	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Estimation Model	Full FE	Full FE	Full FE	Full FE	Full FE	Full FE	Full FE	Full FE	Full FE
Carbon-Water Cycle									
Dry Matter (log)	560.1***	-3275.3***	505.3***	194.9*	-833.4	327.0**			
	(112.2)	(785.1)	(152.4)	(106.6)	(539.6)	(161.7)			
[Dry Matter (log)] ^{2}		212.5***			60.17*				
		(47.77)			(32.83)				
Exotic NEP (gCm2)							-0.709	-0.544	-1.053
							(0.531)	(0.698)	(0.903)
[Exotic NEP (gCm2)] ^{2}								-0.00120	
								(0.00323)	
Soil Moisture Deficit (mm)	-4868.9***	-2832.0*	-22248.2	-841.8	-2359.3*	29083.9	-6038.7	-8565.4	-6750.8*
	(896.8)	(1500.1)	(30961.4)	(620.5)	(1306.1)	(25312.2)	(3702.3)	(7639.2)	(4061.6)
[Soil Moisture Deficit (mm)] ^{2}		-23749.1			17960.3			29389.7	
		(17236.7)			(12273.9)			(72892.8)	
Dry Matter x Soil Moisture Deficit			1846.3			-3253.9			
			(3285.4)			(2753.4)			
NEP x Soil Moisture Deficit									10.05
									(18.52)
Number of observations	*62,712*	*62,712*	*62,712*	*136,002*	*135,999*	*135,999*	*23,406*	*8,199*	*8,196*
Adjusted R^2	*20.5%*	*20.5%*	*20.5%*	*1.9%*	*1.9%*	*1.9%*	*26.1%*	*3.4%*	*3.4%*
Intraclass correlation coefficient	*0.829*	*0.825*	*0.828*	*0.771*	*0.773*	*0.773*	*0.704*	*0.739*	*0.739*
F test of dry matter non-linearity		*16.25****			*2.65**			1.02	
F test of soil moisture deficit non-linearity		*12.86****			*1.66*			*1.35*	

5.5. Other robustness tests

In the main analysis, we focus on the effects of soil moisture deficit (SMD)—which primarily reflects water shortages in the top 0–90 cm of soil—on farm profitability. However, an important question not addressed in the core analysis remains: To what extent does groundwater availability, which is not currently captured by the Biome-BGC model, influence farm economic outcomes? To explore this, we incorporate two indicators from the 2000–2014 national groundwater dataset: (i) groundwater rainfall recharge rate and (ii) groundwater table depth. The first is a time-varying indicator that captures the spatial and temporal distribution of rainfall that goes beyond the soil and infiltrated deeper into the ground to recharge aquifers. The second represents the long-term average depth to the water table below ground level, serving as a proxy for groundwater accessibility in deeper aquifers (see **Fig. 4**).



(a) Mean monthly rainfall recharge in 2000-2014

(b) Groundwater table depth in m below ground level (mbgl)

Figure 6 The spatial variation in groundwater table across New Zealand. Rainfall recharge to groundwater was taken from a national New Zealand rainfall recharge dataset that contains monthly estimates of recharge from January 2000 to December 2014, including an uncertainty estimate. These recharge values are fed into national maps of National Water Table model of groundwater table depth below ground level. The water table depth is relatively deep in higher mountainous regions, but water table elevation clearly follows the terrain elevation (Westerhoff et al., 2018).

We then re-estimate the full specification of Eq. (1), incorporating the additional groundwater-related variables. The sample size is reduced by half, as the analysis is now restricted to the 2003–2013 period. We continue to use a fixed effects (FE) estimator; however, this approach has limitations, particularly in capturing variation in groundwater table depth, which is largely time-invariant and only changes when farms shift location. The result of this analysis is shown in Appendix S11.

Interestingly, the results reveal a statistically significant *negative* marginal effect on dairy farms but not for sheep and beef farms or forestry farms. One plausible explanation is that high recharge areas often coincide with low-lying floodplains, where excess water may delay pasture access or increase farm management costs. An alternative, and perhaps more probable, explanation, is that the recharge variable represents *total rainfall recharge,* that is, the volume of water infiltrating past the root zone, rather than *net recharge* that actually contributes to groundwater storage. Additionally, the national groundwater model operates at a coarse spatial resolution and lower quality, which may not accurately reflect local geological conditions. This mismatch may distort the relationship and lead to the unexpected negative association between recharge and dairy profitability. As for groundwater table depth, we hypothesized that shallower depths would reduce irrigation costs and thereby increase profits, particularly in regions such as Canterbury, Waikato, or Southland with extensive alluvial aquifers. However, we find inconsistent effects for this variable as well.

In our main analysis, we use a sample spanning the past 20 years (2003–2023), which involves merging two Agricultural Production Survey (APS) datasets covering 2002–2012 and 2013–2023 into a single longitudinal database. To ensure that our results are not driven by structural changes in the agricultural sector or shifts in data collection methods over this period, we also re-run the analysis separately for the two sub-periods. The results, presented in Appendix S13, show a notably stronger effect of both water-carbon cycles in the post-2013 period.

6. Conclusion

Economic modelling using the subset of carbon, water and farm data on a national dataset showed a significant positive association between dairy farm profits and dry matter production and a negative association with soil moisture deficit. The analysis of groundwater is limited by the lower-quality data but suggest that an increase in total groundwater recharge is associated with decreased profit.

Similarly, for sheep and beef farms, we find that an increase in dry matter is associated with an increase in profit. While the absolute gain in profit is smaller than dairy farms, the relative impact is more substantial given that sheep and beef farms are generally less profitable and have a lower profit margin. Sheep and beef farms are likely more affected by interannual variability in climate and pasture production because of the less intensive nature of the farm systems. However, unlike dairy farms, the effect of contemporary soil moisture deficit is not observable for sheep and beef farms. This is because a lag in the impact of drier conditions of at least three years.

Forestry did not show any significant effects of carbon and water indicators on taxable profit. While initially counterintuitive, it is likely due to the long harvest cycle in wood production as well as how the NZ ETS is designed. NZUs are allocated based on standardized, modelled carbon exchange in advance of actual harvest or physical carbon uptake, with no variation due to climate and soil conditions.

The actual timing of carbon uptake (reflected in NEP) thus does not always coincide with when income from NZU sales is realized. As a result, annual NEP may not strongly correlate with yearly profitability, especially in financial records where revenue from NZUs is recognized only upon sale. The long-term nature of forestry rotations and strategic carbon trading behaviour therefore weakens any direct, short-term link between carbon uptake, water availability and net income in the economic models.

Although we did not find a significant association between indicators of farm profitability and groundwater volume or table depth, it does not mean that water availability is not an important factor for land use decisions and economic viability. There might be a significant lag between changes in the groundwater level and storage and farm profit, and we were not able to resolve this with our current models. There is a lack of high-quality, temporally-resolved groundwater information on a national level. With temporally-explicit observed or modelled groundwater storage and the incorporation of time lags, there could still be a significant effect.

