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How climate affects agricultural land values in Aotearoa New Zealand

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Abstract

This paper examines how differences in climate across space influence the value of New Zealand agricultural land. We use the Ricardian approach to price the climate, using property valuation data from 1993 to 2018. We apply the 'spatial first differences' method, which compares differences in climate between neighbours with differences in land values between neighbours. This method allows us to estimate the impact of long-term climate conditions on farmland values across different land-uses, while controlling for sources of bias associated with unobserved heterogeneity. We find that a warmer or drier climate is associated with higher farmland values in New Zealand. As the spatial first differences method accounts for unobserved heterogeneity associated with variables not related to climate, these associations likely represent causal effects on land values of variables tied to climate. While agricultural productivity is one pathway by which climate affects land values, our results may also be due to variation in the value of land improvements tied to climate or amenity values associated with the option value to convert to a residential use.

JEL codes

Q1, Q2 and Q5.

Keywords

Land values; climate change; Ricardian analysis, Spatial First Differences

Introduction

Climate change is a major global issue with far-reaching impacts, presenting a particularly high risk for countries like New Zealand that depend heavily on the agricultural sector. More frequent extreme hot temperatures harm agricultural production, while less frequent cold temperatures can be a benefit (Schlenker and Roberts, 2009). Changes in precipitation patterns also present a risk but may result in improvements in some places. These offsetting costs and benefits of climate change make the scale of the net cost of climate change uncertain (Tol, 2009) and necessitates local measurement to enable local management.

New Zealand's economy relies heavily on productive land: the agricultural and forestry sectors contribute significantly to export earnings (more than half of New Zealand's total export income) and a sizeable proportion of New Zealand's total land is used for primary production (agriculture, forestry, and horticulture) (Stats NZ, 2018). In 2018, New Zealand agricultural land and forest area were 39.8 % and 37.4 % of total land area, respectively (World Development Indicators (WDI), 2018). New Zealand is unusual in that pastoral farming is the major agricultural land use, including substantial amounts of high-production improved-pasture systems. New Zealand is one of the largest milk producers in the world, with more than 4.9 million dairy cows producing over 21.2 billion litres of milk annually (DairyNZ, 2019). Dairy farming contributes 34% to New Zealand's total export revenue (DairyNZ, 2019), and sheep/beef (considered a single industry) is the second-largest contributor with 16.2% (Beef+lamb New Zealand, 2020). This institutional context provides another motivation for bespoke economic analysis to assess the costs and benefits of climate change locally. New Zealand regional climate models project temperature increases everywhere, greater increases in the North Island than in the South Island, with the greatest warming in the north-east by the end of the 21st century (Mullan et al. 2018). Projected precipitation changes vary around the country, with increases in the south and west, and decreases in the north and east (MfE, 2018).

The productivity of a parcel of land is reflected in its land value, which can differ from one parcel to another depending on climate factors, soil type, fertility, and groundwater available for irrigation (Tewari *et al*., 2013), as well as improvements. While productivity is an important driver of variation in rural land values and is vulnerable to climate change, the option value to convert to urban or other uses can also be a substantial contributor related to the climate. Rural land areas become more attractive for alternative non-farm uses as nearby urban areas grow and residential developments expand (Curran-Cournane *et al*., 2016). Climate can potentially affect this option value as people are willing to pay to enjoy a better climate in, for example, warmer or drier parts of New Zealand. Thus, climate-induced differences in land values can arise from productivity differences (including productivity driven by improvements) as well as from differences in amenity values.

In this paper, we explore the relationship between agricultural land values and the climate for different land-uses in New Zealand from 1993 to 2018 by applying the cross-sectional Ricardian approach to land-climate pricing. The big-picture goal of this type of research is to help understand how climate affects economic outcomes related to agriculture, thereby informing both local adaptation policy and global mitigation tradeoffs. While the use of panel methods to contribute to this goal is common (Auffhammer and Schlenker, 2014; Pourzand *et al.*, 2020; Bell *et al.*, 2021), a cross-sectional approach may better reflect the impact of adaptation choices that occur over long periods (such as land-use choice). Thus, to complement the panel-regression-based evidence on the impact of climate on agriculture, we apply the cross-sectional Ricardian approach to the New Zealand context.[1]

The main difficulty with using the Ricardian approach to find the relationship between land values and climate is that many variables that contribute to land value are correlated with climate, despite not being caused by climate differences. These variables include elevation, slope, ruggedness, soil quality, and distances to airports, beaches, ports, and urban centres. Omitting these variables using standard methods confounds the estimation of the relationship between climate and land values.

To address this concern, we use the spatial first differences (SFD) method described in Druckenmiller and Hsiang (2018), which compares climate differences with land value differences between neighbours to account for omitted variables that are common to the neighbours. The identifying assumption is that the remaining unobserved heterogeneity (the difference in land values between neighbours not explained by climate differences) is uncorrelated with climate differences. For omitted variables to bias our estimates, they would have to have spatial differences that are incidentally correlated with spatial differences in climate. If any such confounding variables are present, based on the experience in Druckenmiller and Hsiang (2018), they are unlikely to cause bias in the resultant estimates of the climate-land value relationship at a scale that is economically significant.

[1] For discussions of the advantages and disadvantages of various empirical approaches to measure climate impacts see Hsiang (2016), Blanc and Schlenker (2017), Mendelsohn and Massetti (2017), and Kolstad and Moore (2019).

One advantage of the SFD approach is that estimates can be computed between neighbours defined in both the West–East direction and the North–South direction, to exploit different variation in land value and climate difference variables. Because the North–South SFD method uses different pairs of neighbouring meshblocks compared with the West–East method, the method provides a natural check for robustness. This check is helpful because spatial patterns in unobserved heterogeneity along one direction might be different along the other direction (Druckenmiller and Hsiang 2018).

To our knowledge, this work is the first Ricardian paper applied to New Zealand that overcomes the problem of unobserved heterogeneity using the spatial first differences method, and one of the first few such analyses applied in the wider literature.

One other work has studied the impact of climate change on farmland values in New Zealand (Allan and Kerr, 2016). They use the Ricardian approach to estimate the effects of climate on land values. Our analysis makes several contributions building on theirs, the main one being that we compute SFD estimates to reduce (or eliminate) omitted variables bias. We also use more recent land value data and examine the effects of climate on both overall rural land values and for various land-uses.

The main results from the SFD estimation show a positive and precise relationship between farmland values and warmer conditions. This result for temperature is not unexpected because much of the agricultural land in New Zealand is in cooler climates. We do not, however, find evidence that positive effect flattens off at higher temperatures, which is surprising. Counterintuitively, we also find that *drier* soils are usually associated with higher farm values. These findings are robust across land-uses for temperature, but we find that “arable” land (primarily annual crops such as corn) shows that drier soils are associated with lower farm values. While puzzling, these results are likely due to some combination of improvement values that vary as a function of the climate, agricultural productivity, and climate amenity value for residential uses. Importantly, the result for soil moisture conflicts with the result in Bell *et al.*, (2021) that shows, more intuitively, that drier soils cause farms to receive lower profits when comparing conditions across time. Additionally, Bell *et al*. (2019) do not find evidence that warmer temperatures cause reliably higher profits as the results in this paper might suggest. Overall, the inconsistency between the earlier panel results and the current cross-sectional results warrants further research.

While theory linking Ricardian results to climate change is well developed for the agricultural productivity mechanism, uncertainty remains about how to interpret Ricardian results that are partially due to differences in improvements caused by climate differences (e.g. irrigation (Schlenker *et al.*, 2005)), as well as results that are partially due to climate amenity values (Ortiz-Bobea, 2020). That land improvements may confound estimates using the Ricardian approach has been known since Schlenker Hanemann and Fisher (2005), but theoretical guidance beyond omitting irrigated areas is missing from the literature to our knowledge. Ortiz-Bobea (2020) suggests using cash rents to isolate Ricardian results to the agricultural productivity mechanism, which is only useful in contexts where that institution exists, the data are collected, and the land rental market performs well enough to correctly reflect agricultural productivity. The welfare implications of climate change on residential climate amenities accounting for housing market equilibrium is also an unexplored theoretical topic to our knowledge.

Future work should aim to develop methods to separate the relative importance of improvements (including land-use differences), agricultural productivity, and amenity values using the Ricardian approach.This paper is structured as follows: section 2 provides an overview of the literature; the following sections present data sources, and the empirical model used; the main results are summarised in section 5; and the last section concludes.

Literature review

Numerous studies have evaluated the impacts of climate change on agriculture, with a particular focus on countries that are highly dependent on agriculture. Mendelsohn *et al.* (1994) developed a technique called the 'Ricardian' approach, where, instead of analysing the yields of specific agricultural products (e.g. Adams, 1989), researchers analyse the sensitivity of land values to climate, geographic, economic and demographic factors (Mendelsohn *et al.* 1994). The Ricardian approach is thus a hedonic method of farmland-characteristic pricing that assumes that a land parcel's value equals the present value of future rents or profits generated through all activities on the farm. Notably, since the climate is considered an exogenous factor in the land-climate Ricardian method, the economic impact of climate change can be effectively captured by variations in farmland values across diverse conditions. This method may sufficiently account for adaptation as land managers are generally assumed to have fully adapted to current climate.

In addition to cross-sectional methods using farm values, panel methods using annual farm productivity measures are also popular in the literature evaluating the effects of climate change on agriculture. For example, the literature finds negative and large short-run estimates of weather shocks in panel studies of U.S. crop yields (Schlenker and Roberts, 2009), farm profits (Deschênes abd Greenstone, 2007; Fisher *et al*., 2012), and total factor productivity (Ortiz-Bobea *et al*., 2018). In New Zealand, Bell *et al.* (2021) find negative effects of dry conditions on pastoral-farm profits that suggest moderate negative impacts of future climate change.

The Ricardian approach confronts a number of limitations. For example, in addition to the problem of omitted variables bias discussed in the introduction, the Ricardian approach does not consider transition costs associated with changing land-use, thus potentially underestimating the cost of climate change across time (Kelly *et al*. 2005).

