Empirical estimation of the impact of weather on dairy production

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Abstract

The vast majority of the land used in agriculture supports livestock systems, with the vast majority of this land in pasture. Due to concern about the environmental effects of changing land uses, and expected future demand increases for animal products, it is crucial to understand how these systems will react to future climate change. Using data on the production and quality of milk produced in New Zealand, this paper estimates the nonlinear relationship between weather and dairy production. I estimate models both restricting response functions to be the same throughout the dairy season and allowing for heterogeneity by time-of-year. I find large and negative impacts of moderate to high temperatures in summer months and large and positive impacts of moderate temperatures during winter months. I give suggestive evidence that allowing for seasonality in responses results in less pessimistic projections of the response to future climate change in this context. I find statistically, but not economically, significant negative impacts of rising temperatures on milk quality.

1 Introduction

Agricultural production depends heavily on the weather, causing widespread and early concern about the effects of global climate change on this sector. In the economics literature, seminal papers have focused on the effects of average temperature on agricultural land values (Mendelsohn, Nordhaus, and Shaw 1994; Schlenker, Hanemann, and Fisher 2005), the effects of contemporaneous shocks to temperature on agricultural profits (Deschênes and Greenstone 2007; Fisher et al. 2012; Deschênes and Greenstone 2012), and the nonlinear effects of contemporaneous temperature shocks on several crop yields (Schlenker and Roberts 2009) (for other work on this topic, see Auffhammer and Schlenker (2014) for a review). More recent research has combined data from agronomic models with global agricultural trade models to suggest that reallocation of crops can moderate projected negative impacts of climate change by around a third (Costinot, Donaldson, and Smith 2014).

However, while crops provide the majority of the supply of most nutritional variables for most places, livestock systems comprise a very large portion of the agricultural system and a substantial portion of nutrition. For example, livestock systems account for most of the land used in agriculture, with the vast majority of this land in pasture, and livestock contributes around 30% of the global protein supply, with this proportion higher in the developed world and projected to increase in the developing world. To date, there has been little work that has examined the effects of climate change on any livestock systems. In the livestock context, changing climates could affect each of feed production, the level of production of final output per unit of feed, and the quality of the final product, potentially resulting in a triple whammy for the food system.

This paper extends the climate and agriculture literature in two ways. Firstly, using data from New Zealand, the largest dairy exporter and a major producer, it examines the effect of climate change on the largest animal sector, as measured by the contribution to both the global protein and calorie supply, dairy, using an empirical panel fixed effects approach. Secondly, it allows for heterogeneity in response functions by time-of-year and examines the impact of this modeling choice on bottom-line conclusions about the costs and benefits of future climate change. In addition to the contributions to the literature on climate and agriculture, this paper also provides calculations of the relative contributions of the major land uses to the global food supply, including those from pasture.

Because livestock is a weather sensitive industry, with weather sensitive feed inputs that may be transported some distance before being consumed by the animal, identification of climate change impacts using weather impacts is complicated by the need to account for upstream impacts in the feed industry. New Zealand is an attractive setting to study the potential impact of climate change on a livestock sector, as it is both a large producer and an industry that primarily uses local feed. Anecdotally, over the time period I study, only around 10% of the feed used is from a source other than direct intake from pasture, and a large proportion of the supplemental feed either comes from on farm or the nearby area. This suggests that I'm able to identify the impact of future climate change using local weather shocks, conditional on the assumption that the historical relationship between weather and output continues to hold (Hsiang 2016).

When restricting the temperature response function to be the same throughout the year, I find large and negative impacts of moderate to high temperatures above 19°C, with a statistically insignificant response to temperature below 19°C. However, when allowing for seasonality in the response function, I still find large and negative impacts of moderate to high temperatures in summer months but the model also shows large and positive impacts of moderate temperatures during winter months. When projecting these response functions forward, using the output from a climate model, I find that the discounted present value of the projected change in revenue is -US$8.4 billion when using the restricted model, and +US$2.1 billion when using the flexible model. The total farm gate value of annual New Zealand dairy production is currently approximately US$8 billion.

Existing evidence on the effect of temperature in dairy systems has shown reductions in dry matter intake with moderate to extreme temperatures, causing reductions in milk output (West 2003). Pasture growth also responds negatively to high temperatures (Cros et al.

2003). Work has also demonstrated direct effects on production of heat stress when controlling for feed intake, as well as suggestive evidence that protein percentage slightly decreases under heat stress (Rhoads et al. 2009). Studies have estimated the production effect of cattle heat stress using a stochastic frontier approach (Mukherjee, Boris E. Bravo-Ureta, and De Vries 2013; Qi, B. E. Bravo-Ureta, and Cabrera 2015). One work combined process and climate models to estimate the impact of climate change on dairy production in the Australian context (Hanslow et al. 2014).

Several studies have reported functions that allow for different responses to weather at different times of the year (Welch et al. 2010; Cooper, Nam Tran, and Wallander 2017; Schlenker and Roberts 2009). I extend the ideas in these studies by examining the impact of this modeling choice on climate change projections. Results from financial econometrics suggest that bias can result by restricting responses to be the same throughout the season (Andreou, Ghysels, and Kourtellos 2010).

This paper proceeds as follows. Firstly, the following section describes where both the dairy industry and pasture-based livestock systems sit in relation to the larger agricultural system. Next, Section 3 describes the sources of my dairy production and weather data, Section 4 describes the theoretical concepts that inform the analysis, Section 5 outlines the econometric specifications I use, Section 6 reports my results and projections of the consequences of climate change in this context, and Section 6 concludes.

2 The importance of dairy and pasture

Since staple crops dominate the climate and agriculture literature, it is useful to consider where each of dairy and pasture stand in relation to the rest of the food system. Table 1 ranks FAO (2014) food balance data for the proportion of world protein coming from different food groups. The FAO food balance data aims to measure the total food available for human consumption by type and country. I present global aggregates in this paper.

Despite their relatively low ratio of protein to other calories, the prevalence of wheat and rice in the global food system makes them the largest contributors to protein consumed, with 19.7% and 12.7% of the world totals, respectively. Dairy is the largest contributor to global protein consumed amongst both animal products and high protein foods (i.e. including beans and pulses) generally. Table 2 provides the same ranking for global calorie contributions. Again, wheat and rice are the dominant calorie sources with 18.3% and 19% respectively, with dairy again contributing the largest proportion amongst animal products with 5.9%.

Table 3 shows estimates of the contribution of different land uses to the global food supply. I use animal contributions to the food supply, assumed feed conversion ratios, and data on the amount of grain feed utilized to calculate the contribution of pasture and crop residues as a residual. I fully describe the calculations in Section A. The "Low" estimate, meaning a low estimate for the contribution of pasture and crop residues to the food supply, assumes that no pasture or crop residues are used to feed pigs and poultry, both high feed conversion animals, and no grain is used to feed bovine animals, goats, and sheep. The high estimate

Table 1: Foods Ranked by Contribution to World Protein

FAO Food Balance Item	World Protein Percentage
Wheat and products	19.7%
Rice (Milled Equivalent)	12.7%
Dairy	10.3%
Fish, Seafood	6.5%
Poultry Meat	6.2%
Pigmeat	5.6%
Vegetables, Other	4.7%
Bovine Meat	4.4%
Maize and products	4.4%
Eggs	3.4%

Source: FAO (2014).

Table 2: Foods Ranked by Contribution to World Calories

FAO Food Balance Item	World Calorie Percentage
Rice (Milled Equivalent)	19%
Wheat and products	18.3%
Sugar (Raw Equivalent)	6.8%
Dairy	5.9%
Maize and products	5.1%
Pigmeat	4.2%
Soyabeans	3.4%
Vegetables, Other	2.5%
Potatoes and products	2.2%
Poultry Meat	2%

Source: FAO (2014).

Table 3: Land uses Ranked by Contribution to World Food Supply

FAO Food Balance Item	World Calorie Percentage including Contribution via Animals	
	Low	High
Rice (Milled Equivalent)	19.2%	19.1%
Wheat and products	18.9%	18.5%
Pasture and Crop Residues	9.7%	14.6%
Sugar (Raw Equivalent)	6.8%	6.8%
Maize and products	7.2%	6%
Soyabeans	3.5%	3.5%
Vegetables, Other	2.5%	2.5%
Potatoes and products	2.3%	2.3%
Palm Oil	1.8%	1.8%
Cassava and products	1.4%	1.4%

[1] The contribution of pasture and crop residues is not directly measured in the FAO food balance data. I fully describe the calculation of this item in Section A. The low estimate assumes that no pasture or crop residues are used to feed pigs and chickens and no grain is used to feed bovine animals, goats, and sheep. The high estimate assumes that all feeds are used with equal proportions for all animals.
[2] Sources: FAO (2014).

assumes that all feeds are used with equal proportions for all animals. All food items that are also used as animal feed include both the contribution via direct consumption and via animals, not accounting for crop residues.

