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October 2022

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ABSTRACT

The IPCC indicates that global mean temperature may increase 2°C or more above preindustrial levels; therefore, understanding weather impacts on staple crops is vital for creating adaptation strategies and maintaining global food security. This study analyses the impact of weather variables on canola and spring wheat using weather data from rural municipalities across Saskatchewan over the period 2011-2020. We first implement a Geographic Information Systems model to interpolate Saskatchewan weather data. We then utilize a panel econometric temperature binning model to analyze the nonlinear relationship between crop productivity and temperatures. We find temperature resiliency for wheat up to daily average temperatures of 21ºC and canola to 19ºC. Beyond these thresholds, increasingly large reductions in potential yield occur as the growing season temperature increases. Wheat yield potential is reduced by 0.05% on average for every additional day where average temperatures are 21-23ºC and reduced by 2% for every additional day where average temperatures exceed 23ºC. Canola yield potential is reduced by 0.2% for every additional day where average temperatures are 19-21ºC, 0.6% for 21-23ºC, and 3.3% for days where temperatures exceed 23ºC.

Key Words: Weather impact on crop yields; temperature; climate change; genetic modification

1. Introduction

Agriculture and the global food supply are susceptible to the impacts of climate change. Canadian agriculture and food security are not an exception. According to the IPCC [1], climate change has already given rise to both positive and negative impacts in agricultural productivity, with the former more common than the latter. While increased atmospheric concentrations of carbon dioxide (CO_2) increase crop yields, higher temperatures tend to reduce crop yields. This issue is addressed in this paper using a GIS model, weather data and crop yields for the province of Saskatchewan, which is Canada's bread basket.

Due to polar amplification, Canada's rate of warming is projected to rise faster than the global rate [2]. For example, Vincent et al. [3] report that over the period 1950–2016, Canada's annual mean surface air temperature warmed by 1.8 °C, while the global mean temperature warmed by 0.85°C during 1880–2012. Furthermore, daily minimum temperatures are rising slightly faster than daily maximum temperatures [4]. Since high temperatures can adversely affect crop yields, it is crucial to understand how Canada's crop yields may change under climate change.

Canada is one of the largest agricultural producers and exporters in the world. According to Agriculture and Agri-Food Canada [5], the agriculture and agri-food sector accounts for one in nine jobs and some 7.4 percent ($139.3 billion) of Canada's gross domestic product (GDP). As Canadian food production far exceeds domestic needs, Canada is the fifth largest exporter of agricultural and agri-food products after the EU, U.S., Brazil, and China.

Major field crops grown in Canada are wheat, canola, corn, barley, and soybeans. When it comes to profitability and crop rotations, wheat and canola are of primary importance. According to Statistics Canada [6], acreage and yields of canola and wheat have recently been increasing, and the crops are significant components of sustainable crop rotations. Therefore, this study focuses on the weather factors that impact the yields of these crops.

Saskatchewan is considered Canada's breadbasket because its rich soils have made the Province a major producer of wheat and canola. In 2020, Saskatchewan's spring wheat and canola production totaled 10.6 and 10.9 million tonnes, respectively, accounting for 41% and 56% of Canada's total spring wheat and canola production [6]. Climatic changes captured by the quantified effects of temperature and precipitation on crop yields measure their economic significance for farmers, and domestic and international commodity markets. Therefore, it is crucial to quantify the impact of climate change on Saskatchewan's crop yield.

Over the past century, there have been three persistent trends in agriculture: increasing crop yields, slowly rising temperatures, and greater atmospheric CO_2. Crops have been subject to various technological improvements pertaining to fertilizer use, fallowing, herbicides, and fungicides [7], as well as information systems and planning [8]. As the world's population continues to grow, food security must continually be assessed and improved upon to mitigate risk of shortages. From an economics standpoint, it is imperative we understand how variation in weather over time affects the variation in yields as indicated by net revenues and land values.

There are many studies that examine how staple crop yields rely on management, technological progress, and climate. The current research seeks to contribute to this growing literature by utilizing data collection, analytical and econometric approaches. The literature on crop productivity and climate change, as well as relevant plant physiology studies, are summarized below.

In this study, we develop an econometric model to capture dynamic temperature and soil quality effects on agricultural productivity in Saskatchewan. Our approach uses a Geographic Information System (GIS) data interpolation methodology to combine regional weather variations with farm productivity data. Farmers maximize profits by working the intensive and extensive margins of production. Our research focuses on the former: improvements to lands already in use. Farmers and central planners alike have a variety of choices that can lead to efficiency improvements. The extent to which these improvements affect productive outcomes is intertwined with a dynamic abiotic environment. How do we disentangle the effect of agents' decisions with the prevailing stochastic weather? To do so, we focus on the extent to which climate change impacts agricultural productivity. There exist causal relationships between weather and crop yields that, after controlling for agent decision-making and non-weather factors, can be used to forecast the efficacy of decision-making and, thereby, improve our understanding of how farmers can make best use of land. Thus, our research contributes to literature that attempts to understand these causal relationships. To do so, we create a novel dataset that exploits spatial and temporal variation of agricultural productivity and weather systems.

2. Literature Review

The argument for crop research is simple: improve the land currently allocated to agriculture and retain or improve global food security. In doing so, we prevent land otherwise used to meet other needs from being brought into use [9]. In economic terms, we improve the agricultural system at the intensive margin. Stevenson et al. [9] point out that, between the mid-1960s and mid-2000s, global population grew by 93% and cereal yields by 112%, while the area harvested increased only by 1.6%. This discrepancy between intensive and extensive margins is monumental and implies that farm-level technological improvements and adaptation have focused largely on the intensive margin. The question remains: how much of a role has variation in weather, specifically temperatures, and atmospheric CO_2 played?

Studies investigating crop yield response to weather variables have become increasingly popular because of concerns about climate change. Many econometric modeling studies have explored the impact of climate change on agricultural output and provided mixed results partly attributed to the weather data employed, model specifications, and geographic location. Since Rosenzweig and Parry [10] produced one of the first assessments of climate change impacts on global food supply, numerous studies have examined the potential adverse effects on global crop yields, particularly the effect of rising temperature [11-15].