Another shortcoming of the Ricardian approach for valuing climate change is that it makes use of historical price expectations. These price expectations are unlikely to be related to cross-sectional differences in climate and thus would not affect the estimated land value-climate relationship in the Ricardian approach. However, a full evaluation of the effect of climate change on land values needs to account for how agricultural output prices would change due to climate change (Quiggin and Horowitz, 1999). Ricardian analysis also does not reflect climate-induced future changes in expectations regarding technology and agricultural policies.

The Ricardian approach reflects the benefits of land improvements (including land-use change) caused by differences in climate but does not reflect the differential costs of these improvements. For example, a warm-climate perennial crop may take longer to establish than one in a cooler climate. Land prices would be higher in the warm location because of the higher value of the standing crop but would not account for the extra costs imposed to establish that crop. An example is an absence of irrigation (an important land improvement) in previous Ricardian analysis; however, some studies have addressed this specific issue. Schlenker *et al.* (2006) examine the impacts of climate change on US farmland values by restricting their analysis to rain-fed regions, to avoid the bias associated with irrigation.

Ortiz-Bobea (2020) applies the Ricardian approach to US farm rents and shows small long-run effects of climate change. They argue that cash rents better reflect expected near-term agricultural profits, removing the confounding influence of variables such as residential amenities. Although cash rents might be a good indicator of farm profitability, we believe directly using long-run average farm profits would be a superior approach to achieve the same goal as it would be a good measure of expected profits while avoiding any issues associated with the functioning of the land rental market. In NZ, for example, a large bulk of the land rental arrangements are not arms-length and/or also involve some form of profit sharing. Still, unvestigating the impact of climate on land rental rates or long-run average profitability in NZ would be an interesting topic for future research.

Despite the limitations, the Ricardian approach is a practical tool for estimating the potential effects of global climate change on agricultural land values. Extensive literature estimated the impacts of climate change on agricultural land values by applying the Ricardian approach across various countries, including the US (Mendelsohn and Nordhaus, 1999; Mendelsohn *et al*., 2001; Quaye *et al.*, 2018; Massetti and Mendelsohn, 2020), Canada (Reinsborough 2003), Europe (Moore and Lobell, 2014; Passel *et al.*, 2017; Bozzola *et al.*, 2018), South Africa (Gbetibouo and Hassan, 2005), Sri Lanka (Seo *et al*. 2005), and Pakistan (Hussain and Mustafa 2016).

These studies have broadly established a non-linear relationship between farmland values and temperature and precipitation. Mendelsohn and Massetti (2017) summarised that the Ricardian model's estimates show that net farm revenue falls by 8–12% under global average temperature increases of 2°C and precipitation increases of 7%. The Ricardian approach has also established that climate change impacts differ by regions. Agricultural areas in warm regions are likely to be a net loser, while those in cold regions may benefit.

Data

Land value data

Data on land values come from Quotable Value New Zealand (QVNZ), which compiles government valuations for all New Zealand properties from 1989.[2] A property valuation includes estimates of both land value and improvements value, the sum of which is referred to as 'capital value'.

These government valuations are commissioned by 61 local authorities from a range of providers. There is no national official documentation on how government farm valuations are conducted in New Zealand; the exact method is left to valuers subject to compliance with some

2 New Zealand's largest valuation and property services company, QVNZ, conducts property valuations for tax purposes for around 80% of New Zealand's Territorial Authorities (TAs). QVNZ purchases the valuations for the other TAs from other valuation companies to compile a database of all properties in New Zealand.

high-level standards that do not specify that climate must be included explicity in the valuation process. Based on several conversations with industry experts and valuers, the process is primarily based on recent property sales in the area, construction market trends, productive land area, land quality that can be easily assessed, and any improvements done on the land. Since, to our understanding, valuers do not use climate explicitly in their valuation methods, the climate signal should be correctly accounted for via recent nearby sales and appropriately scaled using productive land area. Standard concerns about hedonic analyses reproducing the (incorrect) functions used by the valuers should thus not apply to this paper.

Our data are available to us at the meshblock-year level by land use from 1993 to 2012, and by parcel from 2013 onwards. For both time periods, we filter to parcels in a primary production land use. Since these property valuations are updated approximately every 3 years, we then match these data to the Territorial Authority (TA) valuation cycle where available and keep the data for the first year post-revaluation. Where the valuation cycle is not available, we remove all records where the farmland value does not change from the previous year, thereby keeping only parcel-years with new valuations. For the parcel-level data, we drop observations with capital value or land area either missing or 0. For data quality, we remove properties smaller than 5 hectares (ha) as they are often primarily for residential use.[3]

Finally, we aggregate our data to the meshblock-year level for analysis by calculating the area-weighted average capital value per hectare for each land use (dairy, sheep/beef, forestry, horticulture, arable/cropping, and deer farming) as well as across all primary production land. We also remove observations with capital values per ha below the 2.5% quantile and above the 97.5% quantile to avoid data errors and properties with unusual improvements, leaving 71,862 meshblock-year observations for analysis.

While the Ricardian approach is a cross-sectional method, our dependent variable sample is a panel from 1993 to 2018, including both spatial and temporal variation in farmland value. Thus, we use a panel estimator in this (Massetti and Mendelsohn, 2011).

[3] Very small properties in New Zealand tend to have very high variation in the quality of improvements. This can result in very large values per hectare.

Climatic Variables

To compute the climate variables, we use the Virtual Climate Station Network (VCSN) data provided by the National Institute of Water and Atmospheric Research (NIWA). VCSN data predict daily weather in a regular grid of approximately 5 × 5km covering all of New Zealand (11,491 grid points). The VCSN includes daily temperature (minimum and maximum) and soil moisture and spatially interpolates raw station observations across space using a trivariate (elevation, latitude, and longitude) thin plate smoothing spline model. The spatial averaging for a given day uses 100 sample points in a regular grid within each meshblock. For each of the 100 points, we average the weather data from the four nearest VCSN grid cells using bilinear interpolation to ensure climate variation in our data between neighbouring meshblocks, which can be small relative to the VCSN grid cells. These daily meshblock-level data are then averaged across 30 years (1981–2010) for both temperature (averaging minimum and maximum temperature) and soil moisture. To model nonlinearities, we compute polynomials in these aggregated values.

Methods

Ricardian approach

The Ricardian approach is a cross-sectional method that estimates how climate causes changes in land values across space (for further details on the Ricardian approach's theory see Mendelsohn *et al.* (1994)). The standard Ricardian model relies on a quadratic formulation of climate (Mendelsohn *et al.*, 1994; Seo and Mendelsohn, 2008) and include quadratic terms in temperature and soil moisture to measure any nonlinear effects of these variables. Our empirical model is of the form:

$$\log(LV_{itu}) = \beta_1 T_i + \beta_2 T_i^2 + \beta_3 SM_i + \beta_4 SM_i^2 + \gamma_{tu} + \varepsilon_{itu} \qquad (2)$$

Where LV_{it} is the capital (land) value[4] per hectare in meshblock i and year t for land use u, T_i is long-run average annual temperature, and SM_i is long-run average soil moisture.[5] γ_{tu} is a

[4] Recall that capital value includes the value of improvements whereas land value does not. Capital and land values are inflated to real values using the 2017 Consumer Price Index (CPI). While this operation is unnecessary for our empirical model with log land values and time-fixed effects, it does affect our summary statistics.

[5] We use soil moisture variable to directly measure water availability in our model.

time-fixed effect, and ε_{itu} is a standard noise term. We use a log-linear functional form as is standard in the Ricardian studies (Mendelsohn *et al.*, 1994; Mendelsohn & Dinar, 2003).

Spatial First Differences

The Spatial First Differences (SFD) model described in Druckenmiller and Hsiang (2018) is a cross-sectional research design that compares data between adjacent neighbours to identify causal effects in the presence of omitted variables. The identifying assumption is that spatial differences in relevant unobservable variables are uncorrelated with spatial differences in the climate. This assumption is likely to be met when spatial data are densely packed across physical space (Druckenmiller and Hsiang, 2018), such as meshblock-level data. Two neighbouring meshblocks have common characteristics and are more similar than two otherwise random meshblocks. The model classifies all neighbouring meshblocks into a two-dimensional grid, with each spatial unit assigned a row (channel) and column (layer) index. Within each row, differences are taken across adjacent columns (neighbouring meshblocks).

When we restrict comparisons to neighbouring meshblocks, much of the influence of omitted variables regarding local geographical, political, and economic conditions are differenced out by the SFD approach (Druckenmiller and Hsiang, 2018). Thus, using this method we can establish whether a change in climate conditions causes a change in farmland values given all adaptation mechanisms and improvements. The estimating equation is a 'spatially first differenced' version of equation (2), where the 'Δ' operator denotes differencing between neighbouring meshblocks:

$$\Delta\log(LV_{it}) = \beta_1\Delta T_i + \beta_2\Delta T_i^2 + \beta_3\Delta SM_i + \beta_4\Delta SM_i^2 + \tilde{\gamma}_t + \tilde{\varepsilon}_{it} \quad (3)$$

Where $\Delta\log(LV_{it})$ is the spatial difference in property value between adjacent meshblocks i and $i-1$ within year t. ΔT_i and ΔSM_i are similar spatial differences in the level of average annual temperature and soil moisture. ΔT_i^2 and ΔSM_i^2 are similar spatial differences in square of average annual temperature and soil moisture. Note that the SFD method is well-suited to capture non-linear effects, as the quadratic terms are computed *before* differencing.[6] We also add a year-fixed effect ($\tilde{\gamma}_t$) to the SFD model to potentially improve the efficiency of the model

[6] For example, we would construct the SFD estimator for the model $\log(LV_{it}) = \alpha_1 T_i + \alpha_2 T_i^2$ by writing $\Delta\log(LV_{it}) = \log(LV_{it}) - \log(LV_{i-1,t}) = \alpha_1(T_i - T_{i-1}) + \alpha_2(T_i^2 - T_{i-1}^2) = \alpha_1\Delta T_i + \alpha_2\Delta T_i^2$. The coefficient α_2 maintains the same interpretation as in the level model.

and account for unobserved time-variant factors common to the country and affect spatial differences (such as commodity prices). $\tilde{\varepsilon}_{it}$ is a new noise term equavelent to $\varepsilon_{it} - \varepsilon_{i-1,t}$.

