Manaaki Whenua
Landcare Research

Empirical effects of drought and climate change on farms and rural communities

Prepared for: Deep South National Science Challenge

March 2021

Empirical effects of drought and climate change on farms and rural communities

Contract Report: LC3930

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Summary

As the impacts of climate change are being felt more widely, questions are being asked about how large further impacts will be on rural communities. Future climate change is expected to primarily affect farm productivity with subsequent effects on rural employment, local spending, and other economic and social outcomes.

The aim of this report is to address a 'quantification gap' in the Aotearoa New Zealand (Aotearoa) literature on the implications of climate change for rural communities. While it is well-accepted that climate change will have some impact on rural communities, it is unclear how large such impacts might be.

This report provides one of the first studies to quantify the impacts of climate change on economic outcomes in Aotearoa, based on the estimation of historical statistical relationships (Hsiang 2016; Hsiang et al. 2017). The report is divided into two parts: the first examines the impact of drought and climate change on pastoral-farm profits, and the second examines the impact of drought on agricultural employment.

We combine unique data on individual businesses with daily weather data at a fine spatial scale to estimate the historical impact of drought on, respectively, farm profits and agricultural employment. To do this, we use modern econometric techniques that use the full daily distribution of both soil moisture and temperature to identify both the effects of weather changes in normal times and the effects of extreme conditions, such as drought. We also account for delays between the timing of the weather events and when the effects appear in our outcomes.

The first part of our analysis focuses on the impacts on two primary industries – dairy and sheep and beef. The analysis of employment effects, however, encompasses all agricultural sectors. While changes in rural employment are, in principle, affected by changes in profits, there are also other pathways that may link weather changes to employment. Thus, we perform our analyses independently to allow for all possible mechanisms by which weather may impact employment.

Our results clearly show the link between soil moisture and farm profits, with low soil moisture showing immediate effects on dairy farm profits but lagged effects on sheep/beef farm profits. Each very dry day causes, on average, dairy and sheep/beef farms to experience a loss in annual profits of around one average day. These losses occur in the same year for dairy farms but are spread out over 2 years for sheep/beef farms.

Our analysis also finds suggestive evidence of substantial effects of temperature on sheep/beef farms for two years following both high and low temperature events. This temperature effect is large but quite uncertain.

Translating these results into climate change projections suggests modest negative effects on profits for the remainder of the century due to soil moisture change for both dairy and sheep/beef farms (subject to moderate uncertainty) and potentially substantial negative effects of changes in temperature for sheep/beef farms (subject to large uncertainty). Importantly, these projections account for productivity losses only and do not account for any potential offsetting effects on profit due to future commodity price increases.

Our analysis also examines the implications of historical drought for agricultural employment at the local level. For this analysis, we go beyond sheep/beef and dairy and examine the effects for several other agricultural industries: nursery/floriculture, mushroom/vegetables, fruit and tree nuts, poultry, forestry, deer, other livestock, other crops, forestry support, and agricultural support as well as all agricultural industries aggregated. The results indicate that soil moisture and temperature have different and sometimes offsetting effects across industries. When we combine all industries, the results are quite inconsistent, with some results indicating positive effects of soil moisture and some indicating small or even negative effects. These results may reflect inconsistency in the results across the underlying industries with drought having a negative effect in some industries and neutral or positive effects in other industries.

For some industries, we find that dry soil is associated with an increase in employment whereas in others dry soil is associated with an employment decrease. Dairy has some consistent results, with the relationship between monthly soil moisture and monthly employment indicating that drought would reduce employment. However, when we look at annual employment even in the dairy industry, we find the impact of soil moisture depends on the month. In addition to looking at industries in the primary agricultural sector, we also conduct similar analyses for food manufacturing which show similar results to the industries in the primary agricultural sectors. Further investigation is needed to explore what is driving this inconsistency in employment responses to drought.

Overall, our results clearly indicate that increasing frequency and severity of drought will have a modest negative impact on the profits of dairy and sheep/beef farms. Further investigation is required to clearly determine the extent to which these effects on profits may translate into broader effects on other economic outcomes, such as employment.

1 The impact of drought on pastoral-farm profits

1.1 Introduction

Aotearoa New Zealand enjoys some of the most productive and highest-value farmland globally (Savills Research 2020), and a hospitable climate contributes substantially to these qualities. As climate change continues, however, we are faced with the question of how much this change will affect the productivity of farmland in Aotearoa. This question is important because farm productivity is the basic underpinning of many rural communities' economic well-being and a key contributor to the revenue of many Māori authorities, as well as to national exports, and to the national tax base. Knowing the potential scale of these productivity changes allows both government and industry to make informed decisions about adapting to climate change, because it allows them to trade off the benefits of adaptation actions with the costs of these actions.

A key concern is that future droughts will become more frequent, widespread, and intense than the droughts we have experienced in recent memory (Mullan et al. 2018). These droughts cause harm to production, farm profits, farmer well-being, and community well-being. As the severity of drought increases over time, the risk of greater harm to these important farm and community outcomes also increases. However, there is little information about how large these impacts might be.

In this chapter, we explore the extent to which expected changes in drought and other weather may affect the profitability of pastoral farms in the future and, in turn, gain an indication of the extent to which climate change may threaten the resilience of rural communities. To do this, we use Aotearoa New Zealand's world-leading business microdata database, the Longitudinal Business Database (LBD), which collects detailed firm-level information on farming activities and financial performance from 2000 to the present. We combine these business data with data on both historical weather and climate change.

Using the LBD, we measure operating profit per hectare for every farm in the country and for every year data are available. We then construct a flexible representation of drought and other weather using measures of the full distribution of daily soil moisture and temperature throughout each of the 3 years before the farm reports these profits. We then use fixed-effects regression modelling to find the historical relationship between operating profit and these weather variables. This approach using the daily distribution allows us to estimate the effect of extreme conditions on profits.

Our primary specifications find that low soil moisture on both dairy and sheep/beef farms is associated with lower profits in the same year. These effects also flow on to the following year for sheep/beef farms. A day with very low soil moisture is associated with a reduction in annual operating profits of dairy farms of approximately NZ$4.59 per ha per day, or around 104% of daily-average profits. A day with severely dry soils on sheep/beef farms is associated with a reduction in operating profits of approximately NZ$1.32 per ha per day over 2 years, or around 103% of daily-average profits. We do not see an obvious direct impact of temperature (i.e. separate from the impact via soil moisture) on dairy profits, but do see suggestive evidence of positive impacts of moderate temperatures (up to 20°C) on sheep/beef profits and larger negative impacts of warm temperatures (above 20°C) on sheep/beef profits. The estimated impact of temperature on sheep/beef profits is highly statistically uncertain, however.

At the national level, the estimated soil moisture impacts translate into modest adverse effects of climate change on the expected profitability of farms. To project future climate impacts, we use data on expected climate change from dynamical downscaling of six general circulation models (Sood & Mullan 2020). We project that if the historical effect of soil moisture on profits holds, we would expect an average drop in annual earnings of $65 per ha (20% vs 2016–2018) in 2100 for dairy farms and $15 per ha (7% vs 2016–2018) in 2100 for sheep/beef farms via productivity changes. The central projected effects of climate change on sheep/beef farms incorporating temperature impacts are much larger, with a projected annual loss of $115 per ha (54% vs 2016–2018) in 2100 via productivity changes but noting that this final projection has a high level of uncertainty (95% Confidence Interval: -1–108%).

This chapter makes two contributions to the literature on the consequences of climate change, each with the qualification that there may be other studies we are not aware of. We believe it is the first study to apply climate econometric techniques to study the non-linear effect of weather on the production or profitability of pastoral farms using nationwide data.[1] Pastoral farming in some form accounts for around one-third of global land area and contributes around 7–10% of global caloric production (Bell et al. 2020); thus, tracking how these assets are likely to respond to changing temperatures and water availability is key to understanding the problem of climate change. New Zealand is an appropriate setting to study the effects of climate change on pasture, given that it is the predominant agricultural land use, and that it is a key contributor to the dairy (largest), sheep (top two), and beef (top ten) export markets.

This chapter is also the first statistical study to simulate the effect of climate change using a water availability measurement rather than simply via temperature or precipitation.[2] Modelled measures of water availability can outperform simple aggregations of precipitation as predictors of agricultural outcomes because they use knowledge of the physical water balance to better measure how much water is available for plants to use on a given day. A key barrier to using water availability measures outside of Aotearoa is that many providers of weather and climate data do not routinely compute measures of water availability and make them available to researchers.

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[1] Tait et al. (2005) study the linear impact of seasonal soil moisture on regional milk production in New Zealand. Bell et al. (2020) study the effect of weather on grass production on a single farm.

[2] An exception is Bell (2017), by the lead author of this report. Compared to Bell (2017), the results in this chapter use superior data and are robust to national/regional price effects. Readers should consider the results of this report to supersede those in Bell (2017). Anderson et al. (2015) found that a water availability measure performs well in explaining variation in empirical maize yields in the USA but does not simulate the effects of climate change.

1.2 Further background literature

There are several other macro- and micro-economic studies that estimate the empirical relationship between weather and agricultural/economic outcomes. A study comparing the severity of the 2012/13 drought in New Zealand against previous droughts showed that it was one of the most extreme on record, and that while it was widespread across the country, some regions were more affected than others (Porteous & Mullan 2013). Kamber et al. (2013) looked at the impact of drought using an empirical macroeconomic model to predict the likely effects of the 2013 drought on the broader economy. Their results showed that the 2013 drought was likely to have lowered annual GDP. These authors built on previous research from Treasury, which incorporated weather shocks (including drought events) in their models (Buckle et al. 2002). An OECD (2016) study also estimated that the 2013 droughts reduced annual GDP, based on information from the Ministry for Primary Industries (MPI). MPI incorporates drought events into their annual Situation and Outlook for Primary Industries when predicting production for the year (MPI 2018). Yet both the work by Treasury and by MPI focus on macroeconomic factors as opposed to more localised outcome measures.

Two microeconomic studies examine the impact of weather on productivity: Timar and Apatov (2020) and Pourzand et al. (2020) both aim to estimate the impact of linear representations of drought in New Zealand on farm profits, but neither simulate climate change impacts.[3]

As for agricultural production outcomes under climate change, Baisden (2006) empirically estimated the linear relationship between MODIS-derived annual net primary productivity of pasture (a key input on many New Zealand farms), annual temperature (above 5°C), and soil moisture deficit. Tait et al. (2008) simulate these relationships under climate change and find minor impacts on production. Zhang et al. (2017) estimate the impacts of quadratics in temperature and rainfall on pasture production across the North Island and show that small climate changes could have substantial impacts. Keller et al. (2014), using an ecosystem process model (Biome-BGC) and land-use model (LURNZ), show a relatively small increase in national pasture production in 2050 under climate change scenarios. Their results do, however, show significant regional variation. Projections for 2100 show pasture production for dairy systems increasing or slightly decreasing while pasture production in sheep and beef systems declines.

Tait et al. (2005) simulate general equilibrium impacts of various drought scenarios using empirically estimated linear relationships (by season of year) between milk production and various weather variables.

[3] Apatov et al. (2015) include weather as a predictor of agricultural productivity but provide no discussion of their estimated effects beyond the direction of the effect.

1.3 Data sources and preparation

This section describes how we compiled data on farm performance as well as weather. The time period for this analysis is 2002–2018, and all dairy and sheep/beef farm-years are eligible to be included in the sample prior to filtering for data quality and completeness. We provide detailed steps on cleaning and filtering observations in the appendix and present basic summary statistics in Table 1.

Table 1. Summary statistics

	Dairy			
Variable	**Mean**	**SD**	**1st percentile**	**99th percentile**
Operating profit per ha ($/ha)	1,909	1,508	–1,705	6,304
Total operating profit ($)	293,365	242,016	–252,782	1,033,609
Effective farming area (ha)	174	103	47	503
Taxable profit per ha ($/ha)	580	1,256	–2,606	3,981
Revenue per ha ($/ha)	5,131	3,042	432	15,023
Operating expenses per ha ($/ha)	3,224	2,195	422	10,702
Average daily soil moisture (-mm deficit)	–36.9	17.5	–79.5	11.0
Average daily temperature (°C)	13.3	1.6	8.9	16.1
	Sheep/beef			
Variable	**Mean**	**SD**	**1st percentile**	**99th percentile**
Operating profit per ha ($/ha)	430	399	–447	1,739
Total operating profit ($)	126,102	118,449	–92,864	496,737
Effective farming area (ha)	332	229	50	1,020
Taxable profit per ha ($/ha)	175	427	–825	1,367
Revenue per ha ($/ha)	1,457	964	290	5,193
Operating expenses per ha ($/ha)	1,026	788	160	4 ,172
Average daily soil moisture (-mm deficit)	–43.9	18.1	–94.4	-9.8
Average daily temperature (°C)	12.1	2.0	8.0	16.1

All summary statistics are calculated at the observation level. The samples include 29,340 observations from 4,338 dairy farms and 40,086 observations from 5,598 sheep/beef farms.

1.3.1 Farm performance

To measure farm performance, we use data from Statistics New Zealand's world-leading Longitudinal Business Database (LBD), a restricted database which compiles data on both the financial performance of farms and farm characteristics. First, we identify dairy and sheep/beef farming enterprises using the Agricultural Production Survey/Census (APS/C), which provides industry and farming area by land use.[4] The APS/C aims to collect data on all but very minor farming operations in Aotearoa. Censuses were conducted in 2002, 2007, 2012, and 2017, with other years aiming to survey approximately one out of every three farming enterprises.

The IR10 is a financial statement return required of all enterprises in Aotearoa every year. This return collects basic information, usually recorded in annual financial statements, such as balance sheet and profit/loss items. We extract operating profit from the IR10, which we define as total sales less total operating expenses. We define total operating expenses as the sum of cost of goods sold, repairs and maintenance, wages and other remuneration, subcontractor payments, and 'other expenses' (a category for expenses not otherwise categorised). Bad debts, depreciation, insurance, interest paid, professional fees, rates, rent paid, and research/development are excluded from operating expenses as expenses in these categories typically do not directly contribute to current production. All values are inflated to 2018 dollars. While enterprises can nominate any date as their balance date (the final date of their accounting year), the vast majority of pastoral farming enterprises use 31 March, 31 May, or 30 June. To simplify the process of matching weather data to farm performance data, we restrict the sample to businesses with balance dates in March, May, or June.

To measure farm performance, we then calculate operating profit and divide by effective farming area for each year that is observed in both the APS/C and IR10 data sets. We define effective farming area as the sum of land in pasture and crops.

1.3.2 Farm enterprise location

We observe farm location in the Longitudinal Business Frame (LBF) data set, which provides various metadata associated with business operations. The LBF also provides a second source in which we can observe industry.

Farms report the IR10 return at the enterprise level, meaning at the level of the legal firm entity (company, partnership, etc.) with common ownership. However, enterprises can have multiple operating businesses at different geographical locations in the LBF. Fortunately, the vast majority of farm enterprises have a single operating location with a single set of metadata.

[4] We construct our measure of farming area ('effective hectares') as the sum of pasture and arable cropping area.

For firms with multiple locations, we first remove businesses that are a member of a group of enterprises, have a parent enterprise, or are a parent enterprise. Even if there is a single farming business within one of these arrangements, we are unable to determine in which enterprise revenues and expenditures are recorded. For the few remaining enterprises that have more than one operating location, we average our weather variables using equal weights; there are very few cases where the multiple locations are substantially distant.

1.3.3 Weather

To measure weather for each farm location, we use the Virtual Climate Station Network (VCSN) provided by the National Institute for Water and Atmospheric Research (NIWA) (Tait et al. 2006). This data set provides a spatially-interpolated grid of daily weather for the full period of our sample. We use daily soil moisture[5], minimum temperature, and maximum temperature. The temperature variables are directly measured at weather stations, whereas NIWA calculate the soil moisture variable using the history of temperature, rainfall, and other variables (Porteous et al. 1994; Tait & Woods 2007). [6] We spatially aggregate the daily weather data up to the meshblock level using spatial-overlap-area weights.[7]

Because poor weather can potentially affect farm performance for several years, we include weather for the 36 months prior to the IR10 filing in our analysis, with the exception of returns filed in June, for which we include weather for the 36 months prior to 31 May. We perform this adjustment for June filers because it is unlikely that weather variation in June will cause changes in farm financial performance until at least the following year.

1.3.4 Climate change

We obtain projections of both soil moisture and temperature from NIWA. These projections modify the output of six general circulation models (GCMs) from the fifth Climate Model Intercomparison Project (CMIP5) using a regional climate model to provide higher-resolution output (Sood & Mullan 2020) than the underlying GCMs: BCC-CSM1.1, CESM1-CAM5, GFDL-CM3, GISS-E2-R, HadGEM2-ES, and NorESM1-M. From these data, we use daily projections of soil moisture, minimum temperature, and maximum temperature from 2000 to 2100 for each of the six underlying GCMs, and for each of the climate change scenarios RCP4.5 (representing moderate climate change) and RCP8.5 (representing high climate change). We process these daily projection data using polynomial transformations in the same way as for our historical weather data.

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[5] We use NIWA's measure of soil moisture provided in the VCSN, which is the negative of their soil moisture deficit variable. Soil moisture deficit describes the quantity of water required (in mm) to saturate the soil. The data range from –150 mm, the negative of their assumed maximum capacity (representing a very dry state), to positive values, which represent a state where water would run off.

[6] Note that the soil moisture variable can reset itself during extreme dry and extreme wet periods such that it no longer directly depends on values from times preceding the reset.

[7] There are typically very few grid cells (and often one) that overlap a single meshblock.

1.4 Methods

This section describes our methods. We separate out the descriptions into our historical statistical analysis and our forward projection analysis.

1.4.1 Relationship between profits and weather

The statistical results in this report use panel-fixed-effects regressions to find the non-linear relationship between pastoral-farm operating profits and daily soil moisture/temperature.[8] The primary goal of this approach is to compare how changes in weather from year to year predict changes in profits from year to year on average across the country for both the dairy and the sheep/beef industries.