Chen et al. [16] employed a regression model that allows for spatial dependence in crop yields across counties, finding that, by the end of this century, soybean and maize yields in China are expected to be adversely affected by higher temperatures with more significant yield reductions for soybean than maize. Apart from crop yield reductions, crop yield variability is likely to be impacted by warmer temperatures. According to Lobell et al. [17], global warming is expected to reduce global yields of wheat by 5.5% compared to a counterfactual without global warming—the expected increase in yields is lower than it would be otherwise. Employing a hedonic approach and a nonlinear transformation of the temperature variables, Schlenker and Roberts [18] concluded that different warming temperature scenarios would result in a 10%–25% decrease in U.S. farmland values. For India, Taraz [19] used a flexible temperature binning approach to show that higher temperatures are significantly harmful to yields. Their framework allows for nonlinearity in temperature impacts and is discussed in greater detail in the methodology section of this paper as we expand on this approach for our analysis.

Adverse weather creates systemic risk in the agricultural sector, but also presents opportunities for adaptation and exploitation [20]. One yield improvement is in the genetic engineering of crop species, namely, through increased resistance to insects, disease, and herbicides—which reduce loss—and increased nutritional quality and yields [21].[1] Genetic engineering is also used in the development of drought tolerance among most staple crops to reduce water stress [23,24]. Drought resistance is of particular importance in arid and semi-arid regions. Bapela et al [25] found drought stress led to reductions in potential yield, particularly reducing wheat yield by 63% in Pakistan, 25% in China, 43% in Egypt, and 40% in South Africa. Of similar importance is engineered resistance to high temperatures that makes "plant growth and development possible under heat stress" [26]. The ability for crops to grow in "…high ambient temperature is one of the major constraints in obtaining maximum output," [27] which is imperative to maintaining global food security. These topics, whilst themselves beyond the scope of this research, aid us in the formulation of our analytical framework.

While several studies have concentrated on the adverse effects of global warming on crop yields or agricultural profits, a few studies have examined the combined effects of temperature and precipitation on agricultural output by employing cumulative growing season weather variables [28,29]. For example, Meng et al. [30] investigated the impact of precipitation and temperature changes on canola and spring wheat yield distributions using moment-based methods and found that average crop yields are positively associated with growing season degree-days and pre-growing season precipitation. At the same time, they are negatively affected by extremely high temperatures during the growing season.

One opportunity that has been identified is CO_2 fertilization and its relationship with water use efficiency. Rising atmospheric CO_2 affects crop yields by increasing the rate of photosynthesis and water-use efficiency. Deryng et al. [31] found that the ratio of crop yields to the rate of evapotranspiration will likely increase by 10 to 27 percent by 2080, with much less water required

[1] See Anderson et al. [22] for a more in-depth discussion of genetically engineered crops, their role in managing pest, and global use.

to achieve the same yields. This is crucial given the extent of population growth projected for the next fifty or more years, although projections of population growth remain contentious (e.g., Bricker and Ibbitson [32]). The researchers employ a modelling approach and project crop yields in 2080 under climate change with and without a CO_2-fertilization effect. If CO_2-fertilization effects are ignored, severe negative effects on crop yields occur; but, when CO_2 fertilization is taken into account, these negative effects are "fully compensated for in wheat and soybean, and mitigated by up to 90% for rice and 60% for maize" [31 p. 787]. Deryng et al. conclude that rising atmospheric CO_2 can ultimately provide opportunities to increase food production to meet population growth without straining water resources, particularly in semi-arid and arid regions with rainfed crops.

Long et al. [33] investigated the theoretical maxima of yields, finding that the remaining avenue for further yield improvements exists through photosynthesis. They found that the best means of increasing leaf photosynthesis was through elevated CO_2, although their research indicated that, as temperature rose, CO_2 uptake seemed to change. For example, they found that the existence of a tipping point in gross canopy CO_2 uptake with respect to temperature for C3 crops (e.g., wheat, canola, barley, oats) occurs just above 20ºC [33 fig 3]. The implications of an increasing concentration of atmospheric CO_2 are important for food security, where much of the conversation focuses on global warming. This is especially important for developing countries located in arid regions where crop yield efficiencies are lower (often due to lower levels of fertilizer use), and water is scarcer than in developed countries.

The relationship between CO_2, temperature, and crop yields can give us a notion as to how anthropogenic emissions of CO_2 may impact productivity and potentially mitigate damages from rising temperatures. Further, they provide potential to adapt and harness species of staple crops that thrive under these conditions. One needs to look at farm-level data to observe CO_2-fertilization effects because regional data on a global scale are not readily available.

Lobell and Field [34] simulated crop yields for wheat, rice, maize, soy, barley and sorghum using FAO crop yield data, but they ignored the CO_2-fertilization effect. These authors found large significant negative effects on regional yields from global warming, but their conclusions may well have been quite different if there had been adequate data on CO_2 levels. Without inclusion of CO_2 fertilization, we can treat these results as upper bounds on temperature impacts. Another important relationship they found was that 29% of the annual variation in yields was attributable to temperature and precipitation variability, citing technological advances, rising CO_2, and other non-climatic factors.

Schlenker & Roberts [35] employed a county-level panel statistical model for U.S. maize and soybean yields, finding that yields increase with temperature up until 29°C and 30°C, respectively (p.15594). This suggests nonlinearities in yield-temperature response. Schlenker & Roberts find that area-weighted yields are predicted to decrease by 30-82% across a range of climate scenarios indicating severe damages across the U.S. (p.15595). They also find that "greater precipitation partially mitigates damages from extreme high temperatures" (p.15596)—with precipitation not generally modeled to the same extent as temperature due to its much greater variation across a landscape. The IPCC [1] also projects that "extreme heat thresholds relevant to agriculture" will be exceeded. Again, CO_2 fertilization was ignored.

Zhao et al. [36] find average yield reductions of 6.0%, 3.2%, 7.4%, and 3.1% for every 1°C for wheat, rice, maize, and soybean, respectively. They do note that these impacts are "without CO_2 fertilization, effective adaptation, and genetic improvement," (p.9236) which other studies have shown to be important drivers of productivity improvements and compensatory mechanisms (viz., CO_2 fertilization improving water use efficiency).

Some studies have filled this gap between temperature and CO_2 fertilization. Challinor et al. [37] construct a first differences linear model with yield as a function of temperature, CO_2, and precipitation among other control variables. They find a 5.4% yield reduction per °C and an increase of 6% (=0.06%×100) per 100 ppm of CO_2, as well as a 7.16% increase from adaptative measures. Depending on the climate scenario employed, this suggests that less developed countries are at most risk given a decreased ability to adapt and higher projected temperature increases. They also project agroclimatic responses to the end of the century, finding positive yield changes in temperate regions yet decreases for tropical crops in the latter half.

