The Effect of Climate Change on Canadian Farmland Values: A Ricardian Approach

Nicholas Bannon *Research Assistant, Department of Food, Agricultural and Resource Economics, University of Guelph, Ontario, Canada; nbannon@uoguelph.ca*
Christopher Kimmerer *Research Assistant, Department of Food, Agricultural and Resource Economics, University of Guelph, Ontario, Canada; ckimmere@uoguelph.ca*
B. James Deaton *Professor and McCain Family Chair in Food Security, Department of Food, Agricultural and Resource Economics, University of Guelph, Ontario, Canada; bdeaton@uoguelph.ca*

ABSTRACT *This article estimates the effect of climate change on Canadian farmland values using a unique dataset of 45,000 parcel-level sales between 2017 and 2022. The parcel-level data support a regression approach with unique controls for nonagricultural influences (i.e., census division fixed effects and proximity to urban areas). Our results suggest that by 2070, climate change will positively increase farmland values across our sample of Canadian farmland parcels.* (JEL Q15, Q54)

1. Introduction

How will climate change affect the agricultural sector?[1] Given the centrality of food production to societal well-being, the answer to this question is of broad interest. Importantly, as highlighted in a recent report by the Intergovernmental Pannel on Climate Change, the effects of climate change are expected to be asymmetrical across regions (IPCC 2023). Canada, the focus of this article, is the eighth largest agricultural exporter in the world and plays an important role in global food production (AAFC 2021). Therefore, understanding the effects of climate change on the Canadian agricultural sector is an important and ongoing consideration.

We assess the effect of climate change on the Canadian agricultural sector using the Ricardian approach. Simply put, the Ricardian approach uses historical climate data to empirically assess the association between climate variables and farmland prices (Mendelsohn, Nordhaus, and Shaw 1994). This information is used to construct a counterfactual of farmland prices under various climate change scenarios. By examining the responsiveness of farmland prices to climate change, the Ricardian approach implicitly assumes that farming practices will adapt to climate change over time.

Mendelsohn, Nordhaus, and Shaw (1994) introduced the Ricardian approach in 1994 to assess the effect of climate change on the U.S. agricultural sector. Rather than assessing the specific effect of climate change on a particular crop, they used an innovative approach to assess the effect of climate change on farmland prices. By focusing the analysis on the effect of climate change on farmland prices (assumed to be determined by the discounted stream of future net returns), they argued that the Ricardian approach implicitly accounts for adaptation in the agricultural sector. Mendelsohn, Nordhaus, and Shaw's (1994) findings led them to conclude that previous estimates of the effect of climate change on the agricultural sector—for example, Adams et al. (1988) or Cline (1992)—overstate the damages of climate change. This is because the method used in the earlier studies (the production-function approach) presumes that farmers persist in planting a particular crop,

[1] In this context, the definition of climate change is similar to that used by the IPCC (2023) and refers to natural internal processes and external forces (such as anthropogenic change) that result in identifiable changes in mean climate conditions over extended periods. This article uses 30-year average weather conditions to refer to historical climate. Future climate change scenarios are based on climate forecasts for the 30-year period between 2041 and 2070.

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rather than adapting farm practices as climate changes.[2]

Since 1994, the Ricardian approach has been applied to assess the effect of climate change on farmland prices throughout the world and frequently in the United States (De Salvo, Diego, and Giovanni [2014] provide a comprehensive overview of this research). Three published studies apply the Ricardian approach to Canadian farmland values: Mendelsohn and Reinsborough (2007), Reinsborough (2003), and Weber and Hauer (2003). The few Canadian studies stand in sharp contrast with the more numerous studies that examine this topic in the United States (e.g., Mendelsohn, Nordhaus, and Shaw 1994, 1996; Schlenker, Hanemann, and Fisher 2005, 2006, 2007; Deschênes and Greenstone 2007, 2012; Massetti and Mendelsohn 2011; Fisher et al. 2012; Severen, Costello, and Deschênes 2018; Ortiz-Bobea 2020).

Some of this literature has been critical of the Ricardian approach, which uses farmland prices and historic climate as the key dependent variable and explanatory variables, respectively. For example, Deschênes and Greenstone (2007), like Ortiz-Bobea (2020), are concerned about omitted variables and functional form assumptions associated with the canonical Ricardian approach.[3] Their research suggests alternative dependent variables—farm profits (Deschênes and Greenstone 2007) and rental rates (Ortiz-Bobea 2020)—and alternative measures of key explanatory variables (e.g., short-term weather; Deschênes and Greenstone 2007). These studies include estimates of the hedonic model and are conducted in the United States at the county level.

Although we do not resolve this tension in the literature, some novel features of our analysis are that the price observations are at the parcel level and the focus of our study is Canada. Despite Canada and the United States sharing a border and other similarities, U.S. Ricardian studies cannot substitute for Canadian-specific studies. This point is underscored by Mendelsohn and Reinsborough (2007), who use the Ricardian approach on a joint estimate of farmland values in Canada and the United States and find that the association between climate and farmland prices differs between these countries. They find that Canadian farm prices are less responsive to warmer temperatures compared with U.S. farm prices. They anticipate this outcome because Canadian farms are "generally cooler and drier than American farms" (Mendelsohn and Reinsborough 2007, 1).

One important contribution of this work is to use the Ricardian approach to provide a more recent application of the Ricardian approach in Canada (the last Canadian study was published in 2007). Our study addresses a tension in the previous Canadian applications of the Ricardian approach. Specifically, Reinsborough (2003) estimates statistically insignificant aggregate impacts of climate change. In contrast, Weber and Hauer (2003) estimate a positive and rather large impact of climate change on farmland prices. By 2050, Weber and Hauer (2003) project a 65% (or $1,485/ha) increase in Canadian farmland values attributable to climate change.

A second contribution of this article is our application of the Ricardian approach using parcel-level observation of farmland sales. In contrast to previous literature, which generally relies on observations aggregated to the census or county level, we use more than 45,000 price revelations at the farmland parcel level. The spatial scale of data used in Ricardian studies is important to consider because differences in the empirical findings of two previous Canadian applications of the Ricardian approach were attributed to differences in the granularity of the observational unit. Specifically, with respect to the effect of climate change on farmland prices in Canada, Reinsborough (2003) uses only 267 data points (at

[2] When considering static production decisions, Adams et al. (1988) and Cline (1992) estimate annualized damages of $6–$33 billion and $20 billion per year, respectively, on U.S. farmland values resulting from climate change. Comparatively, Mendelsohn, Nordhaus, and Shaw (1994) estimated annualized impacts ranging from $8 billion in damages to $2 billion in benefits to farmland values using the Ricardian approach.

