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Weather Indexes as a Guide to Facilitate Planning of Winter Wheat and Conservation of Migrating Waterfowl Habitat

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Growing Forward

Abstract

Increased planting of winter wheat is seen as one means to increase breeding habitat for migratory waterfowl. Winter wheat benefits farmers because it reduces costs of machinery operations, spreads tasks, reduces soil erosion and leads to potentially greater yields as emerging plants can take better advantage of early spring moisture availability. The only drawback is the high risk of winterkill. In this study, we demonstrate that successful planting of winter wheat depends on long-term climate events, as represented by the El Niño and North Atlantic Oscillation (NAO) climate indexes. We also demonstrate that financial weather derivatives can be used to protect farmers against variability in crop yields, although heat (as measured by growing degree days) is less important than spring precipitation in this regard. We speculate that financial products based on the long-term climate indexes could be used to incentivize farmers to plant more winter wheat, although more research is required to determine their efficacy. This is true as well when it comes to financial weather products for leveling income variability, products based on precipitation. Certainly, it is necessary to determine why such products are little used in agriculture.

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1. Introduction

Canada is one of the world's largest agricultural producers and exporters of oilseeds, wheat and coarse grains. Although the proportion of the population engaged in agriculture and its contribution to Gross Domestic Product have fallen dramatically over the 20th century, the agricultural sector still remains an important element of the Canadian economy. The goods and services produced by the agriculture and food sectors together account for about 8% of Canada's gross domestic product. Despite its size, agricultural land occupies only 7.3% of Canada's total land, with cropland concentrated in the southern part of the country, mainly the Canadian prairies and southern parts of Ontario and Quebec. Wheat is grown throughout, but the major wheat-growing region is the western Prairie grain belt. Globally scale, Canada is the seventh largest wheat producer with average annual production in 2012 of around 27.2 million metric tons, approximately 4% of world production. Thus, any fluctuations in Canadian production due to weather variability can have a significant impact on global wheat supply.

Wheat can be planted in the spring, but also in the fall. Spring wheat is generally planted in May and harvested from August to as late as October; winter wheat is planted in September and into October. Planting of winter wheat is concentrated in eastern Canada and the southern portions of the western grain belt, and harvested in July and August. Although spring wheat dominates on the Canadian prairies, winter wheat has certain benefits. Because it gets established in the fall, the growing season is longer as plants have a head start in early spring. Along with improved access to early spring moisture, winter wheat's longer growth period results in a higher yield potential. The only drawback to winter wheat is the risk that plants will not survive the winter.

Until the early 1980s when seeds were planted directly into stubble ('stubble-in' method) to increase the probability of survival, winterkill prevented winter wheat from being planted outside of southern Alberta. Stubble-in winter wheat production prevents soil erosion, provides crop with greater access to moisture, and increases agricultural productivity by reducing tillage operations and spreading a farmer's workload. Additionally, from an environmental perspective, winter wheat can provide important spring breeding habitat for migratory waterfowl.

Given the risk of winterkill, farmers need some means of hedging their risk of planting wheat in the fall. They need some indication that the climate conditions during winter and early spring will lead to successful over-wintering of the wheat plants. An important source for such information is the *Farmers' Almanac*, which is published annually in summer and provides weather forecasts for the next 14 months as a guide to farmers regarding potential climate conditions (McFadden 2012). Typically the *Almanac* projects future temperatures and precipitation on the basis of 30-year averages, adjusted to account for astronomical factors such as sunspot activity and declination of the Moon. As noted by one western meteorologist, the *Almanac* essentially relies on factors correlated with climate indexes, such as the El Niño index, Atlantic Multi-decadal Oscillation (AMO) and North Atlantic Oscillation (NAO).[1] Because winter wheat provides important duck breeding habitat, environmental groups such as Ducks Unlimited are interested in promoting greater planting of winter wheat on the Canadian prairies. A major objective of the current research is, therefore, to determine factors affecting farmers' decisions to plant winter wheat. In particular, we wish to determine whether and to what extent climate factors, such as El Niño, impact the success of winter wheat, and whether such knowledge can help environmental NGOs, for example, promote planting of winter wheat in various regions when it is most likely to be successful and thus beneficial for waterfowl production.

In addition to factors determining producers' decision to plant winter wheat, we also investigate non-human factors affecting crop yield, particularly whether climate factors affect yield outside of the ability of the crop to survive the winter. Indeed, if wheat fails to survive, farmers absorb the loss and plant a spring crop on fields planted to wheat the previous fall. To investigate the effects of climate and weather variability on winter wheat, we employ data from the province of Saskatchewan. As Canada's most important grain-producing region, Saskatchewan accounts for 44% of Canada's total cultivated farmland, supplies 10% of the world's total exported wheat, and produces both spring and winter wheat.

The paper is organized as follows. The next section provides an overview of earlier research related to climate impacts on agriculture and a background to the method used in this paper. Then, in Section 3, we develop a panel regression model and a logistic model to estimate the relationship between crop yields and weather/ climate indexes. The data used in the study are described in Section 4 as is the method used to handle the geographical nature of the data. Section 5 applies the model to estimate crop yields of winter wheat with weather indexes and derives winter wheat's probability of overcoming winterkill in terms of climate indexes followed by a simple Monte Carlo estimate on average crop yields and corresponding variation.

2. Literature Review

Because of concerns about climate change, studies investigating the response of crop yield to climate and weather variables have become increasingly popular. One approach utilizes agricultural crop models with stochastic weather generators to simulate weather effects on crop yields and the variability of yields (e.g., Wilks 1992; Torriani et al. 2007; Xiong et al. 2007). Not surprisingly, these models demonstrate that weather variables have an important impact on both

[1] Personal communication with Dr. Timothy Ball. *The Western Producer* also provides information for farmers concerning climate indexes (e.g., see issue of April 11, 2013, p.31)

the mean and variability of crop yields. Regression models are also used to estimate actual crop yield or profit functions on the basis of various climate measures (Waggoner 1979; Dixon et al. 1994; Segerson and Dixon 1999). For example, Lobell and Asner (2003) found negative impacts from greater warming on crop yields in the U.S. Midwest. Strong correlations between corn yields and July temperatures and May precipitation were found by Almaraz et al. (2009) for the Monteregie region of Quebec. When modeling crop yield distributions, Gallagher (1987) applied a gamma distribution, while Moss and Shonkwiler (1993) employed an inverse hyperbolic sine transformation; Goodwin and Ker (1998) demonstrated the usefulness of nonparametric models, with Ker and Coble (2003) later developing a semi-parametric approach. Antle (2010) linked variable agricultural output to random exogenous input vectors, such as pests and weather, using a feasible generalized least-squares estimation framework. Tack et al. (2012) used moment functions and maximum entropy techniques to show how climate variables affect yield.

For the United States, Schlenker and Roberts (2006, 2009) used a new fine-scale weather dataset and approximated the whole distribution of temperatures between the minimum and maximum within each day and across all days in the growing season. Then they derived the amount of crop growth occurring in each 1°C temperature interval between -5°C and $+50^{o}$C. Robertson (2012) estimated a similar relation between temperature and crop yields for the Canadian prairies. Three different versions of a temperature variable were calculated and used in alternative yield model formulations: average daily temperature, growing degree-days (GDDs), and the Schlenker and Roberts' 1°C intervals from 0°C to 40°C.

While the forgoing studies are potentially useful in predicting how climate change might impact various crop growing regions, they are unable to provide farmers guidance for making management decisions, whether what crop to plant or what weather hedge to purchase (Guo et al. 2013). Therefore, in this study, we develop and estimate simpler relations between crop yields and cumulative growing-season precipitation and GDDs. Further, climate indexes are included in the analysis, although it turns out that these serve primarily as signals for making planting decisions.

