# Crop Yield Response to Climate Variables on Dryland versus Irrigated Lands

Wei Lu,[1] Wiktor Adamowicz,[2] Scott R. Jeffrey,[3] Greg G. Goss[4] and Monireh Faramarzi[5]

[1]*Alberta Department of Energy, Edmonton, Alberta, Canada (e-mail: wlu2@ualberta.ca).*
[2]*Department of Resource Economics and Environmental Sociology, University of Alberta, Edmonton, Alberta, Canada (corresponding author: phone: 780-492-4603; fax: 780-492-0268; e-mail: vic.adamowicz@ualberta.ca).*
[3]*Department of Resource Economics and Environmental Sociology, University of Alberta, Edmonton, Alberta, Canada (e-mail: scott.jeffrey@ualberta.ca).*
[4]*Department of Biological Sciences, University of Alberta, Edmonton, Alberta, Canada (e-mail: ggoss@ualberta.ca).*
[5]*Department of Earth and Atmospheric Sciences, University of Alberta, Edmonton, Alberta, Canada (e-mail: faramarz@ualberta.ca).*

**Key Points:**

- *We examine the response of barley, canola, and spring wheat yields to a set of climate variables on both dryland and irrigated lands in southern Alberta, Canada.*
- *We find that warming and increased precipitation tend to increase crop yields on dryland, increased precipitation in June and July tends to show opposite effects on crop yields on irrigated lands.*
- *Based on regional climate change projection scenarios, we find that climate change decreases crop yields for all the three crops under dryland production. However, yields of canola and spring wheat under irrigation are slightly increased.*

*Few researchers have examined the impact of climate change on irrigated agriculture and crop production. This may be due to an assumption by researchers that irrigation management can offset impacts of climate change. We investigate this issue by examining the response of barley, canola, and spring wheat yields to a set of climate variables on both dryland and irrigated lands in southern Alberta, Canada, with a panel data set at the county level from 1983 to 2007. Our results suggest that warming and increased precipitation tend to increase dryland crop yields, while increased precipitation in June and July tends to show opposite effects on crop yields on irrigated lands. Based on regional projected climate change scenarios, we find that climate change decreases crop yields for all the three crops under dryland production. However, yields of canola and spring wheat under irrigation are increased slightly.*

*Peu de chercheurs se sont penchés sur les impacts des changements climatiques sur l'agriculture irriguée et le rendement des cultures. Il se pourrait que ce soit parce que les chercheurs supposent que les régimes d'irrigation peuvent neutralise les impacts des changements climatiques. Nous examinons cet enjeu en étudiant le rendement de l'orge, du canola et du blé de printemps en fonction de variables climatiques à la fois en sols arides et en sols irrigués au sud de l'Alberta, au Canada avec un ensemble de données de panel provenant des comtés de 1983 à 2007. Les résultats démontrent que le réchauffement et l'augmentation des précipitations semblent accroître le rendement des sols arides mais que cette dernière, lorsqu'elle survient en juin ou juillet, semble engendrer l'effet contraire sur le rendement en sols irrigués. Nous constatons, selon les scénarios hypothétiques de changements climatiques régionaux, une diminution du rendement agricole pour les trois cultures en sols arides. Par contre, le rendement des cultures de canola et de blé de printemps en sols irrigués augmenterait légèrement.*

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## INTRODUCTION

Agriculture is considered one of the most vulnerable economic sectors to climate change. Crop production has been a central focus when estimating the impact of climate conditions. The fundamental step in determining potential costs and then formulating strategies for future crop production under climate change is to understand how climate change affects crop yields. Some studies used field experiments and biophysical simulation models to estimate the effect of changes in climate variables on crop yields (Long et al 2006; Schierhorn et al 2014). Recent studies have used regression models with panel data including county-level yields and variations in climate variables to examine the response of crop yields to temperature and precipitation (e.g., Schlenker and Roberts 2009; Miao et al 2016). These studies estimated crop yields as a function of climate variables while controlling for time-invariant fixed effects such as soil quality and other land characteristics (Hsiang 2016). For example, Schlenker and Roberts (2009) found that yields increase with temperatures for three major crops in the United States. However, temperature showed a negative impact on yields when it reached 29°C for corn, 30°C for soybeans, and 32°C for cotton. They also forecasted that warming could lead to a 30% to 82% decrease in crop yields, depending on the specific climate change scenario. Miao et al (2016) reported that climate change would likely decrease corn production by 7% to 41% and soybean production by 8% to 45% in the United States under various emission scenarios based on different global climate models. Cabas et al (2010) studied corn, soybean, and winter wheat yields in southwestern Ontario, Canada, and found that warmer temperatures would increase average crop yields.

The aforementioned studies and other previous research tend to focus solely on crop yields in dryland production areas. For dryland production systems, precipitation is a direct input and a strong relationship between precipitation and dryland crop yields is expected. Less attention has been paid by researchers to the potential impacts of climate change on irrigated crop production. The use of irrigation is often considered a strategy to improve or at least maintain crop production levels in warmer and/or drier conditions. The lack of studies examining the effect of climate change on irrigated crops may be due to the perception that irrigation serves as a buffer for crop production to changes in climatic conditions. Thus, crop yields under irrigation (unlike dryland yields) might not respond significantly to changes in climate variables.

One exception to this is the study by Marshall et al (2015). They projected that climate change would reduce average yields of many major U.S. field crops, including corn, soybeans, rice, sorghum, cotton, oats, and silage, under both irrigated and dryland production. By contrast, yields of wheat, hay, and barley were projected to increase for both production systems. It was also noted by the authors that increased precipitation might narrow the difference in yields on dryland versus irrigated lands. Given projected reductions of irrigation water supply and higher costs associated with irrigation systems, they forecasted a shift of crops from irrigated lands to dryland.

Fewer research efforts have been undertaken to explore the impacts of climate change on agriculture in more northern regions such as Canada. To the best of our knowledge, no studies have been conducted on the climatic impacts on irrigated crop production in Canada. Understanding how climatic conditions affect crops on irrigated lands is important to aid decision making associated with irrigation use and expansion. In Alberta, Canada, irrigation occurs on approximately 6% of the cultivated agricultural land but generates nearly 20% of the production (Alberta Agriculture and Forestry 2015) that accounts for 60%–70% of total water consumption in the province (Faramarzi et al 2017). Alberta employs a "first in time, first in right" water allocation approach and Alberta's irrigation districts have some of the oldest licenses in the province—indicating that they in principle would have first access to water in conditions of scarcity. The quantity of water available is identified in the license and Alberta's irrigation districts currently hold licenses for more water than has been historically diverted (Bennett et al 2017). Water rights holders do not pay a per unit fee or price to the province. Within irrigation districts water is allocated to farmers with a per unit area of land charge (Renzetti 2009). Thus, there is effectively no marginal cost (per unit water) for water in Alberta. Assessment of climate impacts will provide insights into the discussion for relevant stakeholders and information to advance the technology and improve the efficiency of irrigation for crop producers, as well as provide insights for policy makers. The purpose of this study is to estimate the effects of temperature and precipitation on yields for three major crops in southern Alberta, Canada, specifically, barley, canola, and spring wheat. We further explore the similarities and differences of such impacts on crop yields on dryland versus irrigated lands. In irrigated areas, we also explain trade-offs between climate factors and irrigation practices corresponding to the irrigated crop yields. Finally, based on future climate change scenarios, we forecast how climate change will affect crop yields on both dryland and irrigated lands in southern Alberta.