A literature review by Kulshreshtha [38] identified uncertainties in yield predictions, implying that crop productivity could increase or decrease in a changing climate. Uncertainties in yield also include gaps in our understanding of climatic variability. This includes our understanding of interactions among various teleconnections, such as the El Niño-Southern Oscillation (ENSO), North Atlantic Oscillation (NAO), the Pacific Decadal Oscillation (PDO), and the Atlantic Multidecadal Oscillation (AMO). These climate oscillations are periodically fluctuating oceanic and atmospheric phenomena, which are related to worldwide variations in weather patterns and crop yields.

Another study by Moore et al. [39] parameterizes damage functions for integrated assessment models using agricultural impacts. They find more adverse effects than are currently employed in the social cost of carbon literature. Their analysis derives net benefits and costs of $2.7 and $8.5 per ton of CO_2. In terms of marginal yield effects, they find an 11.5% increase for C3 crops from a doubling of CO_2 from pre-industrial times, but a slightly lower increase of 8.7% for C4 crops which include maize (corn), sugarcane, and sorghum.

3. Data

Canada is one of the top five wheat exporters, with an average of $7 billion exported annually [5]. Almost all of Canada's wheat is produced in Saskatchewan, Alberta, Manitoba, and northwestern BC, with relatively small production in eastern Canada. Together the Canadian Prairie provinces accounted for 97.4% of the total wheat area in Canada in 2020 [6]. In 2020 Saskatchewan accounted for 45% of total wheat grown in Canada. Likewise, western Canada is Canada's primary canola producing region. In Saskatchewan, canola is seeded during May, with bolting and flowering beginning in late June to early July. It is usually harvested mid-August to early September, much like spring wheat. Figure 1 provides the historical trend of canola and spring wheat production by the western provinces, and Canada as a whole, over the period 1966-2020.

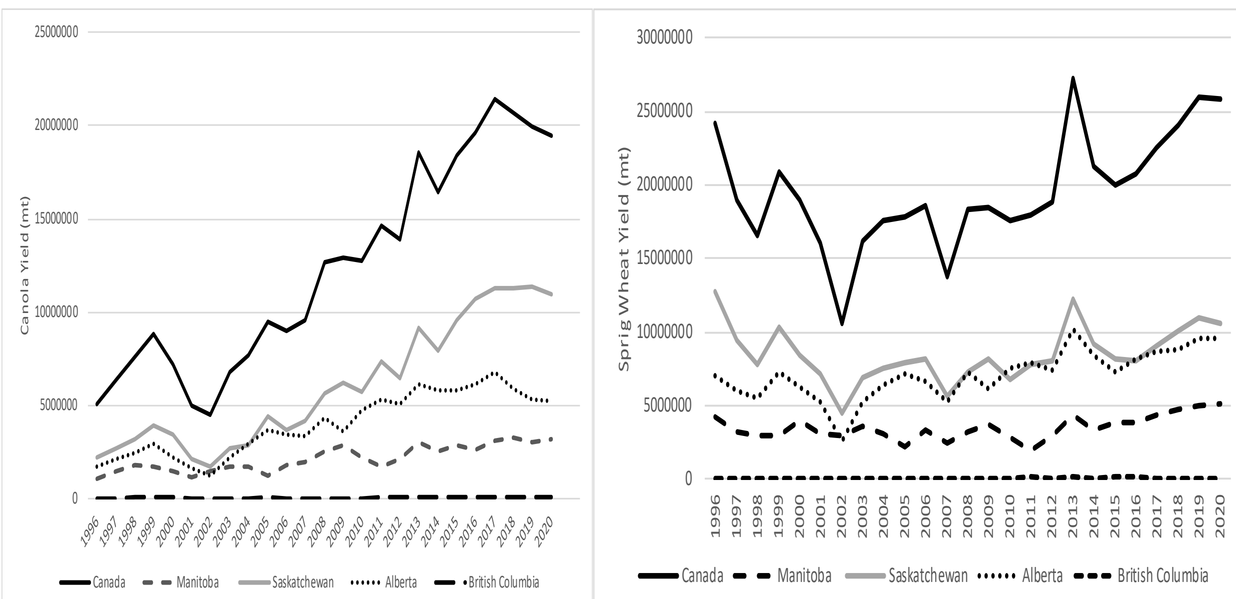

Figure 1: Production (Mt) of Canola (left) and Spring Wheat (right), Western Canada and Total, 1966-2020

We utilize a novel panel dataset that combines crop yields with weather data. We collected monthly weather station data for 10 years across 60 different stations. Each original dataset constitutes daily weather data separated into monthly Excel files. All available months for all 60 weather stations were downloaded separately [41] and then merged into one dataset containing maximum, minimum, and average temperatures, and precipitation data for every single day between 2011-2020. These data were then interpolated to create a complete representation of weather conditions for 200 rural municipalities (RMs) in Saskatchewan. Afterwards, variables representing temperature 'bins' were created—each bin counts the number of days where average temperatures fell within a certain range [19]. This allows for nonlinearity in temperature effects.

The data are then matched up to a time series of yields to create a novel panel dataset. An econometric model is then used to exploit variation in weather, soil quality, and productivity to estimate potential damages from temperature and how they vary across soil zones.

The interpolation employed takes an inverse-distance weighted average of weather stations within a 100 km radius wherein the interpolated temperature for a given rural municipality takes the form:

$$T_{rm} = \frac{T_a}{D_a} + \frac{T_b}{D_b} + \cdots + \frac{T_n}{D_n} \text{ with } D_a + D_b + \cdots + D_n = 1,$$

where T_{rm} is temperature in °C in a RM is a function of observed temperatures T_i weighted inversely by proportional distances D_i for weather stations *i* that are within a 100km radius of an RM. This serves the primary purpose of giving a higher weight to stations in closer proximity. The circle of radius was chosen so that the interpolation considers at least two weather stations for each RM. This same approach is used for interpolating precipitation data. Figure 2 indicates weather stations as red dots and where they are located relative to rural municipalities.