To control for differences in profits across space that may be due to other factors but are correlated with climate, such as topography, we include fixed effects for enterprise. These unit-fixed effects control for all unobservable factors that are fixed across time for a given enterprise, allowing us to better isolate the impact of changes in weather on profits from differences in profits caused by other factors that vary across space.

To control for national and regional input- and output-price effects, we also use time-fixed effects for each region and time period. These time controls are important for two reasons: first, it is well known that variation in the output prices of agricultural commodities is a major driver of variation in farm profits. If output prices are correlated with local productivity, failing to control for output prices would bias our estimates of the productivity effect of weather on profits. This correlation can occur (a) if Aotearoa is a major producer in the international market due to shifting international supply (as in the case of dairy/sheep products); (b) due to the El Niño–Southern Oscillation (ENSO) effect simultaneously causing disruptions to global agricultural markets and causing local productivity changes; and (c) due to global changes in input prices.

Note that changes in both input and output prices due to climate change will be an important determinant of how profitable farming will be in the coming decades. A full accounting of the projected impact of climate change on the profitability of local agriculture requires both expected price changes as well as changes due to productivity effects. Forming expectations about how agricultural input and output prices might change due to climate change is complex and outside the scope of this report. Further note that our analysis includes three overlapping time periods per year, as we include data on firms with balance dates in March, May, and June.

These fixed effects imply that our analysis uses changes in weather across time for farms *compared to how those changes occur at the regional level* to predict changes in farm profits. The remaining variation in weather, after removing farm-fixed effects as well as regional time-fixed effects, is spatial differences within a region in how weather is

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[8] See Hsiang (2016) for an extended description of these methods. See Deryugina & Hsiang (2017) for a theoretical argument supporting the use of this weather-based approach for the valuation of climate change.

changing from year to year. Given that these *differential changes* in weather occur more or less randomly across time and space, this approach provides a natural experiment that allows us to interpret the statistical relationships we recover in the data as the causal effect of changes in the weather on farm profitability (Angrist & Pischke 2009; Hsiang 2016).

Next, there are potentially complicated dynamics that mediate the relationship between weather and profits over time (Fisher et al. 2012; Deschênes & Greenstone 2012). For the context of this chapter, these dynamics can include the storage of grass and other feed, changes in the timing of selling stock, as well as delayed effects because stock sold today and milk/wool produced today come from animals exposed to a history of (potentially) several years of weather. We investigate such dynamics by estimating a distributed lag model with lagged weather of up to 2 years before the year in which profits accrue.

To summarise, the goal of the statistical analysis is to estimate the relationship between operating profit and daily weather, allowing for non-linearity and lags in the response of profit to weather. The estimating equation for our main results is thus of the form:

$$y_{it} = \alpha_i + \gamma_{t,r(i)} + \sum_{l=0}^{2}\sum_{k=1}^{n}\left(\beta_{lk}\,\widetilde{SM}^{k}_{i,t-years(l)} + \delta_{lk}\,\widetilde{T}^{k}_{i,t-years(l)}\right) + \varepsilon_{it} \tag{1.1}$$

where y_{it} is operating profit per hectare for farm i during the year ended on date t (years ending at 31 March, 31 May, and June 30 from 2002 to 2018); α_i is a farm-fixed effect; $\gamma_{t,r(i)}$ is a time-fixed effect specific to each time period t and region $r(i)$; $t - years(l)$ lags date t by l years; k indexes polynomial degrees; and β_{lk} and δ_{lk} are the coefficients on soil moisture and temperature (respectively) for lag time l and polynomial degree k. ε_{it} is the error of the model, which we assume has cluster correlations within years and enterprises.

Following Schlenker and Roberts (2009) and Hsiang (2016), we construct the weather variables $\widetilde{SM}^{k}_{i,t-y\quad(l)}$ and $\widetilde{T}^{k}_{i,t-years(l)}$ to estimate the non-linear impact of changes across the full daily distribution of these variables, including extremes. We calculate $\widetilde{SM}^{k}_{i,t-yea\quad(l)}$ as:

$$\widetilde{SM}^{k}_{i,t-years(l)} = \sum_{\tau\in \mathrm{Days}_{t-years(l)}} S\,M^{k}_{i\tau} \tag{1.2}$$

where τ indexes days, $\mathrm{Days}_{t-y\quad(l)}$ is the set of days in the year ended $t - years(l)$, and the superscript k now represents exponentiation. The method allows us to estimate the effect of extremes in the daily temperature distribution because we compute these polynomial transformations using the daily data before aggregating to the annual level.

For $\widetilde{T}$, we assume temperature follows a sine curve that passes through the minimum and maximum temperature on each day (the 'single-sine' method), and compute the regressors by integrating the polynomial transformations of the sine-interpolated temperature for each day before summing to the annual level[9]:

$$\widetilde{T}^{k}_{i,t-years(l)} = \sum_{\tau \in \mathrm{Days}_{t-years(l)}} \int_0^1 \left(\frac{T^{max}_{i\tau} - T^{min}_{i\tau}}{2} \sin(2\pi(x-s)) + \frac{T^{max}_{i\tau} + T^{min}_{i\tau}}{2} \right)^k dx \qquad (1.3)$$

where $T^{max}_{i\tau}$ is the maximum temperature observed on day τ on farm i, $T^{min}_{i\tau}$ is the corresponding minimum temperature, x is the variable of integration representing time-of-day, and s is a parameter that shifts the timing of the temperature minimum/maximum (s does not enter the solution of the integral). The results in this report will use polynomials k up to degree 4.

1.4.2 Projections of profits under climate change

The weather projection data are provided by NIWA. In this report we use daily projections of soil moisture, minimum temperature, and maximum temperature derived from six dynamically downscaled GCMs (Sood & Mullan 2020). The first step in the procedure to project climate-induced changes in profits forward is to construct annual weather variables using the formulae in equations (1.2) and (1.3) and applied to a single scenario and GCM. We denote this projected weather variable as $\widetilde{X}^{k}_{itsg}$, where i here indexes locations, t indexes years in the projection data, s indexes scenarios RCP8.5 and RCP4.5, g indexes the six GCMs, and $X \in \{SM, T\}$. Next, we compute the following quantity:

$$\widetilde{y}_{itsg} = \sum_{l=0}^{2} \sum_{k=1}^{n} \left(\widehat{\beta}_{lk} \, \widetilde{SM}^{k}_{itsg} + \widehat{\delta}_{lk} \, \widetilde{T}^{k}_{itsg} \right) \qquad (1.4)$$

where $\widehat{\beta}_{lk}$ and $\widehat{\delta}_{lk}$ are the estimated values from equation (1.1). We then aggregate to the national level using area weights:[10]

$$\widetilde{y}_{tsg} = \frac{\sum_{i=1}^{N} \widetilde{y}_{itsg} * \mathrm{Area}_i}{\sum_{i=1}^{N} \mathrm{Area}_i} \qquad (1.5)$$

[9] The code for calculating these integrals is available at https://github.com/kendonB/degreedays.

[10] The area weights are the sum of area across all observations in the data set at location i.

Finally, we convert the quantities into changes over time by taking the full national time series for each scenario s and GCM g and subtracting the lowess-smoothed value for 2018 (smoothing through time):

$$\Delta\,\widetilde{y}_{tsg} = \widetilde{y}_{tsg} - \overline{\widetilde{y}_{2018,sg}} \tag{1.6}$$

$\Delta\,\widetilde{y}_{itsg}$ thus represents the change in projected profits from 2018 to year t for location i, scenario s and GCM g.

We then present lowess-smoothed versions of the resultant time series to indicate how expected profits might move due to the productivity impacts of climate change. In these smoothed results, we also present uncertainty associated with both the statistical estimation based on the estimated variance-covariance matrix, as well as a simple characterisation of model uncertainty by including results for all six GCMs in the distributions (Burke et al. 2014).

We create these lowess-smoothed time series using the following procedure. We first make 1,000 draws from the estimated joint distribution of the $\widehat{\beta}_{lk}$ and $\widehat{\delta}_{lk}$ coefficients. We then compute time series using equations (1.4), (1.5), and (1.6) using each of these 1,000 draws. Next, we lowess-smooth the calculated time series over time. Finally, we compute the 5th, 25th, 50th, 75th, and 95th percentiles for each time period and scenario, pooling the results for the six GCMs.

While these smoothed results can help us understand how normal years' performance might be expected to change, we are also interested in knowing how performance might change during particularly bad drought years. To examine how performance might change in these bad years, for each of the six GCMs we plot the central predictions of $\Delta\,\widetilde{y}_{tsg}$ for each year t and GCM g for RCP8.5.

1.5 Results

This section first describes the regression results that estimate the historical relationship between weather and farm profits. Next, it describes the results projecting those relationships into the future using climate model output.

1.5.1 Regression results

Figure 1 displays our main results that show the historical relationship between daily soil moisture and operating profit per hectare. The two figure panels each plot daily soil moisture on the x-axis and the change in operating profit per hectare compared with 20 mm soil moisture deficit on the y-axis.

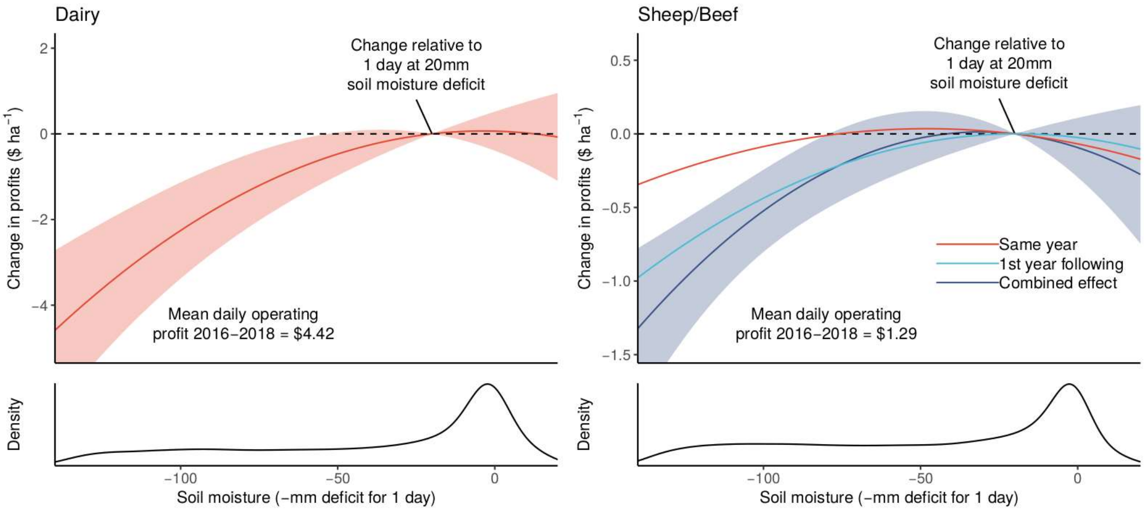

Figure 1. Estimated effects of changes in daily soil moisture on farm profit for dairy (left) and sheep/beef (right) farms.

Notes:

Soil moisture units are plotted as negative soil moisture deficit. Plotted values show the predicted change in profit that would result from changing 1 day from 20 mm soil moisture deficit to other values (ranging from 140 mm soil moisture deficit to 20 mm excess soil moisture). Red lines (dairy and top in sheep/beef) show the effect of soil moisture changes in the same year as that in which the profits accrue. The light-blue line (middle in sheep/beef) shows the corresponding effect on profit for the first year following the soil moisture changes. The dark blue line (bottom in sheep/beef) shows the additive effect on profit over both years. The y-axis of the sheep/beef plot is chosen such that the ratio of the ranges between industries is equal to the ratio of mean daily operating profit 2016–2018 between industries. Annotations showing operating profit are vertically centred at the negative of the displayed values. Shaded areas are 95% confidence bands calculated robust to error clustering by year and farm. Sheep/beef confidence band represents uncertainty associated with the combined effect. Underlying regressions include enterprise and region-by-time-period-fixed effects, with time periods being years ending March, May, and June. Density plots show the daily distribution of soil moisture for dairy (left) and sheep/beef (right) farms.

For dairy farms, we estimate a quadratic relationship that shows drier soils are associated with reductions in profits. Taking 1 day at 20 mm of soil moisture deficit (a relatively wet soil state) and moving it to 140 mm of soil moisture deficit (a very dry soil state) is associated with a decline in profits during the same year of approximately $4.59 per ha, or around 101% of the 2016–2018 daily average operating profit. We do not see clear impacts of soil moisture causing changes in the following 2 years' profit, nor strong evidence of non-linearity beyond that captured by the quadratic (see Figure A.1).

Similarly, for sheep/beef farms we estimate a quadratic relationship that shows drier soils reduce profits. However, for the sheep/beef case we find that soil moisture changes affect profits over 2 years rather than in just the same year. A change in soil moisture from 20 mm deficit to 140 mm deficit for 1 day reduces sheep/beef profit by $0.34 per ha in the same year but by an additional $0.98 per ha in the following year, a combined effect of around 103% of the 2016–2018 daily average operating profit. This temporal pattern probably occurs because stock whose meat and wool are sold today (and counted in this year's profits) have been exposed to environmental conditions for several preceding years.

As with dairy, we do not see clear evidence for further lagged effects, nor non-linearity beyond quadratic (see Figure A.1).

In addition to the clear evidence for soil moisture effects, we find some evidence that year-to-year changes in the frequency of warm temperatures above 20°C cause statistically significant changes in the profits of sheep/beef farms (Figure 2), beyond any changes already captured by soil moisture. We do not find any clear evidence for dairy. Because we do not find evidence that temperatures affect the profit of sheep/beef farms in the same year (see Figure A.1), Figure 2 shows the effect of changes in temperature on profits both 1 and 2 years following the temperature changes.

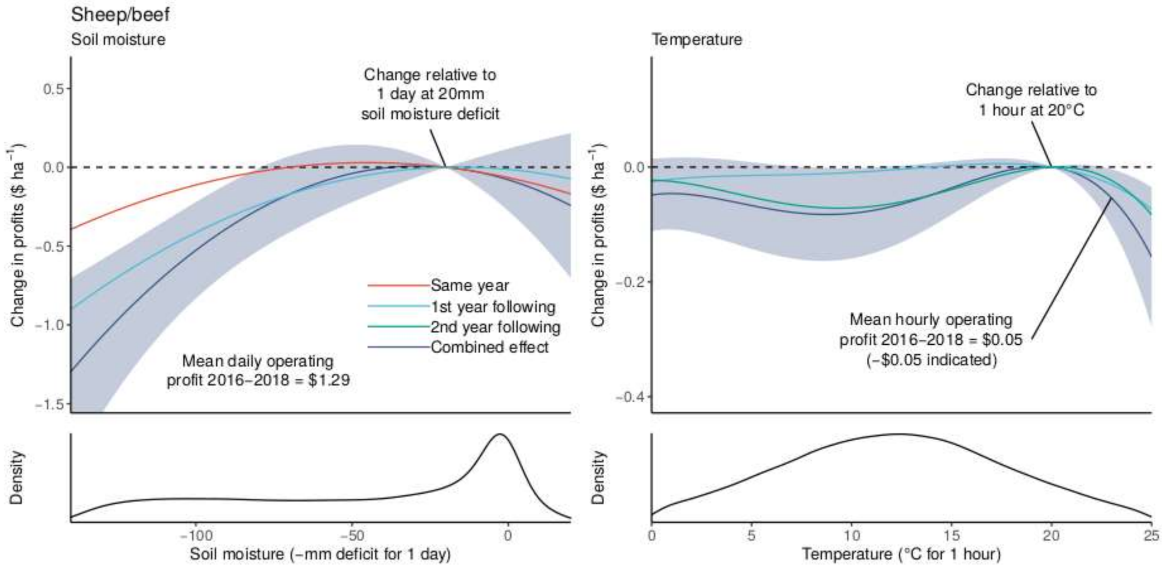

Figure 2. Estimated effects of changes in daily soil moisture (left) and hourly temperature (right) on farm profit for sheep/beef farms.

Notes:

See Figure 1 for a description of the soil moisture (left) plot. Plotted values for temperature (right) show the predicted change in profit that would result from changing 1 day from 20°C to other values ranging from 0°C to 25°C. The light-blue line (top) shows the effect on profit for the first year following temperature changes. The teal line (middle) shows the effect on profit for the second year following temperature changes. The dark blue line (bottom) shows the additive effect on profit over both the first and second years following temperature changes. Shaded areas are 95% confidence bands calculated robust to error clustering by year and farm. Confidence bands represent uncertainty associated with the combined effects. Underlying regressions include enterprise and region-by-time-period-fixed effects, with time periods being years ending March, May, and June. Density plots show the daily distribution of soil moisture (left) and the hourly distribution of temperature (right) for sheep/beef farms.

The point estimates in Figure 2 are *very large*. Moving 1 hour of temperature from just 20°C to 23°C is associated with a loss of approximately 100% of hourly average operating profit (CI: 7–193%), accruing over the 2 years following the year that includes the temperature event. In this model, moving an hour of temperature from 20°C to 25°C results in a loss of approximately 290% of hourly-average operating profit (CI: 65–517%). These changes are, however, statistically noisy and point estimates should be interpreted with caution. These estimated losses from increasing hot temperatures are also partially matched by gains from increasing moderate temperatures (from around 8°C). Moving an hour of temperature from 8°C to 20°C results in a gain of 153% of average daily operating profit (CI: 2–303%).

1.5.2 Climate change projections

Figure 3 shows our results for projected profits under climate change based on the regressions presented in Figure 1. Under the high-climate-change scenario, RCP8.5, our regression results projected forward using climate data suggest that soil moisture change will steadily cause expected profits of Aotearoa pastoral farming to decline up until the end of the century. The pace of the reductions is modest, at around 2.5% of 2016–2018 taxable profit per decade for dairy and around 0.9% of 2016–2018 taxable profit per decade for sheep/beef, resulting in losses of 20% and 7%, respectively, by 2100.