Additionally, if the system is not water-limited (i.e., historical levels of precipitation, ET and groundwater recharge/storage are enough to meet all current needs), and there has not been a historical shortage of water supply, we would not be able to resolve any differentiation among farms as water variables fluctuate from year to year. We only tested annual variables; seasonal effects (especially the timing of precipitation during the growing season) could also be significant. It is possible that in the future, if seasonal patterns of precipitation change or a threshold has been crossed and the system becomes occasionally or frequently water-limited during drought periods, a significant relationship will emerge, and some land uses will incur more costs than others due to irrigation and/or water supply limitations. We leave this avenue for future research.

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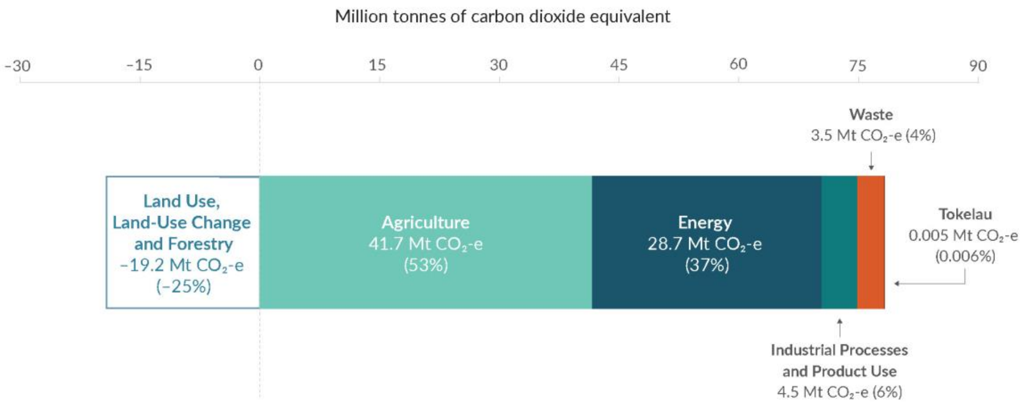
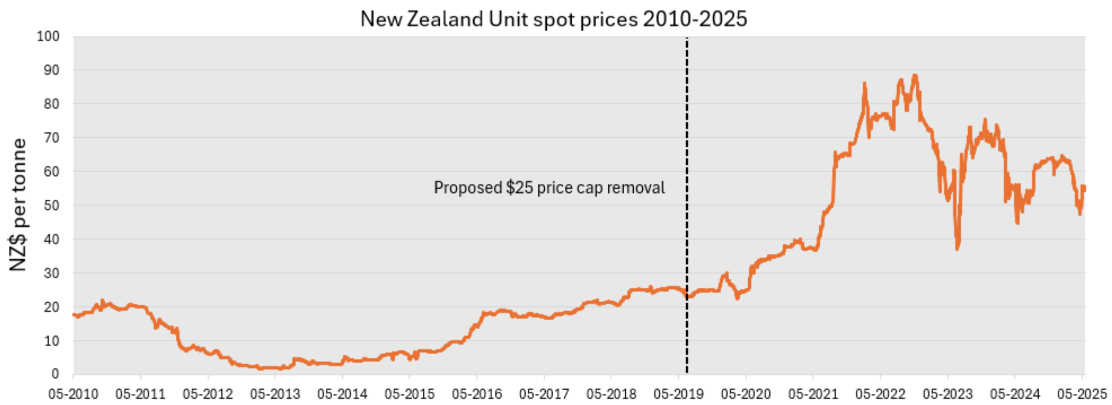
Appendix

Appendix S1. The roles of agriculture and forestry in New Zealand carbon emission profile



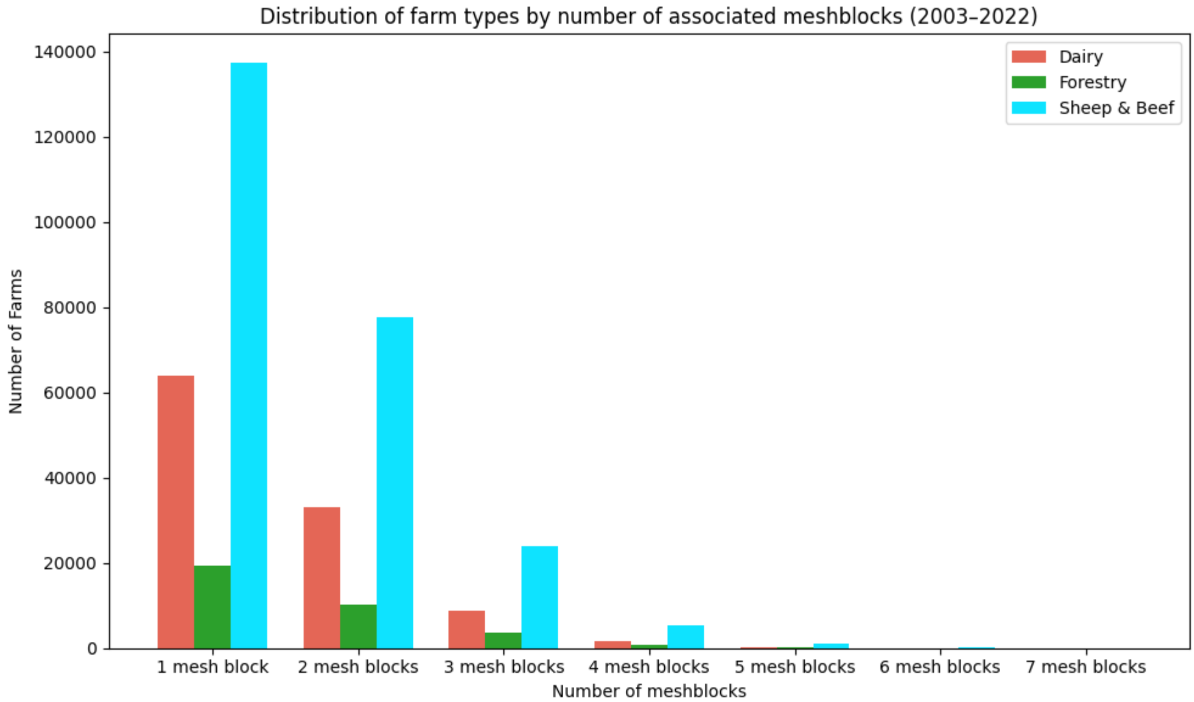
(a) Carbon stocks of New Zealand's natural ecosystems are massive; the above-ground vegetation alone stores around 1,450 million tonnes of carbon (5,343 Mt CO_2e), mostly in native forests. Our annual national carbon emission is 79 Mt CO_2e, of which, agriculture emission contributes to 41.7 Mt CO_2-e and LULUCF contributes (offset) the emission profile by 25%.