3. Methods

Fall planted wheat may not survive the winter, leading to crop failure and the replanting of a spring crop in May, which increases costs. One problem when estimating winter wheat production is the failure to record the winterkill, because it is subsumed in the spring replanting. Thus, we have omitted observations that are relevant to the research. This problem is addressed using a Heckman selection model to estimate the relationship between winter wheat yields and the weather/climate indexes. In this way, it is possible to test if the omitted observations related to unsuccessful winter wheat plantings are indeed a problem. If the 'lost' observations are a problem, it is possible to correct for this in the crop yield model; if not, it is possible directly to examine the effects of weather and climate variables on crop yields.

A Heckman model is composed of two parts, a selection equation and an outcome equation. The selection equation is specified as follows:

[1] $z_t = a_0 + a_1 \bar{E}_t + a_2 \Delta E_t + b_1 \bar{N}_t + b_2 \Delta N_t + \xi_t,$

where z_t is a binary variable that takes on the value of 1 if winter wheat is planted in the fall prior to harvest in year t+1, and 0 otherwise; $\bar{E}_t$ and $\bar{N}_t$ are the standardized average values of climate indexes El Niño 3.4 and North Atlantic Oscillation (NAO) in the six-month period (March to September) during year t; ΔE_t and ΔN_t represent simple trends of these two climate series; and a_i and b_j are parameters to be estimated. (The means and standard deviations of the El Niño and NAO series are found in Table 1 below.) If during the six-month period prior to fall planting, a trend is positive, indicating that the index is rising, it is assigned a value of 1; if the value of the standardized climate index never deviates by more than one unit of the initial (March) value of the index, there is no significant change and the trend is considered to be stable and a value of 0 is assigned; and a value -1 is given if the trend is negative, indicating the index declining.

The selection equation indicates that the probability of harvesting winter wheat in year t+1 is correlated with March-to-September's average El Niño and NAO indexes in year t. If the model shows close correlation between the probability and one or both of the climate indexes, farmers could decide to plant winter wheat on the basis of the previous climate data.

The outcome equation examines the relationship between winter wheat yields (y) and weather variables such as precipitation, temperature and snowfall. It is specified as follows:

[2] $y_{t,j} = \alpha + \Sigma\, \beta_i P_{t,i,j} + \delta_1 G_{t,j} + \delta_2 (G_{t,j})^2 + \gamma S_{t,j} + \Sigma\, \theta_i D_i + \varepsilon_t.$

To make the model's period consistent between the two equations, crop harvest in year t follows planting in t–1. The growing season is April to September, and we use monthly precipitation (P) and total growing-season degree days (G) as independent variables. In addition, because of the nonlinear effects of temperature, the regression equation [2] is assumed to be quadratic in G to take into account any nonlinear effects of G on wheat production. Since winter wheat has to grow through the winter season, snowfall is also taken into account with total snowfall (S) measured over the period from November in year t–1 through March in year t. D_i represents a dummy variable identifying one of the province's three geographic soil zones – black, dark brown and brown (see Figure 2) – and α, β_i, δ_1, δ_2, γ, and θ_i are parameters to be estimated. Finally, $\varepsilon \sim N(0,\sigma)$ by assumption, where σ is unknown and to be estimated as part of the regression.

In the Heckman model, a parameter ρ is calculated, which provides information on the correlation between the selection and outcome equations. A test if ρ=0 is used to determine if there exists a selection problem that biases the outcome results. If ρ=0 cannot be rejected, this indicates there is no selection problem so utilizing a Heckman model is not appropriate. Then the

selection and outcome equations can be estimated separately as a logistic regression equation and a panel regression model, respectively.

4. Data

Three sets of data are employed for analyzing winter wheat yields. First, monthly data for the El Niño and NAO climate indexes were retrieved from Climate & Global Dynamics climate analysis section (Figure 1).[2] Then annual crop yield data for winter wheat at the rural municipality (RM) level were obtained from Saskatchewan Agriculture.[3] The weather indexes, precipitation, temperature and snowfall data came from Environment Canada's data and information archives, which includes historical weather information from weather stations located across Canada.[4] Daily weather data were aggregated monthly to be consistent with the climate index data. Then, because observations on annual crop yield are at an RM level, it was necessary to construct a Geographical Information System (GIS) model and spatially weight data from various weather stations to obtain an aggregated measure of the weather variable at the centroid of each RM. By measuring the distance from the centroid of each RM to the nearest three weather stations, a weight adjusted parameter is calculated: the reciprocal of the distance for a weather station divided by the sum of distance reciprocals for all three stations.

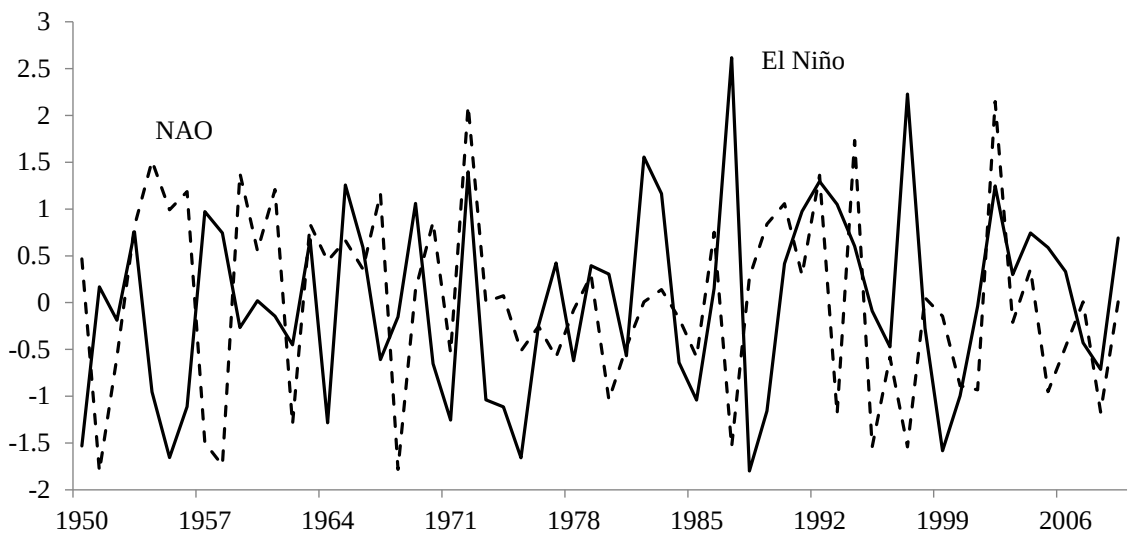

Figure 1: Standardized climate indexes

[2] CGD website: http://www2.cgd.ucar.edu/
[3] Saskatchewan Agriculture website: http://www.agriculture.gov.sk.ca/
[4]Canadian Daily Climate Data (CDCD) found at:
ftp://client_climate:CLIENT@ftp.tor.ec.gc.ca/Pub/Data/Canadian_Daily_Climate_Data_CDCD/