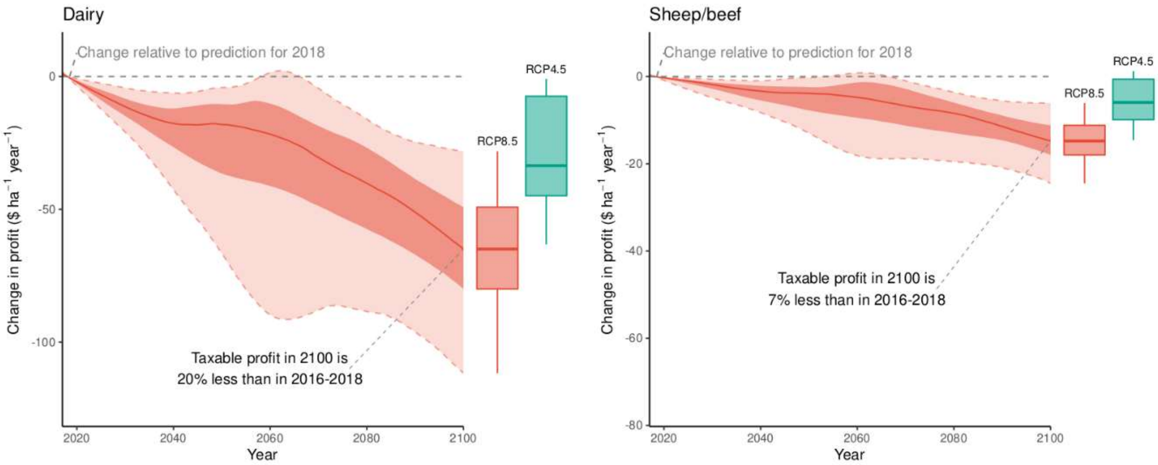

Figure 3. Projected effects of soil moisture change on expected profit of dairy (left) and sheep/beef (right) farms from 2018 to 2100 with both statistical and climate-model uncertainty.

Notes:

Results are calculated using 1,000 random draws of coefficients from the estimated joint distributions. These 1,000 draws are applied to climate projection data derived from each of the six RCMs. Underlying regression results are shown in Figure 1. All values are first lowess smoothed, then differenced relative to the smoothed value for 2018. Solid red lines show the median projection for each year across all GCMs. Inner shaded areas and boxes in boxplots show the 25th and 75 percentile projections for each year across all GCMs. Outer shaded areas, dashed red lines, and whiskers in boxplots show the 5th and 95th percentile projections for each year across all GCMs.

Figure 3 also includes box-and-whisker plots that compare the distribution of lost profits in 2100 under the moderate-climate-change scenario RCP4.5 to that under the high-climate-change scenario. The scale of losses in both industries under this moderate scenario is around half that in the high one, suggesting that reductions in global greenhouse gas emissions will result in benefits to the productivity of New Zealand farmland.

Figure 4 shows our results for projected sheep/beef profits under climate change based on the regression presented in Figure 2, which includes both soil moisture and temperature variables. Because the scale of warming and the estimated negative effects of hot temperatures are so large, Figure 4 shows a projected reduction in the profitability of sheep/beef farming in Aotearoa at a scale much larger than that which we project when changing just soil moisture. At 2100, we project a 54% reduction in taxable profits under RCP8.5, around eight times the size of the estimated reduction when using the soil moisture-only model. However, because the estimated temperature effects are so statistically noisy, the scale of the uncertainty for these estimates is also very large. The 95% confidence interval stretches from a small gain of 1% to a loss of over 100%, noting that for simplicity the projection assumes that all sheep/beef farms in the data continue to operate and that there are no price increases due to climate change. If climate change were to cause output price increases, some of these projected negative effects would be offset. However, any input price increases (e.g. fertiliser costs) would further reduce the returns to pastoral farming.

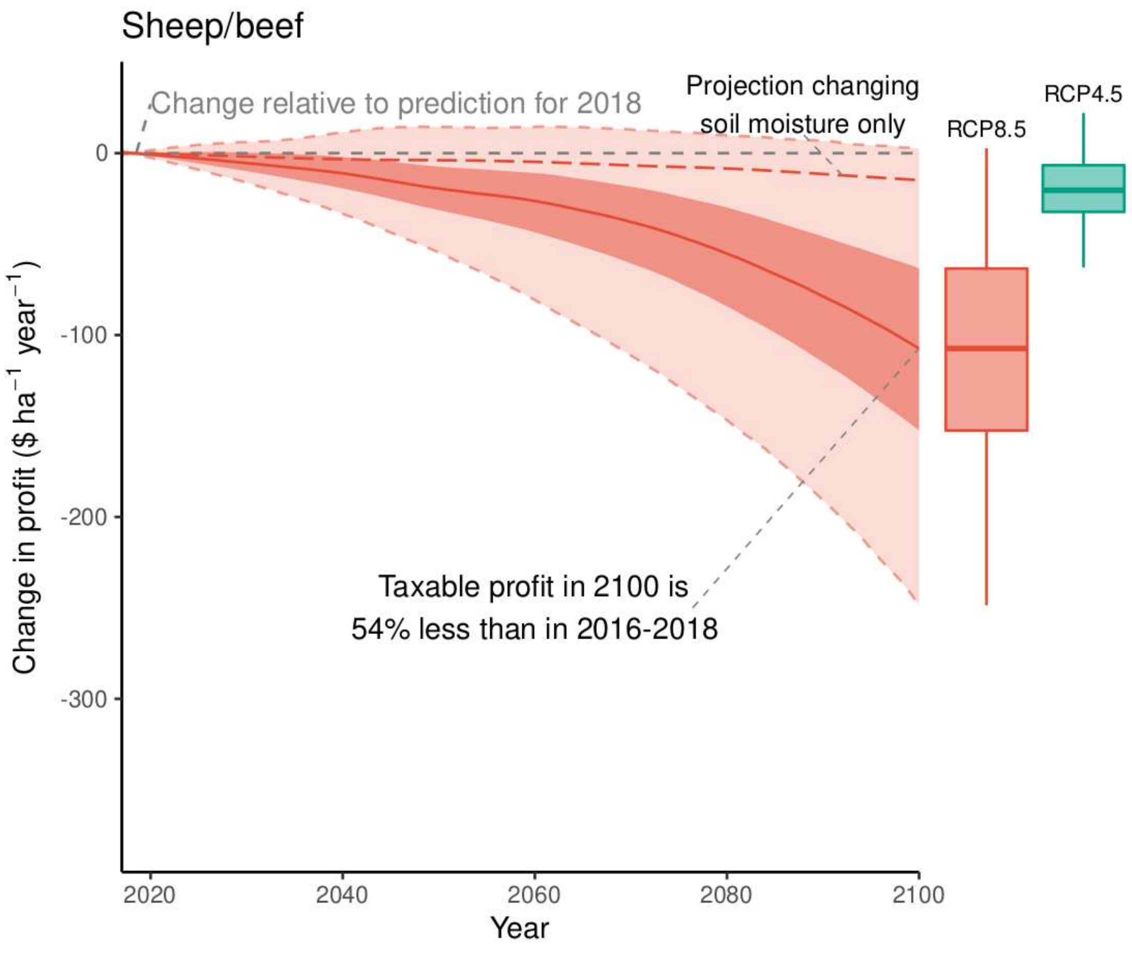

Figure 4. Projected effects of soil moisture and temperature change on expected profit of sheep/beef farms from 2018 to 2100 with both statistical and climate-model uncertainty.
Notes:
Results are calculated using the same procedure as in Figure 3. Red long-dashed line shows the central results from Figure 3.

A surprising feature of Figure 4 is that it projects reductions in the profitability of sheep/farms from day one. This is surprising because the regression model (Figure 2) estimates gains from increasing moderate temperatures from 8°C to 20°C and the bulk of the historical distribution is below 20°C. The negative effects of increasing hot temperatures as well as drying soils outweigh these moderate temperature increases right from the start of the projection.

Figures 5 and 6 show the annual change in profits projected by each of the six GCMs for dairy and sheep/beef, respectively, using the results from our soil moisture-only models (Figure 1). These figures show the central estimates that go into Figure 3 prior to pooling and smoothing. In addition to the projected output from the climate models (from 2001 to 2100; red dots), we also overlay the analogous back projections using the historical observed weather data (from 2002 to 2018; grey dots) with the two lowest historical values showing the 2008 and 2013 droughts.

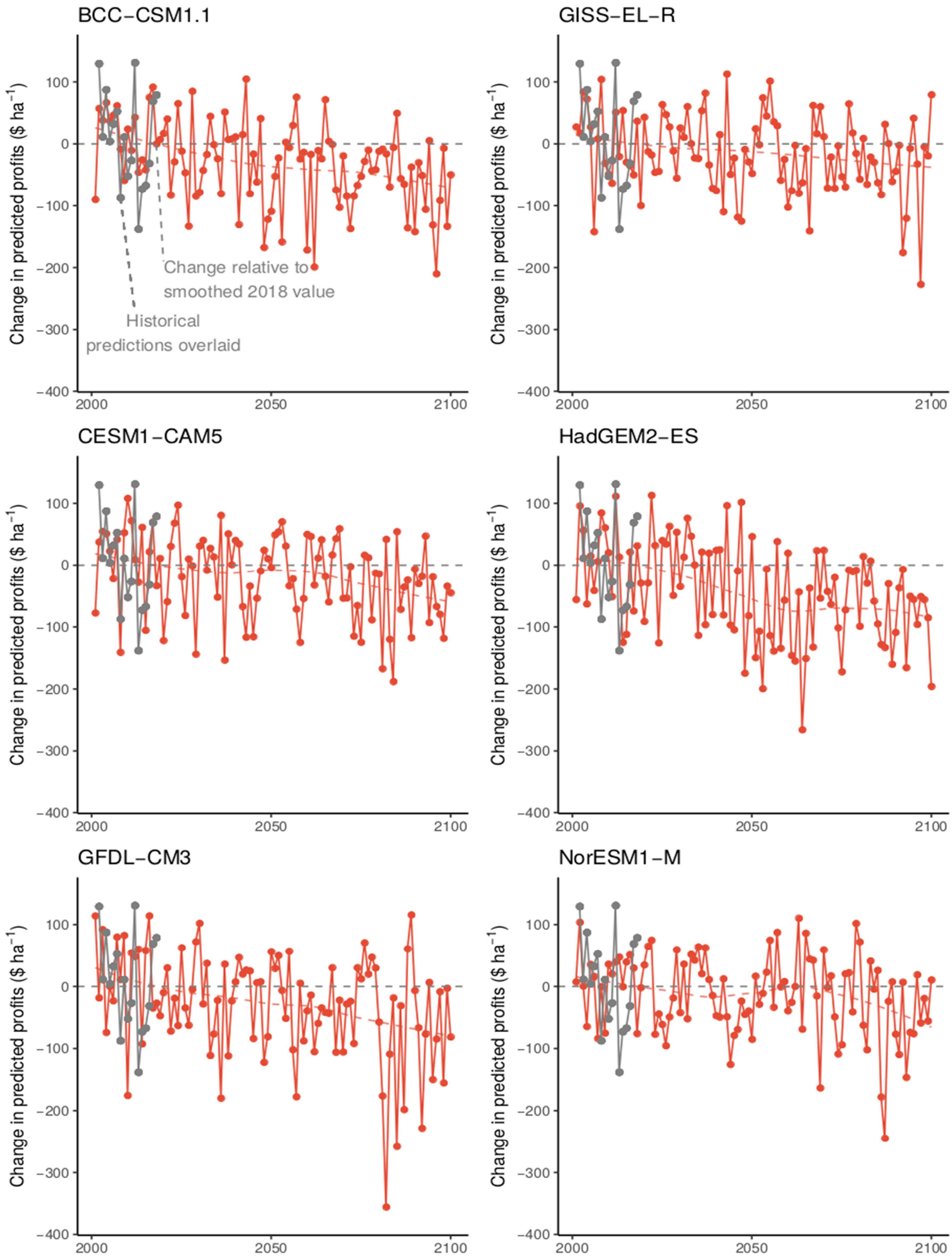

Figure 5. Projected effects of soil moisture and temperature change on annual profit of dairy farms from 2000 to 2100 from six GCMs.

Notes:

Red dots show predicted difference in profit relative to the smoothed value for 2018, calculated using output from each of six GCMs (GCM names are panel titles). Grey dots show predicted values using historical data vertically centred to minimise the vertical distance between the historical predictions (grey dots) and the smoothed GCM predictions (red dashed line).

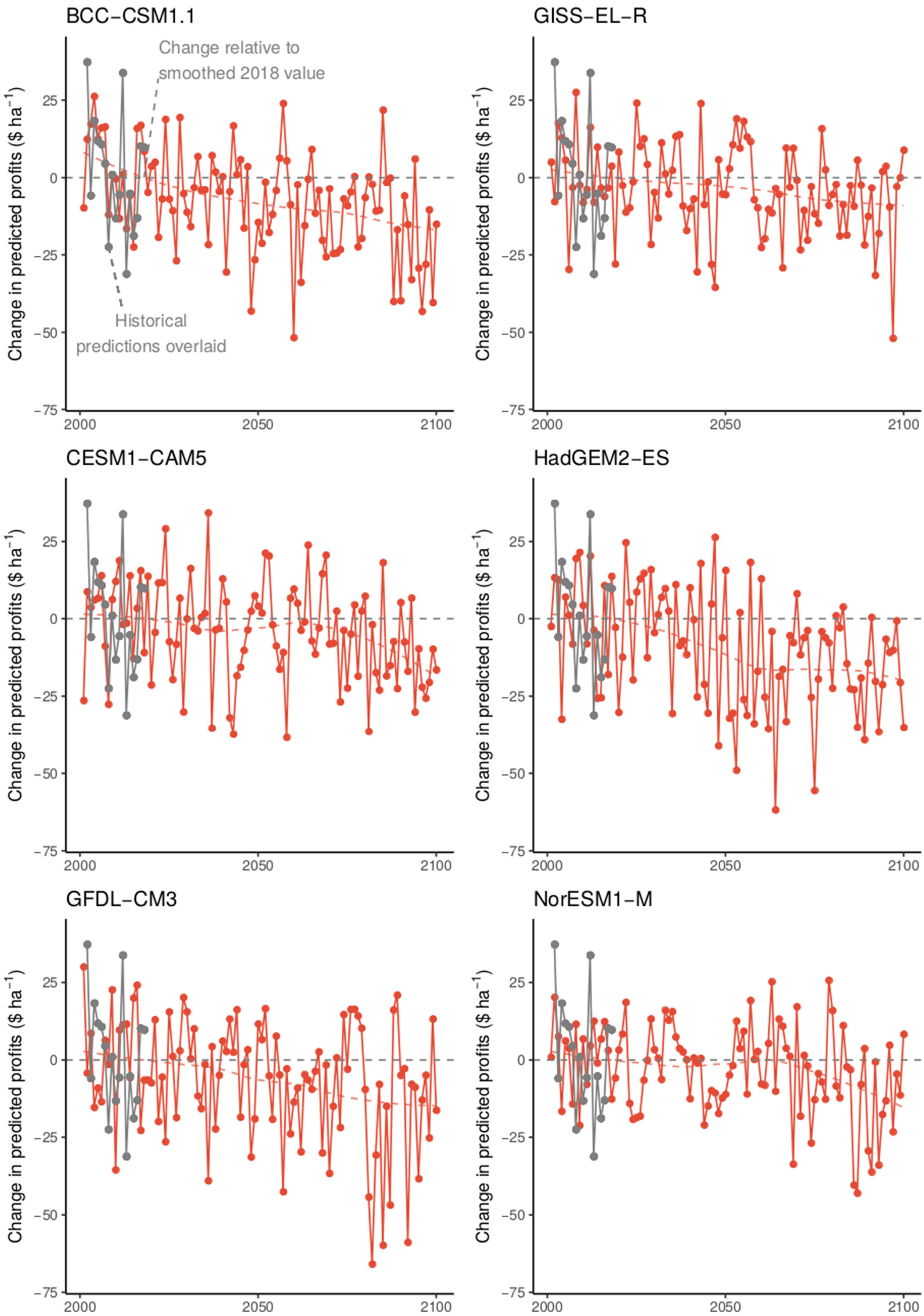

Figure 6. Projected effects of soil moisture and temperature change on annual profit of sheep/beef farms from 2000 to 2100 from six GCMs.
Note: The description in Figure 5 also applies to this figure.

First, the comparison between the historical values and the climate-model back projections over the historical period show that the annual variability in projections in the climate models does tend to approximately match the historical variability (potentially a slight underestimate of the true variability). For example, the simulated drought in 2006 from the GISS-EL-R model approximately matches the scale of the 2013 historical drought.

The figures also show that each of the six GCMs projects declines in average profits over the century; no model projects a gain on average. However, several of the models also show that the decline in projected profits in the worst years is faster than the average decline, meaning that the worst drought years' projected profits exhibit larger deviations from normal later in the century compared to earlier. While normal years are getting worse, in some models the drought years are also getting worse relative to the shifting normal. This pattern is most apparent in the BCC-CSM1.1 and NorESM1-M models, somewhat present in the GISS-EL-R, HadGEM2-ES, and GFDL-CM3 models, but largely absent in the CESM1-CAM5 model.

To give a broad sense of the expected frequency of future large droughts, we can examine the frequency of large droughts before 2050 and compare this to after 2050. The six GCMs show a 2% chance of a drought in dairy land more severe than the 2013 drought before 2050 relative to the shifting normal (i.e. 6 years are worse than 2013 across all GCMs out of 6 × 50 years).[11] The probability of these large droughts increases to 4.2% per year after 2050, indicating that the variability of profits is set to increase over time. In absolute terms, the chance of a drought worse than the one in 2013 increases from 3.7% per year before 2050 to 13% after 2050.