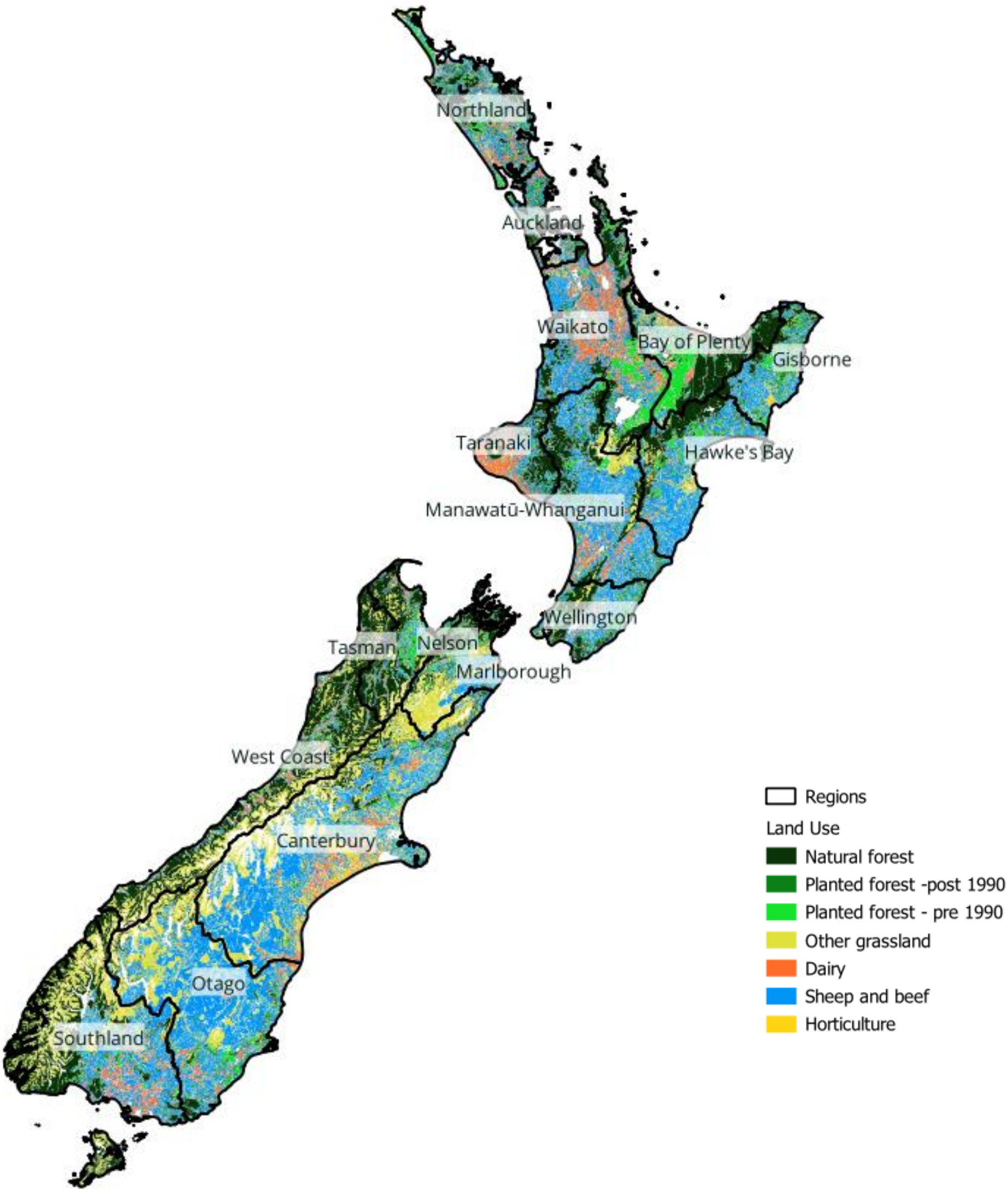
(b) New Zealand Emission Unit (NZU) spot prices remained around NZ$25 per tonne until May 2019, when the government announced a second phase of improvements to the New Zealand Emissions Trading Scheme (NZ ETS) aimed at strengthening incentives for emissions reductions and afforestation. One key change was the planned removal of the NZ$25 fixed price option (FPO) ceiling, to take effect with the introduction of auctioning or by 31 December 2022. Source: self constructed from: https://github.com/theecanmole/nzu

Appendix S2. Breakdown of farms associated with multiple meshblocks over the research period 2003-2022.

In New Zealand context, June 1 marks Moving Day and the start of the dairy season. It is estimated that up to 5,000 dairy farming families and herds relocate to new farms to take on new share-milk contracts. This widespread movement, particularly common in regions like Waikato, Taranaki, Canterbury, and Bay of Plenty, adds further complexity in interpreting farm location changes in the data. Question 8 in APS covers whether the farming business still operates at the existing location or has moved to the new location. Accordingly, in the study period 2003-2022, several farms have mesh block locations that change over time, affecting at least 50% of the sample size. Following Timar and Apatov (2020), we retain these farms, as it is unclear whether such changes reflect genuine relocations, administrative updates, or data errors.

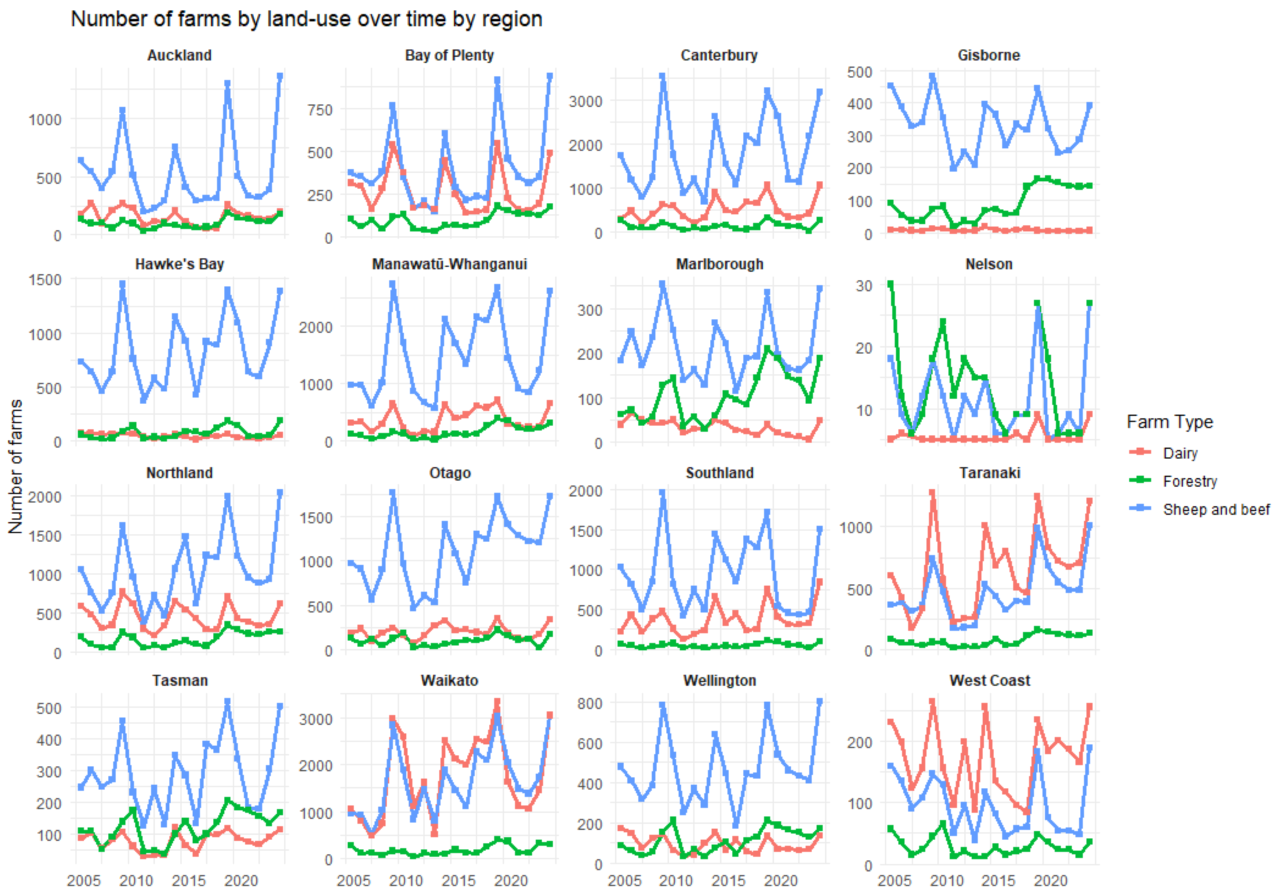


Appendix S3. Agriculture related land use across New Zealand.