To implement the SFD methodology, we use a shapefile for all New Zealand meshblocks obtained from Stats NZ and use the R package functions provided by Druckenmiller and Hsiang (2018).[7] Our main results compute the SFD in a West-East direction, and we check robustness using SFD computed in a North-South direction.[8]

This paper uses panel data to regress capital values against vectors of climate variables for a general agricultural sample over a study period of 1993–2018, following Massetti and Mendelsohn (2011). They argued that, in a cross-sectional method, short-term price shocks could be correlated with climate and essentially cause biased results, much like any other omitted variable. We calculate the Ricardian estimates for various land-uses (dairy farms, sheep/beef, forestry, horticulture,[9] arable and deer farming) to identify how different land values in New Zealand's agricultural sub-sectors respond to climate. These land-use-specific regressions explain how different New Zealand farms are affected by climatic conditions (DePaula, 2020). We also test the sensitivity of the main results using land values as the dependent variable (i.e., omitting the improvement-value component) and using season-specific climate variables.

The climate difference variables may be spatially correlated, as may be the unexplained portion of the model (i.e., unexplained spatial differences in land values). Thus, estimates of standard errors may be biased downwards in the presence of this spatial autocorrelation. To partially correct for this, we calculate the standard errors robust to clusters in all specifications at the regional level. This assumes that the autocorrelation in these variables occurs within each region, and that statistical errors are independent across regions.

Empirical results and discussion

Table 1 reports the summary statistics of the variables used in the SFD estimation. On average, agricultural land capital value was approximately $22,000 per hectare in New Zealand

[7] Code is available at http://www.globalpolicy.science/code

[8] Computing differences in the East-West and South-North directions yields the same estimates as the West-East and North-South models.

[9] Horticulture land-use includes Berry fruits, Citrus, Flowers, Glasshouses, Kiwifruit, Market garden, Pip fruit, Stone fruit, Vineyard, and other horticultural uses.

between 1993 and 2018 (in 2017 dollars). Average annual temperature and soil moisture were about 12°C (ranging from 4.8°C to 16°C) and about 40mm below capacity (ranging from 92mm below to 49mm above capacity)[10] across New Zealand. From the SFD variable for *ln(Capital value($/ha))*, we see that the standard deviation (S.D.) for these differences is large (almost as big as the S.D. for the level of the log (0.75 vs 1)), indicating substantial variation in capital value between a meshblock and its neighbour. Similarly, the standard deviation of SFD of climate variables shows a surprisingly high dispersion in temperature and soil moisture between neighbouring meshblocks.

The signs of the averages of the SFD variables also tell us that temperature (soil moisture) slightly increases (decreases) as we move from West to East along the country, as shown in Figure 1. Overall, the statistics in Table 1 suggest sufficient variation in the SFD variables to estimate the SFD regression. The farm value map (in Figure 1) shows that the meshblock-level farm value data is highly spatially dense. Given that the SFD approach requires that observations are tightly packed together, this map is evidence that this qualification is met.

Figure 2 shows SFD estimates of the effect of long-term climate conditions on farmland capital value, comparing the West–East direction (panel a) with the North–South direction (panel b). The vertical axis displays the log of capital values ($/hectare), and horizontal axes are annual temperature and soil moisture. We find a statistically significant positive relationship between annual temperature and farmland capital values, which is close to linear. A change in average annual temperature from 13°C to 14°C results in a predicted capital value increase of about 232%[11] in land value, holding other things constant. As the annual average temperature is between 4°C and 16°C across the country, the sign of this effect is not surprising; however, we may also have expected the effect to flatten off at the upper end of the temperature distribution.

Drier soils are associated with higher capital values, from an annual average of around 40mm below capacity, with a change in soil moisture from 50mm to 60mm below capacity being associated with an increase of approximately 15%. We do not see a substantial effect of very wet soils in our results. Across the range of temperature, we find that the impact of variation in temperature on land values is much larger than the impact of variation in soil moisture. These

[10] The units of soil moisture in the VCSN are -mm of soil moisture deficit, using a 150-mm capacity model. Soilmoisture deficit is modelled as a function of several historical observed variables, including temperature, rainfall, and sunlight. See (Porteous *et al.*, 1994) and (Tait *et al.*, 2006) for more details.

[11] We convert the log differences to a percentage using (exp(log change) – 1)*100

findings are also consistent across all land-uses. The SFD estimates in the North-South model are quite consistent with those in the West–East model, although the SFD estimates in the West–East model are more precise.

These results, especially for temperature, are large and surprising. It is unlikely that pure agricultural productivity accounts for the soil moisture effects and the temperature effects in the upper range of the distribution, based on prior research (e.g. Bell et al. (2021)). However, other mechanisms might lead to these results. Climate can cause differences in the equilibrium improvements a piece of land tends to have, where warmer areas may tend to receive higher levels of investment to support agricultural productivity (Schlenker et al., 2005). Areas with a warmer, drier climate may also receive a market premium due to climate amenity values. Finally, omitted variables that are tied to the climate may contribute to these results (such as sunlight, which directly affects agricultural productivity via photosynthesis).

If land improvements are a direct function of climate, differences in improvements can still determine changes in capital values. The SFD method cannot remove the effect of improvements tied to climate differences. However, if this mechanism is a major contributor to the climate-land value relationship, it poses a problem when using these results to value climate change: the climate-land value relationship measures only the differences in the benefits of these improvements but *not the differences in the costs*. If, for example, a warmer area tends to have more land-use in wine grapes, the temperature-land value relationship might look positive. Still, the positive relationship would omit the already-incurred costs associated with planting and growing those grapes.

Furthermore, climate has amenity value – people are generally more willing to live in warmer and drier places in New Zealand – which can cause differences in option values to convert agricultural land to urban uses. Again, while this aspect of the climate-land value relationship may be substantial in climate differences across space, it is unclear whether climate change would affect these amenities in the way that the climate-land value relationship suggests. For example, future theoretical research could aim to understand whether the Ricardian approach correctly estimates the welfare impact of climate change in the context of a spatial housing market equilibrium.

To investigate the extent to which improvements drive our results, we also compute SFD estimates using pure land values as the dependent variable, which omits the value of improvements as measured by the respective valuers. The results are shown in Appendix II

Figure A1. We find the same pattern for temperature and soil moisture effects on farmland land values across both West-East and North-South estimates, and they are quantitatively very similar to our main results. We generally prefer the capital values due to uncertainty about how improvement values are identified separately from land values. However, given that the results are almost identical, we do not find any evidence to suggest that our main results are driven by improvements tied to climate.

We also investigate the effects of seasonal temperature and soil moisture on farmland values to check the robustness of our findings from the annual model, following Massetti and Mendelsohn (2011), where the Ricardian model is separately estimated by seasons of a year. Figures A2 and A3 (in Appendix II) show the SFD estimates for the seasonal models for the West-East direction. The seasonal model did not produce precise estimates, likely because of multicollinearity of the SFD variables between seasons. Correlation matrix tables (see Appendix III, Tables A1 and A2) show that differences in temperature and soil moisture across seasons are very highly correlated. The SFD results of the seasonal specifications are also similar for both capital and land values.

Figures 3 to 8 show land-use-specific SFD estimates of the impact of changes in annual climate variables on capital values. The results show that the pattern of annual temperature effects is quite similar across land-uses, consistent with findings of the model using data from all primary land uses. Increasing annual temperature is associated with higher farmland capital values for all land-uses.

The pattern of soil moisture effect does differ across land-uses. We see a positive relationship between dry soil and capital values for sheep/beef, forestry and horticulture, although it is statistically significant only for sheep/beef. However, the response of capital value to annual soil moisture is ∩-shaped for arable. It shows that drier soil is associated with significantly lower capital values.

Conclusion

In this study, we evaluate the impact of cross-sectional differences in climate on New Zealand's primary-production land values. To do this, we use Ricardian hedonic price modelling that links variation in capital values across space with variation in annual climate, between 1993 and 2018. We estimate the Ricardian approach using the 'spatial first differences' (SFD) method to address common concerns about omitted variables bias.

Our results show that a warmer or drier climate is associated with higher capital values. We also confirm that our findings are consistent when the improvement-value element is omitted from the baseline model, suggesting that spatial variation in improvement values tied to climate are not an important factor explaining our results. SFD estimates for land-use-specific models support our main findings of a positive relationship between a hotter climate and farmland values for all land-uses. Arable land is the only land-use that clearly shows a different result for soil moisture, with drier soils quite clearly being associated with lower land values.

One of the primary applications of Ricardian analyses is to determine how land values might shift due to climate change. At least loosely, these shifts are generally interpreted as indicative of the impact of climate change on agricultural producer surplus. The standard theory linking results using the Ricardian approach to climate change assumes that differences in land values tied to climate are due to differences in agricultural productivity. Therefore, if we were confident that our results were primarily driven by differences in agricultural productivity, we could conclude that climate change would increase land values in New Zealand as temperatures warm and this result would indicate welfare improvements for New Zealand farmers. However, given that our results may be driven by climate amenities for residential use, we cannot be confident that New Zealand land values will increase as the climate changes. To be confident that our results indicate overall welfare improvements under climate change, future theoretical research is required to put our results in the context of a spatial housing and land market equilibrium.

Furthermore, New Zealand's annual temperature in our sample period is between 4°C and 16°C, so using these results to extrapolate outside this range should be done with caution.

A reasonable question one might ask is: if we aren't able to distinguish the climate amenity effect from the productivity effect in our results, why is this result useful at all? We still believe our result is useful in that it highlights an empirical puzzle for future research to resolve, which is to what extent can the climate–land-value relationship be explained by agricultural productivity versus climate amenities associated with residential use. Future research could also pursue general methods that distinguish the effect of improvements from the pure productivity effect.