[3] Deschênes and Greenstone (2007) advance discussions of panel studies and U.S. climate impacts. Recent works include Mérel and Gammans (2021) and Mérel, Paroissien, and Gammans (2024).

the census division level) and finds a positive, statistically insignificant effect. Weber and Hauer (2003) use 3,665 data points (at the census subdivision level) and find a substantial, positive, statistically significant effect.[4] Weber and Hauer (2003) argue that the difference in the results between their study and Reinsborough (2003) is explained by differences in the spatial scale of the data. Weber and Hauer (2003) argue that the coarse data used by Reinsborough (2003) fails to adequately model variation in climate and farmland prices. Their argument is consistent with Fezzi and Bateman (2015), who suggest that Ricardian models suffer from aggregation bias when data are aggregated to county levels. We apply the Ricardian approach to a uniquely granular dataset of farm parcel–level transactions, which allows us to use a downscaled 1 km gridded climate dataset and address concerns regarding aggregation bias.

A third contribution of this article is that our empirical approach controls for the potential omitted variable bias arising from nonagricultural influences. Reinsborough (2003) and Weber and Hauer (2003) used data from the Canadian Census of Agriculture measuring the per-acre value of farmland and buildings. Because census data are coarsely aggregated, it is not possible to tell what portion of the value is associated with farmland versus buildings, which may lead to an omitted variable problem. A unique feature of our dataset is that it is at the parcel level, and the land use of each parcel is clearly specified. Therefore, we are able remove parcels with buildings on them and only include land classified as cultivated, fruit or pasture. In addition, because of the granularity of our dataset, we are able to control for fixed effects at the census division level and include proximity measures from parcels to the nearest urban center with a population equal to or greater than 90,000.[5] The application of the Ricardian approach in this article addresses previous concerns regarding omitted variable basis and incorporates a novel proximity variable across a pooled sample of farmland parcel transactions between 2017 and 2022.[6]

2. Methodology

The Ricardian Approach: Climate and Nonagricultural Uses of Farmland

The Ricardian approach assumes that farmers are profit-maximizing and that their land use decisions reflect the most profitable land use. As the climate changes, farmers are assumed to alter their production practices (including their use of land and crop choice) to maximize the present value of net returns. This adaptive process is assumed to be reflected in the future stream of net returns associated with farmland, which are in turn revealed in the price of farmland. In their seminal article, Mendelsohn, Nordhaus, and Shaw (1994) provide a useful example of how a wheat farmer adapts to higher temperatures by planting corn when changing temperatures allow it to become more profitable than wheat. By focusing on the relationship between climate change

[4] The positive effect of climate change on Canadian farmland values estimated by Weber and Hauer (2003) is generally consistent with the literature examining farming and farmland in northern regions of the world. For example, Mendelsohn, Nordhaus, and Shaw (1994) project increases in farmland prices due to climate change of upward of $1,300 per acre (in 1985 dollars) in many northern latitude U.S. counties. Van Passell, Massetti, and Mendelsohn (2017) project farmland value increases of upward of 500% for some areas of northern Europe, such as Sweden, due to climate change. These findings are consistent with more general literature where Canada is often considered a "net winner" due to climate change. For example, Hannah et al. (2020) project increases in farmland area in Canada, and Rosenzweig and Parry (1994) expect productivity increases from climate change. Our empirical findings (i.e., that climate change is expected to have a positive effect on Canadian farmland values) are consistent with this emergent theme.

[5] A census division is the Canadian equivalent of a U.S. county. The 90,000-population threshold was chosen because Statistics Canada defines a large urban population center as a population center with a population of 100,000 or more, but this definition excludes important regional centers such as Thunder Bay, Ontario.

[6] Massetti and Mendelsohn (2011) argue that estimates generated from Ricardian models using a pooled dataset are more robust compared with models that only use a single year cross section of data. Unlike Massetti and Mendelsohn (2011), we do not have a panel dataset, as there are few repeat sales between 2017 and 2022. However, we include year fixed effects in our pooled cross section approach.

and farmland prices, the Ricardian approach implicitly incorporates adaptivity. This stands in sharp contrast to a static production-function approach that examines how climate change affects the returns to a specific crop.

Authors often rely on the capitalization model to illustrate specific dimensions of the Ricardian approach (see Ortiz-Bobea 2020; Bareille and Chakir 2023). We emphasize the effect of climate and nonagricultural uses of farmland (e.g., residential housing). The capitalization model is

$$LV_t(l, c_t) = \sum_{t=0}^{\infty} \frac{R_{u,t}(p, w, l, c_t)}{(1+\gamma)^t}, \quad [1]$$

where LV_t corresponds to farmland values at time t, $R_{u,t}$ is the rental price from using the most profitable land use (u) at time t, p and w are input and output prices, l is a measure of specific land attributes, c_t is a vector of climatic conditions at time t, and γ corresponds to a discount rate.

Emphasizing the importance of nonagricultural influences on land values, Ortiz-Bobea (2020) extends equation [1] to consider the influence of nonagricultural influences on land values. In its simplest form, Ortiz-Bobea (2020) describes farmland values as a weighted average between farm and nonfarm components. The weight is represented by the function $a(t^*)$, which identifies the optimal time, t^*, for conversion from farm to nonfarm use. Equation [2] details this equation and, similar to Ortiz-Bobea (2020), omits the discount rate for clarity:

$$LV_t(l, c_t) = a(t^*) LV_t^F(t^*, l, c_t) + [1 - a(t^*)] LV_{t^*}^N(\infty, l, c_t). \quad [2]$$

When conversion from agricultural to nonagricultural land use is distant ($t^* \rightarrow \infty$) and ($a(t^*) \rightarrow 1$), prices will equal the farm use component (LV_t^F). Similarly, when conversion from agricultural to nonagricultural land use is imminent ($t^* \rightarrow 0$) and ($a(t^*) \rightarrow 0$), price will equal the nonfarm component $\left(LV_t^N\right)$. Importantly, this means that Ricardian estimates must consider the influence of nonagricultural benefits on farmland values. For this reason, our Ricardian model includes novel control variables for nonagricultural influences.