I find that, consistent with the prior two tables, that rice and wheat are the dominant contributors to the food supply, each with almost 20% of global caloric production. Pasture and crop residues is then the next highest category, providing 9.7% using the low estimate and 14.6% using the high estimate, with pasture contributing approximately 70% of the category (Wirsenius 2003). The contribution of pasture is then of a similar magnitude to that for maize, or possibly larger.

3 Data

3.1 Dairy Production Data

I use New Zealand dairy production data at the territorial local authority (TLA)[1] and dairy season[2] level from the New Zealand Dairy Statistics series published by Livestock Improvement Corporation (LIC) and DairyNZ, both industry-owned bodies. In this paper, I will refer to TLAs as districts. The production statistics are compiled from raw data collected from all major New Zealand dairy companies and can be considered a near census of production.[3] The variables I use from these publications are the number of cows milked at least one day during the season, the number of farms, production of milk per farm, production of protein per farm, and production of milkfat per farm. Data are available annually from 1999 to 2015, and the dairy production data define the period of study for this paper.

Figure 1 shows the distributions of each of the main outcome variables of interest in this paper, the yield of milk per cow per day, the proportion of milkfat, and the proportion of protein.

3.2 Weather Data

New Zealand's primary atmospheric research unit, the National Institute of Atmospheric Research (NIWA) provides a gridded weather data product, the Virtual Climate Station Network (VCSN), which provides a rich array of weather variables on a daily scale and on a regular grid of approximately 5km $\times$ 5km. The variables I use from the VCSN are daily rainfall, maximum and minimum air temperature, and soil moisture. Following Schlenker and Roberts (2009), I interpolate minimum and maximum air temperature using the single sine method, and compute linear spline transformations of all variables.

[1]Similar to US counties or cities.
[2]In New Zealand, this is June 1 to May 31.
[3]A very small amount of boutique local supply milk is not counted in these data.

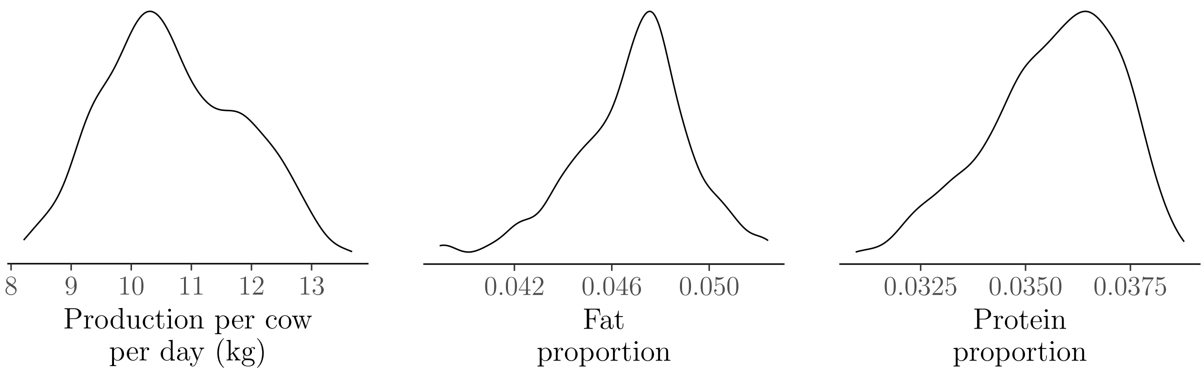


Figure 1: Density plots of the distributions of dairy outcome variables. Annual LIC data from New Zealand from 1999-2015.

I obtain the 2015 proportion of each VCSN grid cell that is covered by dairy land from the Ministry of Primary Industries. I use these proportions to weight the weather grid cells when aggregating spatially. I aggregate the dairy-land-weighted weather grid cells using a dataset of district polygons using area-overlap weights.

All transformations are first done at the grid cell-day level, then aggregated spatially and temporally. I include distributions of all included variables in the Results section.

The soil moisture variable used in this paper is modeled from a time series of historical temperature and precipitation data as described in Porteous, Basher, and Salinger (1994). These authors report that the model yields results with quite high accuracy, though I do not know of more recent validation exercises.

4 Conceptual Framework

In this paper, the big-picture parameter of interest is the change in producer surplus in a local production center under climate change. Local production regressions that use historical data are able to recover information about the production function as it relates to weather variables; however, these regressions are unable to be used to estimate changes in surplus under climate change due to induced changes in either input prices, output prices, or management actions which are not available on the same time-scale of the shocks used to estimate the regression parameters (Hsiang 2016). While the data used in this paper are not rich enough to give indications of potential changes in input prices, output prices, or long-run management changes, I would like to be explicit that these are missing pieces to be filled in by future research, as is the potential impact on consumer surplus, where several downstream industries (processing, logistics, and retail), complicate a full accounting. In this section, I formalize these ideas using a standard production function framework that considers a final consumption good produced in a competitive market, where environmental conditions enter the production function directly, as well as affecting the prices of both inputs and output.

Production of the good in the local region, y, depends on inputs that are adjustable in the short-run, $\boldsymbol{X}_s$, inputs that are fixed in the short-run, $\boldsymbol{X}_l$, and local environmental conditions $\boldsymbol{E}_\ell$. Examples of inputs that are adjustable in the short-run are fertilizer, water use, and use of off-farm feed, while examples of inputs that are fixed in the short-run are milking infrastructure, cooling infrastructure, and on-farm feed species.

$$y = f(\boldsymbol{X}_s, \boldsymbol{X}_l, \boldsymbol{E}_\ell) \tag{1}$$

Given the assumption that there are global markets for all commodities, prices of both inputs and outputs will depend on environmental conditions in all locations the goods are produced in, which I denote as $\boldsymbol{E}$, with $\dim(\boldsymbol{E}_\ell) < \dim(\boldsymbol{E})$. Profit, π, for the competitive firm, is then:

$$\pi = p_y(\boldsymbol{E}) f(\boldsymbol{X}_s, \boldsymbol{X}_l, \boldsymbol{E}_\ell) - \boldsymbol{p}_{\boldsymbol{X}_s}(\boldsymbol{E}) \cdot \boldsymbol{X}_s - \boldsymbol{p}_{\boldsymbol{X}_l}(\boldsymbol{E}) \cdot \boldsymbol{X}_l \tag{2}$$

The firm's optimization implies that optimal output, y^*, depends on both local and outside environmental conditions:

$$y^* = f(\boldsymbol{X}_s^*(\boldsymbol{E}_\ell, \boldsymbol{E}_{-\ell}), \boldsymbol{X}_l^*(\boldsymbol{E}_\ell, \boldsymbol{E}_{-\ell}), \boldsymbol{E}_\ell) \tag{3}$$

where $(\boldsymbol{E}_\ell, \boldsymbol{E}_{-\ell}) \equiv \boldsymbol{E}$. In this framework, I represent global climate change as a change in the full vector $\boldsymbol{E}$, denoted by $\Delta\boldsymbol{E}$. To simplify the exposition, I make the assumption that prices do not depend on supply in the local region: $p_y(\boldsymbol{E}) = p_y(\boldsymbol{E}_{-\ell})$, $\boldsymbol{p}_{\boldsymbol{X}}(\boldsymbol{E}) = \boldsymbol{p}_{\boldsymbol{X}}(\boldsymbol{E}_{-\ell})$, where $\boldsymbol{p}_{\boldsymbol{X}} \equiv (\boldsymbol{p}_{\boldsymbol{X}_s}, \boldsymbol{p}_{\boldsymbol{X}_\ell})$.

Omitting cross terms, the change in production is then:

$$\begin{aligned}\Delta y^* \approxeq\ & \underbrace{\frac{\Delta f}{\Delta \boldsymbol{E}_\ell} \cdot \Delta \boldsymbol{E}_\ell}_{\text{Direct production effect}} + \underbrace{\frac{\Delta f}{\Delta \boldsymbol{X}_s} \cdot \frac{\Delta \boldsymbol{X}_s^*}{\Delta \boldsymbol{E}_\ell} \cdot \Delta \boldsymbol{E}_\ell}_{\text{Short-run adaptation effect}} + \underbrace{\frac{\Delta f}{\Delta \boldsymbol{X}_l} \cdot \frac{\Delta \boldsymbol{X}_l^*}{\Delta \boldsymbol{E}_\ell} \cdot \Delta \boldsymbol{E}_\ell}_{\text{Long-run adaptation effect}} + \\ & \underbrace{\frac{\Delta f}{\Delta \boldsymbol{X}} \cdot \frac{\Delta \boldsymbol{X}^*}{\Delta p_y} \cdot \frac{\Delta p_y}{\Delta \boldsymbol{E}_{-\ell}} \cdot \Delta \boldsymbol{E}_{-\ell}}_{\text{Output price effect}} + \underbrace{\frac{\Delta f}{\Delta \boldsymbol{X}} \cdot \frac{\Delta \boldsymbol{X}^*}{\Delta \boldsymbol{p}_{\boldsymbol{X}}} \cdot \frac{\Delta \boldsymbol{p}_{\boldsymbol{X}}}{\Delta \boldsymbol{E}_{-\ell}} \cdot \Delta \boldsymbol{E}_{-\ell}}_{\text{Input price effect}}\end{aligned} \tag{4}$$

where $\boldsymbol{X} \equiv (\boldsymbol{X}_s, \boldsymbol{X}_l)$. Equation (4) highlights that long run environmental shocks can affect output through several channels. The first term represents the direct impact climate has on production; in this context through changes in on-farm feed growth and heat stress. The second term represents the impact of climate change on production through adjustments in short-term inputs. In the regression framework, the sum of these first two terms is able to estimated with a standard fixed effects approach, which this paper implements. With a long dataset, researchers can estimate the sum of the first three terms using a long-differences approach (M. Burke and Emerick 2016), which involves a trade-off in terms of statistical power (Hsiang and M. B. Burke 2013). However, the estimation of the final two terms depends on global market responses to climate change, so is not able to be informed by data on production in a single area.