Land use as of 2020: The LUCAS (Land Use and Carbon Analysis System) Land Use Map (LUM) is a collection of land use maps that provide essential information on how New Zealand's land use is changing over time. These maps are used for estimating greenhouse gas emissions and removals associated with various land-use activities in our national greenhouse gas inventory. Twelve land use classes are mapped in the LUCAS LUM including three forest classes, which contain most of our carbon stores, and nine non-forest classes. In New Zealand, the Grassland category is used to describe a range of land cover types, grouped into three main classes: high producing, low producing and with woody biomass and is further divided into dairy and non-dairy grazing.

Appendix S4. Number of farms by land-use type over time by region.



Similar to the national dataset, we observe consistent peaks in the census years 2017 and 2022 and dips in between, especially in the Covid period 2019-2020, and a slight decline in the full sample between the two census years that could reflect either lower survey response rates or an organic decline in farm numbers across all regions.

Appendix S5. Data source and variable description.

Panel (a) Data source description. Source: Fabling and Sanderson (2016)

Abr.	Name	Description
URC	Stats NZ Urban Rural Classification (URC) 2022	This dataset is the definitive set of annually released urban rural boundaries for 2022 as defined by Stats NZ. This version contains 722 urban rural features. Urban rural is an output geography that classifies New Zealand into areas that share common urban or rural characteristics and is used to disseminate a broad range of Stats NZ's social, demographic, and economic statistics.
LUCAS	New Zealand's LUCAS Land use map 2020	The LUCAS NZ Land Use Map 2020 v005 classifies land use across New Zealand into 12 categories at five time points: 31 December 1989, 2007, 2012, 2016, and 2020. These reference dates align with reporting requirements under the Paris Agreement and the former Kyoto Protocol. Land use areas and changes identified in the map are used to estimate greenhouse gas emissions and removals from the Land Use, Land Use Change and Forestry (LULUCF) sector. This information feeds into New Zealand's Greenhouse Gas Inventory and Biennial Transparency Report, submitted to meet obligations under the UNFCCC and the Paris Agreement.
LENZ	NZLRI LENZ - Soil particle size	The raster data defines the average particle size based on the soil information (from the NZLRI) and the mapped parent material. This particle size data layer is differentiated into five classes, silt and clay (Class 1), Sand (2), Gravel (3), Coarse to very coarse gravel (4), Boulders to massive (5). The class defined as "0" signifies areas where there is no soil attributes recorded (i.e. high peaks of the Southern Alps).
LUC	NZLRI Land Use Capability 2021	The New Zealand Land Resource Inventory (NZLRI) is a national database of physical land resources, based on aerial photography, fieldwork, and reference materials. It records five key factors—rock type, soil, slope, erosion, and vegetation—using a homogeneous unit area approach at a 1:50,000 scale. Each area is assigned a Land Use Capability (LUC) rating, reflecting its potential for sustainable agricultural use based on physical characteristics, climate, land use history, and erosion risk. The NZLRI covers the country in 11 regions, each with its own LUC classification.
APS	Agriculture production survey	The Agricultural Production Survey (APS), run by Statistics NZ, collects data on agricultural, horticultural, and forestry activity to support GDP estimates for these sectors, which are excluded from the AES. The survey targets "farms"—land blocks managed as single agricultural operations. Earlier surveys were conducted at the sub-KAU level (contiguous land blocks by industry) but have since transitioned to the GEO level. When a farm is operated by someone other than the owner (e.g., a sharemilker), the owner typically completes the survey with input from the operator.
IR10	Tax-filed accounts information	The IR10 is a simplified financial statement submitted to Inland Revenue (IR) in place of full accounts, covering profit/loss and balance sheet information. It supports IR's policy, research, and compliance functions. In the 2012/13 tax year, the IR10 was revised and renamed the IR10 Financial Statements Summary, with changes reflected in the LBD from the 201303 data year onward.
LBF	Longitudinal Business Frame	The Longitudinal Business Frame (LBF) is a panel dataset derived from Statistics NZ's former Business Frame (BF), used until April 2014 as the main sampling frame and for compiling business demography statistics. The LBF reconstructs historical BF data to track firm and plant characteristics over time. It underpins the Longitudinal Business Database (LBD), enabling linkage to other firm-level datasets. In May 2014, the BF was replaced by the Business Register (BR).

Panel (b): Variable description

Variable	Source	Description
Operational scale		
Total land use (ha)	APS	The total land area of the farm on 30 June every year. This doesn't count land leased to others or used by other, or land share milk on, but include land lease from other.
Beef (lsu)	APS	Total beef calves and beef cattle on the farm whether they were own by the farming business or not.
Dairy (lsu)	APS	Total dairy cattle on the farm whether they were owned by the farming business or not, including dairy cows and heifers in milk or in calf, not in milk, not in calf, dairy bulls, and dairy heifers and heifer calves, and all other
Sheep (lsu)	APS	Total sheep on the farm whether they were own by the farming business or not, including ewes, ewe lambs, hogget, rams, wethers and other
Harvested wood (m^3)	APS	Total harvested wood in m^3
Economics outcome per ha		
Taxable profit per hectare (NZ$/ha)	IR10	Net taxable profit/loss before tax divided by the total land use area
Gross output per hectare (NZ$/ha)	IR10	Total income from production minus stock adjustment divided by the total land use area (to avoid destocking phase or restocking phase)
Intermediate expense per hectare (NZ$/ha)	IR10	It is calculated as the sum of purchases and total expenses minus wages, bad debt, interest expenses and depreciation. Intermediate expenditure includes ongoing costs such as those of animal feed and fertilizers.
Current loan per hectare (NZ$/ha)	IR10	Current loans reflect farms' short-term debt, including cheque and income tax account liabilities and overdrafts, but excluding non-bank debt and long-term liabilities such as mortgages.
Farm characteristics		
Farm age (year)	LBF	Derived from the current reporting year minus the emprise year in LBF dataset.
Māori business indicator (yes/no)	LBF	An optional indicator that helps business to self-identify as Māori business on the NZBN register or if it is fully or partially owned by a person or people who have Māori whakapapa. This data has a lot of NA values which is imputed with "non-Māori" if not filled in.
Farm Spatial		
Distance to town (km)	Stats NZ IUR 2022	Distance from the centroid of the farm-meshblock to the nearest polygon of large and small urban areas.
Mean soil class (1-8)	LRIS LUC 2021	The mean land use class of the farm meshblock. LUC= 1: Land with virtually no limitations for arable use and suitable for cultivated crops, pasture or forestry, LUC=8: Land with very severe to extreme limitations or hazards that make it unsuitable for cropping, pasture or forestry
Mean slope (1-8)	LRIS LUC 2021	The mean slope class delineating from physiographic areas of relatively homogeneous average slope class. Slope= 1: Flat to gently undulating (0-3^o), and 8: Precipitous (>42^o)
% neighbour land for dairy	LUCAS	The fraction of land use in the meshblock dedicated to dairy activities, including "Grassland – high producing" - "Grazed, dairy". Data is available for year 2012,2016, 2020 and is interpolated in between.
% neighbour land for sheep/beef	LUCAS	The fraction of land use in the meshblock dedicated to sheep and beef activities, including "Grassland – high producing" and "Grassland – low producing", "Grazed, non-dairy". Data is available for year 2012,2016, 2020 and is interpolated in between.