However, while the frequency of large droughts is projected to increase substantially, the GCMs do not show the scale of these droughts increasing many-fold. Across the six GCMs, there are just two droughts at least 50% more severe than the 2013 drought after 2050 (a 0.7% per year chance) relative to the shifting normal. There are no such droughts predicted by the models before 2050. There is a 3.6% chance of a drought more than 50% larger (in absolute terms) than the 2013 drought after 2050, and the models predict no such very large droughts before 2050. The largest drought in the projections data is around twice the severity of the 2013 drought.

1.6 Discussion

The results in this chapter show the extent to which variation in soil moisture and temperature affect the profitability of livestock farms in Aotearoa: as a result of 1 day in a severe drought, both dairy and sheep/beef farms experience a drop in annual operating profit of around 1 average day's worth. The fact that for both dairy and sheep/beef the effect of a dry day is around 100% of daily average operating profit should give readers confidence in these results. It is very intuitive that if the farm is so dry that no grass grows,

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[11] For brevity, we describe these changes in probabilities for dairy only. See Figure 6 for the sheep/beef annual data.

the farm then produces no net income that could go towards covering capital costs. It is also intuitive that, for sheep/beef farms, these effects will primarily accrue in the year following the dry spell.

While uncertain, our results for sheep/beef also suggest that hot temperatures may be very damaging to profitability. Given that the results show the potential scale of damage from a warming climate is so large, these results warrant significant effort from future research to determine these relationships with more precision. This future research could involve better modelling heterogeneity as well as better controlling for (currently) unmeasured contributors to profits, collecting higher-quality data, or waiting for more data from warmer years.

This chapter also shows that climate model outputs suggest that these historical relationships would translate into modest reductions in expected profits over the coming century, with projected losses of around 20% and 7% of total taxable profit for dairy and sheep/beef farms, respectively, due to reduced productivity under climate change. The climate projections suggest that the future droughts will become much more frequent and somewhat larger in scale. Future droughts, however, are not projected to become several times worse in severity than recent years. The pace of these reductions in profitability is unlikely to be sufficient to cause substantial industry exit (i.e. land-use change), especially from dairy farms that have substantial sunk capital investments. Any climate-change-induced price increases in livestock products (relative to other land product prices) will work against any pressures arising due to these productivity losses.

One potential use of these results is to better understand how future climate change might encourage or discourage changes in land use as well as other adaptation actions. Given that animal agriculture is a major contributor to both climate and water pollution, understanding the extent to which climate change might affect baseline pollution is important for anti-pollution policy over the coming decades. However, what's important is the *relative* attractiveness of animal versus other land uses. Thus, to gain a full understanding of how climate change might affect land-use pressures, we require profit-weather functions for all relevant land uses, in addition to those provided here for dairy and sheep/beef.

A limitation of the methods employed in this chapter is that they do not account for costs that change with the climate but are fixed in time. Farms in drier/warmer areas may have made costly investments that allow them to reduce the effect of year-to-year changes in weather on operating profits. The benefits of these investments are captured in the average effects we estimate here, but the capital costs of those investments are not. One potential solution to this problem, proposed by Deryugina and Hsiang (2017), is to allow the effect of year-to-year weather to vary by baseline climate.[12] A future iteration of this work could see the extent to which their method affects the conclusions of this report.

[12] The mathematical argument for why this works is technical, and interested readers are encouraged to read the aforementioned paper.

While the productivity of animal agriculture and employment (see chapter 2 of this report) are important contributors to the economic well-being of many in Aotearoa, there are several other important outcomes that may be affected by climate change and that have been identified and measured using similar data-driven quantitative methods to those we use here. These include human health (Carleton et al. 2020), cognitive performance (Graff Zivin et al. 2018), crime and conflict (Hsiang et al. 2013), and energy use (Auffhammer et al. 2017). There are also efforts to combine these estimates into summary measures that describe the comprehensive net costs of changes to the climate for the USA (Hsiang et al. 2017) and the globe (work in progress presented by Greenstone 2016). A missing piece in these efforts is any study that aims to quantify the effect of climate change on ecosystem services such as species preservation. Future research could move through these other important outcomes to try to measure the extent to which they may suffer damage (or accrue improvements) under climate change.

Understanding the scale of the expected impacts of climate change across all sectors is key for central government when considering future budgets for adaptation support. If, for example, the scale of expected net damages to agriculture was 1% of the expected net harm to human health, it would be difficult to justify putting 50% of central government's adaptation budget into agriculture (numbers are for illustration only and are not necessarily correct). However, these quantitative comparisons are not yet straightforward, because the underlying quantitative studies have not yet been executed across all sectors.

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2 Empirical effects of drought on agricultural employment

2.1 Introduction

Most of the international and New Zealand research studying the impacts of drought or of climate change has focused on either macroeconomic or agricultural outcomes (e.g. Gross Domestic Product, agricultural yields, and agricultural prices). This chapter, however, adds to the broader global research effort by focusing on the implications of historical drought for agricultural employment, earnings, sales, and purchases at the local level.

Since the impacts of drought on vulnerable communities are most likely to arise from local economic slowdowns, we start by examining the historical impacts of drought on employees and businesses. As the effects of drought intensify and begin to affect local farms, we would expect to see an impact on the wages and employment of workers on these farms, which, in turn, means these workers and farms are spending less in the local community. This would be especially true for areas that rely on seasonal, migrant, and temporary workers during their busiest times. As the drought intensifies, we would expect to see these effects ripple through the local economy as local businesses see a slowdown in their revenues.

For our analysis, we employ methods from the climate econometrics literature (Hsiang et al. 2013; Schlenker & Roberts 2009) that use empirical data to value expected future changes in the climate. In this literature, researchers estimate historical relationships between weather and socioeconomic outcomes and then make projections of future outcomes using forecasts of climate change. The climate econometrics field aims to inform global climate policy as well as identify opportunities for adaptation. These works have documented impacts of climate change on GDP (Burke et al. 2015), agriculture (Schlenker & Roberts 2009), civil conflict, energy use (Auffhammer et al. 2017), labour supply (Graff Zivin & Neidell 2014), and international migration (Cai et al. 2016), among other economic and social outcomes. These methods have both empirical tractability as well as clear theoretical justifications (Hsiang 2016; Lemoine 2018), including the conditions under which the use of year-to-year variation in weather to identify historical relationships is appropriate to identify the impact of a change in climate.

There are a variety of other literatures into which this work fits: the economic impacts of drought in New Zealand, the effects of climate change on agricultural firms and production, and the economic costs of natural disasters. Our work is the first to leverage detailed, linked employee-employer microdata to better understand the relationship between drought and employment in New Zealand. Much of the domestic work looking at the economic impacts of drought does not assess the implications of changes in the prevalence and intensity of drought under climate change and generally looks at the broader New Zealand economy, with no assessment of local and regional effects. Kamber et al. (2013) look at the impact of drought using an empirical macroeconomic model to predict the likely effects of the 2013 drought on the broader economy. Their results showed that the 2013 drought was likely to lower annual GDP by 0.3%. Their model, however, did not look below the national level to see how businesses, employees, or communities were likely to fare during and after the drought; nor did they look at regional impacts.

Kamber et al. (2013) build on previous research from Treasury, which incorporates weather shocks (including drought events) in their models (Buckle et al. 2002). The Ministry for Primary Industries (MPI) also appear to incorporate drought events into their annual Situation and Outlook for Primary Industries when predicting production for the year (MPI 2018). Yet, the work by both Treasury and by MPI focuses on macroeconomic factors as opposed to more localised outcome measures.

Other work in New Zealand has focused on the impacts of weather or drought on land use, land values or agricultural productivity (Allan & Kerr 2016; Apatov et al. 2015; Timar 2016), but it has not gone further to look at these effects on employment, earnings, or other firm outcomes.

The literature closest to our proposed work examining the impact of drought on local community outcomes is that of the local economic impacts of natural disasters, which uses similar data to examine the effects of these disasters on employees and local businesses. From a methodological standpoint, the closest such work includes the following: Fabling et al. (2014) assessing the effects of the Canterbury earthquakes on businesses and workers; Groen et al. (2017) assessing the effects of hurricanes in the US on individual employment and earnings; and Bastos et al. (2013) examining the long-term effects of drought on local labour markets in Brazil. Basker and Miranda (2016) also assess the impact of a major hurricane on business survival. All find significant impacts on employees and businesses in the affected areas.

Our analysis is different from these works because it is not looking at the effects of a discrete event, where the effects are felt in a relatively short amount of time. The effects of drought tend to accumulate over time, which makes identifying the start and end of the event difficult. So, instead of a binary drought indicator, we use a flexible representation of drought, which we construct using measures of the full distribution of daily soil moisture and temperature. We use these constructed weather variables combined with our outcomes measures in a fixed-effects regression model, which allows us to estimate the effect of extreme weather conditions on employment, earnings, sales, and purchases.

2.2 Data sources

This section describes the data we use for analysis, which include both monthly and annual approaches. The monthly data analyses use the time period April 1999 to September 2019, while the annual analyses, use the time period 2000–2018 (to include only those observations with 12 full months of data).

2.2.1 Outcome measures

We obtain data on firms from the LBD[13] provided by Stats NZ, which covers the time period April 1999 to September 2019, one of the most detailed sources of business data

[13] For more detailed information about the LBD, see Fabling & Sanderson 2016.

available to researchers in the world. In the LBD, data are primarily available at two different firm levels, which reveals information about the structure of the firm: the enterprise and the geographic unit. The enterprise (ENT) level pertains to a tax-reporting legal entity (e.g. sole proprietor, partnership, company). Each enterprise is given a permanent enterprise number (PNT) to allow the enterprise to be tracked over time, even if there is a change in the type of legal entity. For example, if a partnership decides to change to a limited liability company but is otherwise essentially the same entity, its PNT will remain the same.

The second level is the geographic unit (GEO), which is also known as the establishment or plant level. These units could be storefronts, headquarters, farms, warehouses, or plants. Each GEO has also been given a permanent, unique identifier (PBN), which allows us to track continuing activity at the same location. Establishment location is available at the meshblock level, which has an average size range of 30–60 dwellings (around 60–120 residents). Note also that GEOs and ENTs are assigned separate industry codes, which can differ even across the Level 1 (Division) ANZSIC06 industry classifications[14].

The LBD also contains detailed employment information, which is sourced from the Employer Monthly Schedule (EMS)[15] data from Inland Revenue (Fabling & Sanderson 2016). The EMS data provide enterprise-level payroll information, including individual employees' monthly earnings and the total wage bill paid by the enterprise each month. Stats NZ links the employees in the EMS data to the enterprise's physical locations (i.e. establishments) using a matching algorithm, as described in Fabling & Maré 2015. Employees have also been assigned unique identifiers, which allows us to track them over time and across employers. Hence, if an employee works at multiple jobs in a given month or changes jobs across months, we can track their employment as long as they are employed as an employee in New Zealand. We primarily rely on the derived employment tables as described in Fabling & Maré 2015, which include a measure of full-time equivalency (FTE) for employment in the month and whether or not the employment spell is a short spell (less than 3 months in duration).

Stats NZ also receives records of Inland Revenue's GST returns, which are filed on a monthly, bi-monthly or six-monthly basis (depending on the size of the firm) by the enterprise. We use the GST data to examine sales and purchases as measures of firms' health. We use the monthly GST tables, as described in Fabling & Maré 2019. Given that GST returns are at the enterprise level, we calculate establishment-level GST amounts (for sales and purchases) using the establishment's share of total enterprise employment and using the establishment's share of total enterprise FTEs. Since these data are at a fairly high frequency[16], we can see changes evolve as drought conditions intensify.

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[14] The full classification system is available at https://www.abs.gov.au/ausstats/abs@.nsf/0/20C5B5A4F46DF95BCA25711F00146D75?opendocument

[15] The EMS is filed by all businesses with employees as part of the administration of the Pay-As-You-Earn income tax system.

[16] These data are reported at 1-, 2-, or 6-month intervals depending on the size of the firm, but the majority report at 2-month intervals.

Our outcome measures then include the following:

- *employment*: measured in terms of worker-jobs (distinct worker-enterprise combinations) in the month
- *FTE*: a measure of full-time equivalency that is based on earnings in the month relative to the earnings at the minimum wage, as described in Fabling & Maré 2015
- *short spells*: measured in terms of the worker-job employment spell being less than 3 months, as described in Fabling & Maré 2015
- *gross earnings*: gross earnings of employees, as reported in the EMS data
- *GST sales:* total GST-inclusive sales apportioned to month and to establishment
- *GST purchases:* total GST-inclusive purchases apportioned to month and to establishment.

All of the outcome measures are first determined at the establishment-level, which is used to assign the industry and meshblock codes. Industry and meshblock measures are then aggregated based on the establishment-level data. Annual measures are sums of the monthly totals.

For these analyses, we start with data aggregated across all industries categorised as 'Agriculture, Forestry, and Fishing', excluding any establishments categorised as 'Aquaculture' (A02) or 'Fishing, Hunting and Trapping' (A04). Hereafter, we refer to all of the included industries as 'All Industries'. We also run separate analyses for 'Food Product Manufacturing' (C11), since this industry could also be affected by drought conditions for its inputs. Our data are grouped using Level 3 (Group) ANZSIC06 classifications, which are based on the establishment's industry.

2.2.2 Weather

A detailed description of the weather data appears in the previous chapter (see section 1.3.3). The only change made for this chapter is to divide the soil moisture variables by 1,000 (with the exception of the soil moisture quartic variable, which we divide by 100,000) to aid the display of the coefficients in the tables.

2.3 Methodology

The statistical approach we use is two-way panel fixed effects. The identification of the statistical relationships using this approach relies on comparing how variation in drought intensity from time period to time period is associated with changes in the outcome variable, controlling for effects that are common across the country in a given time period. The primary advantage of the fixed-effects approach is that it allows us to control for unobservable factors that are specific (i.e. fixed) to a location (e.g. soil quality) or time period (e.g. agricultural prices). The random variation in drought intensity across both time and space provides a natural experiment that allows us to identify the effects of drought on our outcomes of interest.

Similar to the work of Deschenes and Greenstone (2007), Fabling et al. (2014), and Groen et al. (2017), we track how the impacts of drought persist or evolve over time. For example, a severe drought in a community heavily dependent on agriculture could affect its employment and growth for years into the future. We examined these effects using contemporaneous weather for estimation, and also 12 months of lagged drought conditions to link earlier droughts to current outcomes.

Using this basic framework, we examined differences between the effects of weather conditions and our outcome measures, as outlined in section 2.1.1

Our general framework is based on the following specification:

$$Y_{it} = \alpha_i + \gamma_t + \sum_k f_{t-k}(\boldsymbol{W}_{\boldsymbol{i},t-k}) + \varepsilon_{it}$$

The dependent variable will be the outcome of interest, Y_{it}, for unit i (establishment or meshblock) in time t.[17] This could be, for example, monthly employment or monthly earnings for the establishment or for the meshblock. The α_i terms are the unit-fixed effects that control for unobservable determinants of Y_{it} that are fixed within the unit over time; the γ_t terms are the time-fixed effects, which control for factors that are common to the sample in time t. The $\boldsymbol{W}_{\boldsymbol{i},t-k}$ variables will primarily be measures of the weather (temperature, soil moisture) for unit i but k periods before t, and following current practice in the climate econometrics literature, the function $f_{t-k}\left(\boldsymbol{W}_{\boldsymbol{i},t-k}\right)$ allows for the non-linear estimation of the relationship between the daily weather measures, $\boldsymbol{W}_{\boldsymbol{i},t-k}$, and the outcome, Y_{it}, but still allows us to compare outcomes for different time periods to examine the persistence of the effects of drought.

A way to think about these f functions is that they summarise the daily distribution of the weather variables using a small number of variables, aggregating them up to the level of (possibly annual) time period t.[18] This methodology allows us both to compare the f functions over time (i.e. different k's) and to examine the persistence of the effects of drought on communities relative to similar communities without drought. The $\boldsymbol{W}_{\boldsymbol{i},t-k}$ variables are primarily the monthly soil moisture and temperature variables.

We cluster the standard errors on the cross-sectional variable (i.e. either at the establishment or meshblock level) and use heteroscedasticity-consistent covariance matrices, though using heteroscedasticity- and autocorrelation-consistent covariance matrices does not change the results. Moreover, the panels are unbalanced. Using balanced panels would exclude establishments and meshblocks that do not have consistent employment over the entire sample, which may exclude some of the interesting variation.

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[17]We start with months as the basis for time periods, but also aggregate to annual measures, primarily for the growing year (July to June).

[18] We refer interested readers to section 4.1 of Hsiang (Hsiang 2016) for the mathematical details of this method. This method has successfully been applied in the New Zealand context in Bell 2017.

2.4 Results

This section begins with descriptive analysis of key variables and then looks at the regression results. While we produce results for all our outcome measures, we find that the patterns we see for employment are representative of those that we see for the other outcome measures. For the sake of brevity, however, we only present the results for employment. Moreover, we run a similar analysis for food manufacturing, but we find few effects beyond those presented for the primary agricultural products. Again, for the sake of brevity, we do not publish all of those results in this chapter.

2.4.1 The agricultural sector

Figures 7 to 14 show monthly employment over the analysis period for all industries included in our analysis, as well as a sample of individual sectors: Fruit and Tree Nut Growing (A013), Sheep and Beef Farming (A014), and Dairy Farming (A016). These figures show that employment – whether measured as worker-jobs, FTE, or short spell jobs – in the agricultural sector has a high degree of seasonality, with employment typically peaking in the summer months and then bottoming out in the winter months. For all industries, worker-jobs ranged from approximately 65,000 to over 80,000 in the troughs during the analysis period; whereas around the peaks, worker-jobs range between 98,000 and 118,000.