A panel data approach was used to investigate the effects of climatic conditions on the yields of barley, canola, and spring wheat at the county level in southern Alberta on dryland and irrigated lands, for the period between 1983 and 2007. Consistent with previous Canadian studies (e.g., Carew and Smith 2006; Cabas et al 2010; Robertson et al 2013), we found that warming and increased precipitation tend to increase crop yields on dryland. However, the effect of the pattern of precipitation is different on irrigated lands for which increased precipitation in June and July shows a negative impact on crop yields. Based on regional projected climate change scenarios, we found that climate change decreases crop yields for all the three crops under dryland production. However, yields of canola and spring wheat under irrigation are increased slightly.

The rest of the paper proceeds as follows. We first present an overview of the study area. It is followed by an illustration of data and the model used in this analysis. We then present the results and discussion. The last section provides concluding remarks.

## DATA AND METHODS

### Study Area

Alberta is Canada's second most western province and is located between 49–60°N and 110–120°W. The value of crop production in the province in 2014 was estimated at $5.9 billion, which accounted for 22.4% of Canadian crop production (Alberta Agriculture and Forestry 2015). Barley, canola, and spring wheat were the three most dominant crops in Alberta, with a total seeded area of 6,371,775 hectares. This accounted for approximately 70% of the total seeded area in 2014 (Alberta Agriculture and Forestry 2015). The yield performance of these three crops is of paramount importance to the success of crop farmers in the province as well as the livestock sector, which relies on the output for feed.

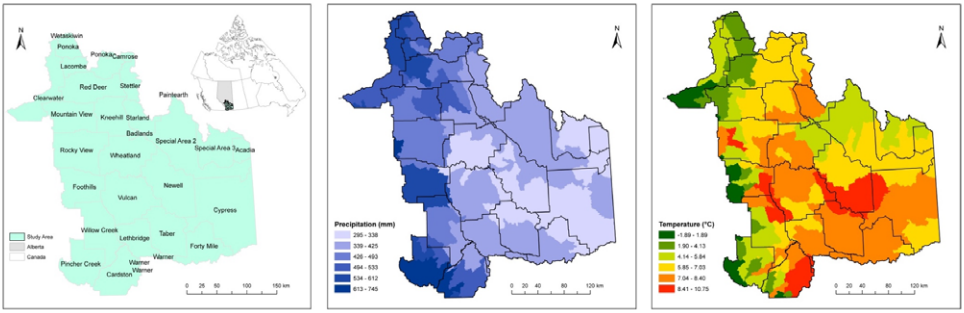


Figure 1. Study area[a] (left); average annual precipitation (mm) from 1983 to 2007 (middle); and average annual temperature (°C) from 1983 to 2007 (right)
Note: [a]The counties included in this study are Acadia, Badlands, Camrose, Cardston, Clearwater, Cypress, Foothills, Forty Mile, Kneehill, Lacombe, Lethbridge, Mountain View, Newell, Paintearth, Pincher Creek, Ponoka, Red Deer, Rocky View, Special Area 2, Special Area 3, Starland, Stettler, Taber, Vulcan, Warner, Wheatland, Willow Creek, and Wetaskiwin.

Approximately 70% of Canada's total irrigated area is in Alberta. In 2013, the total irrigated area in Alberta was about 690,000 hectares (Paterson Earth & Water Consulting 2015), of which 97% was located in the South Saskatchewan River Basin (SSRB). This study focused on the counties located in the SSRB region in order to compare the impacts of climate change on crop yields on dryland versus irrigated lands. Specifically, the study area for the current analysis comprises the 28 counties with crop production that are fully or partially located within the SSRB (see Figure 1). The basin has an overall semiarid climate with an annual precipitation between 200 mm and 500 mm (Faramarzi et al 2015). The climatic conditions during the period from 1983 to 2007 vary across the studied counties, with average annual precipitation ranging from 300 mm to 600 mm, the average daily temperature in January ranging from –19°C to 3°C, and the average daily temperature in July ranging from 8°C to 26°C. Irrigated lands generated higher average yields for the three crops relative to dryland production during the study period (see Figure 2 and Tables 1, S1, and S2). The gross return per hectare from irrigated agriculture is more than three times the return from dryland agriculture (Irrigation Water Management Study Committee 2002). The higher productivity of irrigated farms located in the SSRB is due to the additional water supply provided by irrigation (Samarawickrema and Kulshreshtha 2008). High summer temperatures increase plant evapotranspiration that is beneficial for crop growth when there is no moisture constraint (Samarawickrema and Kulshreshtha 2008).

## Data and Methods

We estimated a yield response function by specifying a fixed-effect panel model as follows:

$$Y_{ijt} = \beta_{i0} + \beta_{i1}\theta_{ijt} + \beta_{i2}\tau_{ijt} + u_{ij} + \varepsilon_{ijt} \tag{1}$$

where $Y_{ijt}$ is the annual yield of crop $i$ in county $j$ during year $t$, $\theta$, and $\tau$ are vectors of climate variables and time trends, respectively, $\beta_{i0}$, $\beta_{i1}$, and $\beta_{i2}$ are parameter estimates, $u_{ij}$ is a county-level fixed effect, and $\varepsilon_{ijt}$ is an error term. As noted earlier, the model

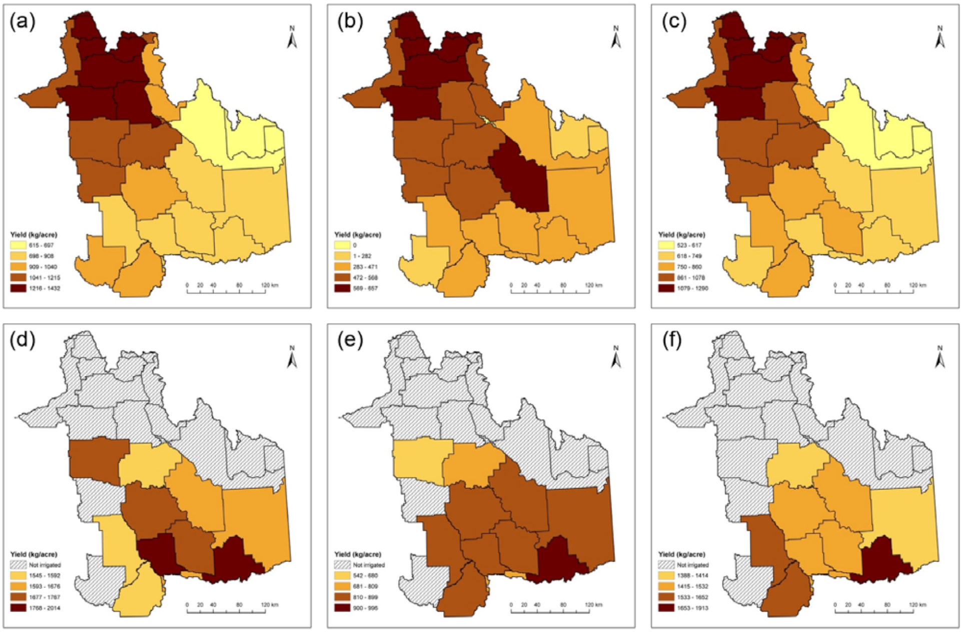


Figure 2. Average annual yields of barley on dryland (A) and irrigated lands (D) from 1983 to 2007; average annual yields of canola on dryland (B) and irrigated lands (E) from 1983 to 2007; average annual yields of spring wheat on dryland (C) and irrigated lands (F) from 1983 to 2007