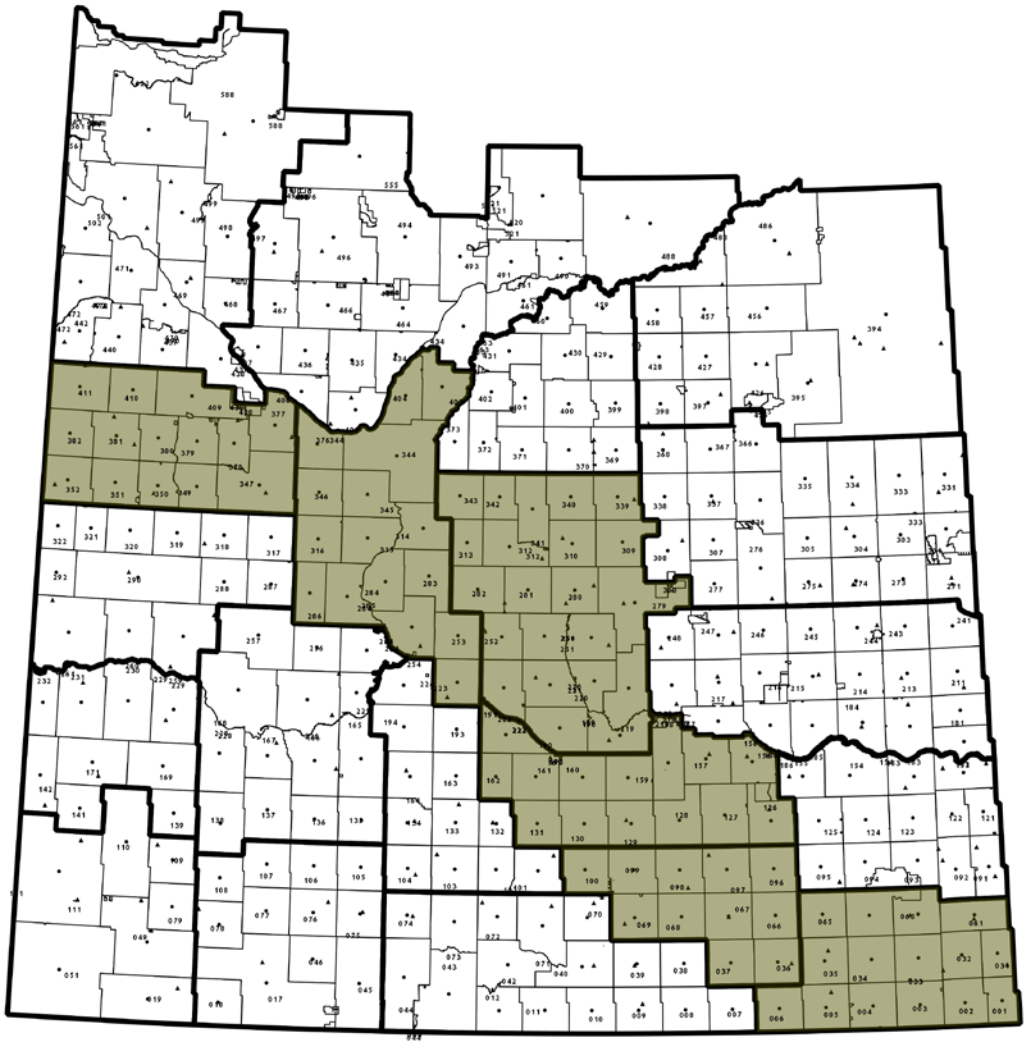

Figure 2: Rural municipalities, crop districts, weather stations and soil zones in Saskatchewan

The Saskatchewan government divides the entire province area into 298 administrative regions called rural municipalities, numbered from 1 to 622. Figure 2 provides RM information for the southern, grain-growing region of Saskatchewan. In addition, 20 Crop Districts merge multiple RMs into larger entities, and these are identified in the figure by bold lines. The government records various crop yields in each RM region every year.

There are 8,121 observations on RM-level spring wheat yields over the period 1950-2006, but only 684 observations on winter wheat because no official data exist for winter wheat prior to 1992. In Figure 3, average annual yields of spring and winter wheat indicate that, although winter wheat is not as popular as spring wheat, the average yield is 10% to 20% higher.

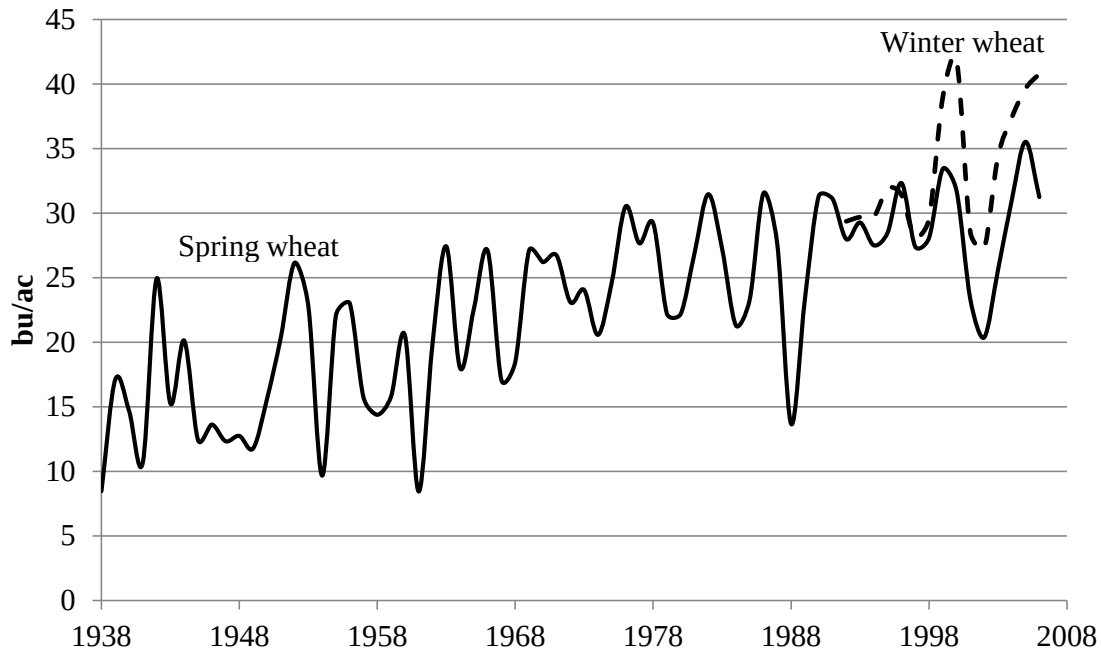

Figure 3: Yearly average yields for winter wheat and spring wheat

Saskatchewan is characterized by three soil zones – black, dark brown and brown (Figure 2). The black soil is located in the northeast; it has the lowest temperature and greatest annual precipitation. The brown soil zone lies in the southwest; it is the driest and generally has the longest growing season. The in-between, dark brown soil zone is shaded in the figure.

Before transforming weather station data, it is necessary to apply some filters. There are 671 weather stations located in Saskatchewan, but not all are used continuously – some stations have been abandoned while new ones have appeared. Therefore, not all stations' weather data are used. Since the earliest winter wheat plantings were not recorded until 1992, any stations not providing weather information for 1992 and thereafter are excluded, leaving only 247 weather monitoring sites. Then, those stations providing only partial data or having large gaps in the data are also removed. This left 142 weather stations, which are indicated with triangles in Figure 2.

For each individual weather station, snowfall is summed over the days for the winter period (November through March), while precipitation is cumulated on a monthly basis. Average daily temperatures are used to create two monthly series – an average daily temperature and total growing degree-days for each month. Average daily temperature over a month is easy to calculate, while monthly growing degree-days (G) are calculated as follows: If the temperature is higher than 5°C, the degree days is the difference between the observed temperature and this value; if the temperature is 5°C or lower, G=0. Daily growing degree-days are thus calculated as:

[3] $$G_{j,d}(T_{j,d}) = \begin{cases} T_{j,d} - 5 & if\ T_{j,d} > 5°\text{C} \\ 0 & if\ \ T_{j,d} \leq 5°\text{C} \end{cases}$$

where j refers to the RM and d to a particular day in a month or some other period over which GDDs are to be measured. Growing degree-days can then be summed over the number of days in a month or over some other relevant time horizon. In this application, let N denote the number of days in the growing season, say N=184. Then the number of growing degree-days in RM j is given as a function of the temperature in j as follows:

[4] $G_j(T_j) = \sum_{d=1}^{N} G_{j,d}$.

