Climate Change Effects on Agricultural Crop Prices in Canada

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I. Introduction

According to the National Oceanic and Atmospheric Administration, the average surface temperature of Earth (including land and water) in 2021 was 0.84 degrees Celsius warmer than the 20th century average and 1.04 degrees Celsius warmer than the pre-industrial average (Lindsey and Dahlman 2022). The rapidly warming climate has many implications on global agricultural food systems, with some adapting to benefit from a warming climate due to the ability to plant different crops, and others suffering severe losses in crop yields. For example, JP Morgan Research projects that U.S. corn yield "could decrease as a result of extreme weather risks" and corn prices have "a potential 20-30% upside on the basis of supply-side disappointments" which include adverse weather conditions ("Climate Change and the Impact on Agriculture," *J.P. Morgan*). This effect is only expected to worsen, as scientists project at the current rate of emissions the earth will warm *at least* 3 degrees Celsius further by the end of the century (Lindsey and Dahlman 2022).

Narrowing our focus to Canada's agricultural sector, we wanted to see if this effect was already being felt, and if there was a quantitative effect on agricultural prices as hot weather days increased. The Government of Canada reports that "a rise in the incidence of days over 30 degrees Celsius will bring challenges to both crop and livestock producers. Some crops, such as canola and wheat, are particularly vulnerable to heat stress" ("Climate change impacts on agriculture," *Government of Canada*). This is extremely consequential for Canada's agricultural output, as canola and wheat are the two most produced crops (in metric tonnes) in the country ("Estimated areas, … " *Statistics Canada*). If these crops are "particularly vulnerable" to hot weather, there are broad implications for Canada's ability to maintain previous levels of agricultural and economic output.

II. Review of Related Literature

Recently, there has been an increase in the literature on climate effects and agricultural issues as a whole. Research to note includes Vogel et al's 2019 analysis of climate extremes on global agricultural yields, where the authors found "climate variables considered in this study … explain 20-49% of the variance of yield anomalies at the global scale" (Vogel et al 2019). Their model also found that the regions most affected by this result are "North America (for maize, spring wheat and soy production), Asia (maize and rice), and Europe (spring wheat)" (Vogel et al 2019). As explained in the introduction, this has severe implications for Canadian agriculture, as wheat is the single most produced crop in the country. The way Vogel et al measure climate variables is similar to how the regression models in this paper do; they take the mean monthly temperature and maximum monthly temperature during the growing season to see its effects on yields (Vogel et al 2019). Taking a step further from the effect on crop yields, however, is the effect on prices, which is what we seek to study.

The relationship between global agricultural prices and exogenous shocks is studied in a 2018 paper from De Winne and Peersman, whose results show how important this issue is. They estimate "an exogenous rise in global agricultural commodity prices by 1% on impact (which further increases to 1.5% after one quarter) ultimately reduces average real GDP across countries 0.11%" (De Winne and Peersman 2018, 4). This shows how shocks to agricultural prices extend far beyond just the food commodity markets, and how they can spread to affect broader national and global economies.

A 2021 report on the relationship between climate change and price stability from the European Central Bank studied 48 different economies and the effects of hot weather on different price measures, one of which was the food component of CPI (Consumer Price Index) (Faccia et al 2021). The report finds that the largest impact of extreme weather changes on overall prices is due to hot summers (as compared to hot autumns or cold winters); they further analyze this effect and find “the higher prices arising in the short term from hot summers is mostly due to the impact on food prices” (Faccia et al 2021, 6). The regression used by the ECB had separate dummy variables for extreme temperature overall and for extreme seasonal temperature, with *Temp* = 1 if temperatures exceeded the country’s historical average (Faccia et al 2021, 22). This form of measuring extreme temperature is an important way of separating general trends and avoiding multicollinearity to get at the real effects of extreme temperature. We did not measure extreme temperatures in this way, which may have hindered our regression and results; this will be further explored in later sections.