In the New Zealand dairy context, because such a large proportion of feed comes from on-farm, I would like readers to interpret $\Delta f / \Delta \boldsymbol{E}_\ell$, the direct effect of the environment, as being the combined effect of the environment directly on cows as well as via shocks to local feed. In the extreme, the supplemental feed portion of $\boldsymbol{X}_s$ is then at a corner solution where feed consumed is equal to zero, which is often the case in New Zealand. In this context, I am able to provide information on the response of pasture to environmental shocks, via the effect on dairy production.

When focusing on the level of production, y, we expect that the direct effects will dominate the climate change induced changes in production. However, as aforementioned, the big picture quantity of interest for this line of research is the change in producer surplus, which also includes first-order changes in both output and input prices. Omitting both cross terms and second-order terms, the change in producer profit is:

$$\Delta\pi^* \approxeq \underbrace{\frac{\Delta f}{\Delta \boldsymbol{E}_\ell} \cdot p_y \cdot \Delta \boldsymbol{E}_\ell}_{\text{Production effect}} + \underbrace{\frac{\Delta p_y}{\Delta \boldsymbol{E}_\ell} \cdot y^* \cdot \Delta \boldsymbol{E}_\ell}_{\text{Output price effect}} + \underbrace{\frac{\Delta \boldsymbol{p}_{\boldsymbol{X}}}{\Delta \boldsymbol{E}_{-\ell}} \cdot \boldsymbol{X}^* \cdot \Delta \boldsymbol{E}_{-\ell}}_{\text{Input price effect}} \tag{5}$$

Yield studies like this paper contribute to the estimation of the first term in Equation (5), but a global analysis would be required to estimate the second and third terms, which is a task for future research.

In summary, the fixed effects models that I show in this paper are able to estimate the sum of the direct production effect of weather via thermal stresses on cows, the direct production effect of weather via impacts on locally grown feed, and the indirect production effect of weather via changes in inputs that are adjustable in the short-term. Output and input prices have a first-order effect on producer surplus but are not included in the estimation in this paper.

5 Methods

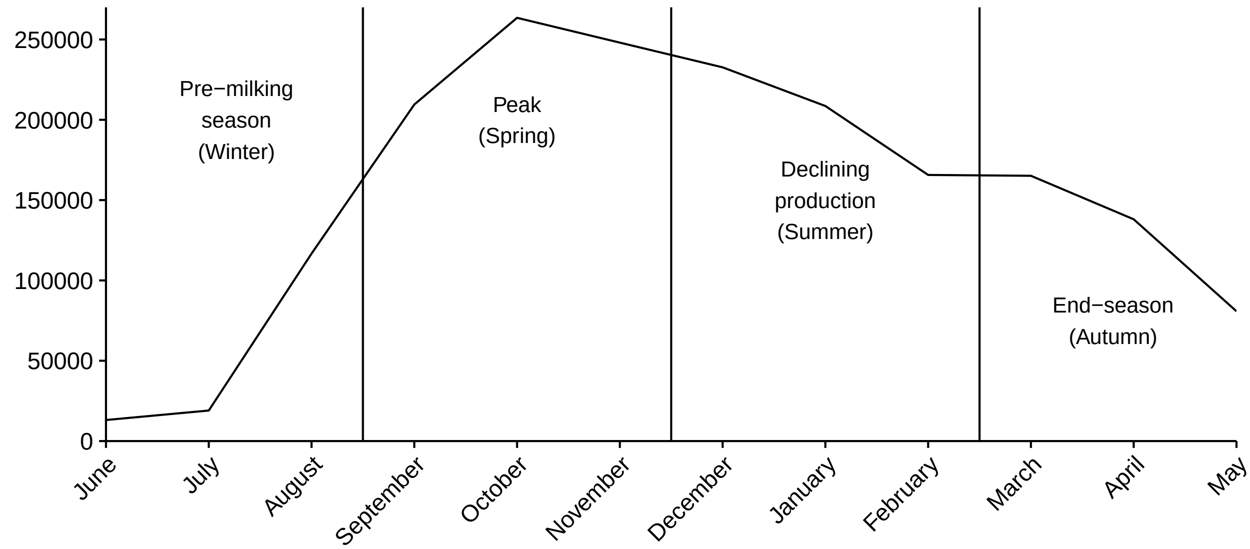
This paper uses established econometric methods to estimate the relationship between weather and my economic variable of interest, the average milk yield per cow, within a district. For a review of the econometrics of weather and climate, see Hsiang (2016). Following Schlenker and Roberts (2009), for my primary specifications I use linear splines, with knot locations estimated using nonlinear least-squares (NLLS). I can express each of the estimating equations in the following form:

$$y_{it} = f(\boldsymbol{T}_{it}) + g(\boldsymbol{M}_{it}) + \delta_{i0} + \delta_{i1}t + \varepsilon_{it} \tag{6}$$

where y_{it} is dairy production outcome of interest for district i and year t. In this paper, y_{it} is one of the average milk yield per cow, the average protein content of milk, or the average fat content of milk, each within a district. f is a function of the full vector of daily temperature within a district-year ($\boldsymbol{T}_{it}$), g as a function of the full vector of daily soil moisture within a district-year ($\boldsymbol{M}_{it}$), and $\delta_{i0} + \delta_{i1}t$ is a unit specific affine trend.

In all specifications in this paper, f is a linear spline function in temperature interpolated using the single sine method and g is is a linear spline function in daily soil moisture, each

Figure 2: New Zealand production by month in 2015-2016

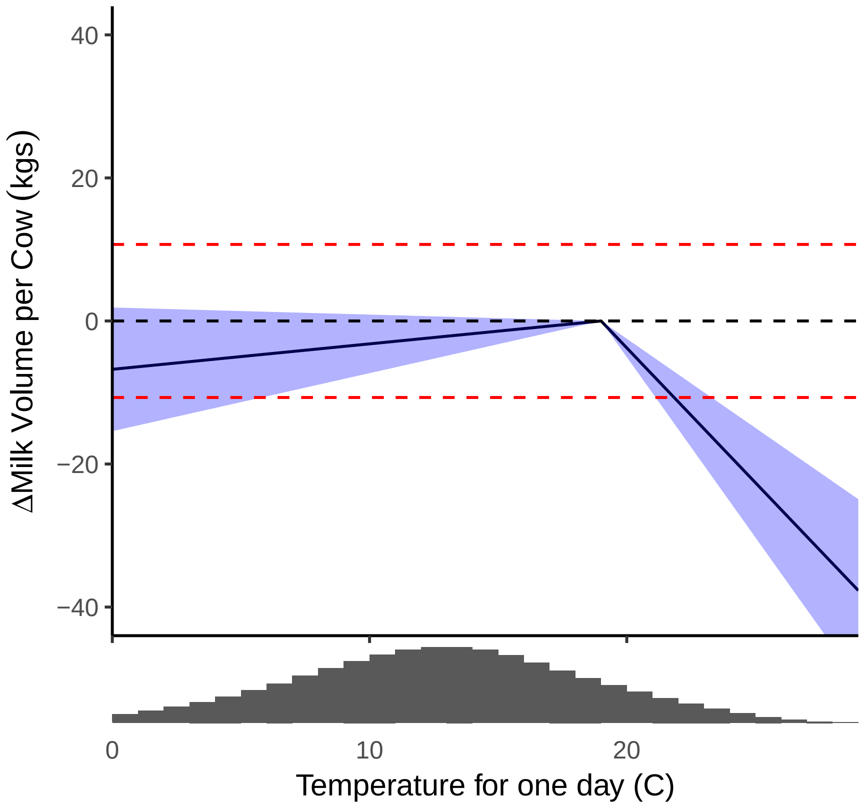


with a single knot. I estimate each specification using NLLS, restricting all knot locations to be between the 10th and 90th percentiles of daily support of the regressors.

Figure 2 shows country-level monthly production in the 2015-2016 dairy season. The plot clearly shows the seasonality in dairy production in New Zealand. Importantly, the seasonality motivates me to relax the assumption in the standard model that a weather shock in different stages of the dairy season has the same impact. One might expect that a weather shock in spring would have a larger effect on annual production than an equivalent shock in autumn, both because there is more production to impact, and a longer amount of time remaining in the aggregation period for lagged effects to realize.