3. Empirical Approach

Stage 1: Hedonic Regression

We estimate the relationship between climate variables and farmland values using a pooled dataset spanning six years.[7] Our regression framework closely resembles the pooled model approach used by Sanghi and Mendelsohn (2008) and Bareille and Chakir (2023). Equation [3] describes the hedonic regression used to estimate the climate coefficients:

$$\ln\left(LV_{i\,m\,p}\right) = \beta' C_{i\,m\,p} + \theta' Q_{i\,m\,p} + \lambda' N_{m\,p} + \alpha' D_{i,m,p} + Y^{FE} + M^{FE} + P^{FE} + u_{i,m\,p}. \quad [3]$$

$LV_{i\,m\,p}$ represents the per-acre sale price of a parcel of farmland i, in county m and in province p. The matrix C includes climate characteristics for seasonal temperature and precipitation, while Q and N represent matrices for quality characteristics of the farmland and nonagricultural variables. Quality characteristics include measures for soil quality and slope. Nonagricultural variables include population density and median income at the census subdivision level. D represents the distance of a parcel to the nearest population center of 90,000 people or more.[8] M and P correspond to census division level and provincial-level fixed effects, respectively. Results are presented for models that use only census division fixed effects, provincial fixed effects, and no fixed effects (referred to as the base model). Y represents year fixed effects and indicates which calendar year the transaction occurred. Last, u corresponds to unobservables at the parcel, census division, and provincial levels. β', θ', λ', and α' are all sets of parameters to be estimated.

[7] All previous Canadian studies used a single-year cross section of farmland values.

[8] We provide results with and without a linear and quadratic term of the proximity variable.

Following previous studies, the per-acre value of farmland is log-transformed (Schlenker, Hanemann, and Fisher 2007; Massetti and Mendelsohn 2011; Van Passel, Massetti, and Mendelsohn 2017).[9] In addition, we include seasonal climate variables measuring historical climate conditions in January, April, July, and October. Seasonal precipitation and temperature measures were selected over alternative climate measurements, such as growing degree days, because they better capture the effect of climate on farmland values outside of the growing season (Massetti, Mendelsohn, and Chonabayashi 2016).[10] In addition to a linear term, climate variables include a squared term to capture nonlinearities. Including seasonal climate variables in linear and quadratic form is consistent with previous studies (see De Salvo, Diego, and Giovanni 2014, table 1).

Stage 2: Aggregate Impacts

The second stage of the Ricardian approach seeks to estimate the aggregate impacts of climate change on farmland values by multiplying the climate coefficient estimates from the first stage by the difference between historical and projected climate data. When Mendelsohn, Nordhaus, and Shaw (1994) first introduced this approach, the estimated coefficients were multiplied by a uniform climate change scenario. Other studies, including Canadian studies like Reinsborough (2003) and Weber and Hauer (2003), used a similar approach to determine aggregate impacts.

Rather than multiplying the estimated climate coefficients from stage 1 by a uniform climate change scenario, the strategy used here involves subtracting the predicted historical farmland value from the predicted future value. The predicted historical price uses the coefficient estimates from stage 1 and multiplies them by the historical value for each covariate. The predicted future price uses the same coefficient estimates but changes only the values of the climate variables (based on downscaled 1 km gridded climate projections), while keeping the values for the control variables constant. This allows for the estimate of the expected change in farmland values to be the result of changes in only the climate variables.

This procedure also allows for the impacts to be determined at the parcel level and then averaged across the whole sample. The granularity of the dataset and the availability of climate forecasts at high spatial resolutions make this procedure possible and enables an examination of regional impacts in addition to Canada-wide impacts. Equation [4] shows the calculation used to determine the expected per-acre change in farmland values resulting from climate change for each parcel in the sample:

$$\Delta LV_i = \exp\left(FV_i\right)\times\exp\left(\left(\frac{RMSE^2}{2}\right)\right) - \exp\left(HV_i\right)\times\exp\left(\left(\frac{RMSE^2}{2}\right)\right), \qquad [4]$$

where ΔLV_i corresponds to the change in land values for parcel i. FV_i corresponds to the predicted future log value of parcel i, and HV_i corresponds to the predicted historical log value of parcel i. $RMSE$ is the root mean squared error, which estimates the error variance. This adjustment is needed because the error terms only have a mean of zero in log units. Simply exponentiating the predicted dependent variable would result in predictions of farmland values that are systematically underestimated (Newman 1993; Wooldridge 2009).

4. Data

The dataset used in this article is derived from several sources with information on farmland values, historical climate, climate forecasts,

[9] This transformation is necessary because land values are log-normally distributed, with the median per-acre price below the mean price (Palmquist and Danielson 1989; Nickerson and Lynch 2001).

[10] Growing degree days measure the sum of degrees that the mean temperature on a given day is above a certain temperature threshold. Because this measurement acts as a benchmark for whether the temperature is warm enough to support plant growth, it does not measure temperature outside of the growing season, which has been shown to influence farmland values (Massetti, Mendelsohn, and Chonabayashi 2016).

Table 1
Statistics for Farmland Sales Data

	2017	2018	2019	2020	2021	2022	Total
Mean							
Total (Can$)	578,900	507,687	425,418	457,303	517,767	582,647	507,874
Price/acre (Can$)	10,836	8,920	8,142	9,743	11,671	11,300	10,176
Acres	153	117	96	95	98	99	106
SD							
Total (Can$)	860,079	693,685	601,353	639,455	882,670	977,641	793,251
Price/acre (Can$)	37,839	24,482	25,101	31,319	37,239	41,941	33,872
Acres	251	144	102	75	106	71	128
Median							
Total (Can$)	347,700	290,000	243,861	263,755	275,000	322,000	286,000
Price/acre (Can$)	2,924	2,747	2,500	2,758	2,800	3,118	2,807
Acres	100	97	95	94	95	95	95
Observations	5,097	6,297	7,860	8,294	10,034	8,124	45,706

soil quality, and socioeconomic characteristics. We provide an overview of the various data sources and summary statistics for the data discussed. Appendix Table A1 gives a definition for each variable in the empirical analysis.