Table 1: Summary statistics

Variable	Mean	St. Dev.	Min	Max
Capital value($/ha)	22,327.540	23,702.130	735.765	201,925.9
ln(Capital value($/ha))	9.506	1.061	6.601	12.216
Δln(Capital value($/ha)) (WE)*	0.004	0.745	-4.751	4.803
Annual temperature (°C)	12.508	1.872	4.813	16.084
ΔAnnual temperature (°C) (WE)*	0.009	0.333	-4.406	3.736
Annual soil moisture (-mm deficit)	-40.356	16.832	-92.577	48.805
ΔAnnual soil moisture (-mm deficit) (WE)*	-0.141	3.671	-46.954	48.434

* Differences are computed in the West-East (WE) direction.

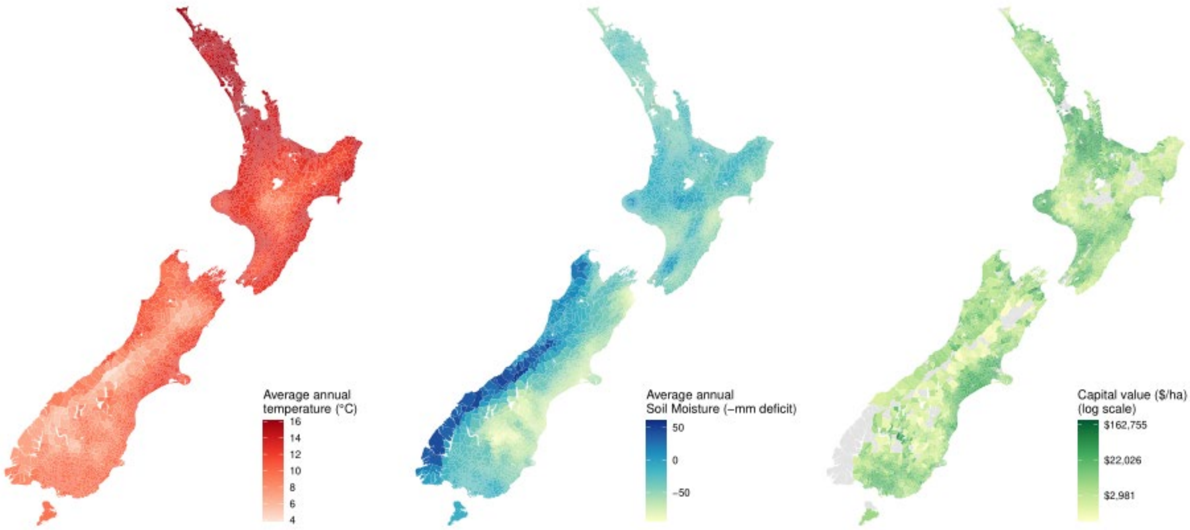

Figure 1: Spatial distribution of 30-year average annual temperature (°C), soil moisture (-mm deficit) and average farmland values (log($/ha)) from left to right, respectively. On average, climatic maps show warmer conditions in the North Island and drier conditions in the South Island. The East Coast of the country experiences a hotter and drier climate than the West coast, on average. We calculate average deflated farmland values from 1993 to 2018 for each meshblock in New Zealand. The meshblock-level farm value map shows that the meshblock data is very spatially dense, indicating that the identifying assumption of the SFD is met. The farm value map shows that average farmland values tend to be higher in the North Island. For display purposes, farm values are winsorised at 10th and 90th percentile.

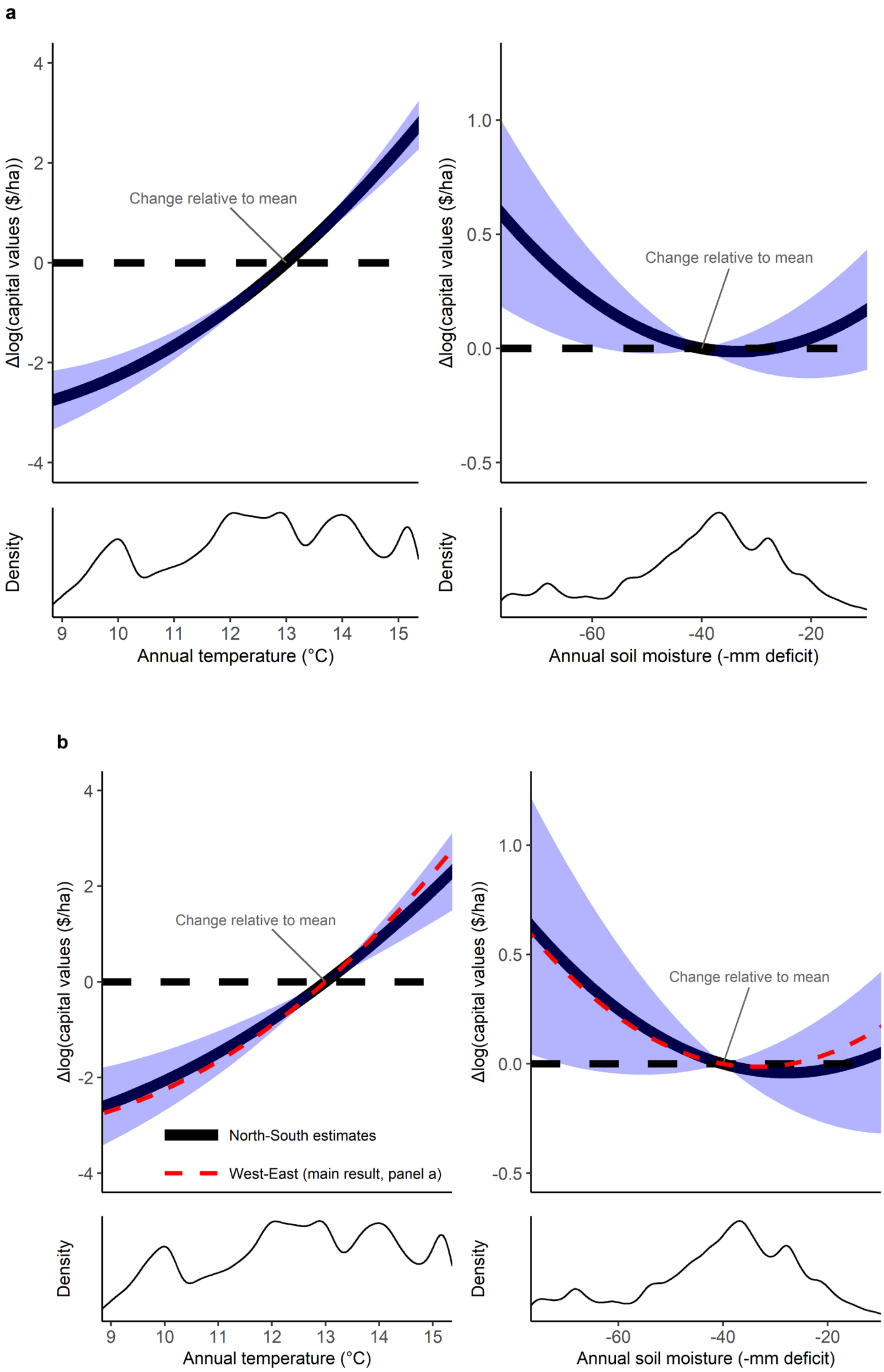

Figure 2: Capital value response to annual temperature and soil moisture, 1993–2018. Quadratic SFD estimates are computed in a) the West–East direction, and b) the North–South direction. The black line is the centred predicted values, which are calculated by subtracting the mean from all observations. The red dashed line is the main result which is SFD estimates for capital land values computed in the West–East direction. The blue area shows the 95% confidence band – centred at the mean. Histograms present the number of observations used to estimate the response function. The temperature range is between 2.5th and 97.5th percentiles. Regressions are computed on 71,862 and 71,491 observations for WE and NS directions, respectively.

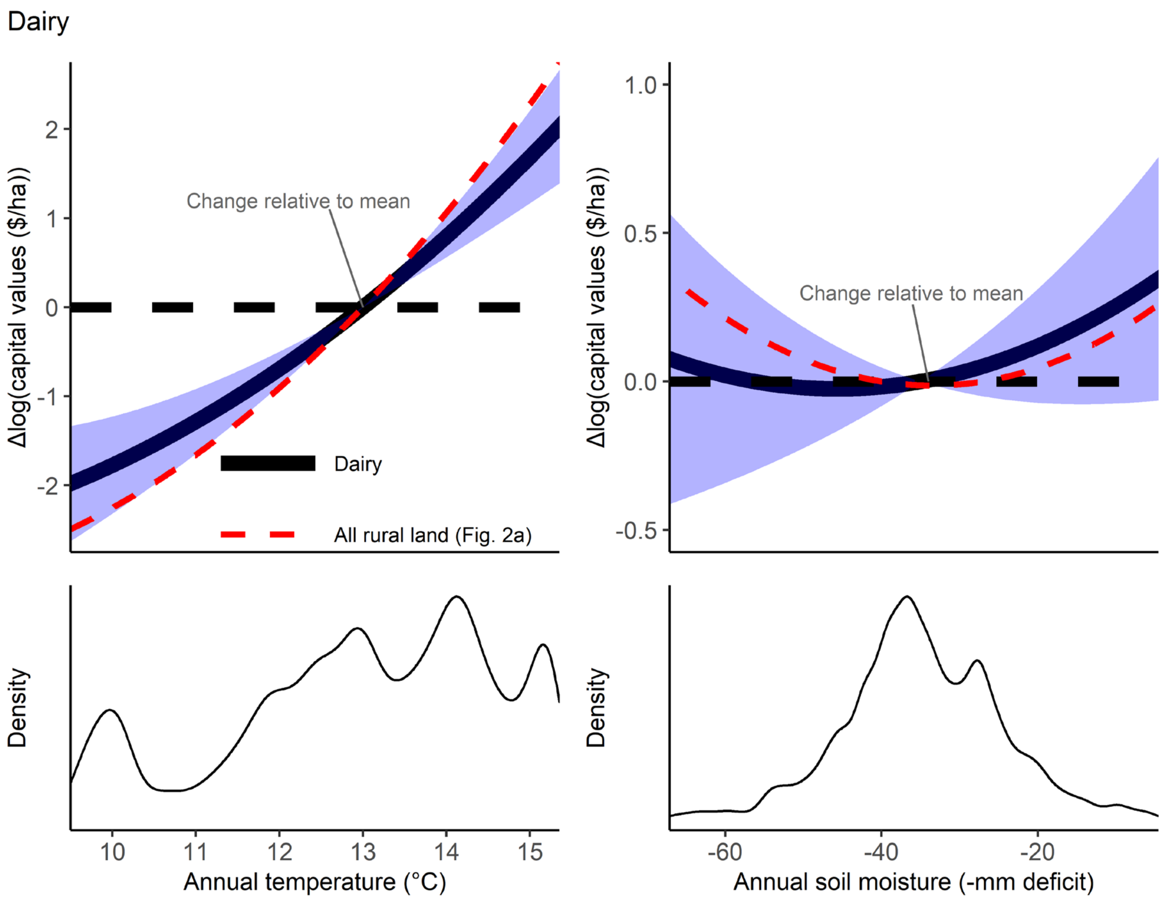

Figure 3: Capital value response to annual temperature and soil moisture for dairy farming, 1993–2018. Quadratic SFD estimates are computed in the West–East direction. Regressions are computed on 34,204 observations. See Figure 2 for more details.