Table 1. Summary statistics of data set used in barley yields response analysis, 1983–2007

| | Barley | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Dryland | | | | Irrigated | | | |
| Variables | Mean | Std. dev. | Min. | Max. | Mean | Std. dev. | Min. | Max. |
| Crop yields (kg/acre) | 1,010.8 | 384.3 | 39.0 | 1,821.0 | 1,706.7 | 337.2 | 676.0 | 2,615.0 |
| Growing degree days (GDDs) | 1,383.8 | 270.4 | 414.8 | 1,944.0 | 1,564.2 | 177.2 | 991.6 | 1,944.0 |
| Overheat degree days (ODDs) | 0.3 | 1.1 | 0.0 | 13.6 | 0.6 | 1.7 | 0.0 | 13.6 |
| Precipitation in May (mm) | 51.2 | 30.0 | 3.9 | 210.6 | 49.6 | 28.6 | 4.5 | 210.6 |
| Precipitation in June (mm) | 83.4 | 45.7 | 2.0 | 373.9 | 78.5 | 48.0 | 2.0 | 260.9 |
| Precipitation in July (mm) | 62.5 | 42.1 | 2.6 | 230.2 | 43.1 | 32.2 | 2.6 | 180.3 |
| Precipitation in August (mm) | 53.8 | 29.9 | 0.0 | 136.8 | 42.9 | 25.7 | 0.3 | 125.7 |
| Temp. deviation in May (°C) | 11.4 | 1.1 | 7.2 | 14.4 | 11.9 | 1.0 | 8.7 | 14.4 |
| Temp. deviation in June (°C) | 12.0 | 1.4 | 8.4 | 16.0 | 12.7 | 1.4 | 9.3 | 16.0 |
| Temp. deviation in July (°C) | 13.8 | 1.9 | 9.6 | 20.0 | 14.8 | 1.8 | 10.0 | 20.0 |
| Temp. deviation in August (°C) | 13.8 | 1.7 | 10.0 | 18.6 | 14.5 | 1.5 | 11.4 | 18.2 |

Source: The crop yield data are from Alberta Agriculture Financial Services Corporation. The climate variables are from Faramarzi et al (2015).
Notes: There are 674 observations for dryland and 255 observations for irrigated lands. Temperature deviation for each month was calculated as the difference between average monthly maximum temperature and average monthly minimum temperature.

is constructed for the period from 1983 to 2007, for barley, canola, and spring wheat, separately. The vector of climate variables, $\theta$, includes measures of temperature, heat, and precipitation calculated over the growing season; that is, from May to August. The length of the growing season was selected for the three crops based on the information from Alberta Agriculture and Forestry (2015). The time trend vector $\tau$ consists of a linear and a quadratic form of time trend to capture technological progress and the improvement of agronomic practices. The county-specific effect, $u_{ij}$, is to reflect other time-invariant characteristics for each county and each crop such as soil quality.

Temperature and precipitation are the two common indicators of climate conditions used when estimating the climatic impacts on crop yields. A common approach in modeling temperature effects on crop yields is to use average temperature for a specific period (e.g., Cabas et al 2010; Cohn et al 2016). However, as argued by Schenkler and Roberts (2009), if temperature has a nonlinear effect, crop yields may initially increase with temperature but then decrease when the temperature reaches a certain threshold. Using average temperature to study crop yields may mask the negative yield effect of extreme temperatures.

An approach incorporating extreme temperatures and based on daily growing degree days (GDDs) was used to address this limitation in this study. GDD, a measure of accumulated heat, was calculated for the entire growing season from May to August by summing daily GDDs. Daily GDDs are calculated using daily maximum ($T_{\max}$) and minimum temperatures ($T_{\min}$) and a base temperature ($T_{\text{base}}$), as follows:

$$\text{GDD} = \max\left(\frac{T_{\max} + T_{\min}}{2} - T_{\text{base}},\ 0\right) \tag{2}$$

Based on Robertson et al (2013) and following the approach by Miao et al (2016), 5°C was selected as the base temperature for calculating GDDs. Robertson et al (2013) estimated crop yields as a function of different temperature and rainfall variables and reported critical minimum temperatures of 5°C, 5°C, and 5°C for barley, canola, and spring wheat, respectively. They also reported critical maximum temperatures of 28°C, 29°C, and 29°C for barley, canola, and spring wheat, respectively. Daily GDDs were calculated for days with minimum temperatures above 5°C and maximum temperatures below 29°C. GDD was included in the yield response function both linearly and as a squared term, to allow flexibility in modeling the impact of heat on crop yields. To capture the impact of extreme (i.e., hot) temperatures on yields, a variable, called overheat degree days (ODDs), was calculated for the entire growing season (from May to August) and included in the model. ODD was defined as the sum of daily GDDs for days with maximum temperatures above 29°C.

Climate change not only concerns the magnitude of change in temperature but also the degree of temperature variability. Crop yields are affected by intra-annual temperature variability (McCarl et al 2008; Miao et al 2016). We therefore included monthly temperature deviations as explanatory variables. For each month in the growing season, this was calculated as the difference between average monthly maximum temperature and average monthly minimum temperature.

In the case of precipitation, not only the amount but also the timing of growing season precipitation is important. Thus, instead of seasonal total precipitation, monthly cumulative precipitation variables were defined and used in the model to capture the impact of timing of seasonal variation and seasonal shift in precipitation on crop yields.

In some cases, there is both irrigated land and dryland land within a county. Due to data availability, we were not able to identify the locations of dryland and irrigated land within a county. In addition, the variability within a county in terms of precipitation and temperature is deemed not significant. Therefore, the same set of climate variables was used for both irrigated and dryland yield for a given county.

Annual county-level crop yield data for barley, canola, and spring wheat were obtained from Agriculture Financial Services Corporation (AFSC) for the period from 1983 to 2007. The daily historical climate data (i.e., precipitation, maximum and minimum temperature) were obtained from the study by Faramarzi et al (2015), where an extensive qualification of climate data was conducted using the Soil and Water Assessment Tool, a process-based crop growth and a hydrology model. The study tested various climate time series from different sources (e.g., recorded data of meteorological stations, gridded data of regional, national and global models) to examine hydrological and crop simulation response of the input data. The authors used a data discrimination approach to find time series of locally representative temperature, precipitation, and other hydrological data at the subbasin scale. Table 1 presents the summary statistics of the variables used in the barley yield analysis. The summary statistics of the data sets for canola and spring wheat yields analyses are presented in Tables S1 and S2 in the Support Information.

Projected values of daily climate data for future period (2010–34) were obtained from the Pacific Climate Impacts Consortium (PCIC 2014; Cannon 2015). The PCIC provides statistically downscaled Canada-wide climate data of the Intergovernmental Panel on Climate Change (IPCC) Coupled Model Inter-Comparison Project Phase 5 (CMIP5) for precipitation, minimum and maximum temperature at a resolution of 300 arc seconds ($\sim$10 km). In this study, we used the downscaled data for two extreme scenarios of the IPCC Representative Concentration Pathways (RCP) (IPCC 2014) including of RCP2.6 and RCP8.5.