Next a distance-adjustment method is used to 'aggregate' the weather information from discrete stations to the centroid of each RM, indicated in Figure 2 by round dots. Using Quantum GIS (QGIS), a geographic software package,[5] we calculated the distances between the centroid of each RM and its nearest three weather stations. A distance-weighted average of the three observations for each relevant weather variable is then used to establish a weighted average for that observation at the centroid. The weight on an observation from weather station k used in the construction of a weather variable for RM j is $w_{k,j} = \frac{1}{d_{k,j}} / \sum \frac{1}{d_{k,j}}$ where $d_{k,j}$ is the distance between the weather station k and the centroid of RM j.

In the case of temperature, an additional adjustment is made for elevation. For each 100 meter increase in elevation, the temperature falls by 0.6°C. [6] Therefore, before aggregating temperatures, the weather station temperature readings are modified by the elevation difference between the station and the centroid of the relevant rural municipality. The temperature at the centroid of RM j is then determined as follows:

[5] $T_{j,d} = \sum_{k=1}^{3j} w_{k,j}[T_{k,j,d} - 0.006(e_{k,j} - e_j)]$,

where 3j refers to the three weather stations nearest to RM j, $T_{k,j,d}$ is the temperature reading at weather station k near RM j on day d, $e_{k,j}$ is the elevation at weather station k and e_j is the elevation at centroid j.

Table 1 provides summary statistics of the climate indexes and weather indexes. A plot of the standardized climate series is provided in Figure 1, where the NAO and El Niño indexes appear to move in opposite directions. Table 1 also provides summary statistics for monthly precipitation for the period April to August, total winter snowfall, and GDDs. The data indicates that precipitation in June averages 77.19 mm, the most of any month. Average GDD is about 1,454°C from April to August and average winter wheat yield is 33.34 bushels per acre.

[5] QGIS is free to download from http://www.qgis.org.

[6] As an average, the International Civil Aviation Organization defines an international standard atmosphere (ISA) with a temperature lapse rate of 6.49°C/1,000 m from sea level to 11 km.

Table 1: Summary Statistics for Weather Variables and Climate Indexes

Variable	Mean	Std. Dev.	Min	Max
Winter wheat yield	33.34	9.86	5.00	70.00
El Niño (non-standardized)	27.37	0.53	26.33	28.47
NAO (non-standardized)	-0.34	0.98	-1.50	1.88
April precipitation	24.13	18.12	0.00	97.80
May precipitation	44.62	31.96	0.70	176.67
June precipitation	66.10	42.31	0.00	183.72
July precipitation	53.21	38.60	0.05	191.10
August precipitation	43.02	34.68	1.00	135.24
Growing degree days (April to August)	1,020.57	526.38	68.58	1,708.15
Snowfall (November to March)	87.43	81.05	0.05	259.55

The weather data in Table 1 are also provided in Table 2 but by soil zone. Further, the number of observations of winter wheat plantings by crop district is also provided in Table 2. Notice that winter wheat is found throughout the study region; in the black soil zone, winter temperatures tend to be a bit colder, but there is more snow to protect seedlings. In the brown soil zone, there is less snow but winters are also milder and snow melt occurs earlier, with seedlings taking advantage of this moisture since growing season precipitation is less than areas to the north and east. Winter wheat yield is highest in the black soil zone, which has the most snowfall, the highest precipitation in April, July and August, and the greatest number of growing degree-days. Yet, out of 288 observations on successful winter wheat plantings in the black soil zone, 86.5 percent or 249 observations are found in crop districts 1B, 5A and 5B, which are located in the most southern part of the black soil zone (Figure 2), where conditions are more favorable than farther north. There are much fewer observations on winter wheat occurrence in Crop Districts 8 and 9 than in southern districts. The same is true for winter wheat grown in the dark brown soil zone – these are found closer to the U.S. border as opposed to higher latitudes.

5. Empirical Analysis

We have 684 uncensored observations on winter wheat plantings. For the Heckman model, the Likelihood Ratio test for selectivity (H_0: $\rho=0$) has a χ^2 value of 1.55, while the p-value for $\chi^2>1.55$ equals 0.21. This indicates that sample selection bias is not a problem in the data. Therefore, we can estimate the logistic (selection) and the panel regression (outcome) models separately. The regression results for the logistic model explaining why farmers choose to plant winter wheat are provided in Table 3, while the panel model regression results for the outcome equation explaining crop yields are provided in Table 4.

Both the El Niño index and its trend have a positive effect on the probability of planting and subsequently harvesting winter wheat (Table 3). A higher value of the El Niño index in the period before the decision to plant winter wheat is indicative of a greater chance that fall-planted wheat will survive and be successfully harvested the following summer. Although the sign on the

climate variable differs, the NAO index and its trend provide similar information. If the NAO index is low and trending downwards in the period before planting winter wheat, the higher is the probability that the crop will survive winter and be successfully harvested.

Table 2: Average Value of Weather Variables by Soil Zone[a]

Variable	Black	Dark Brown	Brown
Winter wheat yield	34.99	33.62	30.11
	(9.56)	(10.1)	(9.34)
April precipitation	27.75	26.22	21.04
	(20.1)	(17.8)	(16.4)
May precipitation	45.83	51.93	47.34
	(31.1)	(35.7)	(27.7)
June precipitation	75.74	75.96	74.17
	(47.9)	(39.6)	(38.1)
July precipitation	67.75	56.84	46.02
	(41.4)	(36.9)	(34.8)
August precipitation	60.23	51.89	41.83
	(44.6)	(42.1)	(31.7)
Growing degree days (April to August)	1406.98	1473.43	1511.31
	(240.5)	(337.9)	(310.1)
Snowfall (November to March)	98.12	88.24	70.73
	(39.2)	(42.0)	(32.8)
Observations	288	269	167
	Observations by Crop District [# obs]		
	1B[72]	1A[78]	3AS[28]
	5A[78]	2A[17]	3AN[12]
	5B[49]	2B[24]	3BS[33]
	8A[26]	6A[64]	3BN[29]
	8B[28]	6B[35]	4A[33]
	9A[11]	7B[11]	4B[19]
	9B[24]		7A[13]

[a] Standard deviation provided in parentheses; observations in square brackets.

Table 3: Logistic Selectivity Regression for Winter Wheat Planting in Saskatchewan

Variable	Estimated Coefficient[a]	Standard error
Standardized El Niño ($\bar{E}$)	0.77	0.052
Standardized NAO ($\bar{N}$)	-0.25	0.041
El Niño trend (ΔE)	1.64	0.112
NAO trend (ΔN)	-0.43	0.054
Constant	-2.29	0.048

[a] All of the estimated coefficients are significant at the 0.01 level of statistical significance.