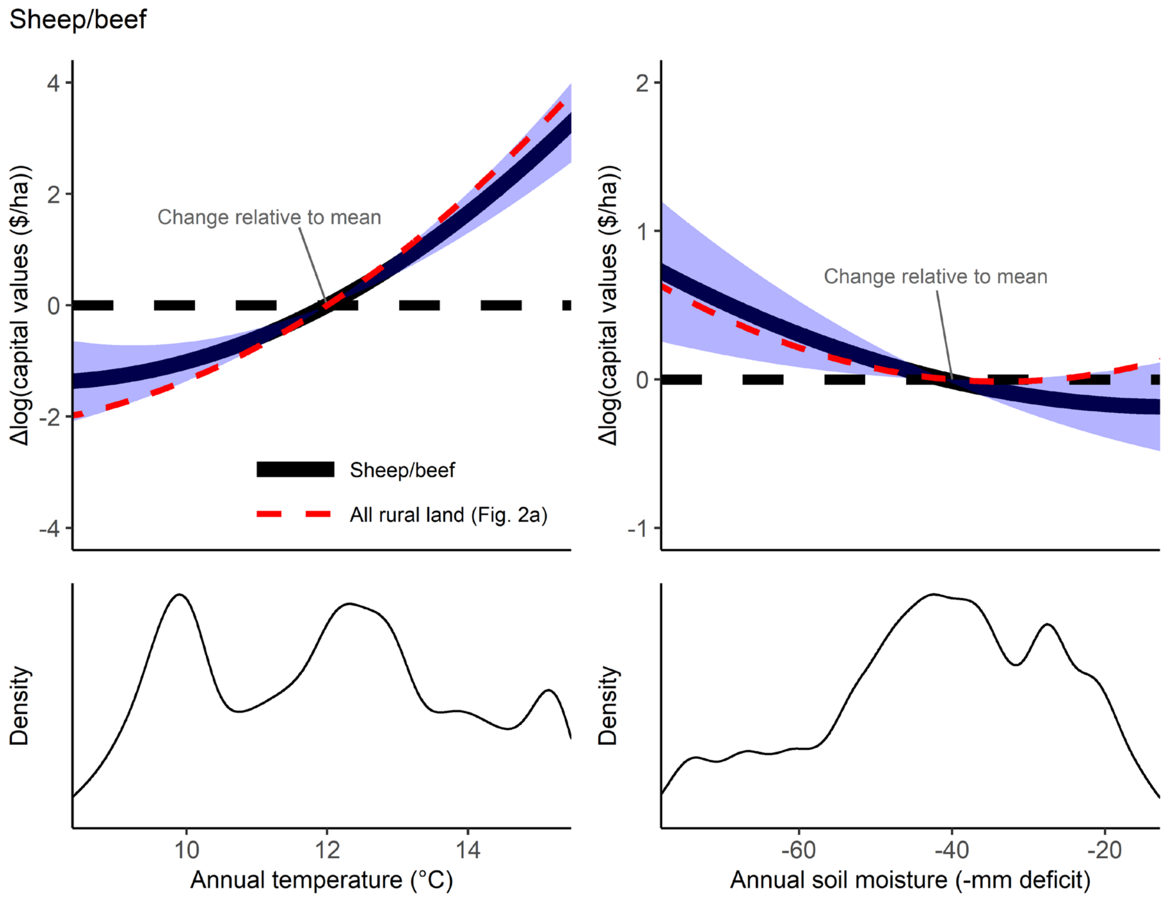

Figure 4: Capital value response to annual temperature and soil moisture for sheep/beef farming, 1993–2018. Quadratic SFD estimates are computed in the West–East direction. Regressions are computed on 13,340 observations. See Figure 2 for more details.

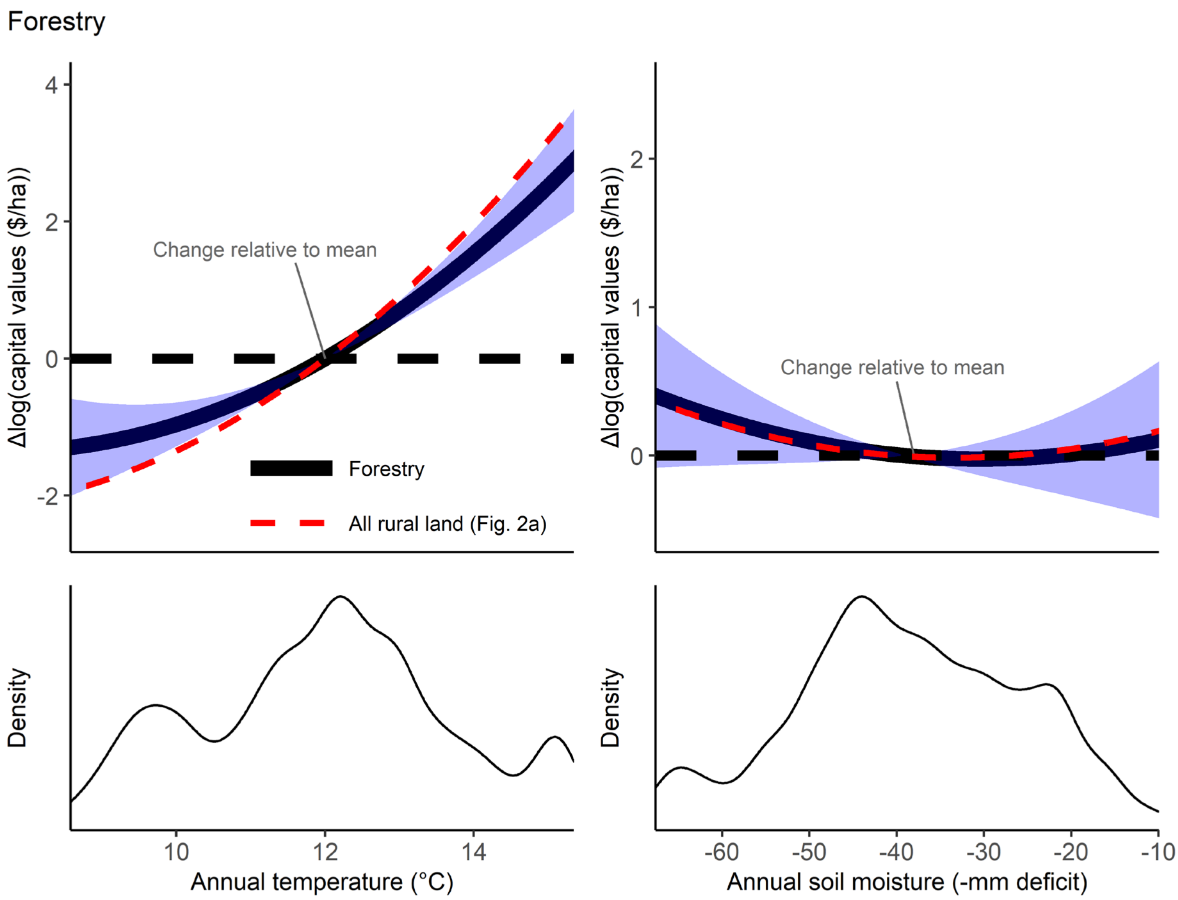

Figure 5: Capital values response to annual temperature and soil moisture for forestry, 1993–2018. Quadratic SFD estimates are computed in the West–East direction. Regressions are computed on 6,174 observations. See Figure 2 for more details.