A Wooldridge test (Wooldridge 2002, pp. 282–283) was used to test for serial correlation (see Table S6). We failed to reject the null hypothesis of no autocorrelation for all specifications except canola on irrigated lands. We also used a Modified Wald test (Greene 2000) to test for groupwise heteroskedasticity in a fixed effects model (see Table S7). The null hypothesis of homoskedasticity was rejected at the 1% level for all barley, canola, and spring wheat specifications. To account for the effects of serial correlation and heteroskedasticity, we used robust standard errors clustered at the county level (Hoechle 2007).

## RESULTS AND DISCUSSION

The estimation results for the crop yield response models (i.e., barley, canola, and spring wheat) on dryland and irrigated lands are presented in this section. Specifically, the relationships between yields and relevant climatic variables are highlighted. This is followed by an analysis of future climate change scenarios. These scenarios are used to simulate yields under climate change conditions.

The estimation results for crop yields are presented in Tables 2, 3, and 4 for barley, canola, and spring wheat, respectively. For each crop, four different crop yield response models are estimated; two each for dryland (d) and irrigated (i) yields. All four versions

Table 2. Parameter estimates for barley yield response panel model

| | Model 1d | | Model 1i | | Model 2d | | Model 2i | |
|---|---|---|---|---|---|---|---|---|
| Variables | Coeff. | Std. err. | Coeff. | Std. err. | Coeff. | Std. err. | Coeff. | Std. err. |
| GDD | 1.268*** | 0.3671 | 2.845* | 1.516 | | | | |
| $GDD^2$ ($\times 10^{-3}$) | −0.4403*** | 0.1265 | −0.8525* | 0.4402 | | | | |
| ODD | 2.702 | 6.627 | −19.20*** | 4.773 | −2.224 | 7.009 | −15.36** | 6.073 |
| May Prec. | 0.3058 | 0.4862 | −0.8970 | 0.5998 | −2.036 | 1.480 | 12.31*** | 3.170 |
| June Prec. | 0.4412 | 0.2937 | −1.872*** | 0.4897 | −1.769* | 0.925 | −7.090** | 2.444 |
| July Prec. | 2.610*** | 0.2636 | −0.7686 | 0.7280 | 0.5485 | 1.599 | −6.356 | 3.805 |
| August Prec. | 3.019*** | 0.3804 | 1.685** | 0.7457 | 2.611* | 1.501 | −4.594 | 4.232 |
| GDD × May Prec. | | | | | 0.001706 | 0.001078 | −0.008928*** | 0.002127 |
| GDD × June Prec. | | | | | 0.001725** | 0.0007757 | 0.003280** | 0.001591 |
| GDD × July Prec. | | | | | 0.001743 | 0.001228 | 0.003896 | 0.002424 |
| GDD × August Prec. | | | | | 0.0004583 | 0.001083 | 0.004728 | 0.002913 |
| May temp. dev. | −55.23*** | 15.50 | −73.59** | 25.89 | −73.69*** | 12.93 | −76.65*** | 18.46 |
| June temp. dev. | 2.134 | 9.806 | 10.49 | 21.00 | 9.139 | 10.20 | −2.915 | 16.57 |
| July temp. dev. | −72.28*** | 10.70 | −72.79*** | 23.17 | −80.59*** | 11.02 | −76.86*** | 18.47 |
| August temp. dev. | 47.58*** | 9.518 | 45.67** | 16.66 | 38.92*** | 9.039 | 60.54*** | 10.78 |
| Time trend | 12.73*** | 4.070 | 43.21*** | 10.79 | 12.98*** | 4.032 | 41.59*** | 12.63 |
| Time trend squared | 0.09108 | 0.1591 | −0.6206 | 0.3903 | 0.06928 | 0.1624 | −0.5563 | 0.4542 |
| Constant | 509.9*** | 282.4 | 270.3 | 1,228 | 1,723*** | 231.0 | 2,652*** | 404.5 |
| Number of obs. | 674 | | 255 | | 674 | | 255 | |

Notes: Models 1d and 2d are for crops on dryland, and Models 1i and 2i are for crops on irrigated lands. Robust standard errors are clustered at the county level.
***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 3. Parameter estimates for canola yield response panel model

| | Model 1d | | Model 1i | | Model 2d | | Model 2i | |
|---|---|---|---|---|---|---|---|---|
| Variables | Coeff. | Std. err. | Coeff. | Std. err. | Coeff. | Std. err. | Coeff. | Std. err. |
| GDD | $1.147^{***}$ | 0.1841 | $1.429^{*}$ | 0.6653 | | | | |
| $GDD^2$ ($\times 10^{-3}$) | $-0.3558^{***}$ | 0.1000 | $-0.4215^{*}$ | 0.2126 | | | | |
| ODD | $-14.80^{***}$ | 3.97 | $-17.18^{***}$ | 3.217 | $-15.93^{***}$ | 4.096 | $-14.19^{***}$ | 3.235 |
| May Prec. | 0.2469 | 0.2882 | 0.3226 | 0.2693 | −1.292 | 1.167 | $6.203^{***}$ | 1.698 |
| June Prec. | 0.2425 | 0.1475 | $-0.6321^{***}$ | 0.1099 | 0.2324 | 0.9541 | −0.6041 | 1.593 |
| July Prec. | $1.146^{***}$ | 0.1612 | $-0.8084^{*}$ | 0.4014 | $-2.601^{***}$ | 0.5834 | $-7.704^{***}$ | 1.578 |
| August Prec. | $1.758^{***}$ | 0.2494 | $2.362^{***}$ | 0.6808 | $1.285^{*}$ | 0.6600 | −0.7947 | 2.638 |
| GDD × May Prec. | | | | | 0.001107 | 0.0008089 | $-0.003844^{***}$ | 0.001069 |
| GDD × June Prec. | | | | | 0.00001700 | 0.0006676 | −0.0000770 | 0.001023 |
| GDD × July Prec. | | | | | $0.003024^{***}$ | 0.0004657 | $0.004873^{***}$ | 0.001089 |
| GDD × August Prec. | | | | | 0.0002800 | 0.0005007 | 0.002223 | 0.001730 |
| May temp. dev. | $-30.53^{***}$ | 6.485 | −10.45 | 13.31 | $-39.11^{***}$ | 6.956 | −14.27 | 10.14 |
| June temp. dev. | 7.225 | 6.578 | 2.978 | 7.119 | 8.841 | 6.840 | −2.806 | 6.885 |
| July temp. dev. | $-46.94^{***}$ | 6.794 | −14.04 | 8.893 | $-46.26^{***}$ | 6.819 | −12.91 | 9.409 |
| August temp. dev. | $13.71^{***}$ | 4.899 | 15.65 | 13.65 | 8.564 | 5.315 | $21.09^{**}$ | 9.387 |
| Time trend | $-8.940^{***}$ | 2.515 | 1.095 | 4.614 | $-8.047^{***}$ | 2.595 | 0.9704 | 4.958 |
| Time trend squared | $0.7638^{***}$ | 0.09336 | $0.6107^{*}$ | 0.1377 | $0.7405^{***}$ | 0.09976 | $0.6286^{***}$ | 0.1528 |
| Constant | 76.27 | 157.2 | −438.0 | 752.1 | $1{,}092^{***}$ | 108.7 | $755.9^{**}$ | 271.6 |
| Number of obs. | 621 | | 208 | | 621 | | 208 | |