In specifications that restrict the response to weather to be the same throughout the year, I aggregate the weather variables across the New Zealand dairy season (June-May). In specifications that allow for flexibility in weather responses by time-of-year, I aggregate the weather variables by weather seasons, June-August, September-November, December-February, and March-May, which also corresponds to general stages of the New Zealand dairy season.[4]

Figure 3: Production response function to temperature with no controls



This figure plots f in Equation (6) with $g = 0$ for a single day of temperature, estimated using NLLS. The turning point is restricted to lie between the 10th and 90th percentiles of the full distribution of temperature. The plot is vertically centered so that the change in yield per cow takes a value of zero when temperature is 19° C. The dashed red lines indicate positive and negative average daily production. The plot shows 95% confidence bands calculated assuming error clustering by district and year; confidence bands do not take account of the uncertainty in the knot location. Below the plot is a histogram of the full time series of temperature using single sine interpolation.

6 Results

Figure 3 plots the temperature response function in a regression with no control variables and aggregating the temperature variables across the entire dairy season. The red dashed lines indicate positive and negative average daily production; I include these to give readers a sense of the scale of the impacts. The NLLS estimator finds an optimal turning point of 19°C, with a statistically insignificant effect of increasing temperatures below the turning point and a large and statistically significant negative effect of increasing temperatures above the turning point. To give a sense of the magnitude of the estimated relationship, moving 24 hours of temperature from 19°C to 22°C reduces annual production by the equivalent of that for an average day of the year, a large effect.

Figure 4 plots the temperature response function introducing soil moisture as a control variable. In this response function, one would have to move 24 hours of temperature from 19°C to 24°C to reduce annual production by the equivalent of that for an average day of the year, showing that some of the temperature effect works through its impact on soil moisture. This is a substantial reduction in the direct effect of temperature but it remains large.[5] In unreported results, I find that including precipitation does not provide extra information over the soil moisture variable and, thus, I omit it.

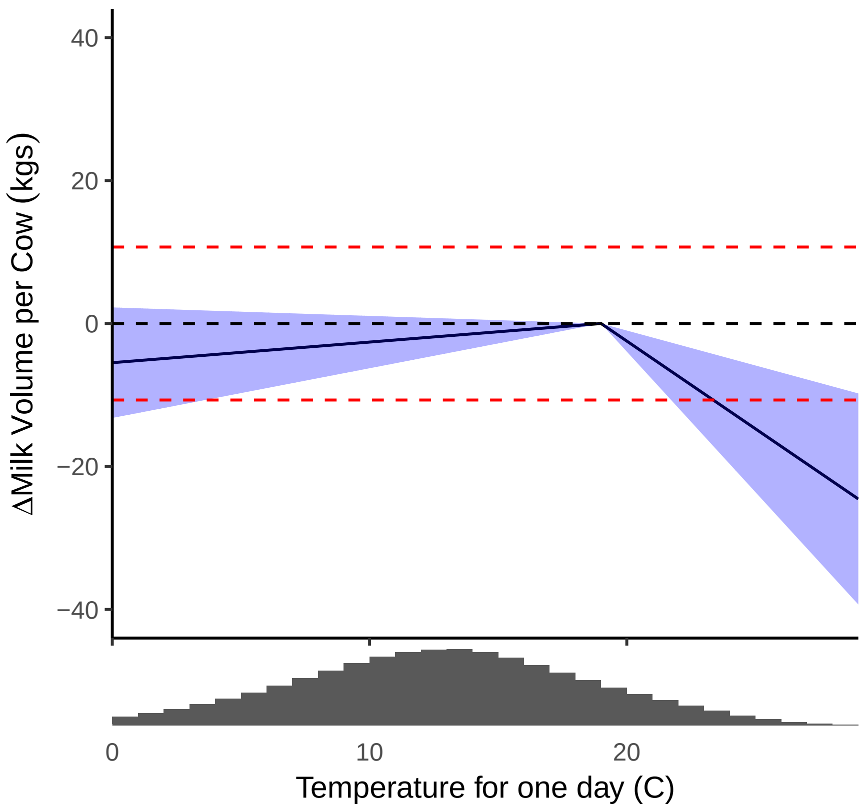
Figure 5 plots the soil moisture response function for the specification where weather is aggregated across the entire dairy season. The NIWA data represents soil moisture as the negative of the "soil moisture deficit", which is the quantity of rainfall required to bring the soil up to capacity. In these units, very dry soils have large negative numbers and very wet soils have positive numbers. The figure finds that extreme wet conditions have large negative impacts on milk yields, and that dry conditions have moderate negative impacts. The main mechanism by which very wet soils impact milk production in the pasture-based context is via soil compaction. Compaction occurs when stock intensively trample wet soil, causing poor subsequent water absorption and lower pasture growth. I find that the overall scale of yield impacts of changes in soil moisture is large but smaller than that of temperature.

Figure 6 shows the temperature response functions estimated separately for the different weather seasons, including soil moisture controls. Several qualitative differences emerge when moving to this more flexible specification. Firstly, I find large and positive impacts of moderate temperatures during the pre-dairy-season winter. This is likely due to pasture responses that both result in improved cow condition before calving and larger pasture stocks

[4] In financial econometrics, the flexible specification is known as the "step function MIDAS" model (Ghysels, Sinko, and Valkanov 2007). This literature examines the econometrics of regressions between variables of differing frequencies. Here, for example, I am regressing *annual* milk yields on *daily* weather. The MIDAS literature is mostly focused on estimators that allow flexible specification of the structure of how response functions change throughout the aggregation period. I use the "step function MIDAS" model, where the aggregation is flat within several subperiods of the low frequency variaable, as it allows me to use OLS estimation, after the estimation of linear spline knot locations using NLLS.

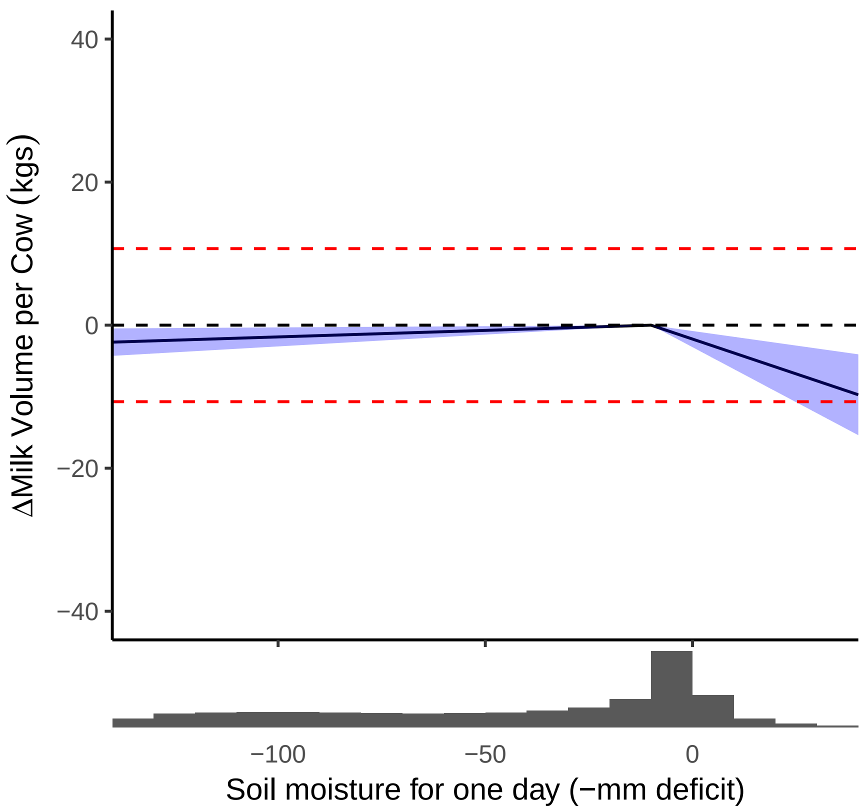
[5] Bell (2017, Chapter 2), in the context of maize in the United States, gives suggestive evidence that the estimated effect of extreme temperature could be partially due to mis-measurement of precipitation. It is possible that the estimation in this paper suffers from the same problem described in Bell (2017). A future iteration of this project will implement the solution suggested in that dissertation chapter.