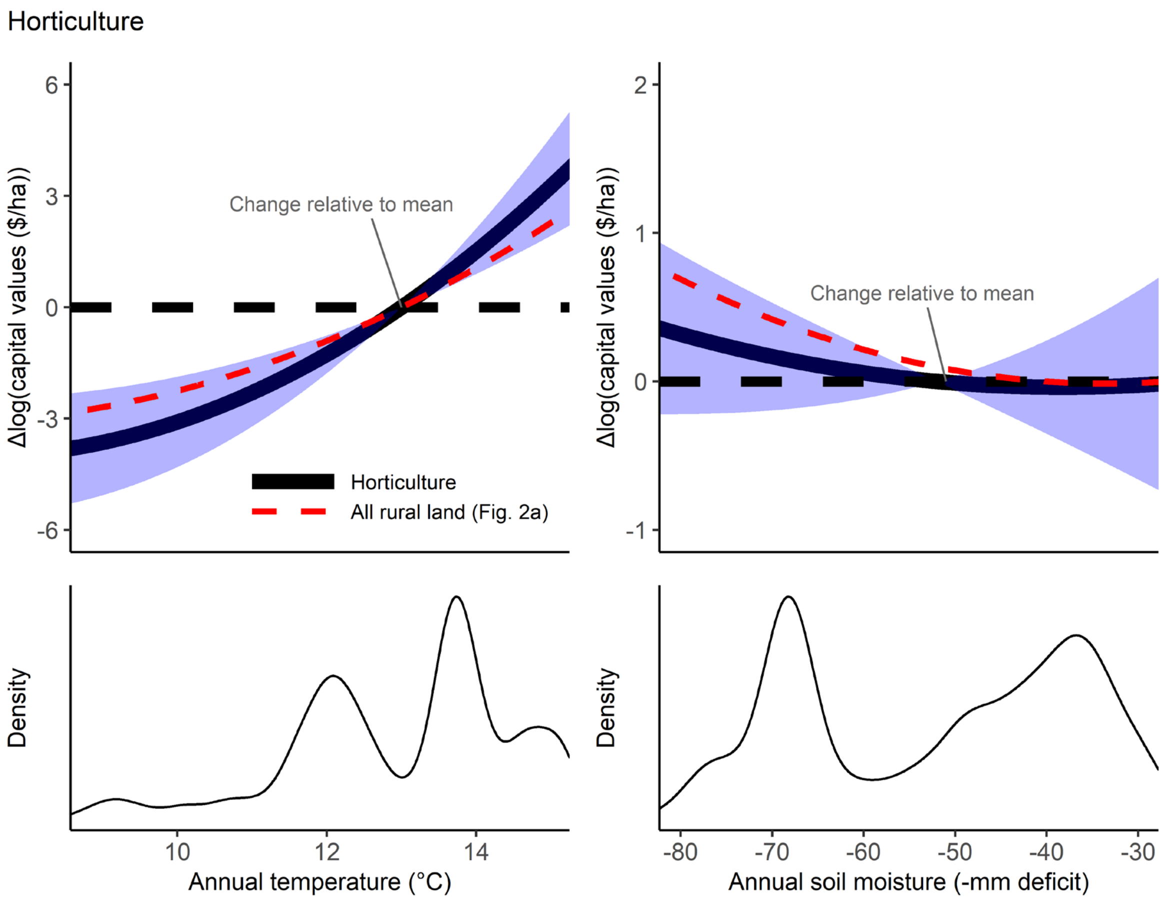

Figure 6: Capital value response to annual temperature and soil moisture for horticulture, 1993–2018. Quadratic SFD estimates are computed in the West–East direction. Regressions are computed on 5,459 observations. See Figure 2 for more details.

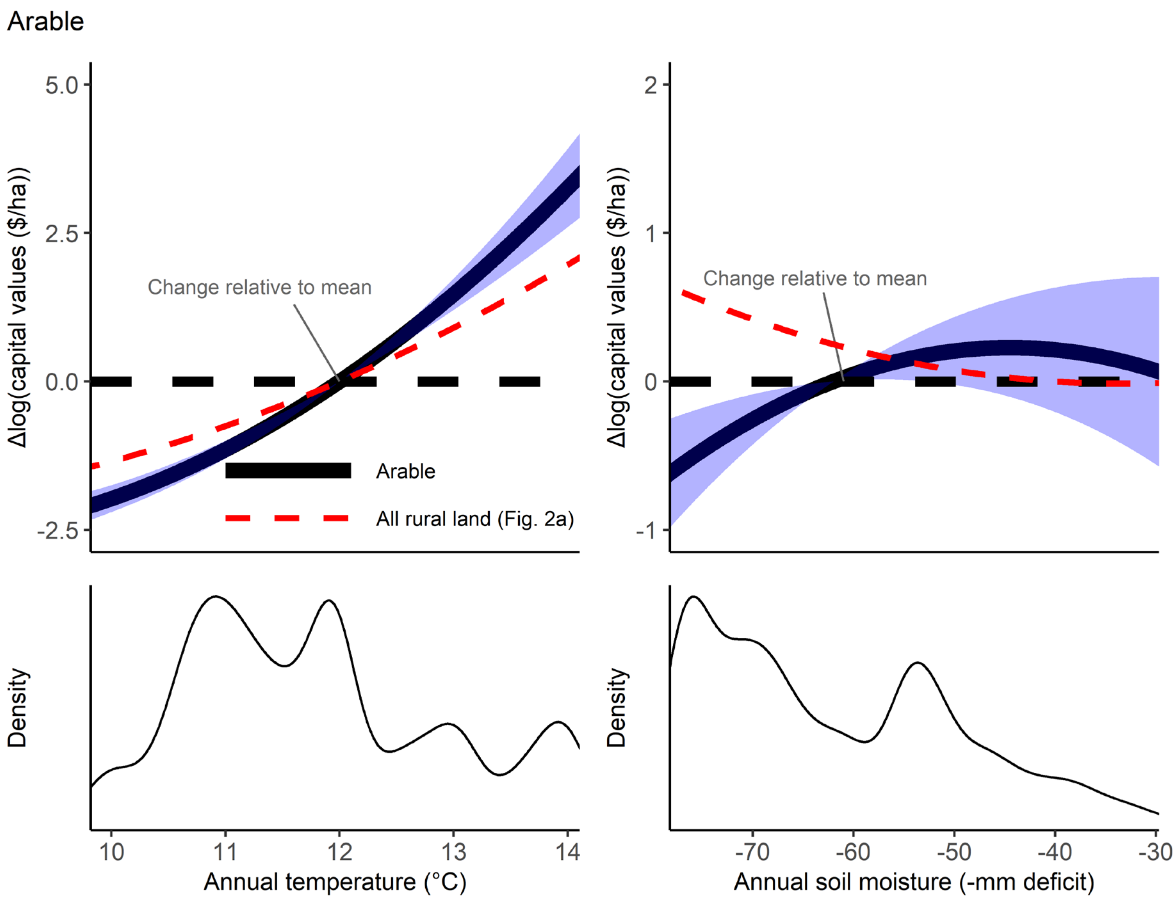

Figure 7: Capital value response to annual temperature and soil moisture for arable, 1993–2018. Quadratic SFD estimates are computed in the West–East direction. Regressions are computed on 4,922 observations. See Figure 2 for more details.

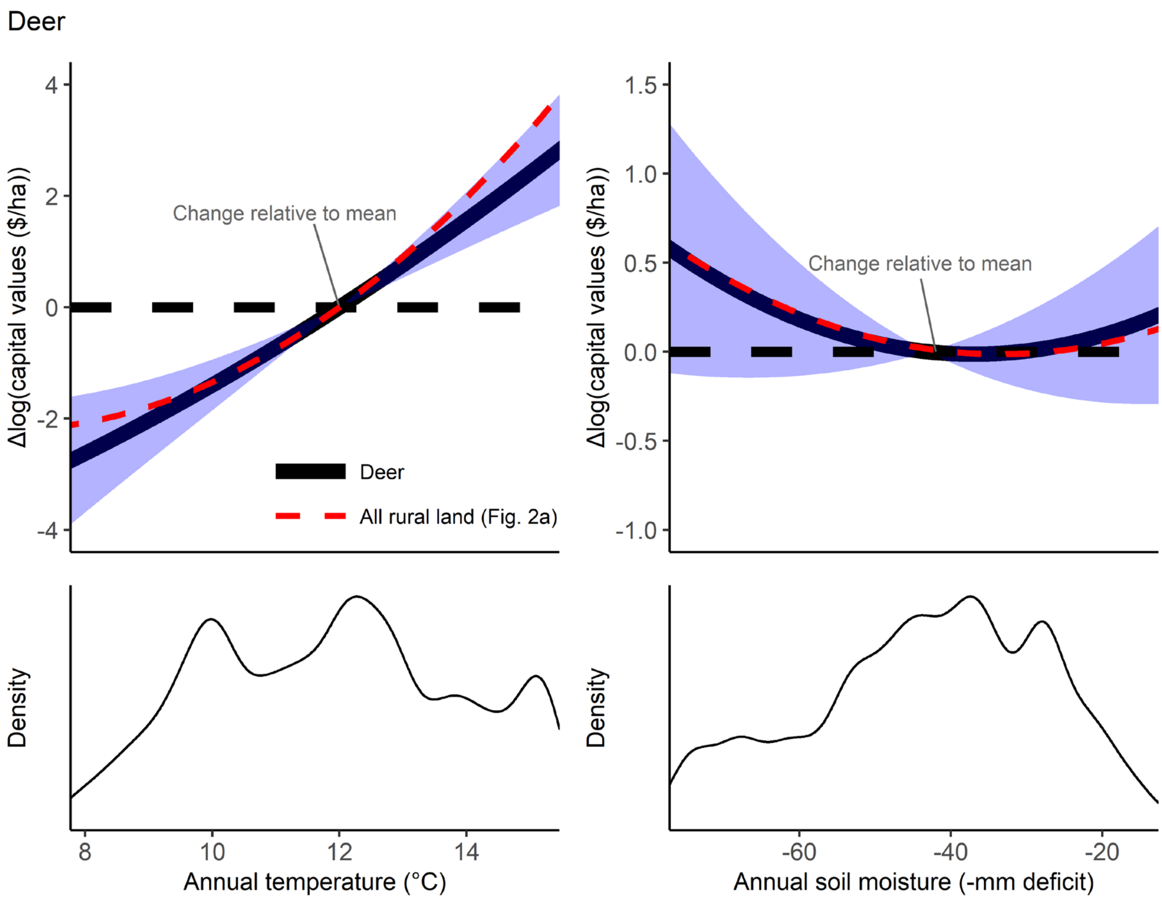

Figure 8: Capital value response to annual temperature and soil moisture for deer farming, 1993–2018. Quadratic SFD estimates are computed in the West–East direction. Regressions are computed on 7,763 observations. See Figure 2 for more details.

References

Adams, R. M. (1989). Global Climate Change and Agriculture: An Economic Perspective. *American Journal of Agricultural Economics*, *71*(5), 1272–1279. https://doi.org/10.2307/1243120

Allan, C., & Kerr, S. (2016). *Money, sunshine, and rain: Exploring the drivers of rural land values in New Zealand over time and space*. 60th Annual AARES conference, Canberra, Australia.