Table 4: Panel Regression Results for Winter Wheat Yield Outcomes[a]

	Model #1		Model #2		Model #3		Model #4	
Variable	Estimated Coefficient	Standard Error	Estimated Coefficient	Standard Error	Estimated Coefficient	Standard Error	Estimated Coefficient	Standard Error
April precipitation	0.1013***	0.0196	0.0875***	0.0202	0.1167***	0.0220	0.1094***	0.0224
May precipitation	0.0633***	0.0115	0.0652***	0.0116	0.0596***	0.0116	0.0597***	0.0117
June precipitation	0.0224**	0.0089	0.0301***	0.0093	0.0201**	0.0090	0.0265***	0.0093
July precipitation	-0.0232**	0.0096	-0.0276***	0.0098	-0.0242**	0.0096	-0.0295***	0.0097
August precipitation	-0.0040	0.0093	-0.0061	0.0099	-0.0006	0.0094	0.0017	0.0101
Snow (Nov through Mar)	-0.0144	0.0095	-0.0184*	0.0096	-0.0116	0.0096	-0.0142	0.0096
GDD (April to August)	0.0069	0.0059	0.0030	0.0059	0.0108*	0.0062	0.0087	0.0061
GDD squared	-4.47E-06*	2.41E-06	-2.93E-06	2.41E-06	-5.10E-06**	2.43E-06	-3.72E-06	2.40E-06
Std. Dev. of GDD					-0.0398*	0.0195	-0.0661***	0.0203
Black soil dummy	30.1908***	3.8012	33.9411***	3.8569	30.9328***	3.8092	35.6752***	3.8655
Dark brown soil dummy	28.6662***	3.6518	32.0331***	3.6929	29.4469***	3.6627	33.7908***	3.7053
Brown soil dummy	25.7662***	3.6347	29.2733***	3.6805	26.5162***	3.6442	31.0641***	3.6947
Standardized El Niño ($\bar{E}$)			-1.2180**	0.4785			-1.4783***	0.4818
Standardized NAO ($\bar{N}$)			0.8874**	0.3632			0.8125**	0.3613
El Niño trend (ΔE)			-0.5688	0.8812			-0.7227	0.8761
NAO trend (ΔN)			1.1284*	0.5769			1.4097**	0.5792
Standard error of residuals	9.1705		9.0644		9.1489		8.9999	

[a] ***, ** and * indicate statistical significance at the 0.01, 0.05 and 0.1 levels of significance, respectively.

In Table 4, we present results of four regression equations used to estimate yields. In all four models, dummy variables are used to represent the three soil zones – black, dark brown and brown. In all cases, the base yield declines in going from the northeast of the Saskatchewan grain belt to southwest Saskatchewan, or from the black soil zone to the brown soil zone. (In Appendix Table A1, we provide separate regression results for each of the three soil zones; the results in this table support those in Table 4 but shed little additional light on the results already provided in Table 4.) The soil zone dummy variables are statistically significant at the 0.01 level of significance or better in all four models. Compared to the brown soil zone, winter wheat yields in the black zone are some 4.6 to 5.4 bu/ac higher while those in the dark brown zone are nearly 3 bu/ac higher. However, it is necessary to keep in mind that winter wheat likely has less chance of surviving winterkill in Crop Districts 8 and 9 in the higher latitudes, as evidenced by much lower plantings for which yield data are available.

Growing Degree Days

When it comes to heat units required for crop growth, the estimated coefficients on growing degree-days are positive (as expected) but, with one exception (Model #3), statistically insignificant. Further, as expected, the negative sign on the estimated coefficient of the quadratic heat term indicates that the effect of heat on crop yield is nonlinear – yields increase at a diminishing rate and might eventually decline as a result of heat stress. However, the quadratic term is statistically significant only in Models #1 and #3. We find that, when precipitation variables are valued at their means, average crop yields are unlikely to exceed 37.5 bu/ac (12.5% higher than average yield) as a result of more heat exposure. Unfortunately, the statistical significance of the estimated coefficients on GDD and GDD-squared are weak overall and the impact of GDD is small at the margin, which suggests that GDD might be a poor weather index on which to basis a financial instrument (see below). This is further supported by the results of Models #3 and #4, where the standard deviation of growing degree days is included in the regressions; the standard deviation has a statistically significant but negative impact on yields. That is, the greater the dispersion (uncertainty) about available heat, the lower is the final crop yield. This suggests that greater detail on the timing of GDDs is required and that any weather index might not be sufficiently attractive to employ as a financial instrument.

Precipitation

Not surprisingly in the Saskatchewan study region, precipitation early in the growing season is the most important contributor to crop yields. In Table 4, the estimated coefficients on April, May and June precipitation are positive and highly statistically significant in all four regression models. While spring wheat is not planted until May, fall-planted winter wheat is able to take advantage of April precipitation (whether in the form of snow or rainfall) to enhance final yield. Indeed, this is one advantage that winter wheat has over spring wheat – better access to available moisture for crop growth. May and June precipitation are also important in contributing to increased yields, but the impact of precipitation in these months on yields is less than that of

April precipitation and, based on the estimated parameters, appears to decline as harvest approaches.

Given the beneficial effect of April precipitation, one might expect snowfall in the period after planting (snowfall during November through March) to also benefit crop production because of the additional moisture provided by spring runoff. However, this is not the case. The estimated coefficient on snowfall in all four regressions is negative but statistically insignificant. Keeping in mind that, in Table 4, we have only observations on fall-planted wheat that has survived winterkill, it would appear that too much snowfall is harmful to winter wheat – some snow protects the crop but too much might reduce yields. As indicated above, large amounts of snow may well be correlated with a later start to the continuance of crop growth in the spring; this is true in the black soil zone, but in the brown soil zone there is less snow and growing season precipitation, so the fall-planted crop will rely to a greater extent on moisture related to snow melt than in the black soil zone. Because the crop has already emerged, April and May precipitation are extremely important to yield, as indicated by the size and statistical significance of the estimated coefficients; precipitation in June is also statistically important, but less important in terms of its contribution to yield. Indeed, 1 mm additional rainfall in April or May increases yield by 0.059 to 0.116 bushels per acre (bu/ac) depending on the month and model, while additional rainfall in June adds no more than 0.030 bu/ac per mm. In contrast, because the crop is often harvested in July and into August, precipitation in those months can actually lower yields, but then only by a maximum of 0.029 bu/ac per mm increase in rainfall.

Harvest of winter wheat begins as early as July and continues into August, depending on the region. Thus, it is not surprising that rainfall in July and August have a negative impact on yields. Rainfall when grain has ripened can delay harvest and damage crop yield. This is evident from the statistically significant negative sign on July rainfall; the estimated coefficient indicates that the reduction in yield caused by an additional millimeter (mm) of precipitation might be of the same order of magnitude as the gain from an additional mm in June – rather small in any event. While the estimated coefficient in August rainfall is also negative, it is statistically insignificant, perhaps reflecting the fact that most of the winter wheat will have been harvested by early August.

From the forgoing results, it would appear that a financial weather instrument that might be of interest to growers of winter wheat would need to be based on precipitation, most likely precipitation for the months of April and/or May as these appear to be the most crucial months. We consider this further in the next section. Before doing so, we examine the impact of the larger climate influences on crop yields.

Climate Indexes: Long Term Impacts

As in the case of the logit model explaining why some farmers adopt winter wheat despite its risks, longer term climate trends are an important factor. It turns out that both the El Niño and

NAO indexes have a relatively large and statistically significant impact on winter wheat yields (Models #2 and #4 in Table 4). In addition, the trend in the North Atlantic Oscillation (ΔN) has a statistically significant impact on crop yield but not the trend in the El Niño (ΔE). To examine the role of these climate indexes further, we used a panel model and regressed growing season GDDs, winter snow, and precipitation for the months April, May and June on the standardized El Niño ($\bar{E}$) and NAO ($\bar{N}$), and the trend in each of these variables, ΔE and ΔN. The results for GDD and winter snow are found in Table 5, where the dependent variables GDD and snow are logged; those for precipitation in April, May and June are found in Table 6, where monthly precipitation has been standardized by subtracting the mean and dividing by the standard deviation. Soil zone dummy variables are included as control variables and, again, these are highly statistically significant in four of the five regressions. May precipitation appears to be evenly spread over the various soil zones (Table 6).