Farmland Values

Our unique parcel-level information on farmland prices and attributes is obtained from Canada's largest agriculture and agri-food lender, Farm Credit Canada (FCC).[11] This dataset contains all of FCC's market sales transactions between 2017 and 2022. For each transaction there is information about the farmland parcel, including the total price, price per acre, latitude and longitude coordinates, land size, land use, and irrigation status. If the sale includes only a single parcel, the per-acre value represents the total sale price divided by the total number of acres. However, it is common for a single sale to include multiple land uses, such as using some land for cultivation and some for pasture. In these cases, the sale is broken up into multiple parcels and the per-acre price represents an assessed value calculated by an FCC appraiser and based on local market conditions. In total, 76% of the parcel observations are for sales that include multiple parcels.[12] In addition, some sales include parcels with buildings or are potentially used for nonagricultural purposes. Although the value associated with the land is separated from the building value, our approach limits the sample to only land classified by FCC as cultivated, fruit or pastureland. After removing observations with incomplete data and non–arm's length transactions and restricting the sample to ensure that the data were representative of true market values, the final dataset included 45,706 parcel observations.[13]

Table 1 provides summary statistics for these observations and presents farmland values in nominal dollars.[14] The sample represents farmland parcels that were purchased or sold through FCC. The sales prices in the dataset are higher than the average per-acre price of farmland published by Statistics Canada. For

[11] We created a data-sharing relationship with FCC. We are able to provide data (that cannot be identified by geography) for replication. The dataset is available at https://doi.org/10.5683/SP3/NCEIJ1. All requests to access the replication dataset will be reviewed by the data request manger to ensure they are for replication.

[12] This figure includes parcels not included in the regression, since transactions could be made up of parcels used for multiple purposes (e.g., cultivated land and rural residential land).

[13] These restrictions include removing observations with a per-acre value of less than $5, less than one acre in size, removing any non–arm's length transactions (meaning sales that occurred between buyers and sellers who have a relationship with each other), and removing parcels with identical latitude and longitude coordinates.

[14] The summary statistics are presented in nominal dollars for ease of interpretation. However, the values used in the regression are converted to 2017 Canadian dollars using the consumer price index–all items (Statistics Canada 2023b).

example, for 2022, the average per-acre price of farmland in our dataset is $11,300 compared with the Statistics Canada published value of $4,527 (Statistics Canada 2023b).

Throughout North America, only a small portion of farms are responsible for the bulk of agricultural production. In Canada, the largest 10% of Canadian farms are responsible for more than two-thirds of all revenue (AAFC 2021). The higher prices in the FCC dataset likely reflect the relatively more productive Canadian farmland, which is actively engaged in generating farmland revenue. In addition, the 2017 mean per-acre price is higher than the 2018 mean, which does not accord with Statistics Canada trends. For this reason, we provide pooled results and results for each cross section. We examine sensitivity in our aggregate effects for pooled results with and without observations from 2017 in Appendix Table A7. As expected, our results are qualitatively robust across these different specifications.

Historical Climate Data

Historical weather data from 1985 to 2021 was extracted at a downscaled 1 km^2 spatial resolution using the ClimateNA software (Wang et al. 2016; Mahony et al. 2022). ArcGIS software was used to match the location of each farmland parcel with the respective historical downscaled weather data that account for geological features that can affect weather, such as elevation. We follow the approaches outlined in previous literature (e.g., Mendelsohn, Nordhaus, and Shaw [1994] and all previous Canadian studies) and construct 30-year climate normals for each year between 2017 and 2022. For instance, the 2022 climate-normal consists of the average weather conditions between 1992 and 2021. Specifically, climate variables used in this study measure average precipitation and temperature for January, April, July, and October.

Climate Forecasts

Forecasts about future climate conditions for the same monthly precipitation and temperature variables were obtained through AdaptWest's database (Wang et al. 2016; AdaptWest Project 2022; Mahony et al. 2022). AdaptWest generates an ensemble climate forecast at a 1 km^2 spatial resolution using the ClimateNA software by downscaling data from projections based on the sixth IPCC report (Wang et al. 2016; AdaptWest Project 2022; Mahony et al. 2022). A unique feature of our dataset is that both the historical and the climate data are already appropriately downscaled.

The downscaled data prevent aggregation bias that arises when using gridded historical climate data and coarse spatial data from general circulation models (GCMs) (Auffhammer et al. 2013). To address concerns regarding aggregation bias (i.e., Auffhammer et al. 2013), previous Ricardian studies add the difference between GCM-predicted historical climate and observed historical climate to the coarse GCM predictions of future climate (e.g., Fisher et al. 2012; Severen, Costello, and Deschênes 2018). Our dataset is generated by ClimateNA software, which uses historical baseline climate data to downscale both historical and future climate variables and thereby harmonizes subregional variation in climate between parcels for both historical and future periods (Wang et al. 2016; Mahony et al. 2022).

Auffhammer et al. (2013) raised concerns about climate researchers selecting one GCM over alternatives. They argue that there is little evidence that one model should be preferred over others. Our climate forecasts are generated by calculating the ensemble mean of different GCMs for various emissions scenarios. Specifically, we present results using the ensemble mean of 13 GCMs under the Shared Socioeconomic Pathway (SSP) 2-4.5 scenario for 2041–2070.[15] The SSP2-4.5 scenario is considered the "middle of the road" scenario, where CO_2 emissions following their historical patterns and do not shift considerably until the second half of the century (Riahi et al. 2017). Table 2 provides summary statistics for historical and predicted climate data.

[15] We consider the sensitivity of our results to alternative climate scenarios in the Appendix. However, we find no substantive changes in our results.

Table 2
Historical and Predicted Climate Data Statistics

	Mean	SD	Median
Historical precipitation (mm)			
January	39.8	35.8	21.4
April	45.0	27.3	29.2
July	74.5	19.2	76.0
October	49.2	35.7	32.2
Historical temperature (°C)			
January	−11.2	4.8	−12.2
April	4.6	1.7	4.2
July	18.5	1.6	18.5
October	5.7	2.5	4.9
Future precipitation (mm)			
January	43.6	36.0	25.0
April	46.7	26.8	33.0
July	72.1	20.2	72.0
October	44.1	32.1	30.0
Future temperature (°C)			
January	−9.9	5.1	−11.1
April	6.8	1.8	6.3
July	21.2	1.7	21.4
October	9.0	2.0	8.5

Note: Future climate variables are based on the SSP2-4.5 scenario for 2041–2070.