While finding mixed and sometimes negative results for medium and long-term effects on food prices, in the short-term the ECB report found “a statistically significant – and economically meaningful – impact on prices arising from hot summer events. Food prices increase by 0.38 percentage points contemporaneously, which is greater than a one standard deviation quarterly change in the series. The positive impact on food prices increases further in the subsequent quarter. In terms of economic mechanisms, the contemporaneous increase in food price inflation could be explained by a negative effect of hot summers on food production, resulting in supply shortage effects” (Faccia et al 2021, 24). This lends confidence to our hypothesis that the impact of extreme hot weather will be reflected in Canadian short-term food prices.

III. Data and Methodology

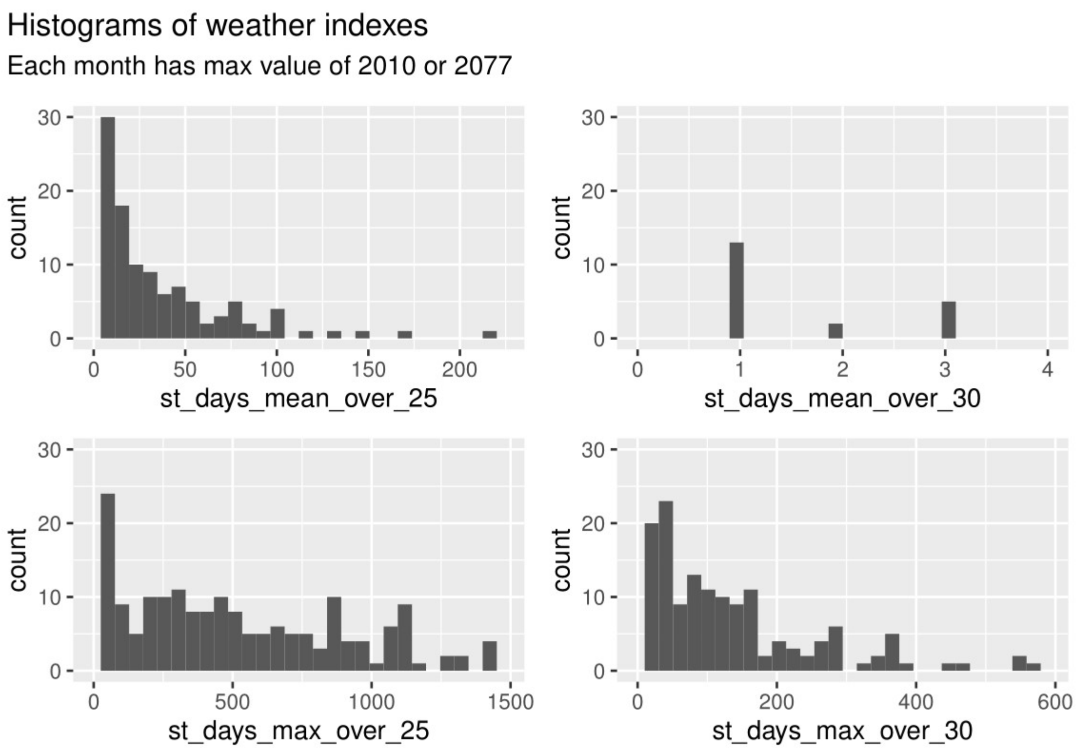
To conduct this research, we began with the assumption that the monthly Canadian Farm Product Price Index (FPPI) for crops would accurately reflect effects of weather on crop yields, should such exist. Depending on the effect of warming temperatures, the price index would either increase or decrease in relation to the effect of weather we sought to capture. One potential avenue of this effect, for example, would be a simple supply-and-demand effect, where more extreme temperatures would lead to a supply shock, that then would cause higher prices, captured by the FPPI. (As we will discuss in later sections, this may have been an inaccurate assumption.) The FPPI (agricultural crops index) was gathered from Statistics Canada for the years 1991 to 2020 ("Farm Product Price Index …," Statistics Canada). In running our regressions, we used as our dependent variable the change in FPPI from month to month, which was given by the difference between FPPI crop in time t and time $t - 1$.