Notes: Models 1d and 2d are for crops on dryland, and Models 1i and 2i are for crops on irrigated lands. Robust standard errors are clustered at the county level.
***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 4. Parameter estimates for spring wheat yield response panel model

| | Model 1d | | Model 1i | | Model 2d | | Model 2i | |
|---|---|---|---|---|---|---|---|---|
| Variables | Coeff. | Std. err. | Coeff. | Std. err. | Coeff. | Std. err. | Coeff. | Std. err. |
| GDD | 1.030*** | 0.2820 | 2.910* | 1.384 | | | | |
| $GDD^2$ ($\times 10^{-3}$) | −0.3243*** | 0.1013 | −1.011** | 0.4188 | | | | |
| ODD | −15.20*** | 5.246 | −15.32* | 6.868 | −15.66*** | 5.073 | −13.32 | 7.493 |
| May Prec. | 1.348*** | 0.3350 | 0.2726 | 0.7985 | 0.9684 | 0.9447 | 14.28*** | 3.821 |
| June Prec. | 0.8724*** | 0.2413 | −0.8382* | 0.4080 | −0.8816 | 0.6057 | −1.710 | 1.645 |
| July Prec. | 2.019*** | 0.2322 | −0.9420 | 0.7268 | −0.8442 | 0.9382 | −16.61** | 5.476 |
| August Prec. | 2.085*** | 0.3065 | 1.772 | 1.088 | 2.931** | 1.193 | 8.444 | 6.158 |
| GDD × May Prec. | | | | | 0.0002514 | 0.0007078 | −0.008934*** | 0.002161 |
| GDD × June Prec. | | | | | 0.001313*** | 0.0004378 | 0.0003477 | 0.001153 |
| GDD × July Prec. | | | | | 0.002308*** | 0.0007189 | 0.009969** | 0.003700 |
| GDD × August Prec. | | | | | −0.0005984 | 0.0008733 | −0.003936 | 0.003819 |
| May temp. dev. | −61.92*** | 8.866 | −13.43 | 25.93 | −69.95*** | 7.995 | −38.27 | 24.64 |
| June temp. dev. | 1.199 | 8.908 | 9.401 | 15.86 | 3.742 | 9.348 | 5.985 | 15.48 |
| July temp. dev. | −49.34*** | 7.263 | −40.73** | 17.42 | −51.08*** | 8.191 | −56.92*** | 14.11 |
| August temp. dev. | 27.02*** | 5.630 | 56.64** | 20.90 | 22.78*** | 5.879 | 55.03** | 21.93 |
| Time trend | −1.446 | 3.211 | 20.44* | 11.01 | −1.314 | 3.261 | 18.45 | 12.58 |
| Time trend squared | 0.6027*** | 0.1134 | 0.7715 | 0.4537 | 0.6036*** | 0.1168 | 0.8368 | 0.4847 |
| Constant | 609.6*** | 221.4 | −1,181 | 887.1 | 1,523*** | 152.57 | 1,487* | 686.16 |
| Number of obs. | 677 | | 176 | | 677 | | 176 | |

Notes: Models 1d and 2d are for crops on dryland, and Models 1i and 2i are for crops on irrigated lands. Robust standard errors are clustered at the county level.
***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

include a common set of explanatory variables, including ODD, monthly precipitation, monthly temperature deviations, as well as a linear and quadratic time trend. The models differ in terms of the specification of GDD. In Model 1, an assumption of additive separability is made regarding the impacts of temperature and precipitation on crop yields. Thus, Models 1d and 1i for each crop include linear and quadratic GDD terms as explanatory variables. However, it can be argued that temperature and precipitation interact in terms of their effects on yield. This issue was explored by incorporating interaction terms for GDD and monthly precipitation into Model 2d and Model 2i, which replace the linear and quadratic GDD variables. Initially, the interaction terms were included with the linear and quadratic GDD variables. However, the interaction terms tended to capture most of the variation in the yield impacts of GDD in the model results, and so the GDD variables were removed to form the final versions of Models 2d and 2i.[1]

In examining parameter estimates in Tables 2 to 4 it may first be noted that the linear and quadratic time trends are mostly positive and significant for all crops. This is not surprising, because progressive technological advancement has increased crop yields in the region over the study period (Stewart et al 2009; Robertson et al 2013).

**Response of Crop Yields to Temperature and Heat**

As shown in Tables 2 to 4, the signs and statistical significance for the temperature and heat climate variables are robust across the different specifications for each crop. The coefficients for GDD and squared GDD are statistically significant (at least at a 10% level) for all three crops for both dryland and irrigated models. The pattern of positive coefficients for the linear GDD term and negative coefficients for the squared GDD terms implies an inverse U-shaped relationship between crop yields and GDD. This indicates crop yields respond positively with increased GDD at a decreasing rate until GDD reaches some threshold level. Beyond that level, further increases in GDD tend to have a negative impact on crop yields. This pattern is consistent with Robertson et al (2013), who estimated dryland crop yield responses to climate variables for major crops in the Canadian Prairie region (including three Canadian Prairie provinces of Alberta, Saskatchewan, and Manitoba).

Comparing the GDD parameter estimates between dryland and irrigated crops, it can be seen that the values are numerically smaller for dryland crops. This may indicate that irrigated crops are better able to respond to increased heat due to moisture not being as limiting as for dryland crops. The marginal effects of GDD on barley, canola, and wheat yields were computed using sample means for the explanatory variables (Table 5). For example, under Model 1, a 1% increase in GDD leads to an increase of 0.05% (0.5 kg/acre) in barley yields, 0.16% (0.8 kg/acre) for canola yields, and 0.12% (1.1 kg/acre) for spring wheat yields for dryland production. The corresponding yield in-

[1] A specification (Model 3) was also estimated that included the linear and quadratic GDD variables as well as the interaction terms, with monthly precipitation being dropped. The parameter estimates and marginal effects are presented in the Supporting Information for the paper (Tables S8 to S11). We also examined the marginal effects to make a straightforward comparison to the results of Model 1 and Model 2. The marginal effects are very similar to Model 1 and Model 2 reported in Table 5 on both sign and magnitude, which indicate our results are robust.

Table 5. Marginal effects of GDD and precipitation on crop yields

| Variables | Model 1d | Std. err. | Model 1i | Std. err. | Model 2d | Std. err. | Model 2i | Std. err. |
|---|---|---|---|---|---|---|---|---|
| | | | | Barley | | | | |
| GDD | 0.04965 | 0.1004 | 0.1947 | 0.2772 | 0.3650*** | 0.06020 | 0.1852 | 0.1744 |
| May Prec. | 0.3058 | 0.4862 | −0.8970 | 0.5998 | 0.3258 | 0.4760 | −1.560*** | 0.3969 |
| June Prec. | 0.4412 | 0.2937 | −1.872*** | 0.4897 | 0.6182** | 0.2764 | −1.993*** | 0.3384 |
| July Prec. | 2.610*** | 0.2636 | −0.7686 | 0.7280 | 2.961*** | 0.2669 | −0.3010 | 0.7092 |
| August Prec. | 3.019*** | 0.3804 | 1.685** | 0.7457 | 3.245*** | 0.4017 | 2.753*** | 0.6912 |
| | | | | Canola | | | | |
| GDD | 0.1603*** | 0.04370 | 0.1197 | 0.1086 | 0.2620*** | 0.04030 | 0.1022* | 0.04730 |
| May Prec. | 0.2469 | 0.2882 | 0.3226 | 0.2693 | 0.2434 | 0.2673 | 0.2294 | 0.2158 |
| June Prec. | 0.2425 | 0.1475 | −0.6321*** | 0.1099 | 0.2089 | 0.1412 | −0.7239*** | 0.1125 |
| July Prec. | 1.146*** | 0.1612 | −0.8084* | 0.4014 | 1.593*** | 0.1767 | −0.1301 | 0.3342 |
| August Prec. | 1.758*** | 0.2494 | 2.362*** | 0.6808 | 1.674*** | 0.2722 | 2.662*** | 0.4990 |
| | | | | Spring Wheat | | | | |
| GDD | 0.1235** | 0.05540 | −0.3358 | 0.2313 | 0.2325*** | 0.0535 | −0.1508 | 0.1260 |
| May Prec. | 1.348*** | 0.3350 | 0.2726 | 0.7985 | 1.317 | 0.3435 | 0.02280 | 0.9008 |
| June Prec. | 0.8724*** | 0.2413 | −0.8382* | 0.4080 | 0.9391 | 0.2117 | −1.155** | 0.4630 |
| July Prec. | 2.019*** | 0.2322 | −0.9420 | 0.7268 | 2.357*** | 0.2320 | −0.7017 | 0.8229 |
| August Prec. | 2.084*** | 0.3065 | 1.772 | 1.088 | 2.101*** | 0.2887 | 2.163 | 1.204 |