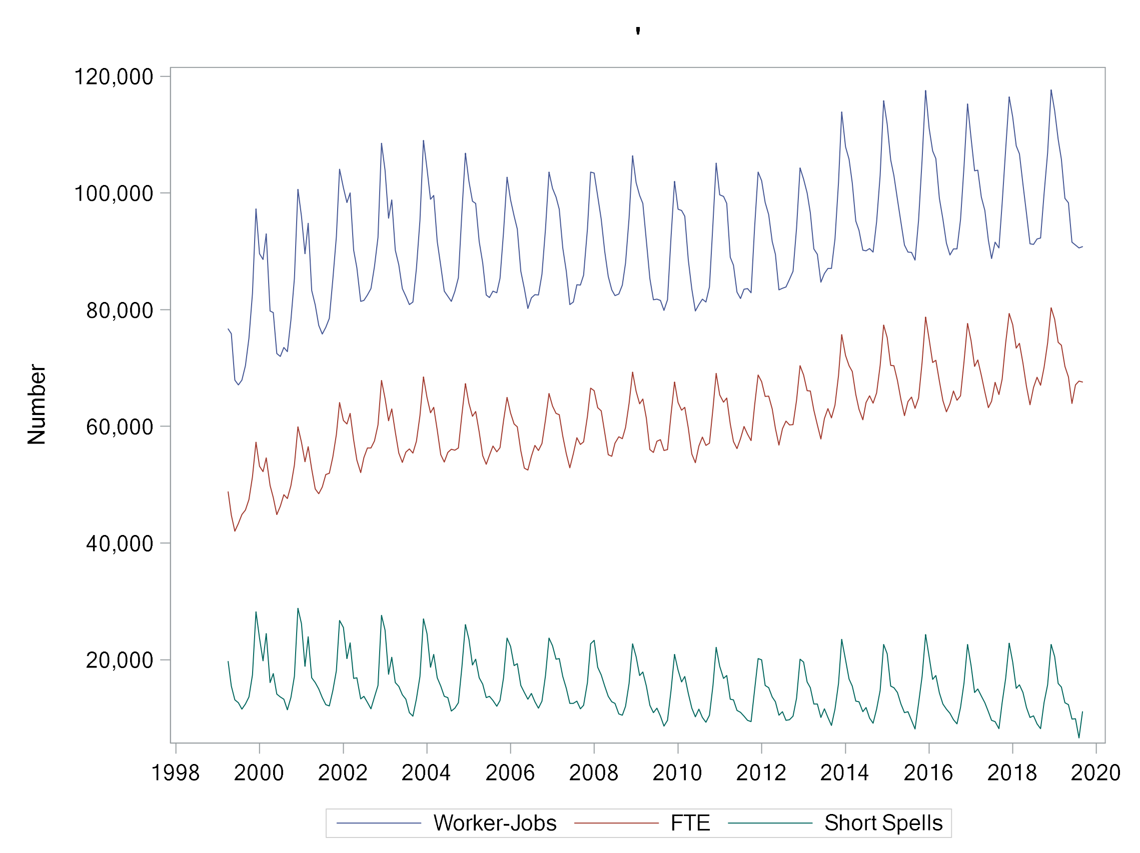

Figure 7. Monthly employment in all agricultural industries, 1999–2019.

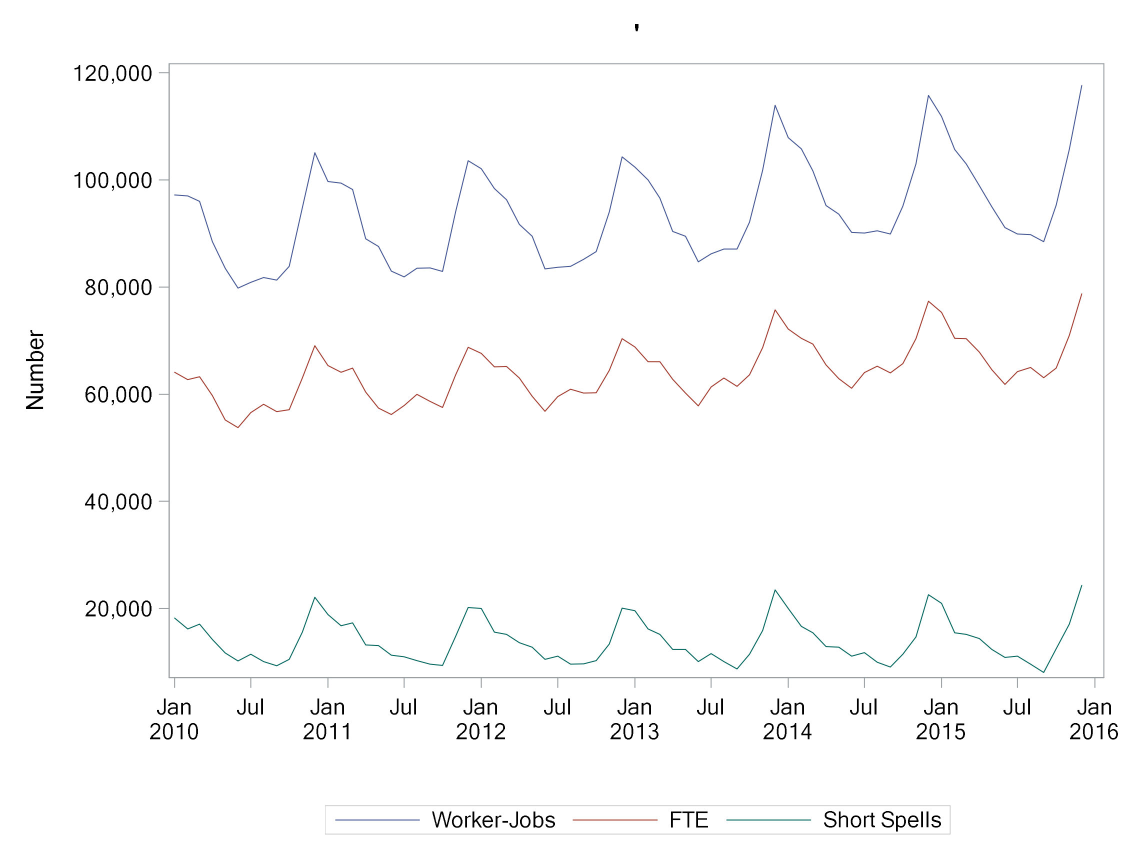

Figure 8. Monthly employment in all industries, 2010–2015.

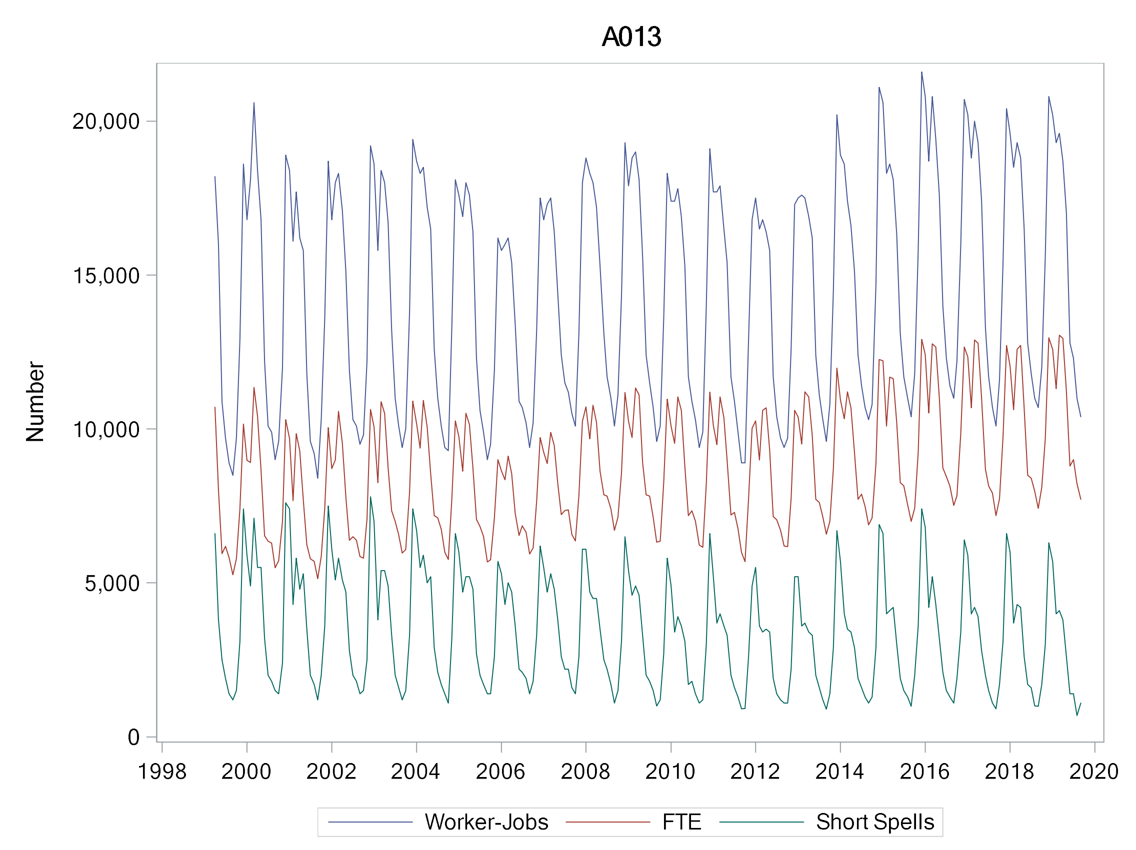

Figure 9. Employment in fruit and tree nut growing (A013), 1999–2019.

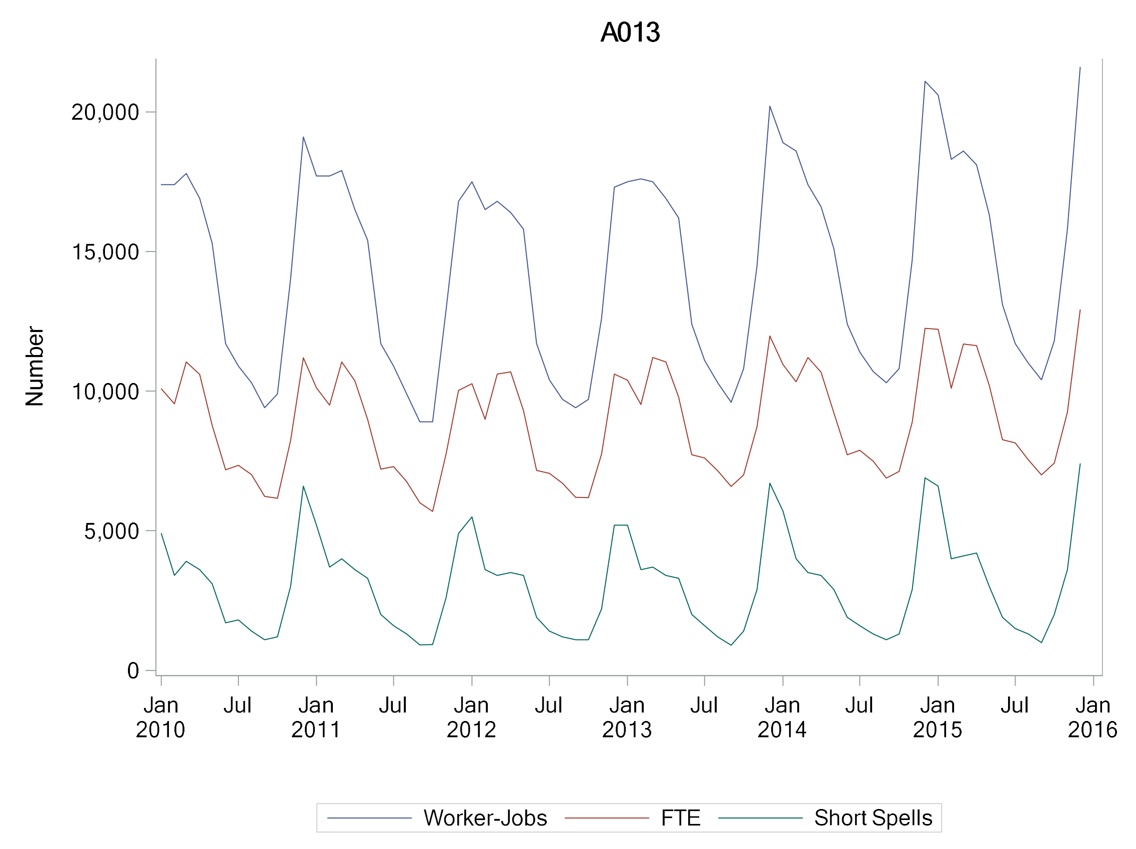

Figure 10. Employment in fruit and tree nut growing (A013), 2010–2015.

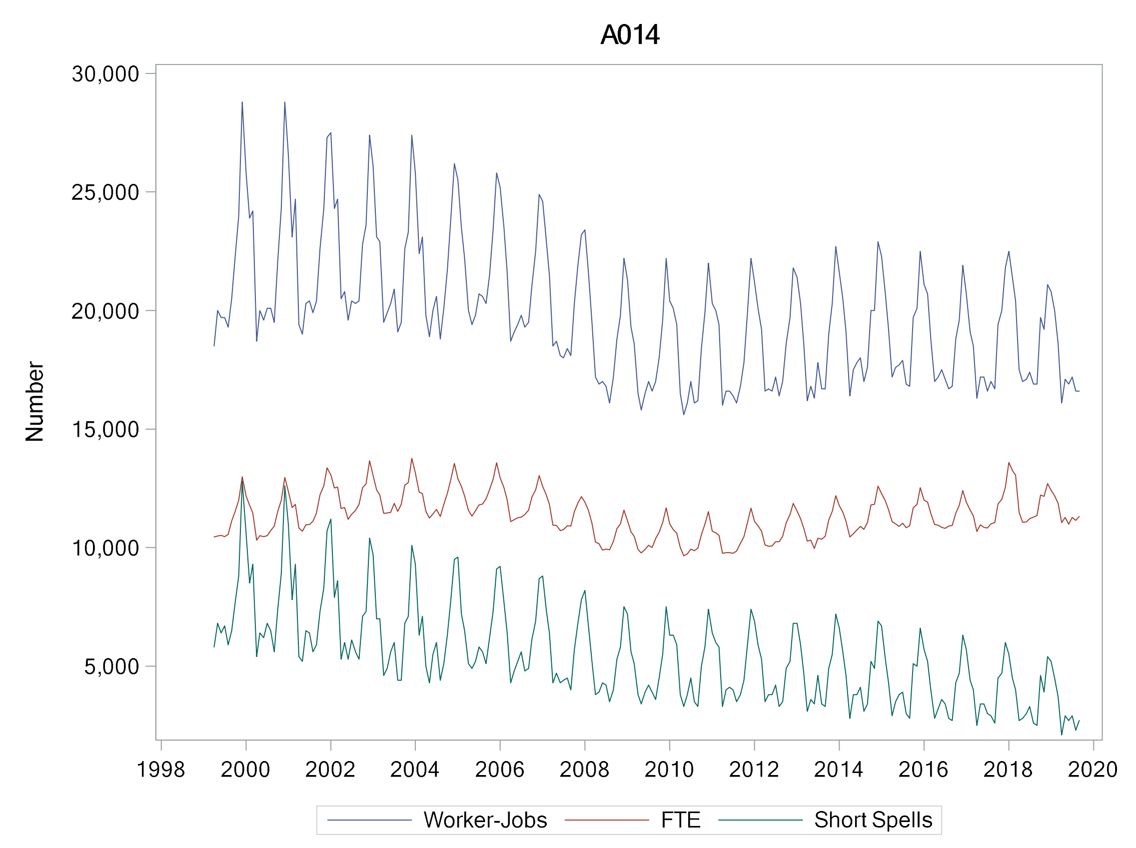

Figure 11. Monthly employment in sheep, and beef farming (A014), 1999–2019.

Figure 12. Monthly employment in sheep, and beef farming (A014), 2010–2013.

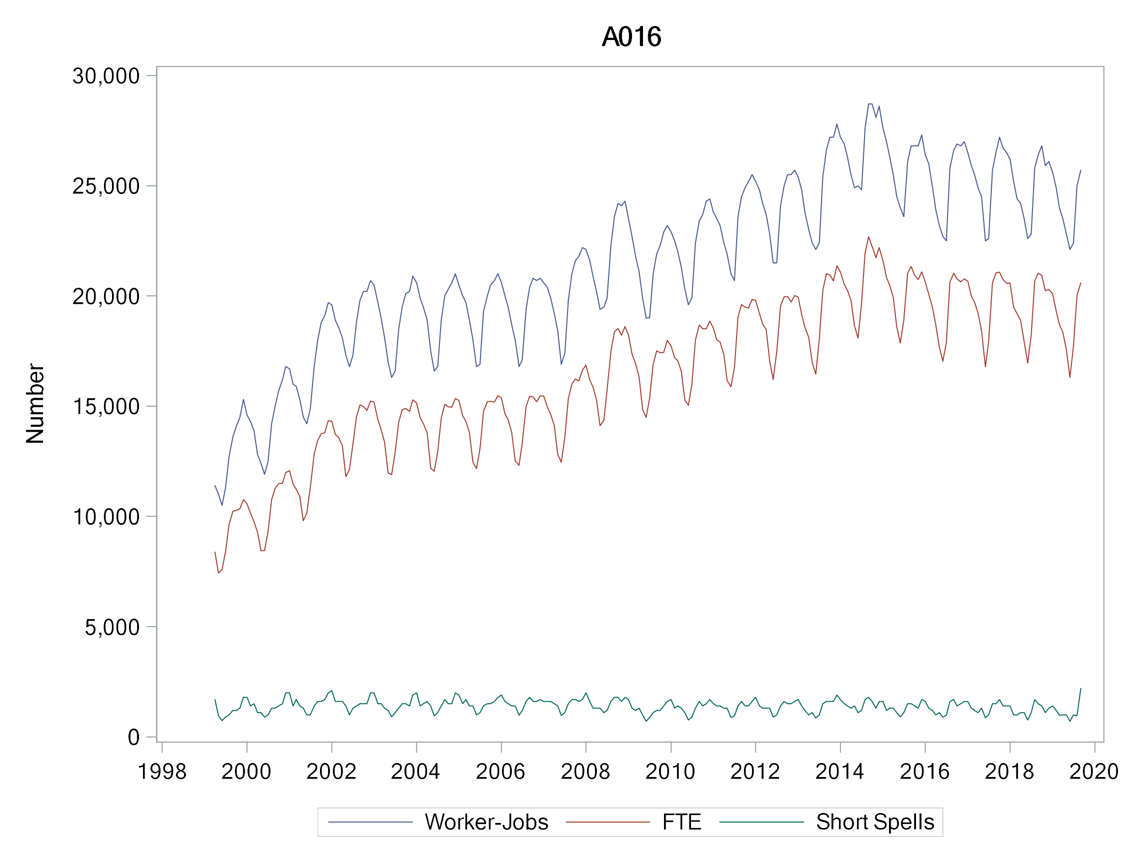

Figure 13. Monthly employment in dairy farming (A016), 1999–2019.