Distance to Nearest Population Center

To provide improved controls for nonagricultural related influences on farmland values, a proximity variable measuring the distance of a parcel to the nearest Canadian population center of 90,000 or more inhabitants as of 2016 was created.[16] Because conversion of farmland to nonagricultural uses is likely inversely related to the distance from a population center, the proximity variable controls for nonagricultural influences on farmland values (Chicoine 1981).

The proximity variable is a novel aspect of the dataset and is derived from the unique information regarding the precise latitude and longitude coordinates of each parcel. The near analysis feature in ArcGIS was used to create distance polygons at 10 km intervals for each population center with 90,000 or more inhabitants. The polygons were overlaid with the location of the parcels to determine the distance to the nearest population center.[17] The regression uses the midpoint of each bin to create a continuous variable. For example, for the bin defined as 10–20 km from the nearest population center, the value used in the regression is 15 km. Table 3 provides summary statistics for selected control variables, including the proximity variable.

Table 3
Statistics for Selected Control Variables

	Mean	SD	Median
Census subdivision median income (Can$)	37,437	6,312	37,675
Census subdivision population density (pop/km^2)	31.6	137.1	1.6
Proximity variable (km)	178	155	135

Note: The proximity variable measures the distance by road to the nearest population center with a population of 90,000 or more.

Soil Quality

To account for heterogeneity in land quality, soil quality and composition data from the Canadian National Soil Database (NSDB) was matched with farmland price data (AAFC 2013). A circular buffer (with the same area of each farmland parcel) was created to intersect the farmland parcel with a map of soil polygons published by the NSDB. The buffer for each parcel was overlaid with the soil polygon map to determine the soil characteristics and components of a particular parcel. In some cases, the parcel buffer intersected multiple soil polygons. For these occurrences, a weighted average of the soil polygons was used based on the percentage of the buffer intersecting each polygon.

Socioeconomic Data

Following previous Ricardian studies, data were collected from the Canadian Census of Population on median income and population density at the census subdivision level. The Canadian Census of Population is conducted every five years, with the most recent version containing 2021 values. This article merges

[16] The distance is calculated from the center of the parcel to the center of the nearest population center. In some cases, it was not possible to place a parcel into a distance polygon because it is not accessible by a road network. For these, the distance from the parcel to the road network boundary was added to the midpoint of the distance bin.

[17] In total, 36 population centers met the 90,000 or more threshold; see Appendix Table A2 for the full list.

2021 census data with farmland sales occurring in 2021 and 2022 (Statistics Canada 2023a). The remaining sales data are merged with the 2016 census data (Statistics Canada 2019).

5. Results

Marginal Effects of Climate on Farmland Values

The discussion of the results emphasizes the results from the pooled model. For completeness, we provide results using yearly cross sections with county fixed effects in Appendix Table A5. Table 4 provides selected coefficient estimates across six pooled models with robust standard errors.[18] Models 1 and 2 include census division fixed effects, models 3 and 4 include provincial fixed effects, and models 5 and 6 include no geographic unit fixed effects. Hereafter, models 5 and 6 are referred to as "base" models. Models 2, 4, and 6 include a linear and a squared term of the proximity variable.

Table 5 presents estimates of the marginal effect for the climate variables in different model specifications. These effects account for the marginal effect of the linear and squared terms of each climate variable on farmland values. The following equation is the marginal effect calculation:

$$\frac{\partial LV}{\partial C_i} = \beta_1 + 2\beta_2 C_i, \quad [5]$$

where C_i is the value of the individual climate variable, β_1 is the estimated coefficient for the linear term, and β_2 is the estimated coefficient for the quadratic term. For additional ease of interpretation, equation [5] is evaluated at the mean of each climate variable and multiplied by 100.[19] For example, the estimated marginal value of April temperature in model 2 is 28.34, implying that 1°C increase in April temperature above the historical sample average would result in a 28.34% increase in farmland values.

Similar to Mendelsohn and Reinsborough's (2007) model for Canada, the results in Tables 4 and Table 5 show a positive association between farmland values and temperature and precipitation, meaning that for a uniform one-unit increase in temperate and precipitation across all seasons, the aggregate impact on farmland values is positive. Consistent with findings from Reinsborough (2003) and Weber and Hauer (2003), warming in April is associated with positive increases in farmland values. This result may reflect the benefits of a longer growing season. Last, for all models in Table 5, the marginal value of October precipitation is negative. Weber and Hauer (2003) obtained a similar result and argue that the harmful marginal value of October precipitation could be explained by an increase in frost risk due to wet weather during harvest.

Models 2, 4, and 6 include a linear and squared term of the proximity (in kilometers) of each parcel to the nearest population center. Across all models where it was included, the coefficient estimate for the linear term of proximity variable is negative and statistically significant. The quadratic term is positive and statistically significant across all models, implying that the negative effective decreases as proximity to a population center increases. This observation is consistent with expectations of farmland values being inversely related to the distance to a population center (e.g., the farther a parcel is from a population center, the lower its value, up to a certain threshold).

Table 4 confirms that the proximity variable is statistically significant and negatively associated with the price of farmland. By this measure, farms farther from population centers of 90,000 are associated with lower prices.[20] Hence, as previous literature discusses,

[18] Although our sample is only a subset of the population of Canadian farmland, we observe all of FCC sales between 2017 and 2022 and examine marginal and aggregate effects of climate change across the sample of sales only. We do not extrapolate our results to all of Canada; rather, they serve as a benchmark for future studies. Thus, clustered standard errors, or adjusting for spatial dependence, was deemed to result in unnecessarily large standard errors (Abadie et al. 2022). For completeness, we provide regression results with standard errors adjusted for spatial dependence following Conley (1999) at a 200 km radius in Appendix Table A3. Complete regression results are in Appendix Table A4.

[19] Individual climate means were calculated corresponding to the sample size in each model.

[20] We explored alternative definitions of a population center (e.g., populations of 30,000 or more) and found similar results.