% neighbour land for forestry (native + planted)	LUCAS	The fraction of land use in the meshblock dedicated to forestry activities, including both native, pre 1989 and post 1989 planted forests. Data is available for year 2012,2016, 2020 and is interpolated in between.
Land use on farm		
Grassland/ tussock land (%)	APS	Derived from the total land area of the farm made out of grassland, tussock and danthonia used for grazing (whether oversown or not) divided by total land use
Forestry land (%)	APS	Derived from the land area of the farm made out of plantations of exotic trees for harvest, harvested exotic forest area awaiting restocking divided by total land use
Horticulture land (%)	APS	Derived from the land area of the farm made out of grain, seed, fodder crop and winter feed land, and land prepared for these crops or commercial horticultural land and land prepared for commercial horticulture divided by total land use
Bush/ scrub land (%)	APS	Derived from the land area of the farm made out of mature native bush, native scrub and regenerating native bush, divided by total land use
Farm Management Practice		
Fraction of irrigation total (%)	APS	Derived from the total area of the farm was actually irrigated during the year, using micro-systems, flood systems, centre pivots and linear moves and all other outdoor, for dairy/grazing/other live stocks and crops.
Fertiliser use (kg) nitrogen	APS	Tonnes of the elements nitrogen (N) were applied to the farm
Fertiliser use (kg) phosphorus	APS	Tonnes of the elements phosphorus (P) were applied to the farm
Fertiliser use (kg) sulphur	APS	Tonnes of the elements sulphur (S) were applied to the farm
Water Cycle		
Soil moisture deficit (cm/ month)	Biome BGC	Soil PED is measured in the topsoil to a depth of 90 cm and expressed in mm/month. It indicates the amount of rainfall required to return the soil to field capacity. PED is determined by daily weather conditions (temperature and precipitation), land cover, and soil texture. A PED value of 0 cm/year reflects saturated (moist) soil, while values approaching field capacity indicate drier conditions.
Total groundwater recharge (mm/year)	NWTM	Annual summation of monthly rainfall recharge to groundwater using a simplified one-layer soil water balance model. It calculates recharge as the surplus of rainfall after accounting for evapotranspiration, soil storage, and correction factors for slope, soil permeability, and geology. Although uncalibrated, the model is informed by case study comparisons and draws inspiration from the WaterGAP model.
Groundwater table depth	NWTM	Depth to groundwater derived from national maps from the NWT model
Carbon Cycle		
Dry matter (kg DM/ha/year)	Biome BGC	A proxy for pastoral farms as it reflects the spatial variations in pasture growth or grass available as food for grazing animals. DM yield is converted from net primary production or the amount of carbon retained in an ecosystem via the ratio of above-ground to below-ground allocation by the inverse of the new fine root.
Net NEP (gC/m²/year)	Biome BGC	Net ecosystem production (NEP) from evergreen broadleaf forest, in grams of carbon per square meter per year (gC/m²/year), as a proxy for potential carbon sink from vegetation and soils from exotic forests.

Appendix S6. Correlation analysis

(a) Dairy farms

Variables	N	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(1) Dairy DM	101,199	1								
(2) Dairy NEP	101,703	0.506*	1							
(3) Soil moisture PED	100,203	-0.294*	-0.202*	1						
(4) Total groundwater recharge	56,793	0.232*	0.042*	-0.587*	1					
(5) Groundwater table depth	103,554	-0.041*	0.007*	0.028*	0.069*	1				
(7) Gross output per hectare	78,168	0.016*	0.039*	-0.020*	-0.046*	-0.079*	1			
(8) Intermediate expense per hectare	78,351	0.005	0.031*	-0.006	-0.053*	-0.076*	0.890*	1		
(9) Profit per hectare	77,592	0.046*	0.063*	-0.055*	-0.021*	-0.058*	0.489*	0.249*	1	
(10) Loan per hectare	77,436	0.007	0.033*	0.007	-0.034*	-0.040*	0.394*	0.405*	0.114*	1

(b) Sheep and beef farms

Variables	N	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(1) Sheep and Beef DM	228,468	1								
(2) Sheep and Beef NEP	229,161	0.319*	1							
(3) Soil moisture PED	223,548	-0.222*	0	1						
(4) Total groundwater recharge	120,669	0.204*	-0.021*	-0.529*	1					
(5) Groundwater table depth	232,383	-0.088*	0.014*	0.086*	-0.079*	1				
(7) Gross output per hectare	173,421	0.012*	0.003	-0.039*	-0.002	-0.122*	1			
(8) Intermediate expense per hectare	174,177	0.011*	0.006*	-0.037*	-0.002	-0.147*	0.841*	1		
(9) Profit per hectare	172,131	0.010*	0.005	-0.030*	-0.011*	-0.009*	0.525*	0.152*	1	
(10) Loan per hectare	164,505	0.015*	0.003	-0.025*	0.002	-0.101*	0.402*	0.440*	0.052*	1

(c) Forestry farms

Variables	N	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(1) Native forest NEP	28,083	1								
(2) Exotic forest NEP	28,080	0.721*	1							
(3) Soil moisture PED	29,397	-0.188*	-0.083*	1						
(4) Total groundwater recharge	14,202	0.276*	0.196*	-0.502*	1					
(5) Groundwater table depth	32,007	0.153*	0.067*	-0.105*	-0.062*	1				
(7) Gross output per hectare	18,615	0.025*	0.01	-0.017*	-0.015	-0.100*	1			
(8) Intermediate expense per hectare	21,903	0.014	0.019*	0.012	-0.024*	-0.111*	0.771*	1		
(9) Profit per hectare	21,696	0.029*	-0.004	-0.051*	0.008	-0.012	0.600*	0.124*	1	
(10) Loan per hectare	18,927	-0.01	-0.01	0.029*	-0.009	-0.066*	0.396*	0.397*	0.079*	1

Appendix S7. Regional variation in impact of water-carbon cycles on farm profitability.