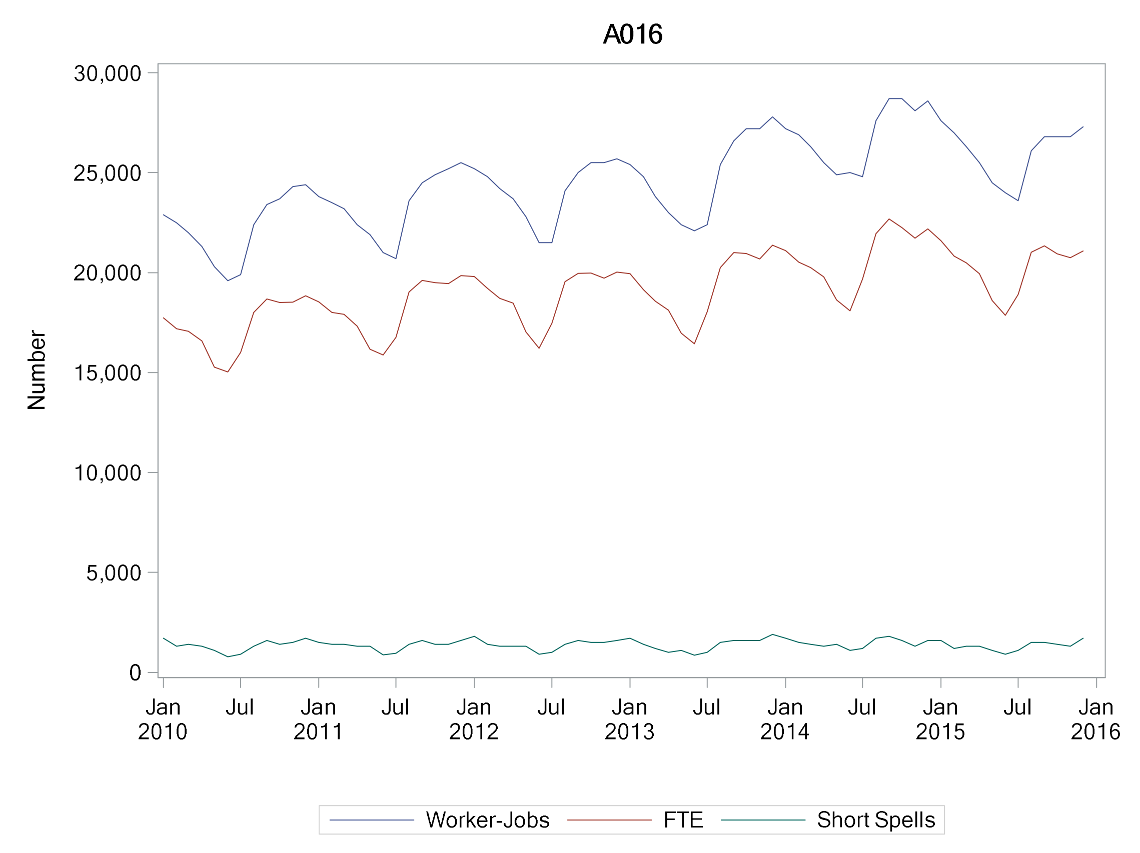

Figure 14. Monthly employment in dairy farming (A016), 2010–2015.

When we focus on our employment measures around the 2013 drought, we see similar patterns, with no discernible change during or after the drought. To further examine the seasonality in the underlying industries, we ranked each month in a year using the total number of worker-jobs in the month, with 1 indicating the month with the lowest employment and 12 indicating the month with the highest employment. Figure 15 shows these results for three individual industries: Fruit and Tree Nut Growing, Sheep and Beef Farming, and Dairy Farming. These results show that employment in summer months is generally higher than in winter months; that in all three industries December generally has the highest employment; and that the seasonal pattern is different for these three industries. Hence, when running the regressions, we should run the analysis separately for the industries.

Table 2 also provides summary statistics for our outcome measures and weather variables by industry (including all industries) for all months and for November to March.

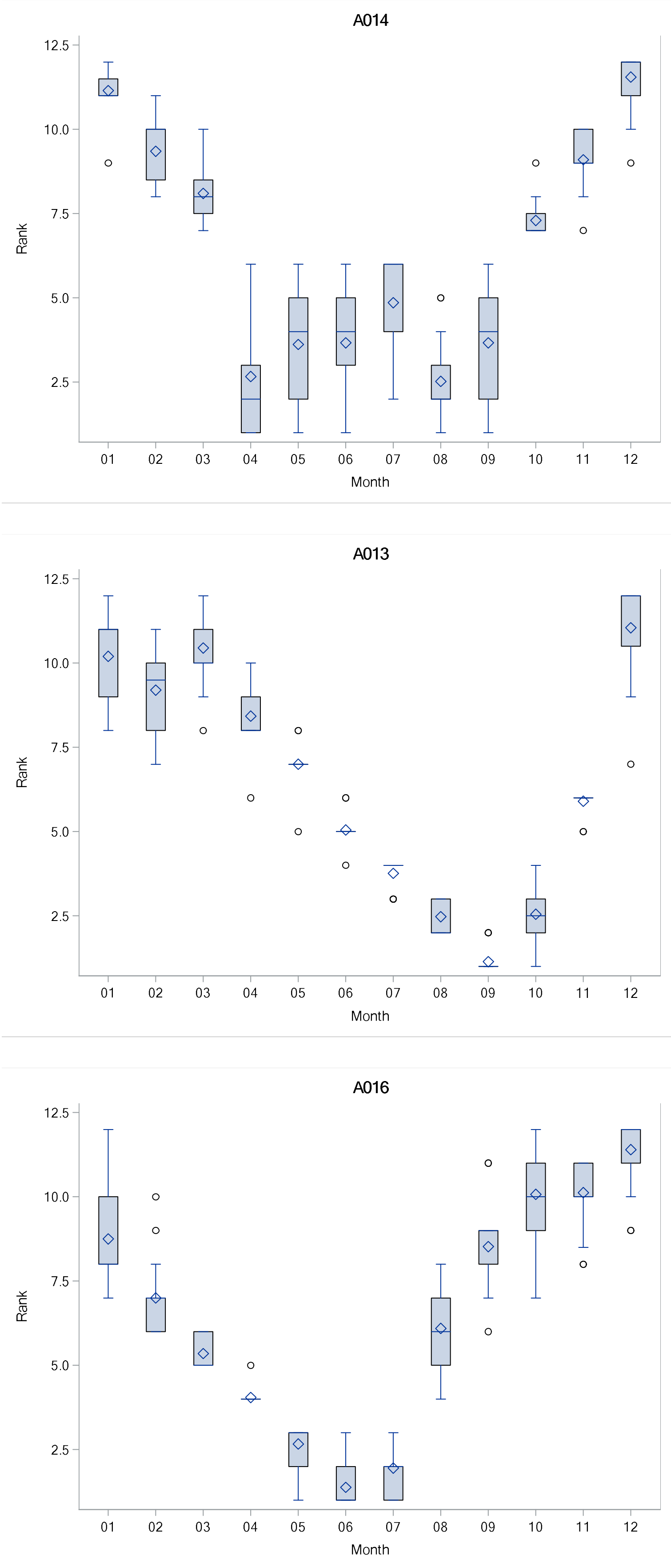

Figure 15. Ranking of monthly (lowest = 1, highest = 12) employment during the year, in sheep, and beef farming (A014), fruit and tree nut growing (A013) and, dairy farming (A016).

Table 2. Means and standard deviations of key variables by industry

Industry	Employment (worker-jobs)		FTE		Short spells		Soil moisture		Temperature	
	All months	Nov–Mar	All months	Nov–Mar	All months	Nov–Mar	All months	Nov–Mar	All months	Nov–Mar
All Agriculture	10.9	11.8	7.3	7.8	1.8	2.2	–1.3	–2.4	12.8	16.1
	22.1	25.0	15.3	16.8	6.2	8.0	1.3	1.1	3.9	2.4
Nursery/Floriculture	8.1	8.3	5.7	5.8	0.7	0.9	–1.4	–2.5	13.5	16.7
A011	13.4	14.1	9.9	9.9	3.8	5.0	1.3	1.1	3.7	2.3
Mushroom/Veges	10.8	11.6	7.5	7.9	1.1	1.5	–1.5	–2.6	13.4	16.7
A012	24.6	25.7	19.1	20.0	3.5	4.2	1.4	1.1	3.8	2.2
Fruit and Tree Nut	14.5	17.0	8.7	9.8	3.4	4.8	–1.5	–2.6	13.5	16.8
A013	32.9	40.3	20.3	23.0	12.5	17.1	1.4	1.0	3.8	2.2
Sheep/Beef	5.5	6.0	3.1	3.2	1.5	1.9	–1.4	–2.4	12.2	15.5
A014	7.7	9.0	4.9	5.8	3.4	4.0	1.3	1.1	4.0	2.5
Other Crop Growing	3.7	3.9	2.5	2.7	0.6	0.7	–1.5	–2.5	12.5	15.9
A015	6.1	6.7	4.4	4.6	2.5	3.3	1.4	1.1	4.0	2.4
Dairy Cattle	6.0	6.3	4.6	4.8	0.4	0.4	–1.2	–2.2	12.9	16.2
A016	7.0	7.2	5.6	5.7	1.0	1.1	1.3	1.1	3.8	2.4
Poultry	10.0	10.0	7.5	7.6	0.3	0.3	–1.4	–2.5	13.5	16.8
A017	19.0	19.0	16.3	16.3	0.9	0.9	1.3	1.1	3.7	2.2
Deer	2.8	2.9	1.9	2.0	0.4	0.5	–1.4	–2.3	11.2	14.7
A018	3.3	3.4	2.6	2.7	1.2	1.3	1.3	1.1	4.1	2.4
Other Livestock	4.4	4.6	3.3	3.5	0.3	0.4	–1.4	–2.4	13.0	16.3
A019	7.1	7.6	6.0	6.3	1.1	1.3	1.3	1.1	3.9	2.4
Forestry	8.3	8.3	7.3	7.2	0.4	0.4	–1.3	–2.3	12.8	16.1
A030	13.4	13.4	12.4	12.4	1.7	1.9	1.3	1.1	3.9	2.3
Forestry Support Services	9.7	9.2	7.7	7.3	0.7	0.6	–1.4	–2.4	12.9	16.2
A051	18.5	17.6	14.7	14.1	2.0	1.7	1.3	1.1	3.8	2.3
Ag Support Services	10.5	11.4	6.6	7.2	2.0	2.4	–1.5	–2.5	12.8	16.2
A052	30.3	33.3	20.9	23.0	7.3	8.8	1.3	1.1	3.9	2.4

2.4.2 Regression results

We begin the analysis using only the linear soil moisture measure. Table 3 shows the results for meshblock monthly employment. The first two columns for Table 3 include all months of the year for the period April 1999 to September 2019, and the second two columns only include the driest months (November to March). The first row of the table shows the pooled result for all of the industries shown in the subsequent rows, and the subsequent rows show the results for each individual industry.

For all industries, the coefficient for soil moisture is insignificant at the 5% level when all months are included in the model, but positive and significant when only using the peak months. For the individual industries, the coefficient on the linear soil moisture measure is insignificant for both specifications for most industries. The exceptions are Fruit/Tree Nut Growing (A013), which is negative and significant when all months are included but insignificant for peak months; Sheep/Beef (A014), which is negative and significant for peak months but insignificant for all months; and Dairy Cattle (A016), which is positive and significant for both specifications. We run the same analysis using the other outcome measures and also using the establishment level, and the patterns remain largely the same. To conserve space, we report only the results for employment at the meshblock level[19].

We also added the polynomial terms for soil moisture (2nd, 3rd, and 4th powers) to the regression. The results of this analysis are shown in Table 4 (all industries) and Table 5 (Dairy). The coefficients themselves are difficult to interpret, so we display the results graphically in Figure 16 (all industries) and Figure 19 (Dairy). Table 4 (all industries) and Table 5 (Dairy) also show the results for including the linear temperature variable (columns 3 and 4) as well as the model with the non-linear soil moisture and temperature measures included (columns 7 and 8) with the graphical results in Figure 17 (all industries) and Figure 20 (Dairy). From these results we see that temperature plays a role in meshblock employment for all industries combined, as well as for Dairy. When using all months for all industries, the coefficient on the linear temperature measure is positive and significant. Moreover, temperature seems to be significant primarily when using all months, both for all industries and for Dairy. This implies that temperature is less important when using only peak months.

To examine the effects of past weather on current outcomes, we also included 12 lags of the linear soil moisture measure with the contemporaneous linear measure in the monthly regressions. In Table 6 we report these results for all industries (columns 1 and 2) with the graphical representation in Figure 18, Fruit/Tree Nut Growing (columns 3 and 4), Sheep/Beef (columns 5 and 6), and Dairy (columns 7 and 8) with the graphical representation for Dairy in Figure 21. These results indicate that for all specifications, lagged effects are significant but vary based on the industry, and that, except for Dairy, the significant coefficients are a mix of positive and negative effects depending on how long

[19] Meshblocks are more consistent over time than establishments, so using meshblocks allows us to include employment from establishments that might otherwise need to be dropped.

the lag is. For Dairy, the coefficients for soil moisture for the contemporaneous month and for all 12 lags are significant and positive. For Dairy using only peak months, the coefficients for soil moisture for the contemporaneous month and most of the lagged months are both positive and significant, with none of the coefficients negative.

Table 3. Two-way fixed effects, monthly employment for meshblocks using linear soil moisture

	Soil moisture (all months)		Soil moisture (Nov–March)	
Industry	**Beta (t value)**	**N (R2)**	**Beta (t value)**	**N (R2)**
All Agriculture	0.006632 (0.20)	19373 (0.6211)	**0.12132* (2.68)**	18592 (0.6565)
Nursery/Floriculture A011	–0.06228 (–0.54)	2090 (0.6428)	–0.13461 (–1.10)	1958 (0.6485)
Mushroom/Veges A012	**–0.35793* (–2.66)**	2307 (0.7797)	–0.13962 (0.3322)	2156 (0.7848)
Fruit and Tree Nut A013	–0.25658 (–1.39)	3437 (0.5296)	0.351134 (0.1082)	3185 (0.6253)
Sheep/Beef A014	–0.01314 (–0.62)	9671 (0.5340)	**–0.09086* (–2.67)**	9215 (0.4930)
Other Crop Growing A015	0.07001 (–1.23)	1702 (0.6737)	–0.00109 (–0.02)	1583 (0.7306)
Dairy Cattle A016	**0.117311*** (7.05)**	7855 (0.6622)	**0.068311** (3.57)**	7582 (0.6666)
Poultry A017	0.028542 (0.24)	609 (0.8502)	–0.11557 (–1.01)	571 (0.8421)
Deer A018	0.000835 (0.04)	1401 (0.6968)	–0.00939 (–0.31)	1274 (0.7005)
Other Livestock A019	–0.0159 (–0.58)	3479 (0.7501)	0.013613 (0.38)	3178 (0.7725)
Forestry A030	0.022464 (0.45)	3113 (0.8153)	0.032169 (0.46)	2840 (0.8178)
Forestry Support Services A051	–0.08394 (–1.39)	1577 (0.7675)	–0.06198 (–0.81)	1437 (0.7782)
Ag Support Services A052	0.136083 (1.59)	8017 (0.6754)	0.159187 (1.75)	7529 (0.7107)

*p < 0.05, **p < 0.001 ***p < 0.0001

Table 4. Two-way fixed effects, monthly employment for meshblocks (all industries)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Soil Moisture	0.007	**0.121****	**0.532*****	**–0.269***	0.034	**0.101***	**0.200***	–0.12437
	(0.20)	**(2.68)**	**(4.8)**	**(–2.35)**	(0.96)	**(2.26)**	**(2.12)**	(–1.14)
Soil Moisture^2			**0.0025***	–0.001			–0.001	0.00214
			(2.09)	–0.41			(–0.42)	(1.49)
Soil Moisture^3			–7.27E-06	**0.00006****			–4.24E-06	**0.000067*****
			(–0.47)	**(3.85)**			(–0.28)	**(4.03)**
Soil Moisture^4			5.87E-06	**0.00004****			0.000013	**0.000031***
			(–0.47)	**(3.35)**			(1.32)	**(2.92)**
Temperature					**0.010*****	**–0.004***	**0.0123***	0.033
					(4.15)	**(–1.96)**	**(1.96)**	(0.72)
Temperature^2							0.001	0.003
							(1.33)	(0.69)
Temperature^3							–0.00014	–0.0004
							(–3.01)	(–1.88)
Temperature^4							3.71E-06	**9.15E-06***
							.	**(2.72)**
Peak (Nov–Mar)	N	Y	N	Y	N	Y	N	Y
Number of MBs	19,373	18,592	19,373	18,592	19,373	18,592	19,373	18,592
R-squared	0.6211	0.6565	0.6212	0.6565	0.6212	0.6565	0.6213	0.6566

*p < 0.05, **p < 0.001 ***p < 0.0001 (t values in parentheses)

Soil Moisture^4 (divided by 100,000) and the other soil moisture measures divided by 1,000 (relative to raw data)