Notes: Models 1d and 2d are for crops on dryland, and Models 1i and 2i are for crops on irrigated lands. The marginal effects were calculated at sample means. Standard errors of the interaction terms were calculated using the delta method in Stata 12 (StataCorp 2009).
***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

creases are 0.19% (3.2 kg/acre), 0.12% (1 kg/acre), and –0.34% (–5.1 kg/acre) for barley, canola, and spring wheat, respectively, for irrigated land. However, most of the marginal effects for irrigated crops (see Table 5) are not statistically significant.

ODD captures the occurrence of extreme temperatures; specifically, days with high temperatures. It would be expected that these conditions are harmful to crop yields and so the model coefficients for these variables should be negative. The results are generally consistent with this reasoning. The coefficients for ODD tend to be negative and statistically significant. The exception is dryland barley yield in Model 1d; the coefficient is positive but not statistically significant.

The model results also illustrate how temperature deviations affect crop yields. For dryland yields, monthly temperature deviations in May and July tend to have negative and significant impacts, while monthly temperature deviations in August tend to have significant and positive effects. Temperature deviations in June tend to show no significant effect.

Temperature deviations in May are more likely due to low temperatures and nights with frost and snow in the region, which hinders soil warming and delays seeding. These factors are harmful to crop yields. Conversely, large temperature deviations in July and August are more likely an indicator of higher temperatures than usual or extreme heat, which can also be detrimental for crop yields. This result holds for July but not for August. However, the positive impact of August temperature deviations is consistent with findings for Ontario wheat yields by Cabas et al (2010). Harvest in the study region usually starts in August. One explanation of the result for August is that warm and dry conditions in August indicated by large temperature deviations are good for harvesting. This may be also because these crops are tolerant to higher critical maximum temperatures in August than in July. For example, Robertson et al (2013) investigated critical maximum and minimum temperatures for major crops in the Canadian Prairie region and found a pattern of higher temperature tolerance in August than in July and June. Specifically, they report critical maximum temperatures of 38°C, 38°C, and 40°C in August for barley, canola, and spring wheat, respectively.

**Response of Crop Yields to Precipitation**

For dryland yields, monthly precipitation during the growing season tends to have a positive impact on crop yields for barley, canola, and spring wheat. This is not surprising, given that water is an essential input for crop growth and the studied area has a semiarid climate. The impacts tend not to be statistically significant in May and June for barley and canola but are statistically significant for July and August for all crops. The explanation for this pattern is that seeding for these crops is usually finished in May, so crop water demand is relatively low in May and June. Water demand is higher in July and early August in order to support plant growth and kernel/seed filling (Alberta Agriculture and Forestry 2015). The significant precipitation effect in May and June for spring wheat likely arises because spring wheat has higher water demand compared with barley and canola (Alberta Agriculture and Forestry 2015). This explanation is also confirmed by comparing the magnitude of the coefficients. As shown in Table 5, monthly precipitation in July and August tends to generate larger impacts on dryland crop yields. For example, for Model 1d, a 1% increase in precipitation in July increases spring wheat yields by 2% while a 1% increase in precipitation in June only increases spring wheat yields by 0.87%. For Model 2d, a 1% increase in precipitation in July leads to a 3% increase in barley yields while a 1% increase in precipitation in June only increases barley yields by 0.62%.

Unlike the case for dryland yields, it could be hypothesized that there is no significant effect of precipitation on irrigated yields. This hypothesis would be based on a presumption that the ability of producers to use irrigation water allows them to supplement moisture available from growing season precipitation. In other words, moisture would not be a limiting factor.

For irrigated yields, the model results for growing season precipitation variables are indeed not consistent with the results for dryland yields. Precipitation in May and August tends to have positive impacts on irrigated yields for canola and spring wheat, with an exception of precipitation in May for barley, which shows a negative impact. However, precipitation in June and July has a negative impact on yields for all three crops and the impacts are all statistically significant in June.

Given the dry conditions of Alberta's crop production, irrigation is applied to maintain certain levels of soil moisture for crops. As noted earlier, in principle, precipitation should not be a limiting factor for crop growth under irrigation. As indicated by Alberta Agriculture and Forestry (2016), the recommended practice is for producers to irrigate to 90% of the soil capacity (based on soil texture), leaving the remaining 10% of capacity to be "filled" by precipitation. If it is assumed that producers follow this (or a similar) practice as a strategy of risk reduction then the model results for precipitation and irrigated yields are reasonable. Since precipitation is not fully predictable, irrigating 90% of the soil capacity can result in the possibility of what appears to be "over irrigating" in conditions of excess precipitation. In addition, June is the wettest month in this region and July is the time that requires the most water for crop development so that more irrigation water is applied. These factors increase the risks of "over irrigating" in these two months. To assess this explanation we also consulted several professionals from Alberta Agriculture and Forestry and our explanation was supported by them. They noted that irrigation farmers irrigate new crops so their shallow roots get enough moisture. When unexpected rainfall occurs soon after, the crops get too much moisture and are stunted or die from excess moisture. In addition, irrigated crops are often cultivated (as opposed to no-till) so they are more susceptible to sealing with irrigation or rainfall. When there is an excess of rainfall, irrigated crops will be affected more negatively than dryland crops. Also, before 2010 (our data are from 1983 to 2007), it was estimated that less than 20% of irrigators used irrigation scheduling tools (i.e., The Alberta Irrigation Management software, https://agriculture.alberta.ca/acis/imcin/aimm.jsp). This is another potential reason for what appears to be over irrigating. These strategies are also consistent with the notion of risk reduction. As discussed above, Model 1 assumes additive separability regarding the impacts of temperature and precipitation on crop yields while Model 2 incorporates interaction terms for GDD and monthly precipitation into the analyses. In general, the interaction terms between monthly precipitation and GDD are positive for all crops and are significant in June and July for dryland yields. This is consistent with Cabas et al (2010) who found that warm and wet conditions were favorable to crop yields. However, the results tend to be less consistent across crops under irrigation.