Figure 4: Production response function to temperature with soil moisture controls



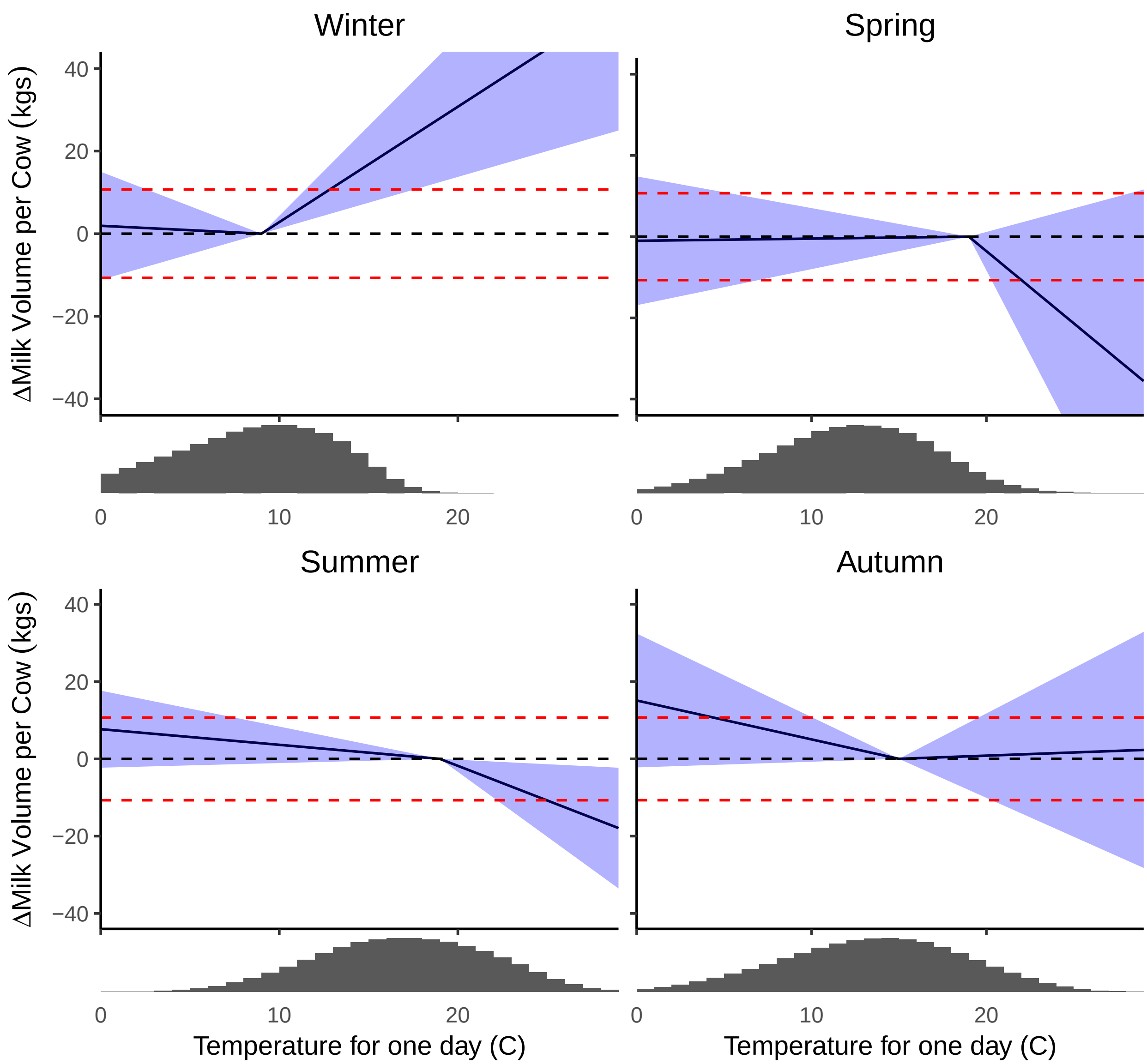
This figure plots f in Equation (6) for a single day of temperature, estimated using NLLS. The turning point is restricted to lie between the 10th and 90th percentiles of the full distribution of temperature. The plot is vertically centered so that the change in yield per cow takes a value of zero when temperature is 19° C. The dashed red lines indicate positive and negative average daily production. The plot shows 95% confidence bands calculated assuming error clustering by district and year; confidence bands do not take account of the uncertainty in the knot location. Below the plot is a histogram of the full time series of temperature using single sine interpolation.

Figure 5: Production response function to soil moisture



This figure plots g in Equation (6) for a single day of soil moisture, estimated using NLLS. The turning point is restricted to lie between the 10th and 90th percentiles of the daily distribution of soil moisture. In the NIWA data, the units of soil moisture are the negative of the quantity of water in mm required to bring the soil up to capacity; this plot uses these units. Positive values indicate the quantity of water running off. The plot is vertically centered so that the change in yield per cow takes a value of zero when the negative of soil moisture deficit is -10mm. The dashed red lines indicate positive and negative average daily production. The plot shows 95% confidence bands calculated assuming error clustering by district and year; confidence bands do not take account of the uncertainty in the knot location. Below the plot is a histogram of daily soil moisture.

Figure 6: Production response function to temperature estimated by weather season



This figure plots f in Equation (6), where the linear spline functions are estimated by weather season, for a single day of temperature, estimated using NLLS. The subplots are vertically centered so that the change in yield per cow takes a value of zero when temperature is at the respective knot locations. The dashed red lines indicate positive and negative average daily production, averaged over the year. The plot shows 95% confidence bands calculated assuming error clustering by district and year; confidence bands do not take account of the uncertainty in the knot location. Below the subplots are histograms of the full time series of temperature, within a weather season, using single sine interpolation.

for spring grazing. Secondly, I find negative and marginally insignificant impacts of moderate temperature in summer and autumn. Thirdly, I find no impact of extreme temperature on milk yields in autumn.

Figure 7 plots the soil moisture response functions by weather season. As in Figure 5, I find small impacts of drying soils and I find that the large negative impact of very wet soils is concentrated in spring. In spring, stock are on pasture much more than in winter, so we would expect to see the negative effects of compaction much more in spring.

Figure 8 plots the response functions of fat proportion to temperature, estimated by season. I choose the knot locations to be the same as in the milk volume regression. Though economically smaller than the impacts on milk volume,[6] I find negative impacts of increasing temperatures across the spectrum in summer, spring, and autumn, with these impacts statistically significant for moderate summer temperatures. I find large negative impacts of increasing cool temperatures in winter and large positive impacts of increasing moderate temperatures in winter. Figure 9 plots the same for protein proportion and finds the same qualitative and similar quantitative results as Figure 8.

6.1 Projections under climate change

To more closely examine the economic significance of the results of the previous subsection, I use the HadGEM-ES climate model to project forward changes in milk production under climate change. Following M. B. Burke et al. (2014), I simulate future weather by adding changes from the climate model to historical weather levels. As in Houser et al. (2015), I randomly choose historical weather years to map to future simulated years.

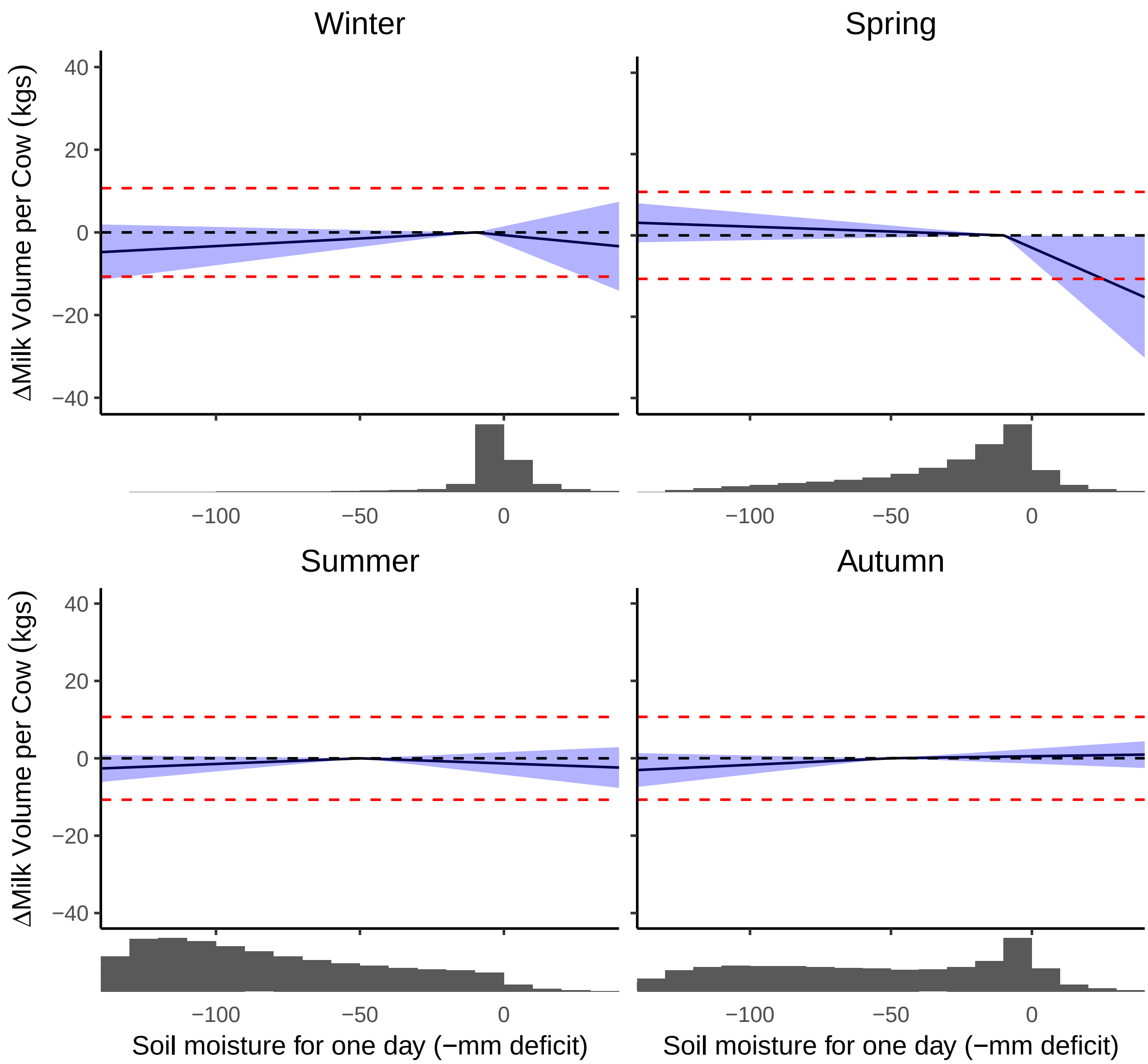
Unlike past work, I compute projections for all future years to 2100. To isolate only decadal variation from the climate model, I compute LOWESS smoothed trends of each variable by month-of-year. The full details of the projection computation is in Section B.