Table 5. Two-way fixed effects, monthly employment for meshblocks (Dairy, A016)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Soil Moisture	0.117***	0.068**	0.278***	0.323**	0.129***	0.069**	0.119*	0.372***
	7.05	3.57	6.44	4.41	7.77	3.65	2.75	4.98
Soil Moisture^2			0.001	0.002			–0.001	0.003
			0.89	1.24			–0.45	1.59
Soil Moisture^3			–0.00002	–0.00002			–0.00002	–0.00002
			–1.35	–1.31			–1.19	–1.3
Soil Moisture^4			–0.00002*	–0.00002*			–0.00001	–0.00002*
			–2.45	–2.72			–1.59	–2.79
Temperature					0.005***	0.0002	0.020***	–0.030*
					10.66	0.25	11.61	–2.44
Temperature^2							–0.002***	0.004*
							–6.54	3.13
Temperature^3							0.00009***	–0.0002***
							4.82	–3.24
Temperature^4							–0.000001	0.000003
							.	.
Peak (Nov–Mar)	N	Y	N	Y	N	Y	N	Y
N of MBs		7,582	7,855	7,582	7,855	7,582	7,855	7,582
R-squared		0.6666	0.6622	0.6667	0.6623	0.6666	0.6625	0.6667

*p < 0.05, **p < 0.001 ***p < 0.0001

Soil Moisture^4 (divided by 100,000) and the other soil moisture measures divided by 1,000 (relative to raw data)

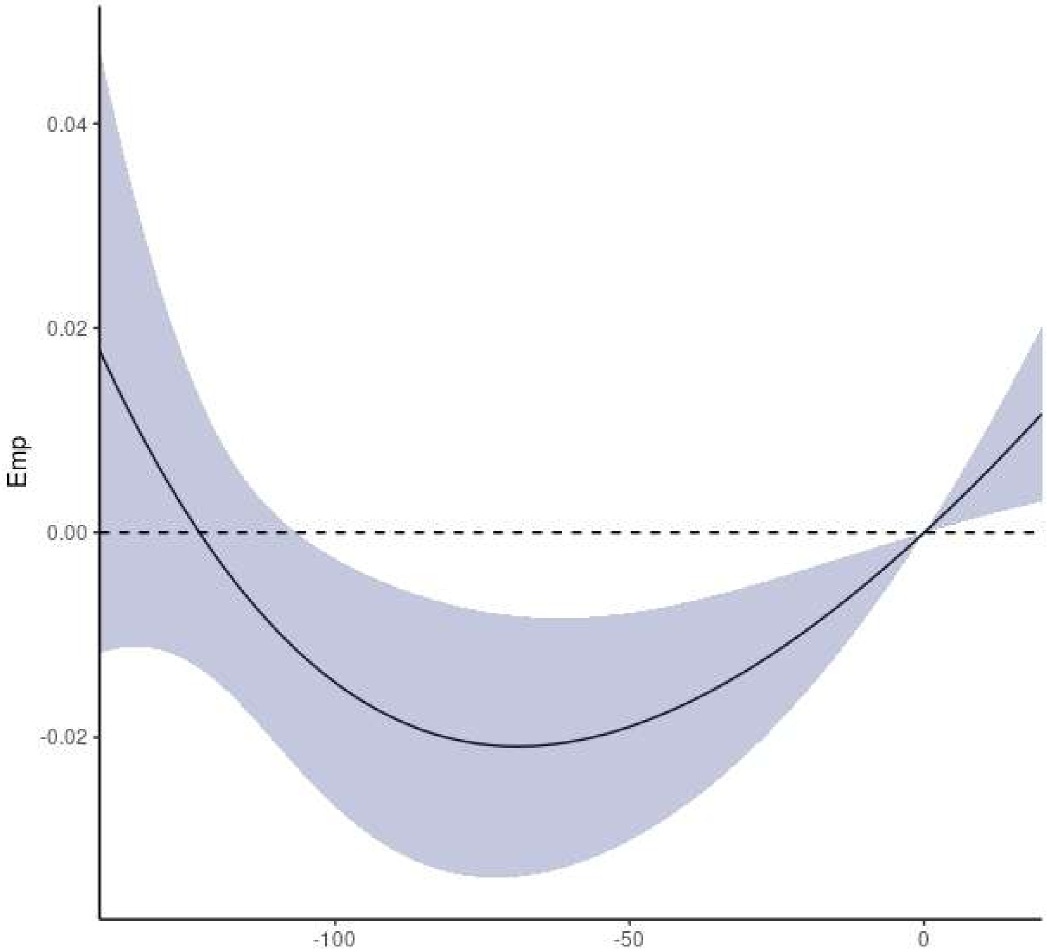

Figure 16. Estimated effects of changes in daily soil moisture on employment for all industries, using all four polynomial terms for soil moisture in the regression.

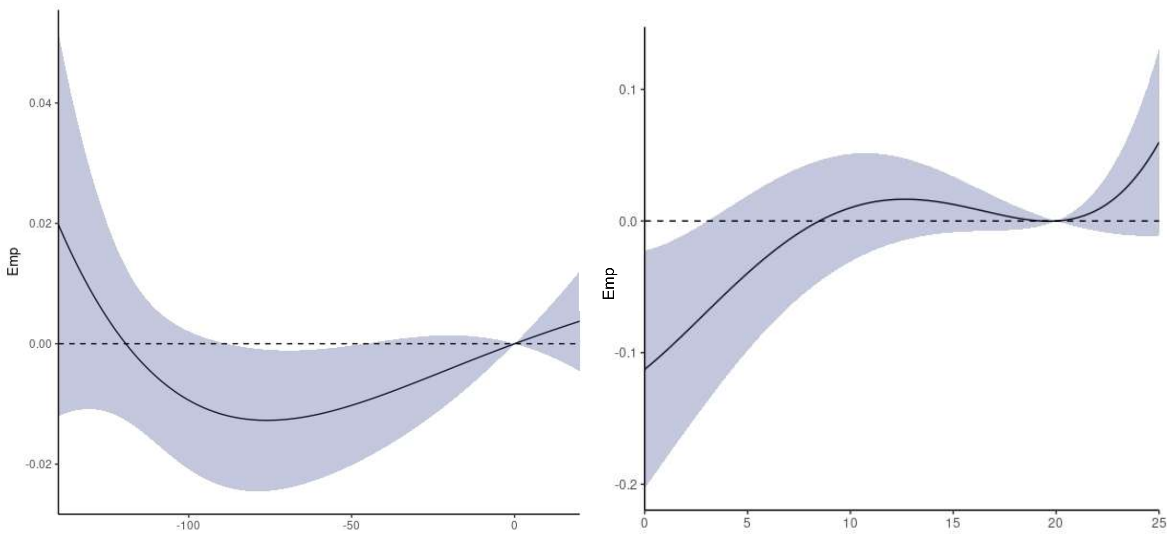

Figure 17. Estimated effects of changes in daily soil moisture (left) and hourly temperature (right) on employment for all industries, using all four polynomial terms for both soil moisture and temperature in the regression.

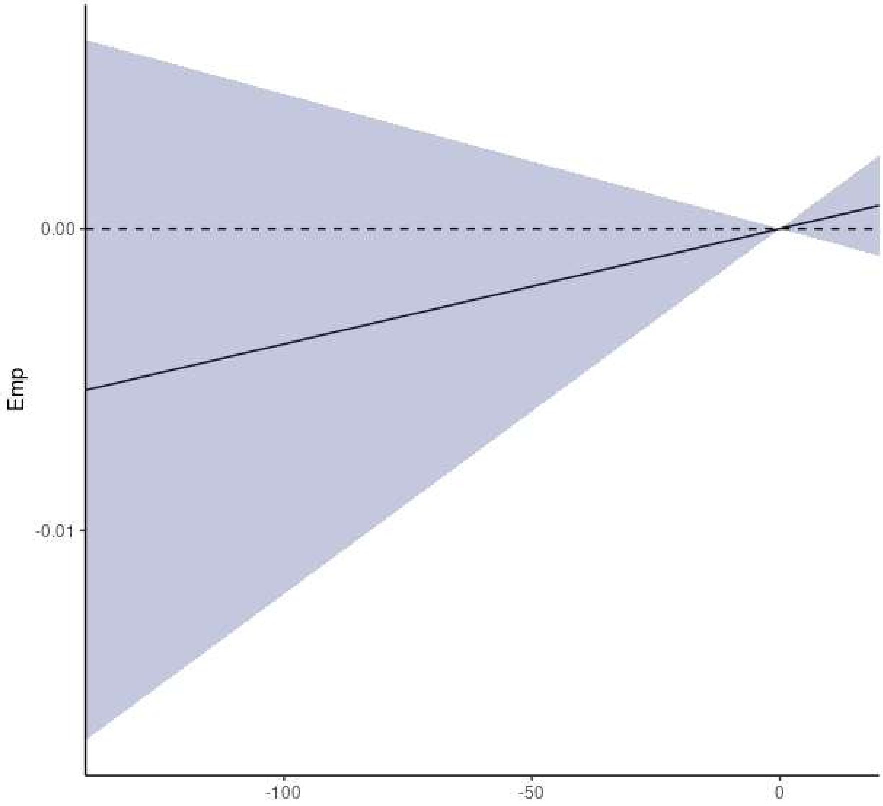

Figure 18. Estimated effects of changes in daily soil moisture on employment for all industries, using 12 lags of the linear soil moisture term in the regression.

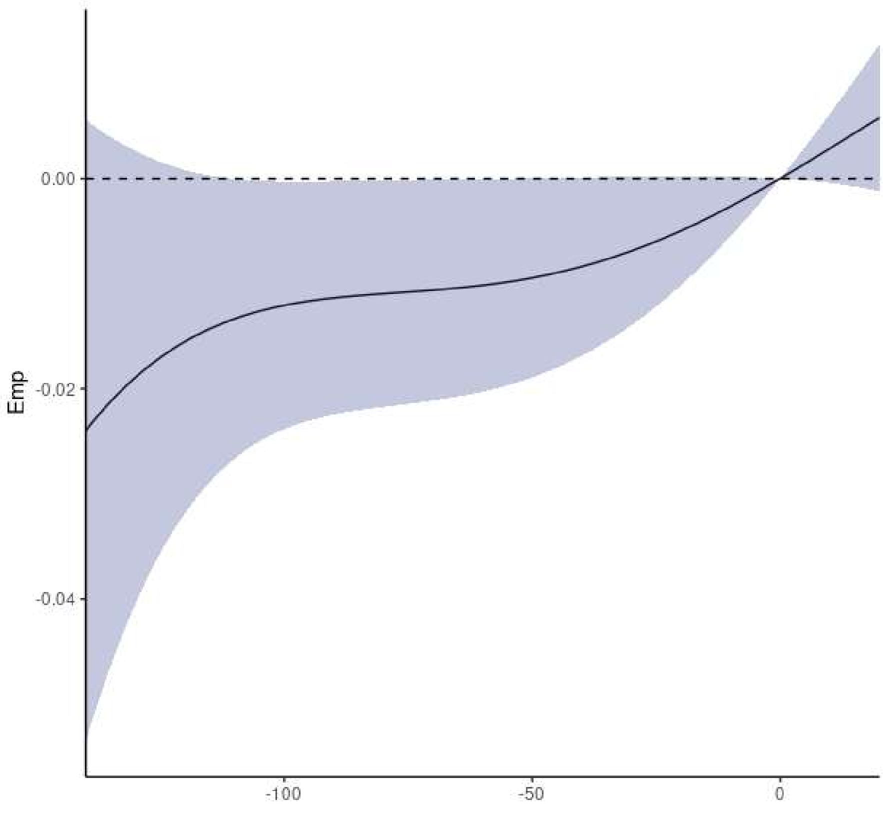

Figure 19. Estimated effects of changes in daily soil moisture on employment for dairy farming (A016), using all four polynomial terms for soil moisture in the regression.

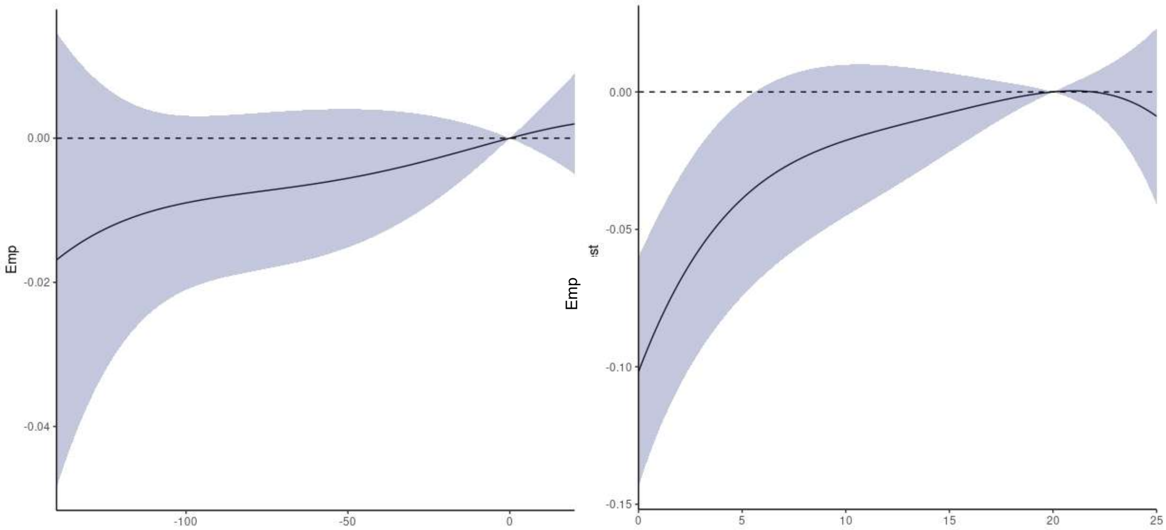

Figure 20. Estimated effects of changes in daily soil moisture (left) and hourly temperature (right) on employment for all industries, using all four polynomial terms for both soil moisture and temperature in the regression.

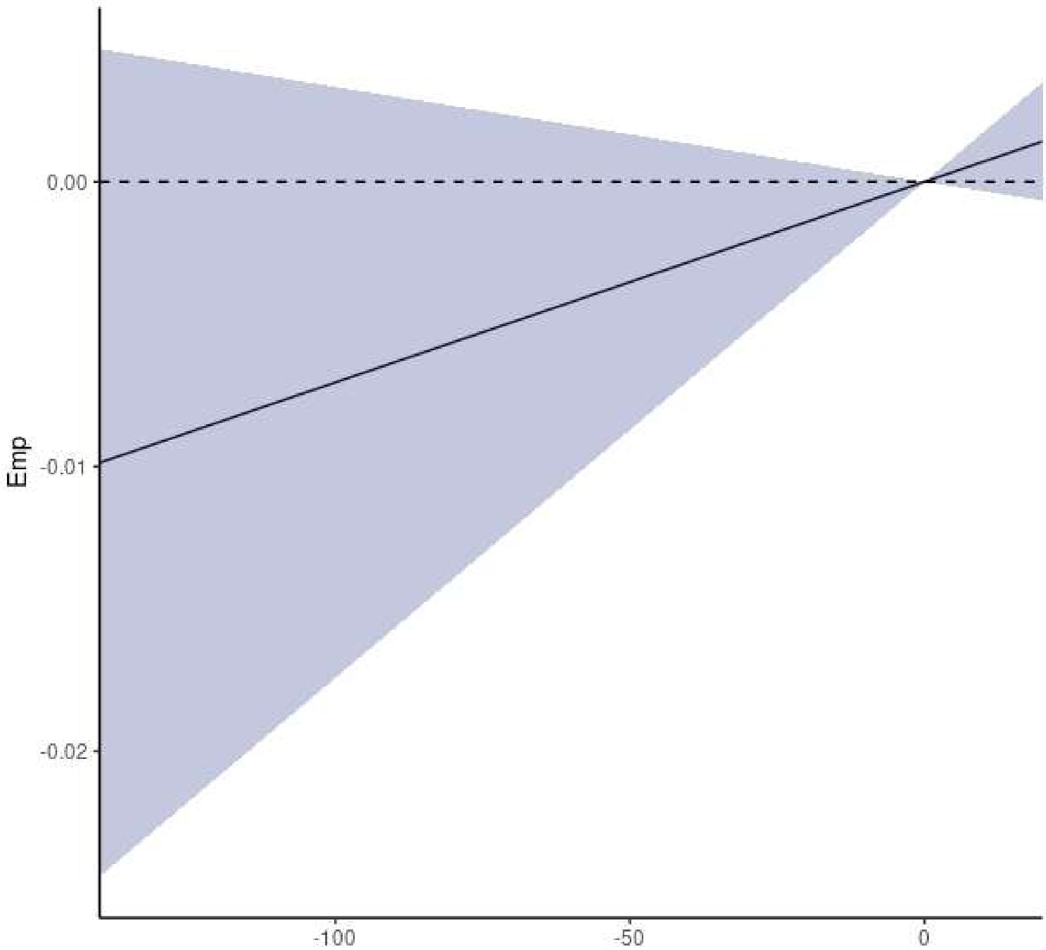

Figure 21. Estimated effects of changes in daily soil moisture on employment for all industries, using 12 lags of the linear soil moisture term in the regression

Our final specification uses annual employment (the sum of the 12 monthly measures) for the growing year as the dependent variable and the monthly, linear soil moisture measure for that growing year as the independent variable. The results for this analysis are shown in Table 7 for all industries (column 1), Fruit/Tree Nut Growing (column 2), Sheep/Beef (column 3), and Dairy (column 4). These results indicate that the relationship between soil moisture and employment varies throughout the year. For example, for all industries, the relationship between soil moisture in November and annual employment is negative and significant, whereas in December and June the relationship is positive and significant. The relationship in the other months is insignificant. For Fruit/Tree Nut Growing, none of the monthly soil moisture measures are significant, and for Sheep/Beef only January is significant, and it is negative, which indicates that too much moisture in January may be a problem. Dairy once again stands out from the other industries with a number of months having positive and significant coefficients (July, November, December, April, and June); however, the coefficient on the May soil moisture measure is negative and significant, and the coefficients for the other months are insignificant.