This table presents estimates of the effect of carbon-water on farm-level profit in regional subset. Controls include geographical/agroclimatic attributes, farm characteristics, land use and farm practice, and time fixed effect, region and farm fixed effects. To conserve space, we report the point estimates and the standard errors (in parentheses) of the main variables of interest only. Heteroscedasticity robust standard errors are reported in parentheses. * p<0.1, ** p<0.05, *** p<0.01.

(a) Dairy farms

Independent Variables	**Dry Matter (log)**		**Soil Moisture Deficit (mm)**	
Region	Beta	Std. errors	Beta	Std. errors
Auckland Region	733.9	(507.9)	-3852.2	(3940.7)
Canterbury Region	197.8	(567.0)	-652.3	(3673.2)
Bay of Plenty Region	2094.2***	(415.4)	-4400.8*	(2636.0)
Gisborne Region	-846.0	(1186.2)	-17620.3	(19076.4)
Hawke's Bay Region	-411.7	(798.7)	-2516.3	(6727.9)
Manawatu-Whanganui Region	536.8*	(322.5)	794.1	(2687.9)
Marlborough Region	-249.1	(247.8)	10334.9	(7360.6)
Nelson Region	178.0	(125.5)	2705.5**	(1068.3)
Northland Region	112.6	(137.5)	-4691.7***	(1230.3)
Otago Region	-734.7	(556.5)	-14729.5***	(4452.8)
Southland Region	979.9**	(497.2)	1283.7	(3234.5)
Taranaki Region	1615.7***	(379.2)	811.3	(2915.7)
Tasman Region	133.2	(440.9)	3395.9	(5834.8)
Waikato Region	806.5***	(195.1)	-6236.0***	(1550.6)
Wellington Region	856.2	(599.9)	6190.5	(4168.6)
West Coast Region	-1618.0***	(542.4)	-10428.7	(6463.9)
National Sample	560.1***	(112.2)	-4868.9***	(896.8)

(b) Sheep and beef farms

Independent Variables	**Dry Matter (log)**		**Soil Moisture Deficit (mm)**	
Region	Beta	Std. errors	Beta	Std. errors
Auckland Region	285.1	(724.8)	3690.5	(4092.0)
Canterbury Region	241.0	(1197.0)	-652.3	(4725.3)
Bay of Plenty Region	255.8	(253.4)	-4400.8*	(1157.8)
Gisborne Region	144.2	(366.6)	-17620.3	(1915.5)
Hawke's Bay Region	284.8	(297.4)	-2516.3	(1893.7)
Manawatu-Whanganui Region	237.9	(270.3)	794.1	(1472.0)
Marlborough Region	-198.2	(464.4)	10334.9	(3561.8)
Nelson Region	2000.7	(2377.6)	2705.5**	(21588.1)
Northland Region	426.2*	(235.9)	-4691.7***	(1443.0)
Otago Region	350.7	(283.2)	-14729.5***	(1128.3)
Southland Region	89.56	(231.7)	1283.7	(2311.2)
Taranaki Region	485.2	(838.7)	811.3	(3482.1)
Tasman Region	-311.8	(572.8)	3395.9	(3025.7)
Waikato Region	62.79	(218.8)	-6236.0***	(1993.2)
Wellington Region	60.72	(359.4)	6190.5	(2980.3)
West Coast Region	5635.7	(3754.0)	-10428.7	(13063.4)
National Sample	194.9*	(106.5)	-841.8	(620.4)

(c) Forestry farms

Independent Variables	**Dry Matter (log)**		**Soil Moisture Deficit (mm)**	
Region	Beta	Std. errors	Beta	Std. errors
Auckland Region	1.114	1.114	4682.1	(10215.8)
Canterbury Region	-4.956	-4.956	-21546.1	(18501.1)
Bay of Plenty Region	0.845	0.845	305.2	(6974.3)
Gisborne Region	-1.607	-1.607	10015.2	(11665.4)
Hawke's Bay Region	0.661	0.661	-19991.3	(17582.1)
Manawatu-Whanganui Region	-3.209**	-3.209**	5941.3	(10567.3)
Marlborough Region	-3.633	-3.633	-9908.9	(12207.0)
Nelson Region	-1.998	-1.998	25886.7*	(13616.1)
Northland Region	-1.475	-1.475	-11240.3	(8969.2)
Otago Region	1.313	1.313	-23140.1	(15751.6)
Southland Region	3.002	3.002	-23678.0	(19992.3)
Taranaki Region	-1.121	-1.121	-15760.8	(19279.3)
Tasman Region	-0.942	-0.942	5349.6	(6520.2)
Waikato Region	-1.167	-1.167	-2246.4	(11400.4)
Wellington Region	1.099	1.099	-9167.7	(11228.3)
West Coast Region	2.966**	2.966**	34901.0	(25256.9)
National Sample	-0.709	(0.504)	-8988.1	(3702.3)

Appendix S8. Yearly variation in impact of water-carbon cycles on farm profitability.

This table presents estimates of the effect of carbon-water on farm-level profit in regional subset. Controls include geographical/agroclimatic attributes, farm characteristics, land use and farm practice, and time fixed effect, region and farm fixed effects. To conserve space, we report the point estimates and the standard errors (in parentheses) of the main variables of interest only. Heteroscedasticity robust standard errors are reported in parentheses. * p<0.1, ** p<0.05, *** p<0.01.

(a) Dairy farms

Independent Variables	**Dry Matter (log)**		**Soil Moisture Deficit (mm)**	
Region	Beta	Std. errors	Beta	Std.
2003	903.9***	(346.2)	-3414.2*	(2005.3)
2004	1075.9***	(263.6)	-2377.6	(1669.2)
2005	695.7**	(299.8)	-4656.5**	(2164.7)
2006	510.7	(312.7)	-3283.9*	(1941.3)
2007	656.3***	(251.0)	-3260.0**	(1472.8)
2008	458.6*	(248.6)	-6942.2***	(1871.8)
2009	-342.6	(341.7)	-10825.6***	(3297.4)
2010	1007.1***	(312.0)	-3748.0*	(1918.8)
2011	-630.1*	(348.1)	-3683.3*	(2177.7)
2012	349.5	(283.9)	-3658.9**	(1533.6)
2013	542.3**	(214.3)	-2603.2	(1756.9)
2014	563.3**	(277.4)	-10783.4***	(1639.0)
2015	1164.8***	(240.5)	-3412.6**	(1418.0)
2016	696.8**	(292.2)	-7893.2***	(1733.0)
2017	711.5***	(198.9)	-90.00	(1560.1)
2018	708.7***	(213.6)	290.5	(1551.3)
2019	625.1**	(256.3)	-3785.3**	(1727.0)
2020	295.4	(232.1)	-6035.4***	(1616.5)
2021	291.6	(286.5)	-4361.8***	(1690.9)
2022	108.2	(417.8)	-5876.6***	(1662.6)
National Sample	560.1***	(112.2)	-4868.9***	(896.8)