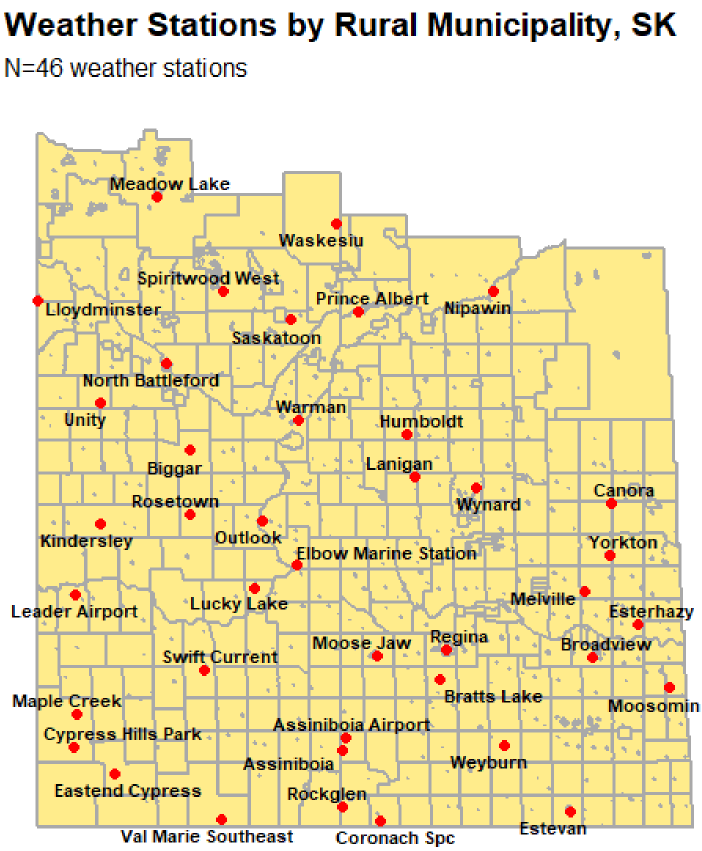

Figure 2: Weather Stations Overlaying Rural Municipality Boundaries, Saskatchewan

Descriptive summary statistics are reported in Table 1. Yields vary from 5 to 57.93 bushels per acre (bu/ac), with an average of 35.604 bu/ac. Bin1 represents days when temperatures fell below 3°C and Bin2 represents days where temperatures are between 3-5°C. These are not employed in the regression framework, however, as these temperatures are below those required for plant growth to occur. The same treatment is given to studies that employ growing degree day frameworks [42]. Growing season precipitation peaks in June and July, whereas May and August represent beginning and end of season rainfall that are of importance. To make up for a lack of explanatory control variables, a two-way fixed effects model is used to capture time-invariant and location-invariant determinants of crop yields. This is discussed in detail in the following section.

Table 1: Summary Statistics for Canola, Wheat, and Weather for Saskatchewan N=2,590[a]

Variable	Mean	Std. Dev.	Min	Max
Canola (bu/ac)	35.604	8.176	5.000	57.930
Wheat (bu/ac)	42.922	11.002	12.340	198.000
Bin1 (<3 ºC)	17.022	6.579	0	32
Bin2 (3-5 ºC)	6.785	3.070	0	18
Bin3 (5-7 ºC)	9.003	3.667	0	19
Bin4 (7-9 ºC)	11.241	3.419	3	23
Bin5 (9-11 ºC)	13.663	4.199	2	26
Bin6 (11-13 ºC)	17.187	4.266	2	32
Bin7 (13-15 ºC)	22.561	6.719	6	44
Bin8 (15-17 ºC)	27.885	5.189	4	44
Bin9 (17-19 ºC)	26.096	5.400	7	43
Bin10 (19-21 ºC)	18.095	4.816	3	32
Bin11 (21-23 ºC)	9.004	4.042	0	24
Bin12 (>23 ºC)	3.226	2.879	0	14
May Precipitation	39.458	30.889	0.000	155.114
June Precipitation	79.068	40.585	0.000	252.100
July Precipitation	61.698	33.559	0.000	189.422
August Precipitation	42.097	25.974	1.900	138.511
North Atlantic Oscillation	0.00001	0.949	-1.080	2.301
Atlantic Multi-Decadal Oscillation	0.002	0.949	-1.299	1.449

[a] All Bin variables are measured in days and all Precip variables are measured in mm

4. Econometric Model

To analyse Saskatchewan agricultural productivity, we devise a linear panel econometric model following Taraz [17] that takes the simplest form:

$$\ln(Y_{r,t}) = \sum_{i=1}^{13} \beta_i T_{r,t}^{i} + u_{r,t},$$

where Y is yield (t/ha) in rural municipality r at time t, T represents the number of days that daily average temperature falls within a bin: <3ºC, 3-5ºC, 5-7ºC, …, 21-23ºC, and >23ºC. The disturbance term, u, captures unobserved determinants of yield.

The underlying relationship is much more complicated. Temperatures vary over the growing season, leading to different yield outcomes. Our approach assumes that the impact of high temperature days does not depend on timing (e.g., a high temperature day after a spell of cold days). The impact of precipitation in certain months depends on timing with respect to the growing season. Precipitation is included only as a control variable because the underlying relationship between soil moisture and crop growth is more complicated than that based solely on growing season rainfall. There are also a host of omitted variables that heavily influence the outcome, such as soil quality, CO_2 fertilization, solar irradiance, and management practices. To address these issues, various solutions are implemented.

The dependent variable in our model is converted to the natural logarithm of crop yields. This serves two purposes: crop yields have been shown to be log-normally distributed as negative yields are not possible [43]; and this formulation lends itself a valuable interpretation of crop-temperature responses. If we assume crops are log-normally distributed, this implies that we can assume normality of the disturbance term. The interpretation of each coefficient changes because of this conversion—we can interpret our linear coefficients as semi-elasticities. That is, they describe the percentage response in the dependent variable to unit changes in our independent variables.

As noted, we employ binning of temperature data to address variability in temperature and its distributional impacts, which allows us to account for growing season variation. It also enables us to provide more insight into the marginal effects than would be found via annual growing season temperature. It also allows for nonlinearity in marginal temperature impacts. In the case of precipitation, not only the amount of rainfall but also its timing during the growing season is important. Therefore, instead of total seasonal precipitation, monthly cumulative precipitation variables were used to capture the impact of monthly variation

Soil quality is an important determinant of farm level outcomes. Soil zones vary by nutrient levels and ability to absorb and maintain moisture. We create dummy variables representing each of the regions to account for spatial variation attributable to higher and lower quality soils across Saskatchewan. Alternatively, the location of RM centroids, as measured by longitude and latitude, can be used as a proxy for soil zone. These centroids are available from the GIS model.