We ran the same analyses for the Food Manufacturing Sector and found similar results to those for the underlying inputs, with even less conclusive results.

Table 6. Two-way fixed effects with lagged effects, monthly employment for meshblocks

Industry	(1) ALL	(2) ALL	(3) Fruit/ Tree Nut Growing A013	(4) Fruit/ Tree Nut Growing A013	(5) Sheep/ Beef A014	(6) Sheep/ Beef A014	(7) Dairy A016	(8) Dairy A016
Soil Moisture	0.038	0.064	–0.136	0.043	**–0.055***	**–0.081***	**0.070*****	**0.044***
	1.38	1.84	-0.97	0.26	**–3.12**	**–3.22**	**5.15**	**2.76**
Soil Moisture LAG1	–0.001	0.049	–0.148	0.102	**0.060*****	–0.005	**0.063*****	**0.048*****
	–0.07	1.7	–1.94	0.62	**5.03**	–0.19	**9.97**	**4.09**
Soil Moisture LAG2	–0.011	**0.079***	0.081	**0.474***	0.018	0.028	**0.060*****	**0.028***
	–0.61	**2.62**	0.73	**3.14**	1.51	1.47	**6.76**	**2.09**
Soil Moisture LAG3	–0.014	0.015	–0.145	**–0.470***	**0.047*****	**0.064***	**0.031****	**0.094*****
	–0.76	0.37	–1.61	**–2.4**	**4.11**	**2.28**	**3.76**	**4.87**
Soil Moisture LAG4	**–0.041***	**–0.442*****	**–0.273***	**–1.964*****	0.003	**0.097****	**0.034*****	0.035
	–2.17	**–5.61**	**–3.04**	**–5.09**	0.28	**3.39**	**3.99**	1.6
Soil Moisture LAG5	**0.046***	**0.239***	**0.384*****	**0.850***	0.011	0.043	**0.028****	**0.083***
	2.57	**3.1**	**3.94**	**2.34**	1.04	1.24	**3.35**	**2.21**
Soil Moisture LAG6	**0.042***	**0.241****	**0.508*****	**1.213*****	**–0.040*****	**-0.138*****	**0.031****	0.024
	2.07	**3.34**	**4.7**	**4.39**	**–3.89**	**–4.46**	**3.78**	1.07
Soil Moisture LAG7	**0.084*****	**–0.104***	**0.410*****	–0.190	**–0.021***	**0.075***	**0.046*****	**0.070*****
	4.36	**–2.14**	**4.78**	–0.75	**–2**	**3.12**	**5.2**	**4.48**
Soil Moisture LAG8	**0.114*****	**0.120***	0.106	**0.490***	**0.038****	0.027	**0.033****	0.023
	4.75	**3.18**	0.83	**2.17**	**3.39**	1.33	**3.86**	1.86
Soil Moisture LAG9	0.005	**–0.090***	**–0.457*****	**–1.121*****	–0.005	0.026	**0.045*****	**0.067*****
	0.26	**–2.93**	**–3.95**	**–5.1**	–0.4	1.19	**5.11**	**5.41**
Soil Moisture LAG10	**0.072*****	**0.077****	–0.117	0.125	**0.042****	0.014	**0.031****	–0.015
	4.18	**3.43**	–1.21	0.96	**3.58**	0.86	**3.42**	–1.26
Soil Moisture LAG11	**0.062***	**0.090****	0.136	**0.665*****	0.004	–0.004	**0.019***	**0.020***
	3.25	**3.76**	1.22	**3.98**	0.39	–0.25	**3.12**	**2.29**
Soil Moisture LAG12	**–0.076***	0.027	**–0.277***	–0.105	–0.004	–0.017	**0.064*****	**0.042***
	–3.34	0.88	**–2.31**	–0.58	–0.3	–1.02	**4.7**	**2.76**
Peak (Nov–Mar)	N	Y	N	Y	N	Y	N	Y
Number of MBs	19373	18592	3437	3185	9671	9215	7855	7582
R-squared	0.6212	0.6565	0.5299	0.6261	0.5341	0.4931	0.6624	0.6668

*p < 0.05, **p < 0.001 ***p < 0.0001

Table 7. Two-way fixed effects with lagged effects, annual employment for meshblocks (growing years 2000–2018)

Industry	(1) ALL	(2) Fruit/ Tree Nut Growing A013	(3) Sheep/Beef A014	(4) Dairy A016
Soil Moisture July	–2.433	–9.650	0.437	**2.267***
	–1.45	–1.34	0.76	**2.31**
Soil Moisture August	1.662	6.734	1.256	1.178
	0.73	0.77	1.14	0.6
Soil Moisture September	1.674	–2.053	–0.915	–2.669
	0.83	–0.28	–0.96	–1.87
Soil Moisture October	1.105	3.678	0.139	–1.583
	0.97	1.05	0.24	–1.81
Soil Moisture November	**–1.887***	–1.479	–0.741	**1.627***
	–2.29	–0.56	–1.57	**2.55**
Soil Moisture December	**1.630***	1.777	0.693	**1.325***
	2.31	0.8	1.65	**2.57**
Soil Moisture January	0.352	0.241	**–0.619***	–0.422
	0.7	0.12	**–1.99**	–1.21
Soil Moisture February	–0.318	–0.168	–0.072	–0.513
	–0.55	–0.07	–0.17	–1.43
Soil Moisture March	0.106	0.595	0.600	–0.702
	0.18	0.24	1.55	–1.83
Soil Moisture April	1.035	–0.249	–0.216	**2.184*****
	1.47	–0.1	–0.59	**4.66**
Soil Moisture May	–0.813	3.568	0.316	**–3.357*****
	–0.81	1.2	0.76	**–4.52**
Soil Moisture June	**2.542***	–0.468	–0.337	**9.717*****
	2.03	–0.13	–0.65	**7.12**
Number of MBs	17775	2949	8778	7257
R-squared	0.7459	0.7538	0.7139	0.6954

*p < 0.05, **p < 0.001 ***p < 0.0001

2.5 Conclusions

Overall, the relationship between drought and employment in New Zealand based on our results appears to be complicated, with soil moisture and temperature having different and sometimes offsetting effects across industries and even within the same industry (for some) over time. Dairy has the most consistent results, with the relationship between monthly soil moisture and monthly employment consistently showing up as strong and positive. However, when we look at annual employment, even in dairy, we find that monthly soil moisture can be positively or negatively related to annual employment depending on the month.

While we focus on employment in this chapter, we also produced results for all of our outcome measures (i.e. employment, FTE, short-spell jobs, gross earnings, GST sales, and GST purchases) for all of our industries at the PBN and at the meshblock level. However, we find that the patterns that we see for employment at the meshblock level are representative of those that we see for the other outcome measures and for the PBN level. For the sake of brevity, we do not present all of the results in this chapter, but only present the results for employment. Moreover, we ran a similar analysis for food manufacturing, but we find few effects beyond those presented for the primary agricultural products. Again, for the sake of brevity, we do not publish all of those results in this chapter.

2.6 References

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3 Acknowledgements

We thank Statistics New Zealand and NIWA for providing data. In particular, we acknowledge Mr Stephen Stuart for setting up the regional climate model and carrying out the simulations, and Dr Abha Sood for bias-correcting and downscaling the RCM data (at 27 km) onto the 5 km VCSN grid, and for calculating soil moisture deficit.

We thank the Deep South National Science Challenge and Manaaki Whenua – Landcare Research for funding. We also thank members of the Deep South Representative User Group and attendees of a farming industry focus group for early feedback on our research design.

Appendix 1 – Detailed cleaning steps for farm profits data set

Tables A.1 and Table A.2 describe the data cleaning steps and the resulting number of observations used in the farm profits analysis. First, we use the data from of the Agricultural Production Survey (APS) to identify dairy and sheep/beef farming operations with land area and animal numbers sufficiently high that we are confident they represent genuine farming businesses. Then, we combine the APS data with the Longitudinal Business Frame (LBF) data, IR10 financial data and the weather data based on the enterprise identification numbers and farm locations. We remove data observations from the combined dataset where there is conflicting information on the type of farming operation or locations, missing data on farm area, or unusual financial information. See the tables for details of each step.

Table A.1 Agricultural Production Survey (APS) data cleaning steps

Variable names in code	Dairy		Sheep/beef		Description
	Remaining enterprises	Remaining observations	Remaining enterprises	Remaining observations	
ever_dairy, every_snb	49, 353	491, 880	79, 728	874, 485	Start with enterprises in the APS which have at least one year with dairy or sheep/beef industry codes.
ever_dairy, every_snb	49, 170	455, 037	79, 494	832, 374	Remove observations with duplicate enterprise number.
ever_enough_LUgrass_dairy, ever_enough_LUgrass_snb	30, 096	321, 069	39, 315	463, 806	Keep enterprises with at least 50 ha of grassland in at least one year to ensure we keep genuine farming enterprises.
ever_enough_LUgrass_dairy, ever_enough_LUgrass_snb	30, 096	273, 447	39, 315	403, 353	Remove observations for enterprises that show as having ceased operations in the APS.
ever_livestock_enough_LUgrass_dairy, ever_enough_LUgrass_snb	28, 827	266, 436	37, 428	388, 467	Remove enterprises with no livestock recorded for all years.
dairy, sheep_beef in dairy_sheep_beef_filtered	15, 741	198, 474	22, 941	298, 026	Keep enterprises with effective area of more than 25ha in at least 3 years (this is to remove lifestyle blocks all the smallest operations).
dairy_sheep_beef_filtered	13, 536	173, 670	18, 384	241, 701	Keep enterprises where the minimum number of cattle equivalent (i.e. counting 5.5 sheep as 1 unit) in a year are higher than 50, in at least 3 years.

Table A.2 Longitudinal Business Frame (LBF) data, IR10 financial data cleaning steps

Variable names in code	Dairy		Sheep/beef		Description
	Remaining enterprises	Remaining observations	Remaining enterprises	Remaining observations	
dairy and sheep_beef in ir10_weather_aps	13, 080	135, 744	17, 739	189, 906	Join iR10 with dairy_sheep_beef_filtered
dairy and sheep_beef in ir10_weather_aps	12, 159	109, 677	16, 284	148, 995	Join with location and weather. Observations drop due to missing location, LBF industry switches during the year, location switches during the year, or LBF industry is not livestock during that year.
dairy and sheep_beef in ir10_weather_aps	12,096	104,202	16,245	145,560	Remove observations that have conflicting industries in LBF and APS for the same year
dairy and sheep_beef in ir10_weather_aps	11,685	59,403	15,900	94,665	Removing observations with missing values for effective ha
data in final_data	10,689	55,050	15,468	92,619	Removing observations from enterprises that do not record industry as dairy/sheep and beef (resp.) for any year of operation remaining in the dataset.
	10,536	53,934	15,354	91,725	Removing observations from enterprises that switch industry more than once in the remaining sample.
	10,536	50,997	15,354	89,736	Keeping observations for the years that they record dairy/sheep beef as industry (resp.) (i.e removing observations from years before or after switching industry).
	7,521	38,058	10,536	63,798	Removing observations from enterprises that have unusual average values (remove enterprises with averages in the top 5% and bottom 5%) in operating expenses, operating expenses per hectare, revenue, revenue per hectare, hectares, operating profit, operating profit per hectare.
	Not removed for dairy	Not removed for dairy	9,762	49,671	Removing years for which area is not within 30% of the mean area for that enterprise.
	4,338	29,340	5,598	40,086	Keep enterprises with at least than 4 years in the sample and keep observations with at least 15 observations with the same balance date in the same regional council and year. Removals performed iteratively to ensure final sample has these restrictions.

Appendix 2 – Further results for farm profits

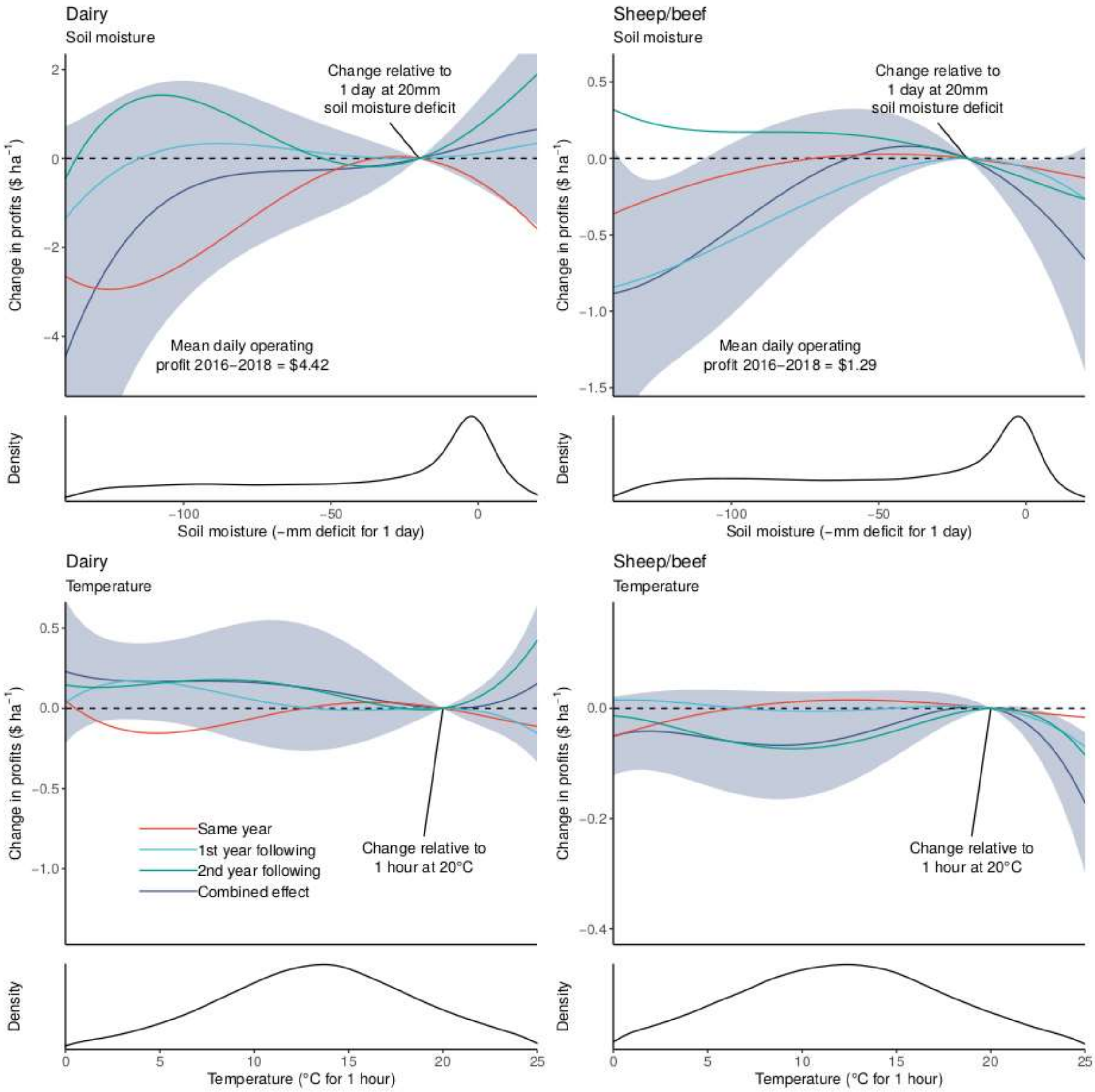

Figure A.1: Estimated effects of changes in daily soil moisture (top) and hourly temperature (bottom) on farm profit for dairy (left) and sheep/beef farms (right).

Note: See Figs. 1 and 2 for descriptions.

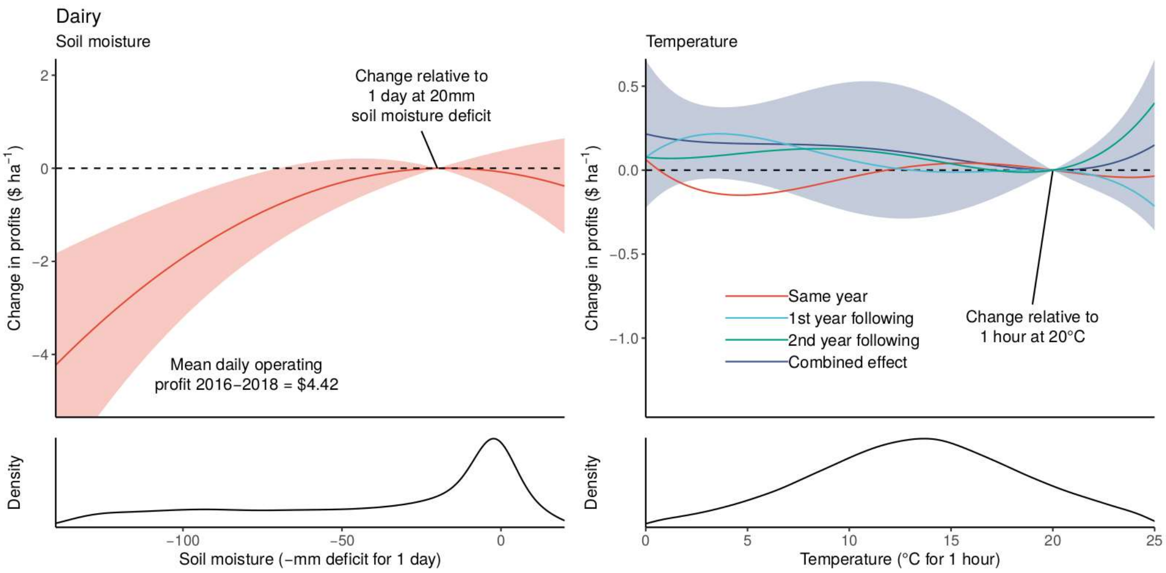

Figure A.2: Estimated effects of changes in daily soil moisture (left) and hourly temperature (right) on farm profit for dairy farms.

Notes: See Figs. 1 and 2 for descriptions.