Auffhammer, M., & Schlenker, W. (2014). Empirical studies on agricultural impacts and adaptation. *Energy Economics*, *46*, 555–561. https://doi.org/10.1016/j.eneco.2014.09.010

Beef+lamb New Zealand. (2020). *Economic and social contribution of the New Zealand red meat industry*. https://www.mia.co.nz/assets/MIA-Publications/Economic-and-Social-Contribution-of-the-NZ-Red-Meat-Industry-Overview.pdf

Bell, K., Samarasinghe, O., Riggs, L., & Pourzand, F. (2021, May 16). *Empirical effects of drought and climate | Deep South Challenge*. Deep South Challenge | Climate Change Tools & Information. https://deepsouthchallenge.co.nz/resource/empirical-effects-of-drought-and-climate/

Blanc, E., & Schlenker, W. (2017). The Use of Panel Models in Assessments of Climate Impacts on Agriculture. *Review of Environmental Economics and Policy*, *11*(2), 258–279. https://doi.org/10.1093/reep/rex016

Bozzola, M., Massetti, E., Mendelsohn, R., & Capitanio, F. (2018). A Ricardian analysis of the impact of climate change on Italian agriculture. *European Review of Agricultural Economics*, *45*. https://doi.org/10.1093/erae/jbx023

DairyNZ. (2019). *New Zealand Dairy Statistics*. DairyNZ Economic Group. https://www.dairynz.co.nz/media/5792398/quickstats-about-dairying-new-zealand-2019.pdf

DePaula, G. (2020). The distributional effect of climate change on agriculture: Evidence from a Ricardian quantile analysis of Brazilian census data. *Journal of Environmental Economics and Management*, *104*, 102378. https://doi.org/10.1016/j.jeem.2020.102378

Deschênes, O., & Greenstone, M. (2007). The Economic Impacts of Climate Change: Evidence from Agricultural Output and Random Fluctuations in Weather. *American Economic Review*, *97*(1), 354–385. https://doi.org/10.1257/aer.97.1.354

Druckenmiller, H., & Hsiang, S. (2018). *Accounting for Unobservable Heterogeneity in Cross Section Using Spatial First Differences* (No. w25177). National Bureau of Economic Research. https://doi.org/10.3386/w25177

Fisher, A. C., Hanemann, W. M., Roberts, M. J., & Schlenker, W. (2012). The Economic Impacts of Climate Change: Evidence from Agricultural Output and Random Fluctuations in Weather: Comment. *American Economic Review*, *102*(7), 3749–3760. https://doi.org/10.1257/aer.102.7.3749

Gbetibouo, G., & Hassan, R. (2005). Measuring the economic impact of climate change on major South African field crops: A Ricardian approach. Glob Planet Chang. *Global and Planetary Change*, *47*, 143–152. https://doi.org/10.1016/j.gloplacha.2004.10.009

Hussain, S. A., & Mustafa, U. (n.d.). *Impact of Climate Change on Agricultural Land Values: An Application of Ricardian Model in Punjab Pakistan*. 28.

Kelly, D., Kolstad, C., & Mitchell, G. (2005). Adjustment costs from environmental change. *Journal of Environmental Economics and Management*, *50*, 468–495. https://doi.org/10.1016/j.jeem.2005.02.003

Kolstad, C. D., & Moore, F. C. (2019). *Estimating the Economic Impacts of Climate Change Using Weather Observations* (Working Paper No. 25537; Working Paper Series). National Bureau of Economic Research. https://doi.org/10.3386/w25537

Massetti, E., & Mendelsohn, R. (2011). *Estimating Ricardian Models With Panel Data* (No. w17101). National Bureau of Economic Research. https://doi.org/10.3386/w17101

Massetti, E., & Mendelsohn, R. (2020). Temperature thresholds and the effect of warming on American farmland value. *Climatic Change*, *161*(4), 601–615. https://doi.org/10.1007/s10584-020-02694-6

Mendelsohn, R., & Dinar, A. (2003). Climate, Water, and Agriculture. *Land Economics*, *79*(3), 328–341.

Mendelsohn, R., Dinar, A., & Sanghi, A. (2001). The effect of development on the climate sensitivity of agriculture. *Environment and Development Economics*, *6*(1), 85–101. https://doi.org/10.1017/S1355770X01000055

Mendelsohn, R., & Nordhaus, W. D. (1999). The Impact of Global Warming on Agriculture: A Ricardian Analysis: Reply. *American Economic Review*, *89*(4), 1046–1048. https://doi.org/10.1257/aer.89.4.1046

Mendelsohn, R., Nordhaus, W. D., & Shaw, D. (1994). The Impact of Global Warming on Agriculture: A Ricardian Analysis. *The American Economic Review*, *84*(4), 753–771.

Mendelsohn, R. O., & Massetti, E. (2017). The Use of Cross-Sectional Analysis to Measure Climate Impacts on Agriculture: Theory and Evidence. *Review of Environmental Economics and Policy*, *11*(2), 280–298.

Moore, F., & Lobell, D. (2014). Adaptation potential of European agriculture in response to climate change. *Nature Climate Change*, *4*, 614. https://doi.org/10.1038/nclimate2228

Ortiz-Bobea, A. (2020). The Role of Nonfarm Influences in Ricardian Estimates of Climate Change Impacts on US Agriculture. *American Journal of Agricultural Economics*, *102*(3), 934–959. https://doi.org/10.1093/ajae/aaz047

Ortiz-Bobea, A., Knippenberg, E., & Chambers, R. G. (2018). Growing climatic sensitivity of U.S. agriculture linked to technological change and regional specialization. *Science Advances*, *4*(12), eaat4343. https://doi.org/10.1126/sciadv.aat4343

Passel, S., Massetti, E., & Mendelsohn, R. (2017). A Ricardian Analysis of the Impact of Climate Change on European Agriculture. *Environmental & Resource Economics*, *67*(4), 725–760.

Porteous, A., Basher, R. E., & Salinger, M. J. (1994). Calibration and performance of the single-layer soil water balance model for pasture sites. *New Zealand Journal of Agricultural Research*, *37*(1), 107–118. https://doi.org/10.1080/00288233.1994.9513047

Pourzand, F., Noy, I., & Sağlam, Y. (2020). Droughts and farms' financial performance: A farm-level study in New Zealand. *Australian Journal of Agricultural and Resource Economics*, *64*(3), 818–844. https://doi.org/10.1111/1467-8489.12367

Quaye, F., Nadolnyak, D., & Hartarska, V. (2018). Climate Change Impacts on Farmland Values in the Southeast United States. *Sustainability*, *10*(10), 3426. https://doi.org/10.3390/su10103426

Reinsborough, M. J. (2003). A Ricardian model of climate change in Canada. *Canadian Journal of Economics/Revue Canadienne d'économique*, *36*(1), 21–40. https://doi.org/10.1111/1540-5982.00002

Schlenker, W., Hanemann, W. M., & Fisher, A. C. (2005). Will US Agriculture Really Benefit from Global Warming? Accounting for Irrigation in the Hedonic Approach. *American Economic Review*, *95*(1), 395–406.

Schlenker, W., Hanemann, W. M., & Fisher, A. C. (2006). The Impact of Global Warming on U.S. Agriculture: An Econometric Analysis of Optimal Growing Conditions. *The Review of Economics and Statistics*, *88*(1), 113–125. https://doi.org/10.1162/rest.2006.88.1.113

Schlenker, W., & Roberts, M. J. (2009). Nonlinear temperature effects indicate severe damages to U.S. crop yields under climate change. *Proceedings of the National Academy of Sciences*, *106*(37), 15594–15598. https://doi.org/10.1073/pnas.0906865106

Seo, S. N., Mendelsohn, R., & Munasinghe, M. (2005). Climate Change and Agriculture in Sri Lanka: A Ricardian Valuation. *Environment and Development Economics*, *10*(5), 581–596. https://doi.org/10.1017/S1355770X05002044

Tait, A., Henderson, R., Turner, R., & Zheng, X. (2006). Thin plate smoothing spline interpolation of daily rainfall for New Zealand using a climatological rainfall surface. *International Journal of Climatology*, *26*(14), 2097–2115. https://doi.org/10.1002/joc.1350

Tol, R. S. J. (2009). The Economic Effects of Climate Change. *Journal of Economic Perspectives*, *23*(2), 29–51. https://doi.org/10.1257/jep.23.2.29

World Development Indicators (WDI). (2018). *New Zeland landuse*. https://knoema.com/atlas/New-Zealand/Agricultural-land-area

Appendix II: Additional Results – SFD estimates for land values

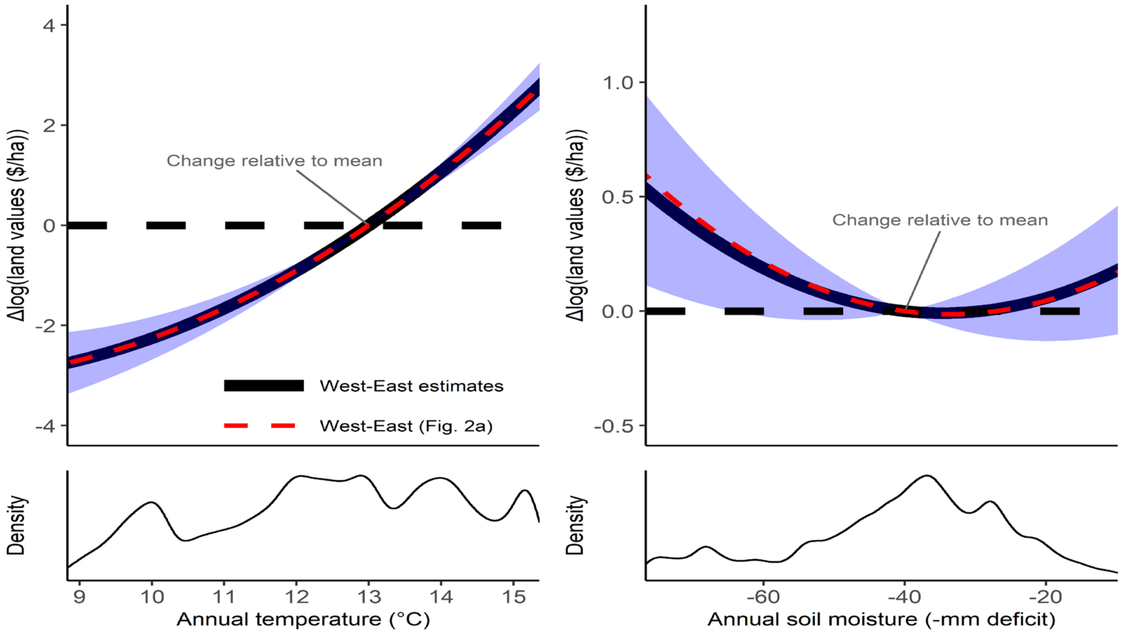

Figure A1. Land values response to annual temperature and soil moisture, 1993–2018. Quadratic SFD estimates are computed in the West-East direction. The black line is the centred predicted values which are calculated by subtracting the mean from all observations. The red dashed line is the main result, which is SFD estimates for capital land values computed in the West-East direction. The blue area shows the 95% confidence bands are centred at the mean. Histograms present the number of observations used to estimate the response function. Regressions are computed on 71862 and 71491 observations for WE and NS directions, respectively.