Data pertaining to CO_2 fertilization, solar irradiance (SI), and management practices are more problematic, because we do not have robust data on CO_2 and SI variability despite their importance for plant growth. Therefore, we employ rural municipality location Fixed Effects (FE). This controls for unobservable determinants of yield that are time-invariant over our 10-year time horizon, although they may vary across RMs. The soil dummy variables are dropped from the FE regressions as these are taken into account by the rural municipality FEs. We also implement year FEs to control for determinants of yield that are common across all RMs that change from year-to-year. This approach serves as a caveat to our model because CO_2 and SI vary continuously throughout the growing season. The benefit of employing this approach is that it controls for *all* unobservable determinants that are common across Saskatchewan, including technological advances and innovations that improve farm productivity. This approach also renders time-invariant unobservable variables non-problematic to our regression framework [44]. A step-by-step description for each of the above improvements is provided in Table 2.

Table 2: Description of Regression Specifications[a]

Specification	Functional Form	Description
(1)	$Y_{r,t} = \sum_{i=1}^{13} \beta_i T_{r,t}^i + u_{r,t}$	Baseline naïve OLS (random effects) that includes only temperature bins
(2)	$Y_{r,t} = \sum_{i=1}^{13} \beta_i T_{r,t}^i + \sum_{\boldsymbol{k=1}}^{\boldsymbol{3}} \boldsymbol{\xi_k\, Soil_r^k + Long + Lat} + u_{r,t}$	Includes control variables for coordinates as well as soil types
(3)	$Y_{r,t} = \sum_{i=1}^{13} \beta_i T_{r,t}^i + \sum_{k=1}^{3} \xi_k\, Soil_r^k + \sum_{\boldsymbol{j=1}}^{\boldsymbol{4}} \boldsymbol{\gamma_j\, P_{r,t}^j} + Long + Lat + u_{r,t}$	Includes monthly precipitation in each of May, June, July, and August
(4)	$Y_{r,t} = \sum_{i=1}^{13} \beta_i T_{r,t}^i + \boldsymbol{\Psi_{rm}} + u_{r,t}$	Excludes explicit fixed effects that do not vary over time (soil zones and coordinates) and includes a fixed effects term for each RM. Without monthly precipitation variables.
(5)	$Y_{r,t} = \sum_{i=1}^{13} \beta_i T_{r,t}^i + \sum_{\boldsymbol{j=1}}^{\boldsymbol{4}} \boldsymbol{\gamma_j\, P_{r,t}^j} + \Psi_r + u_{r,t}$	Includes monthly precipitation to specification (4) for the sake of seeing how the results change with and without precipitation under the fixed effects model
(6)	$Y_{r,t} = \sum_{i=1}^{13} \beta_i T_{r,t}^i + \Psi_r + \boldsymbol{\Phi_t} + u_{r,t}$	Includes time fixed effects in addition to location fixed effects (two-way fixed effects), initially without monthly precipitation
(7)	$Y_{r,t} = \sum_{i=1}^{13} \beta_i T_{r,t}^i + \sum_{\boldsymbol{j=1}}^{\boldsymbol{4}} \boldsymbol{\gamma_j\, P_{r,t}^j} + \Psi_r + \Phi_t + u_{r,t}$	Includes precipitation to specification (6)

[a] Changes over previous specification are shown in bold.

The statistical model that results takes the form:

$$Y_{r,t} = \sum_{i=1}^{13} \beta_i\, Bin_{r,t}^i + \sum_{j=1}^{4} \gamma_j\, P_{r,t}^j + \Psi_r + \Phi_t + u_{r,t},$$

where P is precipitation in month j, Ψ are location fixed effects, and Φ are time fixed effects.

To further establish validity, we employ several robustness checks for different aspects of the model. There are two prominent choices for linear panel models: FE and Random Effects (RE) models. They differ in their treatment of the relationship between the error term and the independent variables [45]. Vaisey and Miles (46 p. 47) point out that RE models assume the observed predictors in the model are not correlated with individual-specific dummy variables, while FE models allow them to be correlated. In our analysis, this would translate to the RE model assuming RM-specific impacts (viz., droughts, location-specific plant disease) are uncorrelated with temperature. *A priori*, we believe this too bold of an assumption and as such we explore diagnostic tests.

This difference in error term treatment can be directly tested with the Hausman [47] test. If we reject the null hypothesis associated with this test, we should use the FE model instead of the RE model because we have evidence that the error term, specifically unobservable determinants of crop yields, are indeed correlated to our observable variables.

After establishing the use of a FE model, we can further check whether location FE are sufficient or if we should account for time FE as described earlier in this section. We can test whether there are time specific effects that are common across municipalities with a Breusch-Pagan (BP) test [48]. This approach simply incorporates dummy variables representing each year and performs a joint Lagrange multiplier test of significance on the inclusion of these variables. We also explore the models for the presence of heteroscedasticity, employing a BP test that tests the null hypothesis of constant variance in the error term. We formally employ statistical tests for each of these diagnostics and report the findings below in Table 3.

Table 3: Diagnostic Tests for the Econometric Model

	Hausman Test	Breusch-Pagan Test for Time FE	Breusch-Pagan Test for Homoskedasticity
Test Statistic	$\chi^2 = (37.81, 166.43)$	$\chi^2 = (5.019, 5.019)$	$BP = (159.03, 207.40)$
P-value	(0.0010, 0.0000)	(0.02507, 0.02507)	(0.0000, 0.0000)
Decision	(reject, reject)	(reject, reject)	(reject, reject)

[a] Values in parentheses correspond to model specifications for (canola, wheat)

The Hausman test indicates that the u_{it} are uncorrelated with the independent variables, which implies that we have statistically significant evidence that the RE model is inappropriate for analysis of the relationship between canola yields and temperature, as expected. On the basis of the BP test, we reject the null hypothesis that time FEs are not important determinants of canola and wheat yields—we have statistically significant evidence that time FEs are jointly significant determinants of canola yields and should be included in the regression model. Based on the BP test for homoscedasticity, we reject the null hypothesis that the variance of the error terms is constant, implying that our error terms display heteroskedasticity (e.g., non-constant variance).