To create a measure for Canadian weather, we needed to find a way to capture the overall weather situation in Canada for each period of our weather data. We compiled our own data set of monthly weather data based on weather station data from stations across the country, using historical weather data from the Government of Canada ("Historical Data," Government of Canada). We sought stations which had more or less complete data for the period of 1991 to 2020; we thus filtered the weather stations for the most complete data sets (i.e. the stations that had the most number of complete observations for our time period). We did not choose stations by random assignment because that lent itself to too many stations with missing data; however, we do not think this method of filtering stations biased our data set because there is no reason to believe the missing data was not random. Another restriction we placed on our weather data set was where the stations were located. Because Canada is such a large country, there is a significant swath of land that is never suitable for agricultural purposes, and we did not want our data to include weather stations from these areas. We were looking to create a measure of weather in areas that are agriculturally significant; for example, weather data from Jasper

National Park is much less useful than the weather in the crop-growing prairies of Manitoba, and including data from Jasper would be detrimental to our analysis. If those kinds of weather stations were included, the regression would not accurately capture the effects of weather on agricultural prices. While it was beyond the scope of our project to filter the data more intensively based on its proximity to significant agricultural production (doing so would have required too extensive research into granular agricultural growing geographic data), we sought to exclude stations which were evidently not reflective of the weather situation in agricultural areas. We thus restricted our consideration of stations by latitude and longitude and also by elevation (we only considered stations under 600m above sea level in elevation, which served to prevent the possibility of stations located in mountains from being included in the data set).

Finally, to make sure that our weather data was weighted in accordance with agricultural production in Canada, we weighted the stations to reflect where crops were grown. To do this, we looked at data on the provincial distribution of field crops in Canada, weighing the number of weather stations from each province accordingly. For example, 46.8 per cent of crops in Canada are grown in Saskatchewan, so 46.8 per cent of weather stations used in our climate index were from Saskatchewan. We ended up with 68 weather stations across the 5 biggest crop-producing provinces: 29 from Saskatchewan, 17 from Alberta, 11 from Ontario, 8 from Manitoba, and 3 from Quebec. The construction of weather data becomes significant given that our independent variables were indexes which captured the number of days of hot weather or the average temperature across stations and thus the weighting of the stations influences these metrics significantly. Weighting more stations more likely to be close to agricultural production locations in Canada would make our weather index more responsive to weather fluctuations where they are likely to matter the most.

We constructed multiple indexes based on the daily weather data of the stations. First, we made an index of the cumulative number of observations across all days in a month for all stations which reported a temperature above 30 degrees celsius (st_days_max_over_30). Then, we made the same index but with a temperature above 25 degrees celsius (st_days_max_over_25). Additionally, we made indexes that, instead of counting the number of maximum temperatures observed across all stations in all days of the month past some threshold, captured how many daily station mean temperature observations had mean temperatures of over 25 (st_days_mean_over_25) and 30 degrees (st_days_mean_over_30) respectively. Finally, we constructed a precipitation index which was the average monthly precipitation across all stations (monthly_precipitation_average). Given that we had 67 stations, and each month had either 30 or 31 days (with February having either 28 or 29 days), the maximum for each index was 2077.



IV. Results

Unfortunately, our results were largely not significant. In what follows, we discuss the various regressions we attempted and the results we achieved for each one. In the following discussion section, we will take up interpretation of the potential errors in our model. To view the code used to compose our indexes and run the following regressions, please refer to **Appendix 2**.

The first regression we attempted was to regress the difference in FPPI from month to month on the mean monthly temperature across all stations. Our results are significant at the 0.01 level, and if interpreted would say that a unit increase in the monthly mean temperature is associated with a 0.031 decrease in the difference between the current month's FPPI and the last month's FPPI (see **Figure 1**). This is about 10% of the median difference in FPPI across all months in the period 1991 to 2020. However, we have reservations about the significance of this result, as will be discussed in further detail below. For now, suffice to say that average monthly temperature is obviously a seasonal variable (highest in summer, dips in winter) and so we cannot immediately assign substantial significance to the statistical significance of the estimated coefficient on monthly mean temperature in our model.

```
Call:
lm(formula = diff_fppi ~ monthly_mean_temp, data = reg_data)

Residuals:
     Min       1Q   Median       3Q      Max
-10.8646  -1.1125   0.0518   1.0184  13.1945

Coefficients:
                  Estimate Std. Error t value Pr(>|t|)
(Intercept)        0.32083    0.13982   2.295  0.02234 *
monthly_mean_temp -0.03119    0.01190  -2.622  0.00911 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 2.512 on 358 degrees of freedom
Multiple R-squared:  0.01884,   Adjusted R-squared:  0.0161
F-statistic: 6.875 on 1 and 358 DF,  p-value: 0.009115
```