The marginal effects of GDD and precipitation on crop yields from Model 2 were calculated and compared with the results obtained from Model 1 (Table 5). As seen from Table 5, adding the interactions into the analysis produces very similar marginal effects in terms of magnitude and sign for both GDD and precipitation compared with those from Model 1. For example, a 1% increase in GDD results in a 0.26% increase in dryland canola yields for Model 2 and a 0.16% increase for Model 1. For irrigated production, the marginal effects of GDD on canola yields are 0.12% and 0.10% for Models 1 and 2, respectively. Thus, the results from Model 1 and Model 2 indicate a consistent pattern. Specifically, GDD tends to have a statistically significant impact on dryland crop yields but not for irrigated crop yields. For precipitation, Model 2 shows positive impacts on yields for the three crops on dryland. For irrigated lands, precipitation tends to show negative impacts on yields in June and July, with that effect being statistically significant in June. These results are consistent with those for Model 1. Therefore, it is concluded that the models are relatively robust to different specifications of climate variables. The results from these models are now used to forecast the impacts of climate change on crop yields.

**Forecast of Crop Yield under Climate Change Scenarios**

The empirical results presented in the previous section suggest that the impact of climate variables on crop yields differs between dryland and irrigated production. This section explores how future climate change will affect dryland crops relative to irrigated crops. In undertaking this analysis, projections of temperatures and precipitation for future climate scenarios are required. There are several climate models available to provide climate projections under various global warming scenarios. Each of these models generates different climate projections based on a unique set of assumptions and modeling relationships. For this analysis, projections of future climate variables were based on the CanESM2 model of the CMIP5 (Tylor et al 2012; IPCC 2014). For more information about the model, please refer to Chylek et al (2011). Specifically, the RCP2.6 and RCP8.5 scenarios were selected to represent "lower" and "higher" rates of global warming, respectively. These scenarios provide the largest range of plausible conditions based on greenhouse gas concentration (not emissions) trajectories adopted by the IPCC for its fifth Assessment Report in 2014. The CanESM2 climate model data have been downscaled based on historical climate data of Canada with a gridded resolution of 10 km (McKenney 2011). The model provides information on daily maximum temperature, minimum temperature, and precipitation.

The downscaled outputs of CanESM2 were used to produce a set of projected climate variable values at the county level from 2010 to 2034 consistent with what was used in the original model estimation. Table 6 provides summary statistics for projected climate variables under both scenarios for the period 2010–34 and also shows the change in average values for these variables calculated over all counties (in the study area) from the historical climate variables over the period 1983–2007. On average, the two future climate scenarios are warmer (i.e., greater GDDs) than the historical climate, although the future climate scenarios tend to have fewer instances of extreme high temperatures. Both future scenarios have larger monthly temperature deviations for each month compared

Table 6. Summary statistics of projected climate variables under both scenarios over all counties, from 2010 to 2034

| | Climate change scenario | | | |
|---|---|---|---|---|
| | CanESM2-8.5 | Difference | CanESM2-2.6 | Difference |
| Growing degree days (GDDs) | 1616.0 | 147.19 | 1673.1 | 204.25 |
| Overheat degree days (ODDs) | 0.079813 | −0.36112 | 0.11755 | −0.32338 |
| Precipitation in May (mm) | 50.771 | 1.3105 | 59.259 | 9.7984 |
| Precipitation in June (mm) | 65.219 | −16.950 | 80.326 | −1.8435 |
| Precipitation in July (mm) | 54.714 | 0.59441 | 80.705 | 26.585 |
| Precipitation in August (mm) | 47.036 | −2.6324 | 43.907 | −5.7616 |
| Temp. deviation in May (°C) | 14.361 | 2.7989 | 14.219 | 2.6565 |
| Temp. deviation in June (°C) | 14.444 | 2.3094 | 14.153 | 2.0192 |
| Temp. deviation in July (°C) | 15.163 | 1.0099 | 15.086 | 0.93316 |
| Temp. deviation in August (°C) | 16.124 | 2.0883 | 14.894 | 0.85846 |

Source: Faramarzi et al (2015).

Notes: Difference is calculated by using the average values of future climate data from 2010 to 2034 under both scenarios minus sample means of historical climate data from 1981 to 2007, respectively. CanESM2-8.5 represents a higher rate of warming scenario compared with CanESM2-2.6 for the entire forecast period. However, the monthly mean temperatures of CanESM2-8.5 are smaller than CanESM2-2.6 until August. As this paper only focuses on the growing season between May and August, that is why we see a larger average GDD value for CanESM2-2.6 than CanESM2-8.5.

Table 7. Cross validation measures by model, crop, and land type

| | Model 1 | Model 2 |
|---|---|---|
| Barley—dryland | | |
| RMSE | 291.6* | 310.6 |
| MAE | 240.6* | 254.2 |
| Barley—irrigated lands | | |
| RMSE | 282.7 | 282.4* |
| MAE | 228.1* | 228.5 |
| Canola—dryland | | |
| RMSE | 156.1* | 159.3 |
| MAE | 124.4* | 127.5 |
| Canola—irrigated lands | | |
| RMSE | 140.5 | 139.5* |
| MAE | 113.7 | 111.5* |
| Spring wheat—dryland | | |
| RMSE | 248.1* | 252.9 |
| MAE | 199.8* | 203.0 |
| Spring wheat—irrigated lands | | |
| RMSE | 237.6* | 241.7 |
| MAE | 189.6* | 195.9 |

Notes: RMSE are the root mean square errors and MAE are the mean absolute errors obtained from a $k$-fold (here $k = 20$) cross validation.
* indicate the smaller RMSE and MAE values across Models 1 and 2.

with the historical climate data. In addition, there is more precipitation in May and July, but less precipitation in June and August, when the future climate scenarios are compared with historical values. Tables S3–S5 in the Supporting Information present the summary statistics of the future climate variables used in the yield forecasting analyses for each crop under dryland and irrigated production, respectively.

When forecasting crop yields for the climate change scenarios, it was decided to use Model 1. This choice was made based on the accuracy of out-of-sample forecasting for each model. Specifically, a $k$-fold ($k = 20$) cross validation was conducted for each crop using both dryland and irrigated yields to assess the fit of the models to a data set that is independent of the data that were used to train the model. The validation process was initiated by splitting the data set randomly into 20 partitions. From the resulting 20 subsamples, a random subsample was retained for use as validation data for testing the model. The remaining 19 subsamples were used as training data. The cross-validation process was then repeated 20 times. The advantage of this method is that each subsample is used as testing data exactly once. The root mean square errors (RMSE) and the mean absolute errors (MAE) were calculated from each of the 20 validation processes, with the mean values being compared for each model by crop and land type. The mean RMSE and MAE values are reported in Table 7. Based on both statistics, Model 1 outperforms Model 2 in forecasting the majority of the time. For the cases where the mean RMSE/MAE of Model 1 is larger than Model 2, the differences are negligible.

By using the projected variable values for the two climate change scenarios discussed

Table 8. Average effects of climate change on crop yield (percentage change relative to sample means from 1981 to 2007) under dryland and irrigation, respectively, from 2010 to 2034

| | Barley | | Canola | | Spring wheat | |
|---|---|---|---|---|---|---|
| Climate scenarios | Dryland | Irrigated | Dryland | Irrigated | Dryland | Irrigated |
| CanESM2-8.5 | −14.26% | −3.93% | −16.58% | 1.93% | −18.69% | 0.57% |
| | (0.2706) | (0.1307) | (0.3483) | (0.1596) | (0.2804) | (0.2007) |
| CanESM2-2.6 | −21.12% | −11.05% | −23.99% | −4.50% | −21.73% | 0.003% |
| | (0.3233) | (0.1458) | (0.4097) | (0.1647) | (0.3457) | (0.1973) |

Notes: The model used for yield forecasting is Model 1 for all the three crops. Numbers in parentheses are standard deviations.

earlier and the parameter estimates from Model 1, predicted annual yields for each crop were calculated for the period 2010–34. The average predicted yields for the 2010–34 period for the three crops were then compared to sample means of crop yields between 1983 and 2007, for both dryland and irrigated production, to quantify the overall impact of future climate change on average yields. Table 8 summarizes the percentage changes in the predicted average yields relative to the historical average yields and the corresponding standard deviations.