We address these diagnostic tests by employing (i) a fixed effects regression framework; (ii) time fixed effects to control for location-invariant determinants of canola yields; and (iii) heteroskedasticy-robust standard errors in all specifications [49]. The regression analysis therefore begins with simple Ordinary Least Squares (OLS), and then progressively adds more to the specification (see Table 2). This analytical approach allows us to observe differences in the model parameters, coefficients of correlation, and F-tests of joint significance across our specifications.

It is worth reiterating that average daily temperatures are used to construct bins, therefore days of average temperatures exceeding 15ºC, for example, could be reflective of daytime temperatures reaching as high as 30ºC at certain points of the day. We also know from the literature that high temperatures are only damaging when there is insufficient rainfall or soil moisture.

5. Results

5.1 Explaining Canola Yields

Regression results for canola are reported in Table 4. Specification (1) reports simple OLS where temperature bins alone explain 20% of the temporal and regional variation in crop yields. The negative signs on nearly all temperature bins, representing days above and below 11-13^{o}C, is indicative of misspecification and omitted variable bias.

Soil type and the inclusion of both oscillatory mechanisms in specification (2) only explain an additional 2.8% of variation in yields. Coefficient estimates for NAO and AMO mechanisms are positive indicating the influence of non-climatic variables. Relative to municipalities located in brown soil zones, yields are 3.8% and 4.7% more bushels per acre in black and dark brown soil zones, respectively. Coefficient estimates for bins do not change much with this addition.

The addition of variables accounting for precipitation between May and August account for an additional 13.3% of variation in yields over the first specification. The coefficient estimates do not change much and still exhibit negative signs for most bins above and below the reference regression. Already economically small differences between soil zones are no longer statistically significant under this specification, implying little to no difference across soil zones in canola productivity.

When we sequentially include soil quality and oscillatory mechanisms, and then precipitation controls to the random effects model in specification (1), the results are largely unchanged. We do, however, have evidence that the random effects model is an inappropriate formulation—our diagnostic test results in Table 3 tell us that the fixed effects approach is valid for both location and time fixed effects.

Table 4: Regression Results for Canola Yields

Dependent variable: log(Yield)	Random Effects			Location Fixed Effects		Two-way Fixed Effects	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Bin3 (5-7ºC)	-0.006***	-0.004***	-0.004**	-0.003**	-0.002	0.008***	0.006***
	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)	(0.001)
Bin4 (7-9ºC)	-0.009***	-0.006***	-0.009***	-0.004***	-0.006***	0.005***	0.004***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)
Bin5 (9-11ºC)	-0.003***	-0.003**	-0.008***	0.0002	-0.006***	-0.005***	-0.006***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Bin7 (13-15ºC)	-0.001*	-0.0005	-0.0004	0.0001	-0.0001	-0.002**	0.0001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Bin8 (15-17ºC)	0.003***	0.001	0.001	0.001	0.001	-0.003**	-0.00002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Bin9 (17-19ºC)	-0.001	-0.002*	-0.002**	-0.004***	-0.004***	-0.004***	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Bin10 (19-21ºC)	-0.010***	-0.012***	-0.004***	-0.014***	-0.007***	-0.003**	-0.002**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)
Bin11 (21-23ºC)	-0.003**	-0.005***	-0.005***	-0.009***	-0.009***	-0.006***	-0.006***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
Bin12 (>23ºC)	-0.027***	-0.027***	-0.031***	-0.032***	-0.039***	-0.030***	-0.033***
	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)
NAO		0.046***	0.032***	0.058***	0.047***	-0.126***	-0.142***
		(0.005)	(0.006)	(0.005)	(0.006)	(0.024)	(0.022)
AMO		0.036***	0.029***	0.036***	0.029***	0.132***	0.116***
		(0.005)	(0.006)	(0.005)	(0.006)	(0.009)	(0.009)
Black SZ		0.038*	0.011				
		(0.02)	(0.02)				
Dark Brown SZ		0.047**	0.025				
		(0.019)	(0.019)				
May Precip			-0.001***		-0.001***		0.001***
			(0.0003)		(0.0003)		(0.0002)
June Precip			-0.001***		-0.001***		-0.001***
			(0.0001)		(0.0002)		(0.0001)
July Precip			0.002***		0.002***		0.0003**
			(0.0002)		(0.0002)		(0.0001)
August Precip			-0.00001		-0.0001		-0.001***
			(0.0002)		(0.0002)		(0.0001)
Location FE	No	No	No	Yes	Yes	Yes	Yes
Time FE	No	No	No	No	No	Yes	Yes
Obs.	2,590	2,590	2,590	2,590	2,590	2,590	2,590
R^2	0.202	0.232	0.366	0.216	0.375	0.512	0.537
Adjusted R^2	0.200	0.228	0.361	0.125	0.301	0.454	0.481
F Statistic	655.2***	779.4***	1,482.6***	58.0***	92.7***	135.0***	121.7***

Note: Heteroskedasticity-robust standard errors reported in parentheses. *p<0.1; **p<0.05; ***p<0.01

In our simple FE model, shown in specification (4), the results are not dissimilar to our previous specifications. The adjusted R^2 shows that it only explains 12.5% of the variation in yields, suggesting that there are omitted determinants of yields, and underperforms in explanatory power when compared to our initial model. Further, adding controls for precipitation quickly increases this explanatory power to 30.1% which is not quite as much as the RE model with full controls at 36.1%.

When we include time fixed effects, we find substantial improvements to the model. In specification (6) the adjusted R^2 increases so that 45.4% of variation in yields is explained after we include dummy variables for each year. This further increases to 48.1% after we include precipitation controls in specification (7). The coefficient estimates are shown below in Figure 4.

Contrasting the simple OLS results in specification (1) with our preferred specification (7), a variety of interesting insights arise. First, reduced yields relative to potential yield do not occur until higher temperatures than initially estimated using our random effects model, specifically, they occur at and beyond 19ºC (Bins 10-12). Days with cooler average temperatures of 5-9ºC are more beneficial than those of 11-13ºC, yet days with average temperatures of 9-11ºC are associated with reduced yields. We are not sure what is driving the latter result. Otherwise, days with average temperatures of 13-17ºC are no more or less beneficial than those of 11-13ºC. Importantly, there exists statistical evidence against any yield reductions. Potential yields appear to be dampened after 19ºC at an increasing rate. Specifically, the average reduction in potential yield is 0.2% for an additional day where average temperatures are 19-21ºC, 0.6% for 21-23ºC, and finally 3.3% for days where temperatures exceed 23ºC. The impact of medium-high temperatures (19-23ºC) are associated with some productivity loss that could add up if high temperatures are sustained. It is easy to see how impactful extreme temperatures could be, but it is important to recognize our results represent the average impact of all days beyond 23°C and could be attributable to low probability, extreme events.