Table 4
Selected Coefficient Estimates

	Census Division Fixed Effects		Provincial Fixed Effects		Base	
	(1)	(2)	(3)	(4)	(5)	(6)
Temperature (°C)						
January	25.678***	30.160***	47.401***	36.551***	30.999***	23.449***
	(1.933)	(1.898)	(1.218)	(1.213)	(1.154)	(1.177)
January squared	1.253***	1.466***	1.989***	1.571***	1.442***	1.151***
	(0.076)	(0.076)	(0.051)	(0.050)	(0.051)	(0.053)
April	23.415***	24.171***	16.225***	11.484***	11.099***	7.277***
	(3.622)	(3.558)	(2.198)	(2.150)	(2.062)	(2.092)
April squared	0.845*	0.458	0.685**	1.353***	1.837***	2.359***
	(0.338)	(0.332)	(0.229)	(0.224)	(0.210)	(0.209)
July	−75.489***	−74.964***	−129.814***	−118.521***	−112.564***	−117.735***
	(11.626)	(11.214)	(8.496)	(8.208)	(8.212)	(8.090)
July squared	1.916***	2.083***	3.722***	3.364***	2.782***	2.854***
	(0.325)	(0.313)	(0.245)	(0.237)	(0.240)	(0.235)
October	29.544***	16.803***	78.684***	45.820***	96.737***	75.814***
	(3.470)	(3.445)	(2.499)	(2.563)	(2.570)	(2.627)
October squared	−3.032***	−2.440***	−6.831***	−4.826***	−6.650***	−5.334***
	(0.276)	(0.271)	(0.166)	(0.170)	(0.167)	(0.172)
Precipitation (mm)						
January	0.655**	0.521**	2.522***	2.279***	2.257***	2.110***
	(0.207)	(0.197)	(0.144)	(0.136)	(0.120)	(0.120)
January squared	−0.002	−0.001	−0.011***	−0.010***	−0.009***	−0.008***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
April	2.307***	2.254***	0.937***	0.834***	2.755***	2.036***
	(0.264)	(0.261)	(0.202)	(0.206)	(0.197)	(0.205)
April squared	−0.009***	−0.009***	0.000	−0.000	−0.005**	−0.003
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
July	3.231***	1.742***	3.978***	2.235***	2.672***	1.451***
	(0.320)	(0.320)	(0.163)	(0.168)	(0.157)	(0.165)
July squared	−0.020***	−0.012***	−0.018***	−0.013***	−0.006***	−0.003**
	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
October	−1.491***	−0.749**	−3.074***	−1.985***	−3.039***	−1.824***
	(0.249)	(0.247)	(0.169)	(0.167)	(0.154)	(0.159)
October squared	0.002	-0.000	0.011***	0.008***	0.005***	0.002
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Distance (km)						
Distance		−0.283***		−0.214***		−0.183***
		(0.011)		(0.006)		(0.006)
Census subdivision controls	Yes	Yes	Yes	Yes	Yes	Yes
Soil quality controls	Yes	Yes	Yes	Yes	Yes	Yes
Census division fixed effects	Yes	Yes				
Provincial fixed effects			Yes	Yes		
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	45,552	45,552	45,706	45,706	45,706	45,706
R-squared	0.803	0.807	0.732	0.742	0.714	0.722

Note: Coefficients and standard errors are multiplied by 100. Robust standard errors are in parentheses. Models 1 and 2 omit census divisions with less than 10 observations. The coefficient estimates (× 100) of the squared distance variables in columns (2), (4), and (6) are 0.000130, 0.000118, and 0.000107, respectively, and all are significant at the 99.99% level.
* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

omitting variables relating to nonagricultural influences could potentially bias Ricardian estimates of the association between climate and farmland prices. (The bias would depend on the correlation between climate measures and urban proximity measures.) Table 5 compares models that include and omit the proximity measure. Generally these results indicate that including the urban proximity variable mainly influences the magnitude of

Table 5
Marginal Impacts of Climate on Farmland Values

	Census Division Fixed Effects				Provincial Fixed Effects				Base			
	(1)		(2)		(3)		(4)		(5)		(6)	
Temperature (°C)												
January	−2.46	(0.74)	−2.76	(0.72)	2.75	(0.50)	1.28	(0.49)	−1.38	(0.51)	−2.40	(0.52)
April	31.11	(2.07)	28.34	(2.07)	22.46	(1.27)	23.80	(1.22)	27.82	(1.07)	28.75	(1.08)
July	−4.53	(2.07)	2.15	(2.07)	8.00	(1.44)	6.02	(1.40)	−9.53	(1.39)	−12.07	(1.40)
October	−5.29	(1.86)	−11.22	(1.86)	0.15	(1.50)	−9.66	(1.48)	20.29	(1.37)	14.50	(1.36)
Aggregate (%)	18.83		16.51		33.36		21.44		37.20		28.78	
Precipitation (mm)												
January	0.52	(0.16)	0.47	(0.16)	1.64	(0.09)	1.47	(0.09)	1.56	(0.08)	1.44	(0.08)
April	1.52	(0.14)	1.45	(0.13)	0.95	(0.10)	0.79	(0.10)	2.29	(0.09)	1.80	(0.09)
July	0.27	(0.07)	−0.01	(0.07)	1.25	(0.04)	0.30	(0.05)	1.71	(0.04)	0.97	(0.04)
October	−1.33	(0.15)	−0.78	(0.15)	−1.95	(0.10)	−1.18	(0.1)	−2.52	(0.09)	−1.66	(0.10)
Aggregate (%)	0.98		1.13		1.89		1.38		3.04		2.55	
Proximity variable			Yes				Yes				Yes	

Note: Marginal impacts represent the percentage change in land values attributed to a one-unit change in a specific climate variable (ceteris paribus). All marginal impacts are calculated at the mean historical climate conditions. Standard errors are in parentheses.

the marginal impacts, rather than the direction of the effect. However, in some cases, the effect appears relatively large. For example, a 1°C increase in July temperature is associated with only 4.53% decrease in farmland values in model 1, but a 2.15% increase in model 2 when the proximity variables are included. These results emphasize the ongoing need to consider measures of urban pressure when using the Ricardian approach.