Figure 1

Motivated by the insufficiency of a significant relationship between average temperature and difference in FPPI from month to month, we next regressed the difference in FPPI on our indexes capturing the number of observations in a month of mean temperature over 30 degrees (see **Figure 2**) and 25 degrees respectively (see **Figure 3**). A slight positive relationship is found, but the coefficients fail even at the 0.10 significance level.

```
Call:
lm(formula = diff_fppi ~ st_days_mean_over_25, data = reg_data)

Residuals:
     Min       1Q   Median       3Q      Max
-11.4223  -1.0797   0.1273   1.1457  12.6941

Coefficients:
                     Estimate Std. Error t value Pr(>|t|)
(Intercept)          0.154271   0.144241   1.070    0.286
st_days_mean_over_25 0.004099   0.004617   0.888    0.375

Residual standard error: 2.533 on 358 degrees of freedom
Multiple R-squared:  0.002197,  Adjusted R-squared:  -0.0005899
F-statistic: 0.7884 on 1 and 358 DF,  p-value: 0.3752
```

Figure 2

```
Call:
lm(formula = diff_fppi ~ st_days_mean_over_30, data = reg_data)

Residuals:
     Min       1Q   Median       3Q      Max
-11.2607  -1.0607   0.1393   1.1393  12.8393

Coefficients:
                     Estimate Std. Error t value Pr(>|t|)
(Intercept)            0.1607     0.1364   1.179    0.239
st_days_mean_over_30   0.3783     0.2614   1.447    0.149

Residual standard error: 2.528 on 358 degrees of freedom
Multiple R-squared:  0.005816,  Adjusted R-squared:  0.003039
F-statistic: 2.094 on 1 and 358 DF,  p-value: 0.1487
```

Figure 3

Motivated by our failure in finding any significant results using mean temperature indexes, we then attempted to regress the monthly difference in FPPI on the indexes of number of observations with maximum temperature observed above 30 degrees (see **Figure 4**). We found a very slight negative effect for a unit increase in the number of days max over 30 but again it was not at all significant.

```
Call:
lm(formula = diff_fppi ~ st_days_max_over_30, data = reg_data)

Residuals:
     Min       1Q   Median       3Q      Max
-11.1665  -1.0872   0.0944   1.0604  12.8716

Coefficients:
                      Estimate Std. Error t value Pr(>|t|)
(Intercept)          0.2395542  0.1509839   1.587    0.113
st_days_max_over_30 -0.0006657  0.0012734  -0.523    0.601

Residual standard error: 2.535 on 358 degrees of freedom
Multiple R-squared:  0.0007627, Adjusted R-squared:  -0.002028
F-statistic: 0.2733 on 1 and 358 DF,  p-value: 0.6015
```

Figure 4

Finally, we tried to regress the difference in FPPI on the difference in CPI, the number of observations of max temperature over 30, and the monthly precipitation (see **Figure 5**). This was motivated by a desire to control for the relationship between CPI and FPPI and also control for the potential effects of precipitation. This didn't change anything in our regression, and we were unable to conclude anything.

```
Call:
lm(formula = diff_fppi ~ st_days_max_over_30 + monthly_precipitation_average +
    cpi_diff, data = reg_data)

Residuals:
     Min       1Q   Median       3Q      Max
-11.1684  -1.0882   0.1029   1.0089  12.9594

Coefficients:
                               Estimate Std. Error t value Pr(>|t|)
(Intercept)                   0.3889085  0.3074413   1.265    0.207
st_days_max_over_30          -0.0002854  0.0013812  -0.207    0.836
monthly_precipitation_average -0.0044076  0.0066200  -0.666    0.506
cpi_diff                      0.1321216  0.3716487   0.356    0.722

Residual standard error: 2.54 on 356 degrees of freedom
Multiple R-squared:  0.002463,  Adjusted R-squared:  -0.005943
F-statistic: 0.293 on 3 and 356 DF,  p-value: 0.8305
```

Figure 5

We thus see that we were unable to observe significant results between weather and agricultural crop prices using the approach we chose. In the following section, we will discuss some of the implications of our research and the limitations of our approach that could be useful for further work on this question.