Under CanESM2-8.5 (i.e., "higher" rate of warming), climate change decreases barley yield under dryland and irrigation production by 14.26% and 3.93%, respectively. Dryland canola and spring wheat yields are also reduced, by 16.58% and 18.69%, respectively. However, there are slight gains in yields for these two crops under irrigation: 1.93% for canola and 0.57% for wheat.

Under CanESM2-2.6 (i.e., "lower" rate of warming), climate change is harmful to barley and canola yields for both irrigated and dryland production. This climate change scenario leads to a reduction in dryland spring wheat yield by 21.73%, but a marginal increase (0.003%) in irrigated spring wheat yield. By considering the results together, the negative effects of climate change are consistent for both scenarios in that the harmful effects tend to be larger for dryland than for irrigated production. The three major crops in Alberta under dryland production suffer from climate change while irrigated production for canola and spring wheat can benefit from these climate change scenarios.

The average impacts of projected climate variables were separated into temperature effects versus precipitation effects on crop yields using parameter estimates from Model 1 and the aforementioned two climate change scenarios for the three crops. The percentage changes in predicted crop yields relative to sample means of crop yields from 1981 to 2007 under two climate change scenarios were calculated with the results being presented in Table 9. The changes in GDD result in increased yields for all the three crops under both climate change scenarios. The percentage increases range from 0.29% to 7.17% depending on the crop and climate scenario. Changes in ODD lead to reduced barley yields but increases in yields for canola and spring wheat. Changes in temperature deviations cause the largest yield reductions for each crop under both climate change scenarios. The total temperature effect presented in Table 9 is the result of summing up the effects of GDD, ODD, and temperature deviation. Overall, the effect of tempera-

Table 9. Decomposition of the effect of climate variables on crop yields (percentage changes relative to sample means of crop yields from 1981 to 2007) under two climate change scenarios

| | CanESM2-8.5 | | CanESM2-2.6 | |
|---|---|---|---|---|
| | | Barley | | |
| Effect of | Dryland | Irrigated lands | Dryland | Irrigated lands |
| GDD | 0.85% | 0.29% | 1.11% | 0.47% |
| ODD | −0.06% | −0.08% | −0.06% | −0.07% |
| Temp. dev | −13.00% | −5.33% | −19.28% | −8.09% |
| Total temp. effect | −12.20% | −5.12% | −18.23% | −7.69% |
| Precipitation | −1.97% | 0.76% | −1.45% | 7.83% |
| | | Canola | | |
| GDD | 5.47% | 1.23% | 7.17% | 2.42% |
| ODD | 0.38% | 1.06% | 0.34% | 0.94% |
| Temp. dev | −18.42% | −7.83% | −25.12% | −8.10% |
| Total temp. effect | −12.57% | −5.54% | −17.60% | −4.74% |
| Precipitation | −2.70% | 0.99% | −2.89% | 7.51% |
| | | Spring wheat | | |
| GDD | 2.24% | 0.52% | 2.97% | 1.06% |
| ODD | 0.39% | 0.72% | 0.37% | 0.65% |
| Temp. dev | −19.24% | −9.33% | −23.82% | −10.18% |
| Total temp. effect | −16.60% | −8.08% | −20.47% | −8.48% |
| Precipitation | −2.05% | 0.71% | −0.14% | 9.11% |

ture change on yields is negative with the effect tending to be greater for dryland crops compared to irrigated crops. Future climate change in precipitation suggests the opposite effect for the three crops under dryland versus irrigated production. The projected changes in precipitation cause yields to decrease by 0.14% to 2.89% for dryland crops. In contrast, projected changes in precipitation cause irrigated yields to increase by 0.71% to 9.11%.

## SUMMARY AND CONCLUSIONS

Agriculture is considered one of the most vulnerable economic sectors to climate change. Crop production has been a central focus when estimating the impact of climate conditions. In this paper, yield response to intraseasonal climatic conditions for three major crops (i.e., barley, canola, and spring wheat) under irrigated and dryland production in southern Alberta, Canada, is investigated. A panel data approach with fixed effects is used that considers a variety of climate variables including seasonal GDDs, ODDs, and monthly precipitation and temperature deviations. The effects of climatic conditions on aggregated crop yields are investigated using the estimation results. The empirical results for dryland crops are consistent with several Canadian studies (e.g., Carew and Smith 2006; Cabas et al 2010; Robertson et al 2013); specifically, warming and increased precipitation tend to be beneficial for crop yields. The results also indicate that timing of precipitation and temperature deviations influence yields differently in terms of the size and significance of the impacts. For example, the precipitation impacts in May and June are smaller and less significant than July and August on crop yields. For irrigated lands, the positive effect of GDD still holds but the impact of precipitation tends to be negative in June and July. This may be because of "over irrigating" in the field due to unpredictable precipitation and risk-averse responses by producers to the potential for droughts.

Using two regional projections of climate change, we forecasted that climate change results in decreased crop yields for all the three crops (barley, canola, and spring wheat) under dryland production. Conversely, canola and spring wheat yields under irrigated production are likely to increase slightly. Irrigation is widely considered an important adaptation to changing production conditions under climate change. The forecasting results of this study also demonstrate this point. Samarawickrema and Kulshreshtha (2008) noted that in the SSRB, the higher productivity of irrigated farms was due to additional water supply relative to dryland production. High summer temperatures increase plant evapotranspiration that is beneficial for crop growth when there is no moisture constraint. In addition, due to additional water availability, irrigation provides conditions conducive to growing high value-added crops such as potatoes and sugar beets, which are not normally planted under dryland in the province. On the other hand, a warmer and longer growing season may benefit dryland agriculture in Alberta if there is no moisture constraint. Climate change is projected to decrease stream flows in the basin, together with the requirement of irrigation infrastructure rehabilitation, indicating potentially higher costs and reduced premiums in applying irrigation to crop production.

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## SUPPORTING INFORMATION

Additional Supporting Information may be found in the online version of this article:

**Table S1.** Summary statistics of data set used in canola yields response analysis, 1983–2007.
**Table S2.** Summary statistics of data set used in wheat yields response analysis, 1983–2007.
**Table S3.** Summary statistics of (climate change) data set used in barley yields response analysis, 2010–34.
**Table S4.** Summary statistics of (climate change) data set used in canola yields response analysis, 2010–34.
**Table S5.** Summary statistics of (climate change) data set used in spring wheat yields response analysis, 2010–34.
**Table S6.** Results of Wooldridge test for autocorrelation in panel data.
**Table S7.** Modified Wald test for groupwise heteroskedasticity in fixed effect regression model.
**Table S8.** Parameter estimates for barley yield response by Model 3.
**Table S9.** Parameter estimates for canola yield response by Model 3.
**Table S10.** Parameter estimates for spring wheat yield response by Model 3.
**Table S11.** Marginal effects of GDD and precipitation on crop yields by Model 3.