(b) Sheep and beef farms

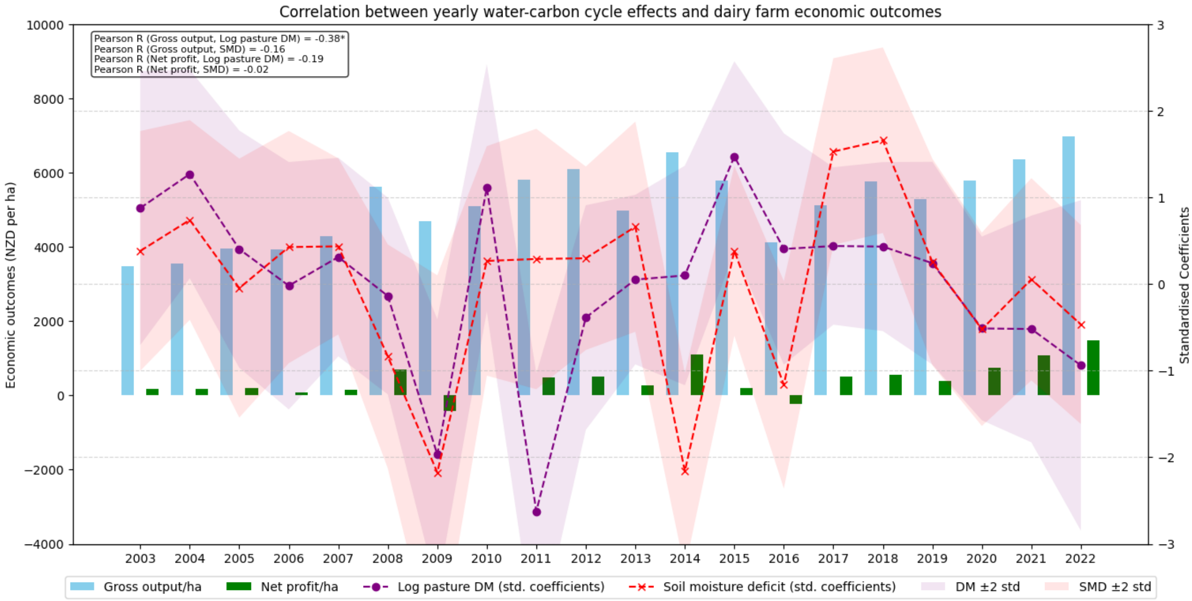
Independent Variables	**Dry Matter (log)**		**Soil Moisture Deficit (mm)**	
Region	Beta	Std. errors	Beta	Std. errors
2003	378.6	(334.2)	3446.2*	(1767.9)
2004	124.8	(281.5)	-2377.6	(1437.5)
2005	-508.7	(675.6)	-4656.5**	(2085.9)
2006	-257.1	(309.1)	-3283.9*	(1645.7)
2007	-10.56	(228.3)	-3260.0**	(1270.0)
2008	382.9	(320.3)	-6942.2***	(1692.6)
2009	-133.5	(646.3)	-10825.6***	(2501.6)
2010	-460.7	(317.7)	-3748.0*	(2173.0)
2011	-554.5	(363.2)	-3683.3*	(2363.2)
2012	-75.46	(236.1)	-3658.9**	(1509.5)
2013	786.5***	(224.6)	-2603.2	(1331.2)
2014	590.2	(577.0)	-10783.4***	(1427.4)
2015	255.6	(228.0)	-3412.6**	(1150.5)
2016	606.7***	(185.5)	-7893.2***	(1132.3)
2017	353.1**	(158.1)	-90.00	(1327.5)
2018	213.5	(222.7)	290.5	(1450.5)
2019	406.6**	(202.2)	-3785.3**	(1392.1)
2020	-120.3	(166.5)	-6035.4***	(1052.9)
2021	-89.60	(242.0)	-4361.8***	(1493.5)
2022	427.6*	(242.6)	-5876.6***	(1365.5)
National Sample	194.9*	(106.5)	-841.8	(620.4)

(c) Forestry farms

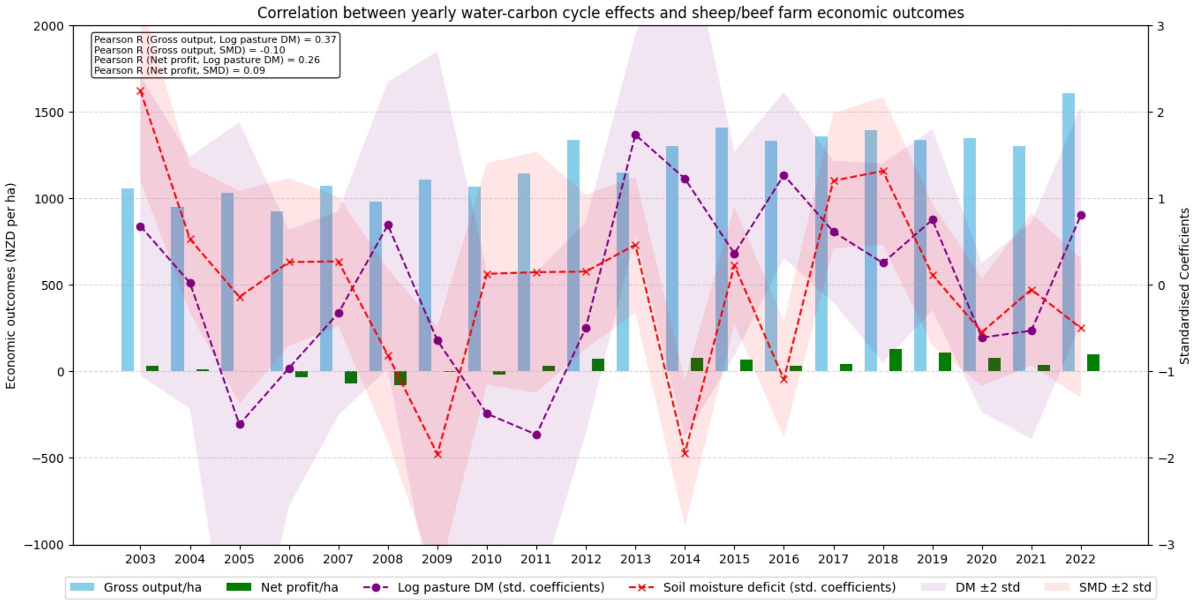
Independent Variables	**Carbon sequestration (log)**		**Soil Moisture Deficit (mm)**	
Region	Beta	Std. errors	Beta	Std. errors
2010	-1.122	(1.669)	-5034.2	(6034.6)
2011	-0.00589	(1.614)	298.9	(7587.2)
2012	2.910	(1.844)	-6009.5	(5900.1)
2013	1.195	(0.986)	-3234.7	(5103.3)
2014	-1.000	(1.666)	-3472.1	(5404.4)
2015	0.0262	(1.090)	-12593.9**	(5695.5)
2016	-4.785***	(1.531)	-16989.3***	(5442.1)
2017	-0.348	(1.519)	-3032.1	(6048.6)
2018	-1.122	(1.364)	2189.0	(6663.0)
National Sample	-0.709	(1.669)	-8988.1	(3702.3)

Appendix S9. The association of yearly variation in water-carbon effects with economic outcomes.