V. Discussion and Implications

We set out with the goal of assessing whether there exists a relationship between increased temperatures and the prices of agricultural goods sold in Canada. There were two plausible theories as to the potential effect of rising temperatures on crop prices, as discussed earlier in in our review of related literature. First, there could be a positive relationship between increasing temperatures and prices of agricultural goods; abnormally high temperatures negatively affect crop growth thereby reducing the supply of goods on the market, which drives up prices. An alternative is that there could actually be a negative relationship between increasing temperatures and prices of agricultural goods; especially in countries like Canada, where average temperatures are generally very low, more heat could actually allow for more favorable growing conditions for crop and thus crops yields would increase thereby increasing supply which would be reflected in a reduction in prices. It should already be noted that such effects are exceedingly complicated to model directly. (Indeed, the textbook example which we consulted about Florida oranges works with futures market data which reflects the wisdom of the market in pricing in the myriad variables which would be relevant to directly modeling the relationship between weather and crop yields, not to mention the relationship between crop yields and prices).

Our relatively simple approach proved insufficient for the complicated task we had set before ourselves. Were we to interpret our results myopically, we would conclude that since there is no statistically significant relationship between the month-to-month change in farm product price index and any of our weather indexes (with the exception of average temperature, which we will discuss later), rising temperature has no effect on farm product prices and we fail to reject our null hypothesis against the two alternative hypotheses outlined above. Such a conclusion, however, would be unjustified and overly hasty. There are many limitations to our approach, and other factors which would have to be explored before we could provide any results that convincingly indicate that there is no relationship between weather and farm prices.

First, a limitation of our research is that we only considered the temperature in the weather stations that we chose, and our selection might be unknowingly biased or otherwise insufficiently representative of the actual weather situation in crop-growing regions. If this were the case, even if everything else was correct about our study, any observed relationship between the weather indexes we constructed and the farm product prices would be spurious and not reflective of any actual effect of weather on farm product prices. Future analysis with a more carefully selected index of weather (or one that is larger and thus captures weather data with more detail) could change results.

Second, we used as our dependent variable the difference in farm product prices from month to month, and as our independent variable the weather indexes for that current month. There are (at least) two problems with this approach. Firstly, weather effects are not likely to be reflected in the difference in farm product prices for this month and the previous month, as crop supply is largely determined by what is already grown and harvested and ready for the market, and not the crops that are currently in the ground. Indeed, a comparison with the Florida oranges textbook example is apropos, because there they use the much more sophisticated and relevant variable of orange future prices which take into account long term supply consequences of current day conditions and price them into contracts; using something like futures data thus captures in a much more convincing way the potential effect of current conditions on prices than the raw comparison of current market prices that we employed by setting diff_fppi as the dependent variable in our regression. Secondly, it could theoretically be possible that increasing temperatures gradually increase or decrease in farm product prices, but it takes time for demand schedules to adjust to more or less supply on the market. Such a change would not be captured in the difference of FPPI from month to month (as, for example, this change could just play out as a streak of months uninterrupted by the cyclical decline in FPPI that would otherwise be observed).

To address this second limitation, there are multiple alternatives that could be explored but for which we lacked the time and technical resources this semester. In order to address the first issue, brought up in the last paragraph, a way to improve the design of our regression analysis would be to include lagged variables for weather and FPPI. This would enable us to observe the changes in price indexes while accounting for the time it takes for the market to adjust to the supply shock. While we briefly explored this approach, the results were not significant (see **Appendix 1** for results from this regression of difference in FPPI on weather indexes lagged three months) and to do this approach justice was beyond our resources. Furthermore, to address the issue of gradual changes, we could have made a trend line of FPPI over time and modeled the effect of weather on deviations from that trend observed in FPPI, but again, doing this was beyond our resources.