Figure 10 plots the projection results as the proportion of lost annual revenue under climate change. The main stark feature from this figure is that the model that restricts response functions to be the same throughout the year results in much more pessimistic forecasts of the response to climate change. While the two projections trend downwards from around 2035, the flexible model both reduces ultimate production by less and includes a larger upward trend at the beginning of the simulation period, which is statistically significant.

To better show the relative economic importance of the initial upward trend to around 2035 versus the subsequent downward trend, Figure 11 plots the same data as the previous figure adjusting all quantities with a 3% discount rate. The proportions plotted in this figure are then discounted revenues as a proportion of current revenue. This figure make clear that the negative impacts in the later period dominate the projection results in terms of economic importance in the restricted annual model, whereas the early period gains balance with the later period losses in the flexible by-season model. When aggregating these values, I find

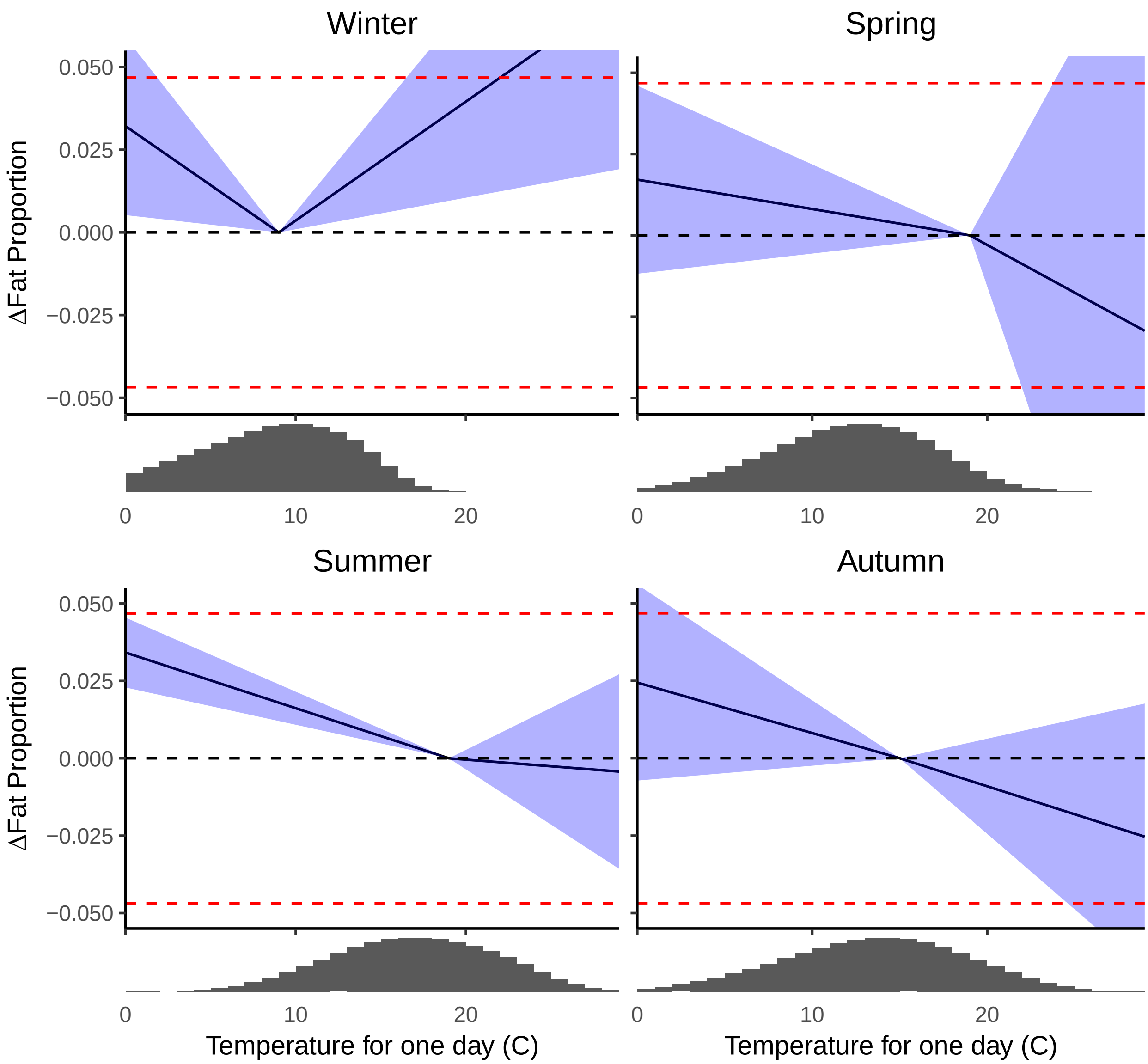
[6] Note that the red dashed lines indicating average daily fat proportion are placed closer to the limits of the plots.

Figure 7: Production response to soil moisture estimated by weather season



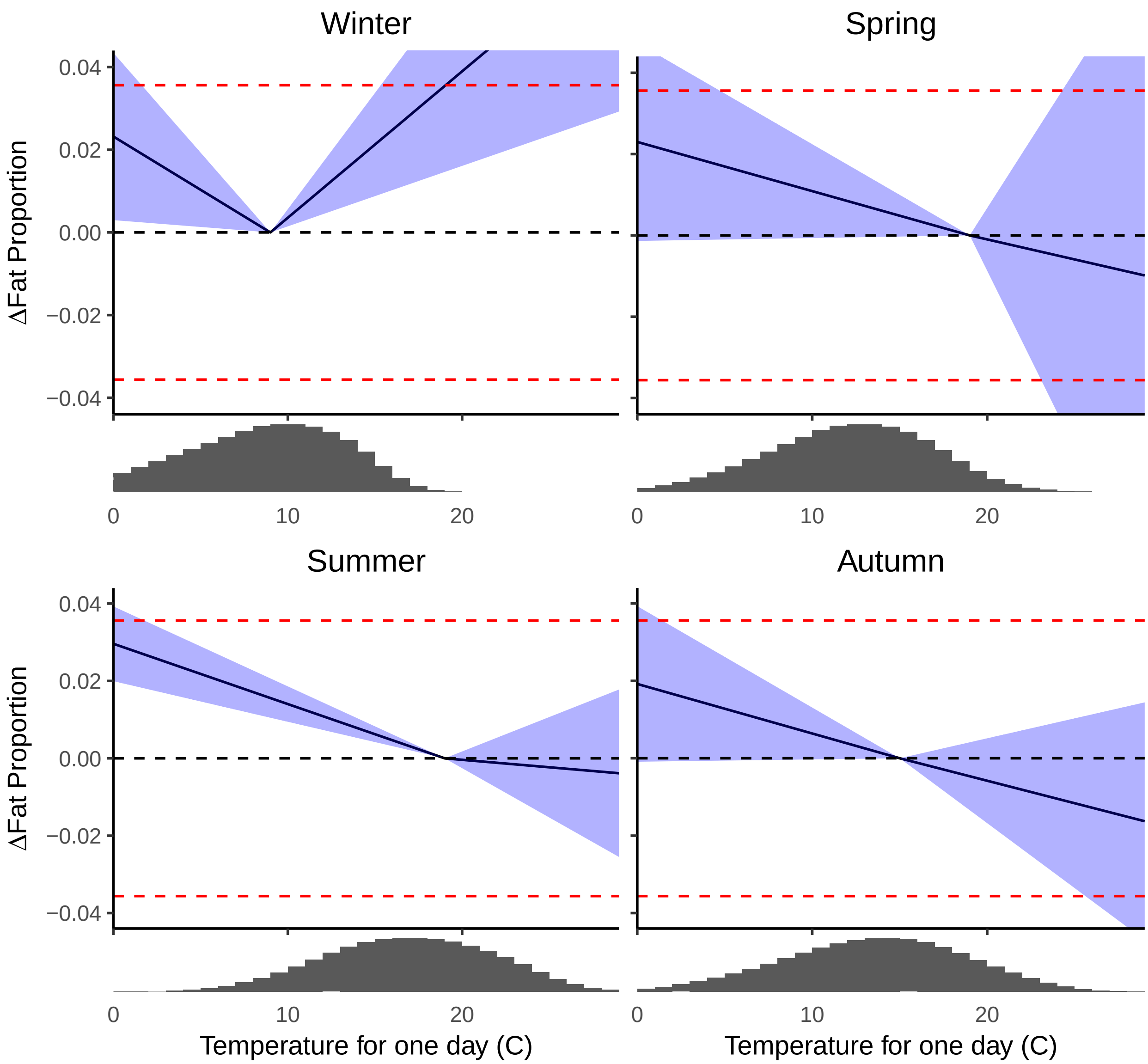
This figure plots g in Equation (6), where the linear spline functions are estimated by weather season, for a single day of soil moisture. In the NIWA data, the units of soil moisture are the negative of the quantity of water in mm required to bring the soil up to capacity; this plot uses these units. Positive values indicate the quantity of water running off. The subplots are vertically centered so that the change in yield per cow takes a value of zero when the negative of soil moisture deficit is at the respective knot locations. The dashed red lines indicate positive and negative average daily production. The plot shows 95% confidence bands calculated assuming error clustering by district and year; confidence bands do not take account of the uncertainty in the knot location. Below the subplots are histograms of daily soil moisture, within a weather season.