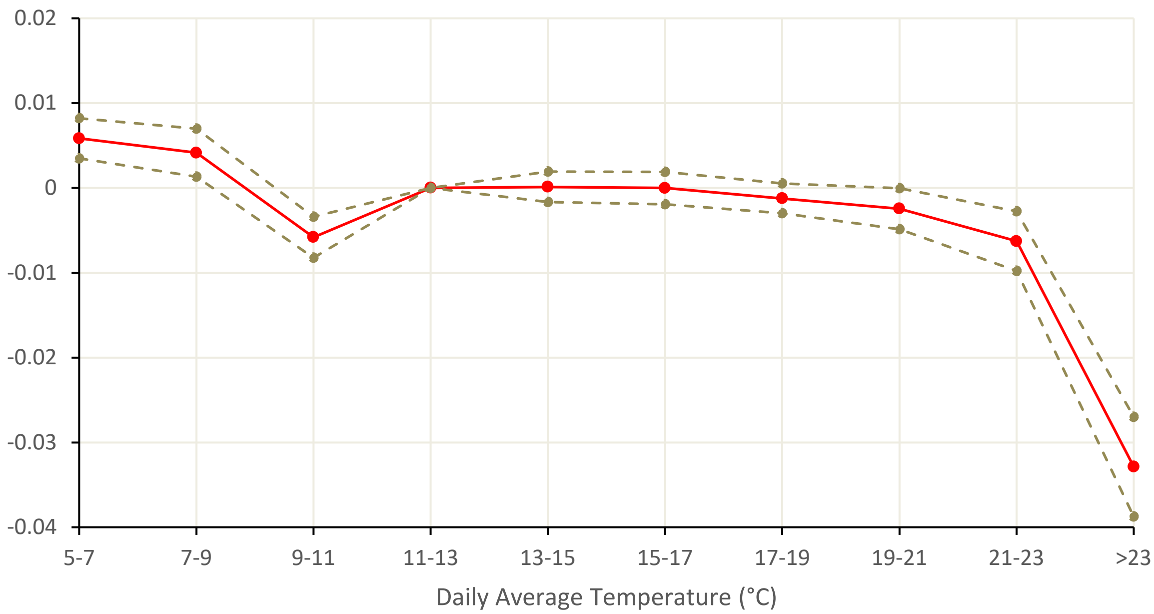

Figure 4: Estimated Semi-Elasticities between Temperature and Yields for Canola

What is also of interest is precipitation's impact on crop yields. The literature tells us that precipitation in May through August is most impactful, yet we arrive at counterintuitive results. More rainfall in May and July is beneficial to crop yields yet rainfall in June and August is negative. There are a few things that could be driving these results. Our time fixed effects are likely accounting for some year-to-year variation in precipitation that is common across all RMs. Previous specifications that include rainfall but not time fixed effects garner largely negative results: additional rainfall in May, June, and August reduce crop yields and rainfall in July increases crop yields. This is counterintuitive as moisture is one of, if not the most, beneficial resources for plant growth. As stated before, however, growing season precipitation is a poor proxy for soil moisture which depends on winter precipitation, soil moisture retention, and many other factors. Thus, these results should not be taken too seriously. We treat precipitation in our wheat regressions similarly, a discussion to which we now turn.

5.2 Explaining Wheat Yields

Regression results for wheat are reported in Table 5. Specification (1) reports simple OLS where temperature bins alone explain 20% of the temporal and regional variation in crop yields. Similar to the canola results, the negative signs on nearly all temperature bins, representing days above and below 11-13°C, is indicative of misspecification and omitted variable bias.

Soil type and the inclusion of both oscillatory mechanisms in specification (2) explains an additional 18.2% of variation in yields, markedly higher than in the canola regression (2.8%). Coefficient estimates for the NAO and AMO indexes are again positive and indicative of non-climate change factors. Relative to RMs located in the brown soil zones (SZ), yields are 25.4% and 17.8% higher in black and dark brown SZs, respectively. These estimates are highly statistically significant. The addition of variables accounting for precipitation between May and August account for an additional 4.4% of variation in yields and slightly reduce SZ estimates to 23.4% and 16.1% for black and dark brown SZs, respectively. Coefficient estimates for low temperatures (<3°C) are no longer statistically significantly negative.

In our FE model, shown in specifications (4) and (5), the results are not dissimilar to those in specifications (2) and (3). The adjusted R^2 shows that specification (4) and (5) only explain 24% and 29.1%, respectively, of the variation in yields; this suggests there are omitted determinants of yields. This is still quite less than that of the RE model that had an adjusted R^2 of 42.6%.