Table 5: Panel Regression Results for Log of GDDs and Winter Snow[a]

	GDD		Winter Snow	
Variable	Estimated Coefficient	Standard Error	Estimated Coefficient	Standard Error
Standardized El Niño ($\bar{E}$)	-0.0142	0.0150	0.0559**	0.0262
Standardized NAO ($\bar{N}$)	-0.0067	0.0112	0.0510***	0.0195
El Niño trend (ΔE)	-0.0047	0.0295	0.1937***	0.0514
NAO trend (ΔN)	0.0164	0.0186	0.0480	0.0324
Black soil dummy	7.2368***	0.0195	4.8048***	0.0340
Dark brown soil dummy	7.2516***	0.0212	4.6447***	0.0369
Brown soil dummy	7.2982***	0.0250	4.4406***	0.0437
Standard error of the residuals		0.3069		0.5340

[a] ***, ** and * indicate statistical significance at the 0.01, 0.05 and 0.1 levels of significance, respectively.

Table 6: Panel Regression Results for Standardized Monthly Precipitation[a]

	April		May		June	
Variable	Estimated Coefficient	Standard Error	Estimated Coefficient	Standard Error	Estimated Coefficient	Standard Error
Standardized El Niño ($\bar{E}$)	-0.0456	0.0471	-0.1427***	0.0483	0.0951*	0.0487
Standardized NAO ($\bar{N}$)	0.2378***	0.0350	-0.0130	0.0359	0.1671***	0.0361
El Niño trend (ΔE)	0.0066	0.0923	0.1023	0.0947	0.2908***	0.0954
NAO trend (ΔN)	0.0951	0.0581	-0.2364***	0.0596	0.1754***	0.0601
Black soil dummy	0.2155***	0.0610	-0.1156	0.0626	1.2581***	0.0631
Dark brown soil dummy	0.1250**	0.0662	0.0963	0.0679	0.9662***	0.0684
Brown soil dummy	-0.1311*	0.0784	-0.0456	0.0804	0.4394***	0.0808
SE of the residuals	0.9609		0.9854		0.9908	

[a] ***, ** and * indicate statistical significance at the 0.01, 0.05 and 0.1 levels of significance, respectively.

Judged by the statistical significance of the estimated coefficients, the climate indexes have no impact on growing degree days – they do not affect the heat available to crops during the growing season. Instead, El Niño and the North Atlantic Oscillation have a strong statistical influence on winter precipitation (snowfall), with the exception of the NOA trend. This supports the logistic model results in Table 3, confirming to some extent that farmers use notions about the climate indexes to determine whether conditions might be right for fall-planted wheat to survive winterkill – El Niño and the NAO help determine winter survival, but snowfall is not an important factor in the determination of crop yields. As indicated in Table 4, April, May and June precipitation are important determinants of winter wheat yields.

From Table 6, we find that the NAO ($\bar{N}$) is a statistically significant determinant of April precipitation, the El Niño ($\bar{E}$) and NAO trend (ΔN) are important determinants of May precipitation, and all four climate indexes are statistically important contributors to June precipitation. This implies that any weather index built on precipitation during these months is subject to potential gaming if the El Niño and NAO are not taken into account. In the remainder of this study, we first develop a precipitation-based weather index and examine its potential use as a hedge against adverse weather conditions and associated low winter wheat crop yields. At this time, we leave for future research the role of the El Niño and North Atlantic Oscillation both in terms of farmers' ability to hedge against the risk of fall-planted wheat not surviving winterkill and the potential of traders to use information about these long-term, climate phenomena to game the markets for crop insurance or options trading.

6. Financial Weather Derivatives to Hedge Crop Yield Risk

Financial Weather Derivatives

Financial weather derivatives and weather-indexed insurance are alternative private-sector instruments that can be used to hedge production risks related to weather outcomes. Payoffs depend on a weather index that has been carefully chosen to represent the weather conditions against which protection is being sought (Jewson et al. 2005). The problems of moral hazard and adverse selection that exist in traditional crop insurance disappear since the value of the weather index does not depend on the individual actions of market participants. Although the two hedging methods – weather derivatives and weather indexed insurance – are essentially similar, there exist mature exchange markets for some financial weather derivatives while weather indexed insurance relies solely on over-the-counter (OTC) contracts.

Trading in financial weather derivatives began in 1997, with an OTC contract based on heating degree days (HDDs) struck between Koch Industrial and Enron Corporation (Brockett et al. 2007). Since then, trading has grown rapidly as the Chicago Mercantile Exchange (CME) began to offer financial exchange-traded weather derivatives based on two weather indexes, HDDs and cooling degree days (CDDs) (Considine 2009). A party wishing to hedge against adverse weather can purchase an option on one of these two weather indexes: A call option can be

claimed when the value of the weather index is above a specified exercise or strike value, while a put option can be claimed when the value of the weather index is below a specified value. The cost of acquiring an option is its premium. For call or put options, buyers take a long position, while sellers take a short position.

Weather derivatives can also be used to protect against crop losses associated with cold weather, extreme heat and/or too much or too little rainfall, although such financial products are generally OTC. For example, a crop producer could insure against too little growing season warmth by holding a put option based on growing degree days, which are similar to CDDs except that the latter are defined with respect to a 18°C threshold compared to 5°C with GDDs. Alternatively, if precipitation is a concern, an option on cumulative spring rainfall (CSR) can be purchased. A farmer could hedge against too few GDDs or too little CSR by purchasing a put option that reduces the financial risk of low crop yield. If the realized weather outcome is at or above the strike value, the farmer would not exercise the option and lose the premium paid for the option contract; in that case, yields are likely higher than expected, which would more than compensate for the premium. If the weather outcome is below the strike value, the farmer receives a payout to compensate for the lower yields and reduced revenue from the adverse weather. Our concern in the current study region is with CSR, rather than GDDs.

A number of studies have focused on methods for pricing weather derivative contracts, including Alaton et al. (2002), Brody et al. (2002), Campbell and Diebold (2005), and Jewson et al. (2005). In these studies, burn analysis and parametric or non-parametric methods were used to specify a probability distribution of the weather index. In agriculture, where financial weather derivatives have not been adopted on the same scale as in the energy sector, studies have looked at rainfall or heat index-based weather derivatives, using historical data to construct such indexes (Turvey 2001; Vedenov and Barnett 2004 ; Musshoff et al. 2011). In the next subsection, we use burn analysis to determine a relationship between winter wheat crop yields and cumulative spring rainfall.

Simulating Winter Wheat Yields: Burn Analysis

In this section, we employ a simple model to forecast the mean and variance of winter crop yields using Monte Carlo simulation. We also use the Monte Carlo simulation to illustrate the relationship between precipitation over the three-month period, April through June, and crop yield. Spring rainfall is later used to construct the weather index upon which the option derivative is based. For each iteration in the simulation, values of each the explanatory variables, estimated coefficients and the error term are randomly drawn from assumed probability distributions. For the explanatory variables, a triangular distribution is assumed, with the observed minimum and maximum values constituting the endpoints of the distribution in each case, and the mean the central measure (mode); the data are provided in Table 1. A triangular distribution is chosen to avoid negative values of the explanatory variables, which is likely in the

case of a normal distribution. However, rather than the maximum spring rainfall derived from Table 1, we set each of the monthly precipitation maxima at 2.0 standard deviations above the mean. For the coefficients and error term, a normal distribution is assumed, however. The estimated values (means) and corresponding standard errors in this case are found in Table 4 for Model #1; for example, the mean of the error term equals zero and its standard error is 9.17. Except for the soil zone dummy variables, the randomly selected variable and parameter values are substituted into the outcome equation to determine a crop yield. Since we compare yield outcomes across soil zones, a random seed employed to ensure that the same random variates are generated with each simulation; for each soil zone, rainfall-yield pairs are determined for 10,000 iterations. The dummy variables are set to one or zero depending on the soil zone chosen for the particular Monte Carlo simulation.