We control for nonagricultural influences and other fixed unobservable influences. In Tables 4 and 5, models 1 and 2 include census division fixed effects, and models 3 and 4 include provincial fixed effects. The impact of including geographic fixed effects appears to have a more noticeable effect on the marginal effects compared with including the proximity variable. This effect is noticeable for the marginal effect of October temperature. In the base model without the inclusion of the proximity variable, a 1°C increase in average October temperature estimates a 20.29% increase in farmland values. When census division fixed effects and the proximity variable are included, the effect becomes negative and estimates an 11.22% decrease in farmland values for a 1°C increase in average October temperatures. A possible explanation is that the base model captures the positive effect that buyers are willing to pay for warmer fall temperatures occurring in specific census divisions, unrelated to the agricultural productivity of a parcel. Once census division fixed effects are included, the nonagricultural related component is controlled for and thereby diminishes the positive marginal effect of warmer October temperatures observed in the base model. This result may signal the negative effect that a reduced number of "chilling days" (the required number of days between a certain temperature threshold before flowering can occur) has on perennial crops (Hatfield and Prueger 2015). A similar observation was found by Weber and Hauer (2003), who estimate a significant negative effect on farmland values for an increase in October temperatures above the median.

Aggregate Impacts of Climate Change on Farmland Values

As a general matter, predicting the future is precarious because there is a great deal of uncertainty that economic models cannot address. The Ricardian model has been criticized (e.g., Cline 1996; Kaufmann 1998; Darwin 1999) for a host of theoretical and empirical limitations (we discuss some of these). For this reason, contemporary research continues to explore empirical methods to enhance the Ricardian approach and its methodology (Schlenker, Hanemann, and Fisher

2006; Severen, Costello, and Deschênes 2018; Ortiz-Bobea 2020; Bareille and Chakir 2023). Like Ortiz-Bobea (2020), we address omitted variable bias; like Severen, Costello, and Deschênes (2018), we are concerned about variation in perceptions of climate change across the regions we study. In this regard, we believe the capacity to include census division fixed effects is an improvement on many previous studies.

Perhaps one of the more notable assumptions associated with the Ricardian method is that the estimated hedonic price function remains stable for the predicted nonmarginal changes associated with future climate. This assumption is a long-standing issue of concern in the hedonic literature (e.g., Freeman 1993). That said, it undergirds previous Ricardian estimates (e.g., Mendelsohn, Nordhaus, and Shaw 1994; Reinsborough 2003; Weber and Hauer 2003).

As mentioned, previous research has raised concerns regarding the sensitivity of the estimated marginal and total effects to functional form assumptions (e.g., Bareille and Chakir 2023). For these reasons, we view all Ricardian estimates with some caution. However, these estimates serve as an ongoing benchmark for the projected effect of climate change on farmland values and enable comparisons to regions in Canada and throughout the world, where similar methods have been applied. With this caveat in mind, we provide estimates of the future effect of climate change on farmland prices. We limit our results to the sample of Canadian farms in our dataset and the climate expected to characterize our sample of farms in 2070.

We use the coefficient estimates from Table 4 and follow the procedure outlined in Section 2 to calculate aggregate impacts. Our results use AdaptWest's climate projections for each climate variable under the SSP2-4.5 warming scenario for 2041–2070 (Wang et al. 2016; AdaptWest Project 2022).[21] The SSP2-4.5 climate change scenario is described by the IPCC as the "middle of the road scenario," where social, economic, and technological trends follow historical patterns (Riahi et al. 2017). The time horizon of approximately 50 years is consistent with Weber and Hauer's (2003) application of the Ricardian approach in Canada and allows for a more direct comparison of results between studies.

Table 6 presents full results across the six pooled models. Ninety-five percent confidence intervals around the sample mean were calculated using 1,000 bootstrap replications for the predicted historical per-acre price and future per-acre price. The final two rows in Table 6 detail the annualized per-acre change (calculated using a 5% discount rate) and the percentage change from the mean predicted historical per-acre value to the mean predicted future per-acre value.[22] Our estimates of the aggregate impacts of climate change imply a 30%–73% increase in the price of farmland by 2070. Alternatively, when the mean per-acre impact is annualized with a discount rate of 5%, it ranges from $151 per acre to $377 per acre. Presently, the average per-acre price of farmland in the dataset is $9,526 (in 2017 Canadian dollars). In addition to aggregate impacts across the entire Canadian sample, we provide a breakdown of average impacts per province from model 2 in Table 7. All provinces are estimated to experience increases in average farmland values due to climate change.

Our aggregate estimates seem consistent with studies estimating the effects of climate change on farmland values in northern U.S. counties and regions of northern Europe (Mendelsohn, Nordhaus, and Shaw 1994; Van Passel, Massetti, and Mendelsohn 2017; Bareille and Chakir 2023). In France, Bareille and Chakir (2023) estimate a 54%–110% increase in French farmland values depending on the climate scenario. In a separate study of farmland values across Europe, Van Passel, Massetti, and Mendelsohn (2017) find future climate change to have beneficial effects on farmland values in countries in the north and harmful effects on farmland values in the

[21] Alternative climate scenarios are considered in Appendix Table A6. The main conclusions do not change.

[22] Because the sample of farmland parcels observed is skewed by higher per-acre parcels, the resulting per-acre change should only be compared to the average per-acre price of parcels in the sample. As a benchmark for the expected change in farmland values for parcels outside of the sample, the values for the expected percent change in values is a more appropriate metric to apply.

Table 6
Average Ricardian Impacts under the SSP2.4-5 2041–2070 Climate Scenario ($/Acre)

	Census Division Fixed Effects		Provincial Fixed Effects		Base	
	(1)	(2)	(3)	(4)	(5)	(6)
Per-acre price (Can$)	9,532	9,532	9,526	9,526	9,526	9,526
Predicted per-acre price (%)	9,884	9,906	10,016	9,997	10,255	10,306
95% confidence interval (Can$)	(9,627, 10,142)	(9,646, 10,166)	(9,725, 10,307)	(9,711, 10,283)	(9,945, 10,565)	(9,993, 10,620)
Predicted future price (Can$)	15,160	15,607	13,039	13,538	17,413	17,843
95% confidence interval (Can$)	(14,851, 15,469)	(15,283, 15,931)	(12,840, 13,238)	(13,282, 13,793)	(17,124, 17,703)	(17,490, 18,197)
Per-acre change (2041–2070) (Can$)	5,276	5,701	3,023	3,541	7,159	7,537
Annualized impacts (5%) (Can$)	264	285	151	177	358	377
% change	53	58	30	35	70	73
Proximity variable		Yes		Yes		Yes

Note: Impacts are in 2017 Canadian dollars (Statistics Canada 2023c), and 95% confidence intervals from 1,000 bootstrap replications are in parentheses. All models include census subdivision and soil controls; only pooled models include year fixed effects. Models 1 and 2 omit observations in census divisions with fewer than 10 observations.