Figure 8: Fat response function to temperature estimated by weather season



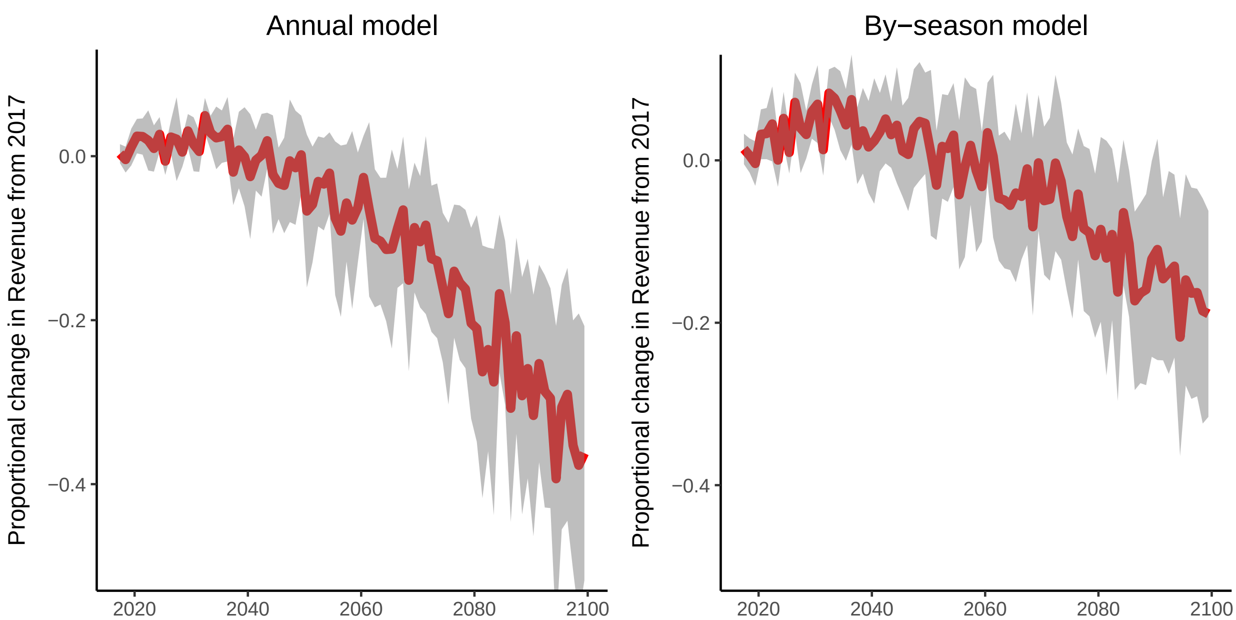
This figure plots f in Equation (6), where the linear spline functions are estimated by weather season, for a single day of temperature, using fat proportion as the outcome variable. I use the same knot locations estimated in the milk yield regressions. The subplots are vertically centered so that the change in yield per cow takes a value of zero when temperature is at the respective knot locations. The dashed red lines indicate positive and negative average fat proportion, averaged over the year. The plot shows 95% confidence bands calculated assuming error clustering by district and year; confidence bands do not take account of the uncertainty in the knot location. Below the subplots are histograms of the full time series of temperature, within a weather season, using single sine interpolation.

Figure 9: Protein response function to temperature estimated by weather season



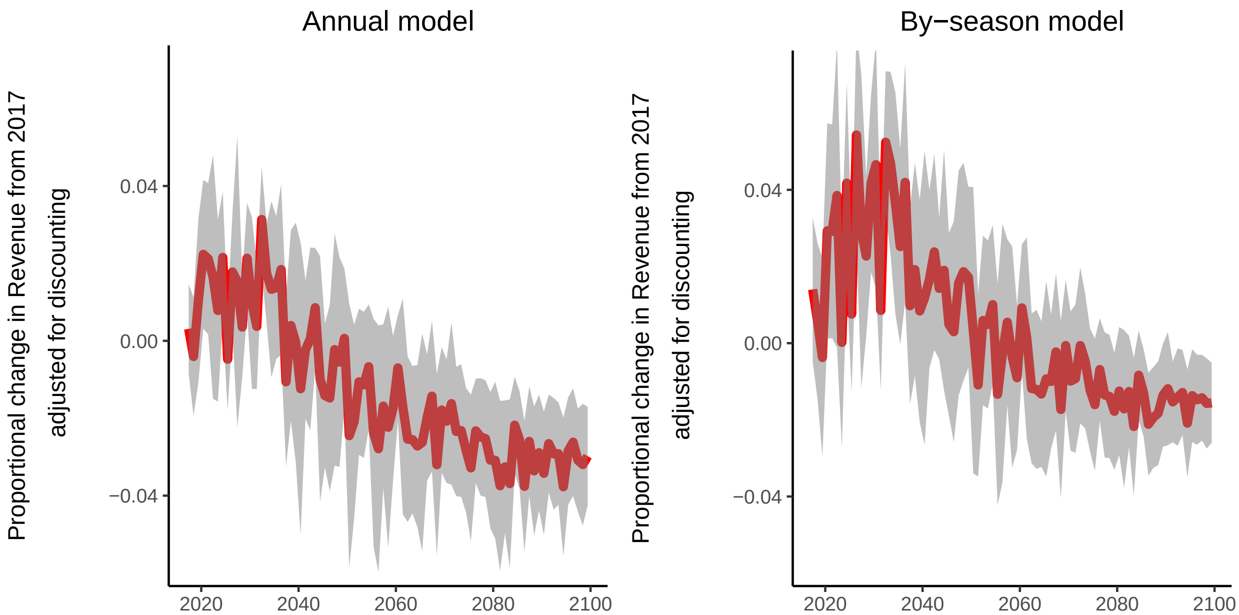
This figure plots f in Equation (6), where the linear spline functions are estimated by weather season, for a single day of temperature, using protein proportion as the outcome variable. I use the same knot locations estimated in the milk yield regressions. The subplots are vertically centered so that the change in yield per cow takes a value of zero when temperature is at the respective knot locations. The dashed red lines indicate positive and negative average fat proportion, averaged over the year. The plot shows 95% confidence bands calculated assuming error clustering by district and year; confidence bands do not take account of the uncertainty in the knot location. Below the subplots are histograms of the full time series of temperature, within a weather season, using single sine interpolation.

Figure 10: Projected change in revenue



This figure plots the projected proportional change in revenue under climate change as simulated in the HadGEM2-ES model for the annual and the by-season models. The current value of annual New Zealand dairy production at the farm gate is approximately US$8 billion. The projection simulation assumes constant output prices and constant milk quality. The simulation projects both temperature and soil moisture forward. At a 3% discount rate, the point estimate of the present value of the change in production is -US$8.4 billion for the annual model, and +US$2.1 billion for the by-season model.

Figure 11: Projected change in revenue with discounting



This figure plots the projected proportional change in revenue, adjusted with a 3% discount rate, under climate change as simulated in the HadGEM2-ES model for the annual and the by-season models. The current value of annual New Zealand dairy production at the farm gate is approximately US$8 billion. The projection simulation assumes constant output prices and constant milk quality. The simulation projects both temperature and soil moisture forward. The point estimate of the present value of the change in production is -US$8.4 billion for the annual model, and +US$2.1 billion for the by-season model.

that the point estimate of the present value of the change in production is -US$8.4 billion for the annual model, and +US$2.1 billion for the by-season model. The current value of annual New Zealand dairy production at the farm gate is approximately US$8 billion.