The simulation results are provided in Table 7, while plots of the relationship between winter wheat yields and rainfall are provided in the Appendix. The actual mean and standard deviation for the spring rainfall amounts are also provided in the table and these are actually used in the analysis that follows. These relationships are used to develop a weather-based index that forms the basis of a financial index that farmers can use to hedge against adverse yields.

Table 7: Simulated Spring Rainfall and Winter Wheat Yields by Soil Zone, and Observed Spring Rainfall

Item[a]	Mean	Standard deviation	Minimum	Maximum	Negative observations[b]
Yield black soil zone	36.48	9.77	-5.67	78.59	8
Yield dark brown soil zone	34.98	9.69	-12.36	78.79	10
Yield brown soil zone	32.10	9.66	-7.97	73.98	27
Spring rainfall (mm)	165.4	41.65	31.27	300.20	0
Observed rainfall (mm)					
Study region total	151.03	56.86			
Black soil zone	149.32	60.54			
Dark brown soil zone	142.55	49.88			
Brown soil zone	154.11	56.21			

[a] Yields are measured in bushels per acre (bu/ac)
[b] Out of 10,000 observations

The results of a crude OLS regression of the simulated yields on simulated spring rainfall leads to the estimated relationships provided in Table 8 for each of the three soil zones. In addition, we ran a very simple regression of annual average yield in the black soil zone on annual average spring precipitation (see Table 8). In the next section, the results for the black soil zone are used to illustrate the use of weather derivatives. For the simulated regression model, we find that, when spring rainfall is at its mean value for the black soil zone (Table 7), expected yield is 35.8 bu/ac, but it is 33.1 bu/ac when spring rainfall is one standard deviation below its mean, or a difference of 2.7 bu/ac. For the simple regression, expected yield is 34.9 bu/ac, but it is 31.2 bu/ac when spring rainfall is one standard deviation below its mean, or a difference of 3.7 bu/ac.

Table 8: Estimated Relations between Spring Rainfall and Winter Wheat Yields by Soil Zone

Soil zone	Intercept	Estimated coefficient on spring rainfall	Regression Information
Black (Simulation)	29.1974	0.0441	$R^2 = 0.0353$
	(0.3928)	(0.0023)	SE residuals = 9.592
Black (Simple regression)	25.7439	0.0801	$R^2 = 0.1545$
	(6.0828)	(0.0399)	SE residuals = 4.429
Dark Brown	28.0439	0.0419	$R^2 = 0.0325$
	(0.3905)	(0.0023)	SE residuals = 9.536
Brown	24.9383	0.0433	$R^2 = 0.0348$
	(0.3889)	(0.0023)	SE residuals = 9.496

One thing is clear from the forgoing analyses: Spring rainfall has a positive and statistically significant impact on winter wheat crop yields. For example, if one examines a plot of growing degree days and crop yield, one does not find the similar upward trend observed in Figure A1 in the Appendix. We now use this relationship between spring precipitation and crop yield to illustrate the use of a financial weather instrument based on cumulative spring rainfall.

Can Farmers Benefit from Financial Weather Contracts?

To determine whether a financial weather contract could benefit farmers who plant winter wheat, we need to keep in mind that the main purpose of financial weather derivatives is to reduce variability in income rather than enhance income. Therefore, we need to compare a representative farmer's utility with and without insurance, using a mean-variance utility function over historical revenues (see Vedenov and Barnett 2004, p.397). To illustrate whether farmers might benefit from financial weather derivatives, we consider a simple example from the black soil zone.

In the absence of a financial hedge, revenue is calculated as $R(CSR) = P\, y_j(CSR)$, where $y_j(\mathrm{CSR})$ is yield in period j as a function of the cumulative spring rainfall CSR and P refers to price. In this application, price is chosen to be constant at \$7.20 per bushel, which is the approximate Chicago Board of Trade's July futures price for wheat as of late May 2013. With the purchase of a financial derivative, the farmer's revenue includes the net payoff associated with a put option on cumulative spring rainfall:

[6] $R(CSR, q, K) = P\, y_j(CSR) + q[\alpha(K - CSR) - O(K)]$,

where α is the tick size (dollar value per unit of the weather index CSR), K is the strike (trigger) level for the put option, $O(K)$ is the option price (or premium) as a function of the strike level, the net payoff to the option is given by $\alpha(\mathrm{K} - CSR) - \mathrm{O}(\mathrm{K})$, and q is the number of options purchased. Cooling and heating degree days are traded on the Chicago Mercantile Exchange at a

fixed price of $20 per CDD or HDD; without loss of generality, we use α = $1 per *CSR*. The option price or premium is a function of the strike level and can be found as:

[7] $O(K) = \int_0^K \frac{1}{x\sqrt{2\pi\sigma^2}} e^{-\frac{(lnx-\mu)^2}{2\sigma^2}} dx,$

where the option premium is the area under the lognormal density function up to the strike level, and x represents *CSR*, μ is the mean of ln(x) and σ^2 is the variance of ln(x).

Consider the black soil zone and the results of the simple regression in Table 8. The stylized results for this regression using the average annual observed rainfall amounts for the black soil zone are provided in Table 9. Notice that the standard deviation of the payoff is identical to that of the cumulative spring rainfall. Further, for a farmer who purchases a weather derivative, average revenue over the 15-year time horizon is nearly $30/ac lower ($272/ac vs $242/ac), but that the variance of the revenue is reduced – the standard deviation of revenue falls from 17.09 to 12.58 with the purchase of a put option on weather. Whether a farmer should purchase such a hedge depends on her attitude towards risk.

Table 9: Potential Impact of Purchasing a Hedge against Too Little Spring Precipitation, Black Soil Zone, Strike Level One Standard Deviation Below Mean Rainfall, *q*=1

				With weather derivative	
Year	Spring rainfall (mm)	Yield (bu/ac)	No weather derivative revenue ($/ac)	Payoff ($/ac)	Revenue ($/ac)
1992	114.3	34.9	251.2	5.6	256.8
1993	144.4	37.3	268.5	-24.4	244.1
1994	170.0	39.3	283.3	-50.1	233.2
1995	142.8	37.2	267.6	-22.9	244.7
1996	128.6	36.0	259.4	-8.7	250.7
1997	124.9	35.7	257.3	-5.0	252.3
1998	193.6	41.2	296.9	-73.7	223.2
1999	178.5	40.0	288.2	-58.6	229.6
2000	165.1	38.9	280.4	-45.1	235.3
2001	118.7	35.2	253.7	1.2	254.9
2002	131.0	36.2	260.8	-11.0	249.8
2003	132.3	36.3	261.6	-12.4	249.2
2004	168.1	39.2	282.2	-48.1	234.0
2005	211.5	42.7	307.2	-91.5	215.6
2006	122.2	35.5	255.8	-2.3	253.5
Mean	149.74	37.72	271.61	-29.81	241.80
Stan dev	29.67	2.37	17.09	29.67	12.58

Because farmers purchase a financial weather derivative to reduce income variability, the objective is not to compare revenue with and without a put option, but, rather, to compare the farmer's utility with and without a hedge against adverse weather, in this case too low cumulative spring precipitation. The expected revenue-variance (EV) utility function is:

[8] $U(CSR, q, K) = E[R(CSR, q, K)] - \lambda V[R(CSR, q, K)]$,

where E and V refer to the mean and variance of the historical revenue and λ is the risk aversion coefficient, which is set equal to 0.40. Given that contracts are over-the-counter and cumulative rainfall is given, the agricultural decision maker must choose a strike level (K) and the number of option contracts (q).