Table 7
Ricardian Impacts by Province under the SSP2.4-5 2041–2070 Climate Scenario ($/Acre)

	British Columbia	Alberta	Saskatchewan	Manitoba	Ontario	Quebec	New Brunswick	Novia Scotia	Total
Per-acre price (Can$)	62,625	3,527	1,704	2,521	13,393	8,510	3,245	4,168	9,532
Predicted per-acre price (Can$)	64,550	3,656	1,729	2,435	14,247	9,206	2,922	3,958	9,906
Predicted future price (Can$)	78,395	4,341	2,361	3,728	32,377	20,711	6,147	8,240	15,607
Per- acre change (Can$)	13,845	685	632	1,293	18,130	11,505	3,225	4,281	5,701
Annualized impacts (5%) (Can$)	692	34	32	65	906	575	161	214	285
% change	21	19	37	53	127	125	110	108	58
Observations	3,549	9,789	14,400	5,044	7,556	4,096	588	530	45,552

Note: Land values have been adjusted for inflation and impacts are in 2017 Canadian dollars (Statistics Canada 2023c). Minimum 10 observations per county are required to be included; all models are pooled cross sections and include year and county fixed effects and the proximity variable.

south. Farmland values in northern European countries, including Denmark, Finland, Ireland, Sweden, and the United Kingdom, are expected to increase under the "moderate" warming scenario (Van Passel, Massetti, and Mendelsohn 2017). Under this scenario, Swedish farmland values are expected to experience the largest increase, rising by approximately 65% by 2100 (Van Passel, Massetti, and Mendelsohn 2017). Similarly, Mendelsohn, Nordhaus, and Shaw (1994) estimate increases of $200–$1,300 per acre (in 1982 dollars) for some northern U.S. counties in their cropland and crop revenue models. Generally, northern latitude areas share similar climate conditions and are expected to experience similar future changes in climate. Thus, Ricardian impacts should be relatively homogeneous across regions with similar current and predicted future climate. Our results are consistent with this expectation.

The empirical results in Table 6 are based on unweighted regressions and rely on the quadratic functional form. Previous research has found that underlying model assumptions influence both aggregate impacts and

Table 8
Average Percentage Change of Per-Acre Farmland Values across Various Ricardian Models

Model	Log-Quadratic: Cultivated Fruit and Pastureland Use	Log-Linear: Cultivated Fruit and Pastureland Use	Weighted Least Squares: Cultivated Fruit and Pastureland Use	Log-Quadratic: All Land Uses
(1)	(2)	(3)	(4)	(5)
Census division fixed effects	53	55	46	67
Census division fixed effects (proximity)	58	43	59	74
Provincial fixed effects	30	120	16	57
Provincial fixed effects (proximity)	35	73	27	68
Base	70	125	32	65
Base (proximity)	73	94	36	75

Note: The weighted least squares model weights each parcel based on the percentage of total acres. The percentage change measures the percentage difference between predicted future and predicted historical prices. All models are pooled cross sections and use the climate scenario SSP2-4.5 for 2041–2070. The log-linear and weighted least squares model restrict the sample to cultivated fruit and pastureland uses.

marginal effects. Bareille and Chakir (2023) find that a log-linear specification, compared with a log-quadratic function significantly reduces the marginal effects of climate. We also find sensitivity. That said, across the various alternative specifications we examine, the price effect of climate change is expected to be positive.

Table 8 provides a summary of the aggregate impacts across a range of sensitivity analyses we conducted. Column (2) identifies the aggregate per-acre results and restricted to only cultivated, fruit and pastureland. The model in column (3) uses the same sample restrictions as our primary model but uses a log-linear function form specification rather than a log-quadratic. This specification for the census division fixed effects (proximity) regression indicates an average increase of 43%, compared with 58% in the log-quadratic model.

Column (4) uses weighted least squares for our preferred, log-quadratic functional form specification. Each parcel is weighted by acreage. These results are generally in line with our current results. In column (5), we provide results for a very inclusive model with no restrictions on land uses. As discussed, a sale can include parcels used for different activities and can include buildings. While the value used in the regression represents the value of the underlying land a building is on, there may be an omitted variable problem. For this reason, we include a dummy variable to categorize any land that is potentially used for nonagriculture-related activities. This is the most inclusive model and a reminder that most farms are a combination of parcels whose current uses vary.[23] In this model, the effects are positive and generally larger relative to our current model.

As a benchmark, our results consistently suggest that climate change will have a positive and significant effect across our sample of Canadian farmland values. That said, as emphasized in previous literature and in our own discussion, the exact magnitude of the positive prediction is difficult to determine precisely and appears sensitive to underlying assumptions.

6. Conclusions

By applying the Ricardian approach to parcel-level observations of Canadian farmland, we find that climate change is projected to place significant upward pressure on farmland prices. We also find evidence to support previous arguments (e.g., Ortiz-Bobea 2020) that the Ricardian approach needs to account for the effect of nonagricultural influences. Consequently, future applications of the Ricardian approach in Canada and other countries may

[23] Previous estimates using Canadian census data rely on at least two levels of aggregation: (1) aggregation of farm price across parcels (which include buildings) by the census survey respondent, and (2) aggregation to the census division level.

benefit from including urban proximity variables and census division (or county) fixed effects. Our aggregate estimates of the per-acre effects of climate change were relatively similar in models with and without the inclusion of the urban proximity variable.

Although our findings do not represent a precise forecast and the Ricardian approach does not identify specific adaptation processes, our findings underscore the idea that Canadian farmers are expected to adapt to climate change. Future research might assess the extent to which changes in farming practices (e.g., new seed varieties, timing of planting) are influenced by climate change and beneficial from the standpoint of net returns. Future research may want to continue to explore the potential for heterogeneous climate effects across the parcels that comprise a farm.

Previous applications of the Ricardian approach to northern latitude countries, such as France and Sweden, suggests that climate change will be beneficial to the agricultural sector. We find similar results for Canada. These favorable findings stand in sharp contrast to the projected effects of climate for more southern latitude regions of the world and serve as an important reminder of the asymmetric effects of climate change across regions and specific sectors. Future research should continue to investigate these asymmetric effects.

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