Indeed, our study leads us to think that our approach was also beset by omitted variable bias. Omitted variables such as global oil prices, the price trend of global agricultural products, transportation costs, and elevation of weather stations, are all factors that may have affected the final price indices of the crops and thus the effect of weather could have either been so marginal to be obscured, or farm product prices could largely be affected by variables which are in the residuals and we fail to account for. Additionally, farm product prices in Canada might just simply be determined to a large degree by imports from abroad and thus growing conditions abroad. All of these complications are potential effects for which we did not control in our models (beyond controlling for CPI, which didn't prove significant) and which are worth exploring further.

Before we conclude, it is important to discuss seasonality, as we were working with time-series panel data. It is worth noting that the first regression we attempted (regression of difference in FPPI on average monthly temperature) did indeed provide us a significant negative relationship between temperature and prices. Taken at face value, one could interpret this as evidence that higher average temperatures somehow affect prices. (In this instance, we would have to say that somehow the current crop prices on the market this month as captured by the FPPI are affected by the average temperature that month). But, this seems implausible, for all of the reasons we have discussed earlier about the tenuous relationship between current period variables affecting growing conditions and the price of harvested goods sold on the wholesale market. A second more plausible explanation is that the FPPI generally follows seasonal trends, with prices rising in colder months and declining in warmer months. There might be an economic explanation that in summer months there is greater supply of crops and so overall prices are cheaper, whereas in winter months there is less supply and thus higher costs. It could, however, be the result of many other factors about the agricultural market or global markets as a whole, of which we are simply unaware. To provide a sophisticated analysis of the relationship between weather data and farm product prices, we would have to conduct more research into the relationship between conditions, supply, and selling on markets of agricultural goods, before attempting to modify our regressions and statistical approach to observing a relationship. One promising avenue for working with this seasonal data would be to use methods which split up the data by seasons, or create trends for seasonal data and then investigate the relationship between prices and deviations from those weather trends. This is the approach mentioned in the review of related literature, where ECB researchers measured weather using a dummy variable which equaled 1 when the weather was above the historical trend. This approach is important in teasing apart effects on prices caused by extreme weather versus just finding a positive relationship of prices and weather as they increase, uncorrelated to each other, over time. These alternative approaches would necessitate both changes to our dependent and independent variables.

Thus, as can be seen from the complexity of the task at hand, and from the various limitations of our design, the problem is a complicated one. Furthermore, as is evidenced by the abundance of literature in the field, examining the impacts of temperatures on different economic factors is a growing field of study. With more time, knowledge and a more appropriate database, it is well worth revisiting this question in the future, and we are confident that our attempts are only the preliminary exploration to a potentially much more informative analysis that could be done.

Appendix 1

We briefly explored using a lagged variable for weather indexes and regression the difference in FPPI on these lagged indicators (with a three month lag). The results are reported in the table below. This is somewhat promising, as we can see that for all three regressions, the p value has shrunk considerably. However, the posited effect is extremely small in each instance, and we are hesitant to read any significance into the observed relationship. As discussed in the main body of the report, further research into the appropriateness and exact construction of lagged variables could potentially be a productive avenue of research on this question, but to do so would be outside the scope of our project for this semester.

Table 1: Lagged regressions

	Dependent variable:		
	diff_fppi		
	Lagged days max over 30	Lagged days max over 25	Lagged monthly mean temp
	(1)	(2)	(3)
lag_st_days_max_30	−0.001		
	(0.001)		
lag_st_days_max_25		−0.001	
		(0.0004)	
lag_monthly_mean_temp			−0.018
			(0.012)
Constant	0.271*	0.340**	0.269*
	(0.152)	(0.163)	(0.142)
Observations	357	357	357
R^2	0.003	0.006	0.006
Adjusted R^2	−0.0002	0.003	0.003
Residual Std. Error (df = 355)	2.543	2.538	2.539
F Statistic (df = 1; 355)	0.935	2.233	2.133
Note:			*p<0.1; **p<0.05; ***p<0.01

Appendix 2

[Link to code repository, regression data, and graphics code]

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