Table 5: Regression Results for Wheat Yields

Dependent variable: log(Yield)	Random Effects			Location Fixed Effects		Two-way Fixed Effects	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Bin3 (5-7ºC)	-0.006***	-0.002	-0.0002	-0.001	-0.0001	0.005***	0.005***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Bin4 (7-9ºC)	-0.008***	-0.003**	-0.003**	-0.003**	-0.003**	0.004***	0.004***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Bin5 (9-11ºC)	-0.005***	-0.005***	-0.006***	-0.005***	-0.006***	-0.004***	-0.003***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Bin7 (13-15ºC)	-0.001	0.001	0.001	0.001	0.001	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Bin8 (15-17ºC)	0.001	-0.004***	-0.004***	-0.003***	-0.004***	-0.002**	-0.002*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Bin9 (17-19ºC)	-0.004***	-0.008***	-0.007***	-0.008***	-0.007***	-0.003***	-0.002**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Bin10 (19-21ºC)	-0.009***	-0.011***	-0.005***	-0.011***	-0.006***	-0.002**	-0.002*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Bin11 (21-23ºC)	-0.008***	-0.009***	-0.007***	-0.009***	-0.008***	-0.005***	-0.005***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)
Bin12 (>23ºC)	-0.021***	-0.018***	-0.022***	-0.018***	-0.022***	-0.018***	-0.020***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
NAO		0.074***	0.062***	0.075***	0.063***	-0.126***	-0.132***
		(0.005)	(0.005)	(0.005)	(0.005)	(0.019)	(0.019)
AMO		0.088***	0.088***	0.088***	0.088***	0.160***	0.150***
		(0.005)	(0.005)	(0.005)	(0.005)	(0.008)	(0.007)
Black SZ		0.254***	0.234***				
		(0.022)	(0.021)				
Dark Brown SZ		0.178***	0.161***				
		(0.023)	(0.022)				
May Precip			-0.001***		-0.001***		0.0002
			(0.0002)		(0.0002)		(0.0002)
June Precip			-0.0001		-0.0001		-0.0003**
			(0.0001)		(0.0001)		(0.0001)
July Precip			0.001***		0.001***		0.0001
			(0.0001)		(0.0001)		(0.0001)
August Precip			-0.001***		-0.001***		-0.001***
			(0.0001)		(0.0001)		(0.0002)
Location FE	No	No	No	Yes	Yes	Yes	Yes
Time FE	No	No	No	No	No	Yes	Yes
Obs.	2,590	2,590	2,590	2,590	2,590	2,590	2,590
R^2	0.203	0.385	0.429	0.319	0.366	0.454	0.461
Adjusted R^2	0.200	0.382	0.426	0.240	0.291	0.389	0.396
F Statistic	656.3***	1,612.8***	1,936.0***	98.8***	89.0***	106.7***	89.8***

Note: Heteroskedasticity-robust standard errors reported in parentheses. *p<0.1; **p<0.05; ***p<0.01

When we include time fixed effects, we see substantial improvements to the model. In specification (6) the adjusted R^2 increases to explaining 38.9% of variation in yields after we include dummy variables for each year. This further increases to 39.6% after we include precipitation controls in specification (7). This outperforms the simple location fixed effects model. The coefficient estimates are shown below in Figure 5.

Reduced yields relative to potential yield occur at and beyond 15ºC (Bins 8-12) though the impact is incredibly small: an additional day where average temperatures are anywhere between 15 and 21ºC is associated with a 0.2% reduction in potential bushels per acre. Similar to the results for canola, days with cooler average temperatures of 5-9ºC are more beneficial than those of 11-13ºC, associated with increases of 0.5% increases in potential yield, yet days with average temperatures of 9-11ºC are associated with a reduction of 0.3%. We are again not sure what is driving the latter result. Days with average temperatures of 13-15ºC are no more or less beneficial than those of 11-13ºC. Potential yields appear to be more dampened after 21ºC. Specifically, the average reduction in potential yield is 0.05% for an additional day where average temperatures are 21-23ºC and 2% for each day where temperatures exceed 23ºC.

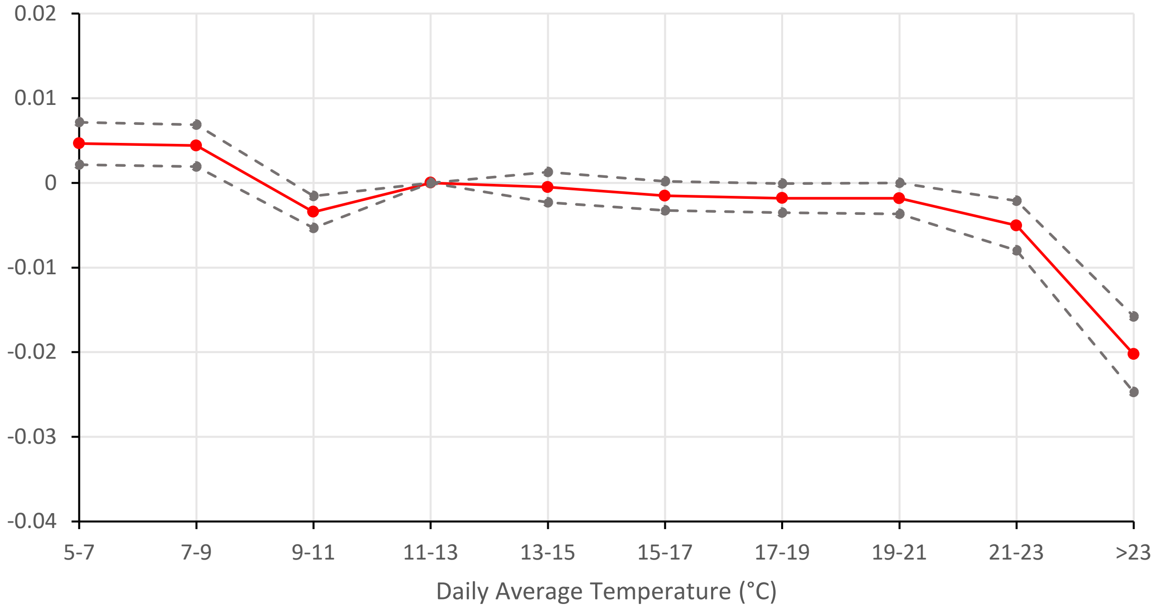

Figure 5: Estimated Semi-Elasticities between Temperature and Yields for Wheat

6. Conclusion

Beyond certain thresholds, rising temperatures are associated with lower yields in canola and wheat. In addition to identifying potential yield reductions, we find evidence of resilience to temperature across a broad range of temperatures, particularly so for wheat. Canola is optimally grown at higher latitudes where days are longer and cooler, aligned with our findings of greater yields at lower temperatures and larger reductions at high temperatures. This is consistent with its prevalence in northern agricultural regions of Saskatchewan.

Let temperature resilience be defined as no significant yield impact relative to average temperatures of 11-13ºC. Wheat exhibits temperature resilience up until 21ºC. Canola exhibits temperature resilience up until 19ºC. Beyond these thresholds, wheat yield potential is reduced by 0.05% on average for every additional day where average temperatures are 21-23 ºC and reduced by 2% for every additional day where average temperatures exceed 23ºC. Canola yield potential is reduced by 0.2% for every additional day where average temperatures are 19-21ºC, 0.6% for

21-23ºC, and 3.3% for days where temperatures exceed 23ºC. These results reflect nonlinearities in temperature impacts, particularly, increasing severity of impacts as temperatures become more extreme. Our analysis is relevant only to the Canadian context as management practices are endogenized in yield responses since adaptation is heterogenous between regions and countries. Therefore, these results do not easily extrapolate to canola and wheat generally.

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