7 Conclusion

This paper estimates the impact of weather variables on dairy production in New Zealand. It finds that restricting the weather response functions to be the same throughout the year results in more pessimistic projections of the consequences of future climate change in the New Zealand dairy context than allowing for responses to be flexible by time-of-year. More generally, it highlights that bias can result in applied research contexts with dependent variables of a lower frequency than independent variables and models that restrict responses to be the same throughout the aggregation period, as has been shown theoretically (Andreou, Ghysels, and Kourtellos 2010).

It also highlights that pasture-based livestock production is highly sensitive to the weather, with large and opposing effects of winter and summer temperatures. New Zealand dairy production exists in a temperate climate, with temperatures seldom moving outside the range of 0-30°C. If these results are indicative of the weather-pasture production relationship in cooler or warmer places, they imply that these areas will respectively experience large gains and large declines under climate change.

While New Zealand dairy producers are highly exposed to the global export industry, an important stylized fact about the industry more generally is that production tends to be close to consumption. While a global market exists for milk powder, cheese, butter, and whey, exports only account for around 10% of global milk production. Fluid milk, in particular, has very high transportation costs both due to the water carrier needing to be transported and spoilage. If my results are indicative of the weather-dairy production relationship in other contexts, this fact suggests that a large portion of the incidence of the costs and benefits of climate change will fall on consumers.

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A Calculation of the contribution of pasture to global caloric production

Table 3 ranks land uses by their contribution to global caloric production; this section fully describes the calculations for this table. The FAO food balance data includes:

1. "Food supply": the quantity of food available for human consumption net of food-system waste, feed utilization, and changes in storage.

2. "Feed": the quantity of the food product utilized as animal feed.

3. "Production": the quantity of new production of the food product.

The data reports each of these items by "food type"; food types include items such as "Wheat and products", and "Poultry Meat". All values are for the most recent year, 2011. The FAO food balance data allows me to calculate the contribution of each land use to the food supply via plant-based foods directly, as these are simply the "food supply" values. Assuming a feed conversion ratio for each feed product also allows me to calculate the contribution of each plant-based land use *that is measured in the food balance data* to the food supply via animals. However, the contributions from both pasture and crop residues are not directly measured in the food balance data, as these are not also food products.

I am, however, able to measure the total contribution to the food supply for each animal product. With an assumed feed conversion ratio, along with the feed quantities, I can calculate the total quantity of animal calories that can be attributed to those feed products. I then calculate the contribution of pasture and crop residues as the residual of this relationship.

Explicitly, my calculation is as follows. Suppose Q_i^F is the "food supply" of food type i, Q_i^A is the feed utilized of food type i, both measured in kcal/capita/day. Total "plated" food supply, both directly through plant-based products, and indirectly through animals, for food type i, is then:

$$Q_i^H = Q_i^F + \alpha_i Q_i^A \tag{7}$$

where i indexes plant-based food/feed types (e.g. Maize and Products), α_i is the average feed conversion ratio for food/feed type i. I calculate the total contribution of plant food products that are measured in the FAO food balance data to animal calories as:

$$\sum_{i \in I} \alpha_i Q_i^A, \tag{8}$$

for $I = \{$Apples and products; Bananas; Barley and products; Beans; Bovine Meat; Butter, Ghee; Cassava and products; Cereals, Other; Cocoa Beans and products; Coconuts - Incl Copra; Dates; Eggs; Fruits, Other; Groundnuts (Shelled Eq); Maize and products; Meat, Other; Milk - Excluding Butter; Millet and products; Mutton & Goat Meat; Oats; Offals; Offals, Edible; Oilcrops Oil, Other; Oilcrops, Other; Onions; Oranges, Mandarines; Peas; Plantains; Potatoes and products; Pulses, Other and products; Rape and Mustard Oil; Rape and Mustardseed; Rice (Milled Equivalent); Roots, Other; Rye and products; Sesame seed; Sorghum and products; Soyabean Oil; Soyabeans; Stimulants; Sugar (Raw Equivalent); Sugar cane; Sugar non-centrifugal; Sunflower seed; Sweet potatoes; Sweeteners, Other; Tomatoes and products; Vegetables, Other; Wheat and products; Yams$\}$. Note that this excludes fish feed types, as these are primarily used to produce other fish food products.

As I can not determine which animals are fed which feeds, I assume $\alpha_i = \alpha \quad \forall i$. To calculate the average feed conversion ratio, I collect typical feed conversion ratios by animal from Searchinger et al. (2013, p. 37), which I show in Table 4. Next, I calculate the animal feed consumed for each land-based animal food product j using:

$$Q^{A,j} = Q_j^P / \alpha^j \tag{9}$$

where α^j is the feed conversion ratio for animal product j and $Q^{P,j}$ is the production of animal product j. $Q^{A,j}$ then represents the total quantity of feed across all feed types, for animal product j. Finally, to obtain α, the average conversion ratio, I use:

$$\alpha = \frac{\sum_{j \in J} Q^{P,j}}{\sum_{j \in J} Q^{A,j}} \tag{10}$$

Table 4: Typical feed conversion ratios for land animal food products

Food Item	Feed conversion ratio
Poultry Meat	0.11
Pigmeat	0.10
Butter, Ghee	0.07
Milk - Excluding Butter	0.07
Cream	0.07
Bovine Meat	0.01
Eggs	0.13
Mutton & Goat Meat	0.01

To obtain the contribution from pasture and crop residues, I use the identity:

$$\sum_{j \in J} Q^{A,j} = \sum_{i \in I}(Q_i^A) + Q_{Pasture}^A \tag{11}$$

which says that the total amount of feed consumed by land animals is equal to the total amount of feed consumed from plant food products, $\sum_{i \in I}(Q_i^A)$, plus the total amount of feed consumed as pasture and crop residues, $Q_{Pasture}^A$. Finally, I calculate the total contribution to the food supply from pasture and crop residues as $Q_{Pasture}^H = Q_{Pasture}^A * \alpha$. I then calculate the final proportions by dividing each Q_i^H by the "Grand Total" food supply value in the FAO data.

The relative contribution of pasture and crop residues is approximately 70% and 30% respectively (Wirsenius 2003).

B Climate change projections

In order to obtain indicative changes in production under climate change, I follow Houser et al. (2015) by simulating future daily weather by randomly sampling historical weather and adding differences generated by a climate model. In the current version of this project, I use a single climate model, HadGEM2-ES.

The following method for computing downscaled future climate projections differs from that in Houser et al. (2015) Secondly, instead of computing weather changes over fixed finite periods (e.g. 1981-2000 to 2040-2059), I compute weather changes and sum the projected impacts for all years.

Other than using a single climate model, my method differs from that in Houser et al. (2015) in two ways. Firstly, I compute projections for all years out to 2100. Secondly, I filter the climate model output using a LOWESS smoother, so that only the first-order trends and decadal variation from the climate model are used.

The full process is as follows: For climate model/emissions scenario/realization i:

1. Extract monthly data for i for all grid cells that overlap with the weather grid cells used in the analysis, from 30 years before the start of the analysis to 2100. Weather grid cells that do not overlap any cell in i are matched to the nearest cell in i. Index the grid cells in i by j.
2. For i, month-of-year, variable, and grid cell j, compute lowess-smoothed monthly data with a smoother span of 0.3[7]. This generates a smoothed path of each variable that preserves decadal variation.
3. For each future year t available in i, randomly select a year s from the weather data available (for NZ, this is 1972-2015). Then for every weather grid cell k in climate model grid cell j, and month in t, add the monthly difference from s to t using the lowess smoothed data.[8]

B.0.1 Soil moisture projections

In CMIP5, soil moisture variables available include total soil moisture across all layers in kg/m^2 and soil moisture in the top 0.1m in kg/m^2. However, neither of these soil moisture units exactly match those in the VCSN. In addition, some climate models do not reproduce the timing of seasonality of soil moisture as in reality. Thus, to obtain the mapping between the soil moisture units in the VCSN and the climate models, I make the assumption that the magnitude, but not necessarily the timing of the seasonality in soil moisture in the climate models is correct. This exploits the largest source of variation in soil moisture that is common between the weather data and the climate model data, the seasons. To operationalize this, I employ the following relationship in constructing the future soil moisture data:

$$\widehat{SM}_{it}^{W} = \min(\overline{SM}^{W}) + \frac{\max(\overline{SM}^{W}) - \min(\overline{SM}^{W})}{\max(\overline{SM}_{i}^{C}) - \min(\overline{SM}_{i}^{C})} * \left(SM_{it}^{C} - \min(\overline{SM}_{i}^{C})\right) \tag{12}$$

where i indexes climate models, t indexes future days, W indicates the weather data, C indicates the climate model data, and averages are computed over all historical years which exist in both the weather data and the climate model data.

[7]In R, this is computed as `lowess(x = month, y = value, f = 0.3)$y`.

[8]In the New Zealand data, years are defined to run from June 1 to May 31. 366-day future years which are matched with 365 day past years use day 365 twice.