(a) Dairy farms



(b) Sheep and beef farms



Appendix S10. Exclusion of adverse years (Covid 2019, GFC, and Drought)

(a) Dairy farms

Subset	Dairy farms				
Sample	Original sample	Exclude Covid years	Exclude GFC	Exclude 2013 Drought year	Exclude all these years
Estimation Model	Full FE	Full FE	Full FE	Full FE	Full FE
Dry Matter (log)	560.1***	515.7***	625.4***	615.4***	660.0***
	(112.2)	(115.6)	(119.4)	(121.4)	(137.6)
Soil Moisture Deficit (mm)	-4868.9***	-5326.3***	-4908.2***	-4910.8***	-5444.6***
	(896.8)	(961.1)	(930.7)	(927.4)	(1048.1)
Number of observations	*62,712*	*57,591*	*58,287*	*58,818*	*49,272*
Adjusted R^2	*20.5%*	*21.3%*	*20.1%*	*0.215*	*0.221*
Intraclass correlation coefficient	*0.829*	*0.962*	*0.844*	*0.833*	*0.961*

(b) Sheep and beef farms

Subset	Sheep and beef farms				
Sample	Original sample	Exclude Covid years	Exclude GFC	Exclude 2013 Drought year	Exclude all these years
Estimation Model	Full FE	Full FE	Full FE	Full FE	Full FE
Dry Matter (log)	191.9*	221.7*	166.0	172.4	154.4
	(106.6)	(114.5)	(109.2)	(112.4)	(125.8)
Soil Moisture Deficit (mm)	-841.8	-860.9	-775.3	-1003.2	-963.4
	(620.5)	(667.1)	(632.8)	(639.2)	(707.8)
Number of observations	*136,001*	*123,414*	*127,366*	*127,441*	*106,219*
Adjusted R^2	*2.1%*	*1.9%*	*2.2%*	*2.0%*	*2.3%*
Intraclass correlation coefficient	*0.771*	*0.765*	*0.797*	*0.771*	*0.793*

(c) Forestry farms

Subset	Forestry farms				
Sample	Original sample	Exclude Covid years	Exclude GFC	Exclude 2013 Drought year	Exclude all these years
Estimation Model	Full FE	Full FE	Full FE	Full FE	Full FE
NEP (gCm2)	-0.709	-0.709	-0.709	-0.649	-0.458
	(0.531)	(0.531)	(0.531)	(0.570)	(0.951)
Soil Moisture Deficit (mm)	-6038.7	-6038.7	-6038.7	-6175.4	6008.8
	(3702.3)	(3702.3)	(3702.3)	(3879.0)	(6244.5)
Number of observations	*8,196*	*8,196*	*8,199*	*7,815*	*4,824*
Adjusted R^2	*3.4%*	*3.4%*	*3.4%*	*3.3%*	*2.9%*
Intraclass correlation coefficient	*0.738*	*0.738*	*0.738*	*0.733*	*0.958*

Appendix S11. Regression results with inclusion of groundwater

This table presents estimates of the effect of groundwater on farm-level profit. Controls include geographical/agroclimatic attributes, farm characteristics, land use and farm practice, and time fixed effect, region and farm fixed effects. To conserve space, we report the point estimates and the standard errors (in parentheses) of the main variables of interest only. Heteroscedasticity robust standard errors clustered at farm-level are reported in parentheses. Number of observations and adjusted R^2 are reported for all specifications. Especially for FE model, we also report Intraclass correlation coefficient which describes how much of the variation in the outcome variable is due to differences across farms, as opposed to changes over time within each farm. * p<0.1, ** p<0.05, *** p<0.01.

Dependent Variable: Taxable profit per ha	Dairy farms			Sheep and beef farms			Forestry farms		
Column	(1)	(2)	(3)	(5)	(6)	(7)	(9)	(10)	(11)
Estimation Model	Full FE	Full FE	Full FE	Full FE	Full FE	Full FE	Full FE	Full FE	Full FE
Carbon-Water Cycle									
Dry Matter (log)	560.1***	156.1	154.7	191.9*	77.13	194.6*			
	(112.2)	(124.0)	(124.8)	(106.6)	(144.2)	(106.9)			
NEP (gCm2)							-0.709	0.137	0.144
							(0.531)	(0.677)	(0.676)
Soil Moisture Deficit (mm)	-4868.9***	-4292.8***	-4299.6***	-841.8	-812.4	-830.2	-6038.7	5005.86	4611.1
	(896.8)	(1346.8)	(1347.0)	(620.5)	(1029.1)	(619.9)	(3702.3)	(5996.7)	(6018.4)
Groundwater recharge (mm)		-0.229**	-0.229**		0.151	0.151		-0.726	-0.777
		(0.0931)	(0.0932)		(0.103)	(0.103)		(0.433)	(0.928)
Groundwater table depth (mbg)			3.179			3.542			-24.87
			(3.335)			(2.585)			(31.23)
Number of observations	*62,712*	*30,762*	*30,762*	*136,001*	*75,618*	*63,836*	*8,196*	*2,818*	*2,818*
Adjusted R^2	*20.5%*	*17.5%*	*17.5%*	*2.1%*	*1.6%*	*1.6%*	*3.4%*	*3.7%*	*3.6%*
Intraclass correlation coefficient	*0.829*	*0.925*	*0.925*	*0.771*	*0.771*	*0.768*	*0.829*	*0.865*	*0.874*

Appendix S12. Regression results before and after 2013

This table presents estimates of the water-carbon effects on farm-level profit before and after 2013. Controls include geographical/agroclimatic attributes, farm characteristics, land use and farm practice, and time fixed effect, region and farm fixed effects. To conserve space, we report the point estimates and the standard errors (in parentheses) of the main variables of interest only. Heteroscedasticity robust standard errors clustered at farm-level are reported in parentheses. Number of observations and adjusted R^2 are reported for all specifications. Especially for FE model, we also report Intraclass correlation coefficient which describes how much of the variation in the outcome variable is due to differences across farms, as opposed to changes over time within each farm. * p<0.1, ** p<0.05, *** p<0.01.

Subset	Dairy farms			Sheep and beef farms			Forestry farms		
Column	(2)	(3)	(4)	(6)	(7)	(8)	(10)	(11)	(12)
Estimation Model	Full sample	2002-2012	2013-2023	Full sample	2002-2012	2013-2023	Full sample	2002-2012	2013-2023
Dry Matter (log)	560.1***	268.5*	956.4***	191.9*	29.22	428.1**			
	(112.2)	(143.7)	(172.8)	(106.6)	(153.1)	(169.1)			
NEP (gCm2)							-0.709	-1.096	-0.896
							(0.531)	(0.464)	(0.639)
Soil Moisture Deficit (mm)	-4868.9***	-842.1	-6774.0***	-841.8	-1523	-464.8	-6038.7	2387.47	-7163.1*
	(896.8)	(1392.6)	(1238.8)	(620.5)	(1126.8)	(777.6)	(3702.3)	(10940.3)	(4306.5)
Number of observations	*62,712*	*23,352*	*39,360*	*136,001*	*49,848*	*86,153*	*8,196*	*1,294*	*6,903*
Adjusted R^2	*20.5%*	*16.0%*	*25.1%*	*2.1%*	*1.3%*	*2.0%*	*3.4%*	*3.1%*	*3.1%*
Intraclass correlation coefficient	*0.829*	*0.653*	*0.938*	*0.771*	*0.787*	*0.938*	*0.829*	*0.800*	*0.938*