Appendix III: Additional Results – SFD estimates for the seasonal model

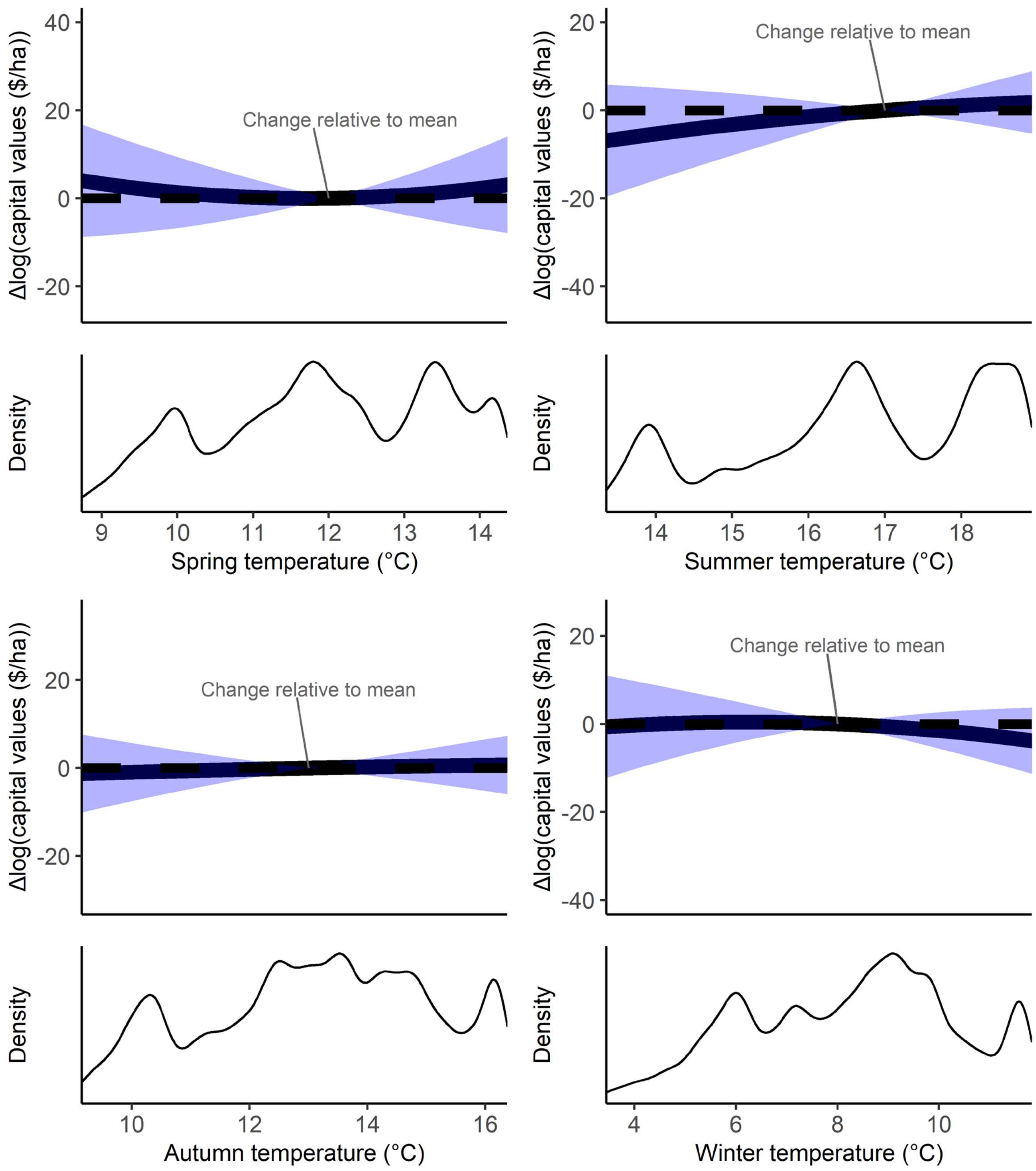

Figure A2. Capital values response to seasonal temperature, 1993–2018. Quadratic SFD estimates are computed in the West–East direction. Regressions are computed on 71862 observations. See Appendix B Figure 1 for more details.

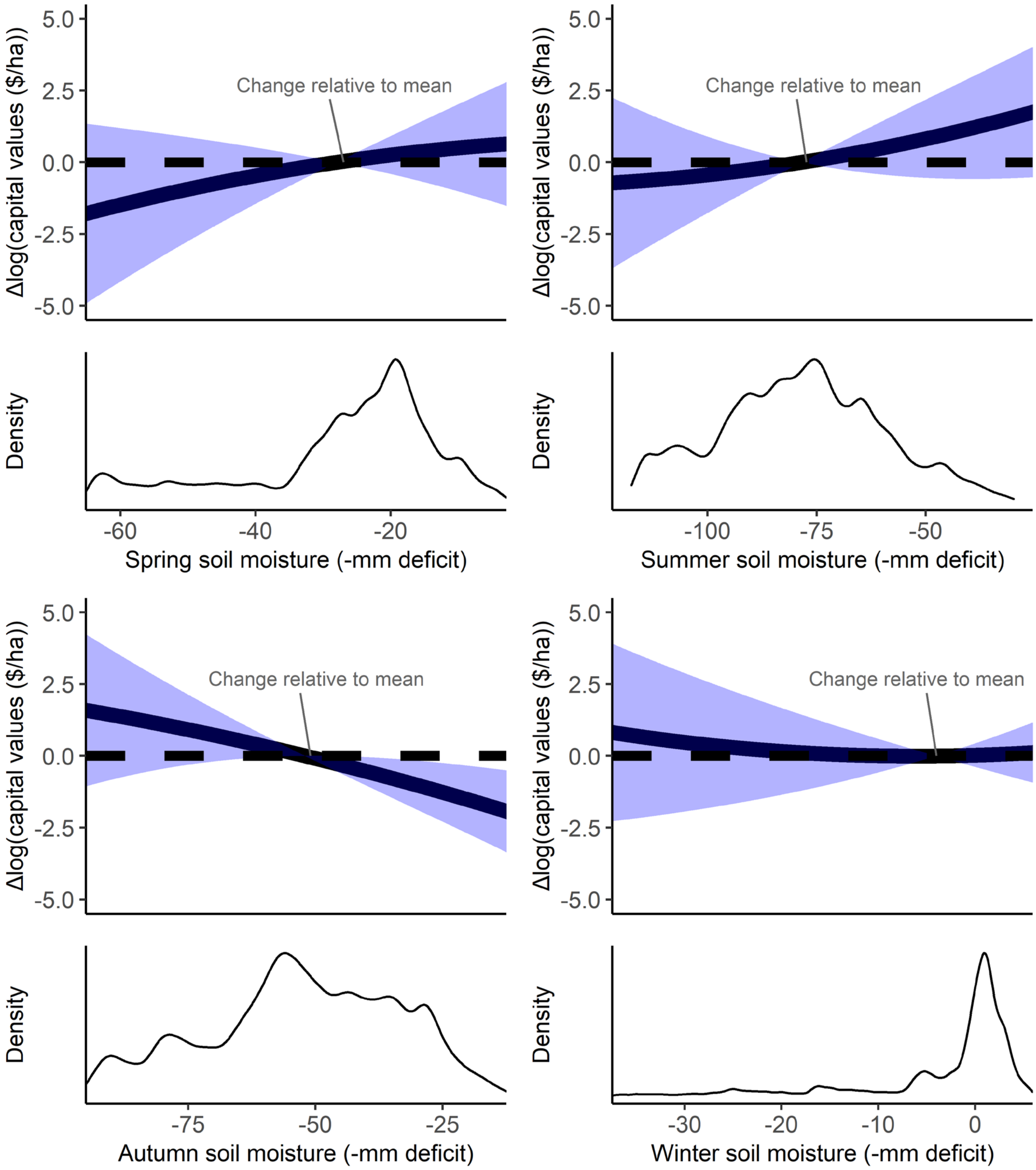

Figure A3. Capital values response to seasonal soil moisture, 1993–2018. Quadratic SFD estimates are computed in the West–East direction. Regressions are computed on 71862 observations. See Appendix B Figure 1 for more details.

Table A1: Pearson correlation matrix for differences in seasonal temperature

	ΔSpring temperature	ΔSummer temperature	ΔAutumn temperature	Δwinter temperature
ΔSpring temperature	1	0.994	0.996	0.982
ΔSummer temperature	0.994	1	0.982	0.956
ΔAutumn temperature	0.996	0.982	1	0.993
ΔWinter temperature	0.982	0.956	0.993	1

Note: differences are computed in the West-East (WE) direction.

Table A2: Pearson correlation matrix for differences in seasonal soil moisture

	ΔSpring Soil moisture	ΔSummer Soil moisture	ΔAutumn Soil moisture	ΔWinter Soil moisture
ΔSpring soil moisture	1	0.927	0.927	0.928
ΔSummer soil moisture	0.927	1	0.978	0.776
ΔAutumn soil moisture	0.927	0.978	1	0.824
ΔWinter soil moisture	0.928	0.776	0.824	1

Note: differences are computed in the West-East (WE) direction.