Denote the utility without a hedge U^0 and that with the purchase of a put option as U^1, where U^1 is given by equation [8]. The ratio of U^1 to U^0 indicates whether the farmer should purchase a hedge or not; if $U^1/U^0 > 1$, then it is worthwhile for the agricultural producer to purchase a put option to protect against too little spring rainfall. In Figure 4, we plot the ratio of with and without utility levels for various strike levels, where a strike level is defined relative to the number of standard deviations that spring precipitation lies below its mean value. Notice that the ratio drops below 1.0 when the strike level is less than that associated with 1.8 standard deviations below the mean (i.e., a cumulative spring rainfall less than 96 mm). In that case it no longer pays to purchase financial protection against rainfall, most likely because the probability that actual *CSR* falls below that amount is too small.

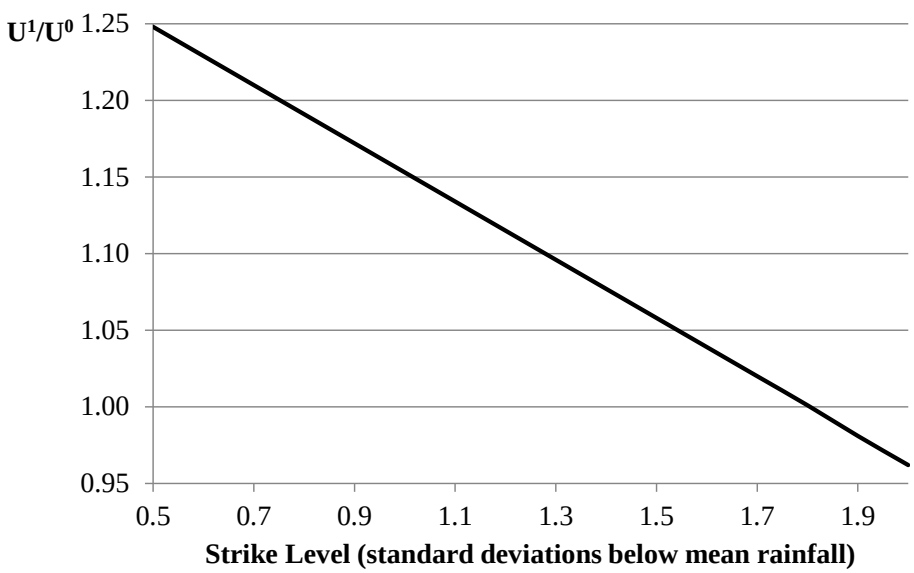

Figure 4: Utility Benefits from Purchasing Protection against Adverse Spring Rainfall Outcomes

In Figure 5, the line $U^1/U^0 = 1$ is plotted for varying levels of the strike and the numbers of options that should ideally be purchased by a farmer facing the personal and environmental

characteristics described above. Points below the threshold indicate combinations of the strike level and quantity of put options that the farmer should optimally purchase. For example, if the farmer purchases one put option per acre (see Table 9) and λ=0.4, then U^1=178.5 and U^0=154.8.

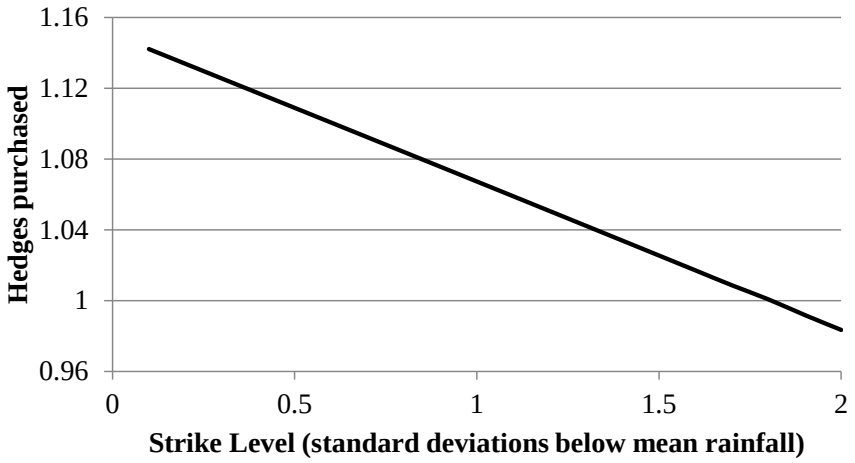

Figure 5: Threshold Determining whether to Purchase a Hedge against Adverse Spring Rainfall Outcomes: Combinations below the Line are Optimal

7. Conclusions

Farmers in the southern prairies of western Canada are interested in fall-planted (winter) wheat as a means of enhancing yields, conserving soil, spreading workload and reducing costs; the only obstacle to greater reliance on fall-planted wheat is the risk of winterkill. In this study, we demonstrated that this risk is reduced if agricultural decision makers have some knowledge about the potential severity of the upcoming winter. The El Niño and NAO climate indexes appear to provide helpful information to farmers deciding on whether to plant winter wheat – the probability of winterkill is reduced with the size of the El Niño and with lower values of the NAO index. Farmers currently appear to obtain information about these climate indexes from one or more unlikely sources, which appear to include the *Farmers' Almanac*, intuition based on trends in mild or severe weather conditions (which are related to trends in the El Niño and NAO), and newspaper articles regarding long-term weather predictions. Given that winter wheat increases available breeding habitat for migratory waterfowl and protects against soil erosion, it would be beneficial for extension agents (whether government, university or private) to provide farmers with information about El Niño, NAO and other factors affecting long-term weather and the potential that fall-planted wheat will successfully survive winter. Environmental NGOs, such as Ducks Unlimited, could also use this type of knowledge to better target incentives to landowners for planting winter wheat, thereby aiding migratory waterfowl.

A secondary objective of the research was to demonstrate the potential for financial weather derivatives to protect farmers against adverse weather. The idea is not to protect against

catastrophic weather events, which is also a possibility and is often the purview of government, but to provide a hedge against adverse weather that reduces crop yields but does not ruin the farmer. Financial weather derivatives offer protection against yield variability from colder and/or drier weather than usual. In the current study, we first examined growing season heat and the potential to use a weather index based on growing degree days to protect against adverse winter wheat yields. However, GDDs summed over the period April through July/August varied insufficiently to impact yields. Rather, the main driver of yield turns out to be cumulative spring precipitation. We found that farmers might be able to reduce their risk of crop yield variability be purchasing over-the-counter financial products based on spring rainfall.

The current state of the research is inadequate to draw further conclusions, however. The research needs to be extended in several directions. First, it is important to further investigate the role of the El Niño, North Atlantic Oscillation, and, perhaps, some other climate indexes, such as the Atlantic Multi-decadal Oscillation, upon the risk that winter wheat survives winterkill. In addition, it is necessary to examine the potential for financial derivatives based on El Niño, NAO or some other index to reduce this risk. Clearly, the regression results in Tables 4, 5 and 6 suggest that winter wheat yields are likely affected by these long-term climate events, and that these events have an impact on winter snowfall and spring precipitation. By getting these relationships correct and developing proper financial instruments to lower risks of planting winter wheat, farmers, migratory waterfowl and the environment more generally could benefit.

Another area of research that needs more attention is the potential for using financial weather derivatives to protect against variability in crop yields. In this regard, because winter wheat can make better use of spring runoff and April precipitation than spring wheat, it is important to examine not only differences in crop yields between winter and spring planted wheat, but also to compare the potential of farmers to benefit from using the financial products described here. An overarching consideration is the extent to which financial weather products can help farmers better adapt to climate change, whether these products can be used to incentivize greater planting of winter wheat, and/or whether they can be deployed to a much greater extent than currently.

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APPENDIX

Further Regression Results for Winter Wheat Crop Yields

Some additional regression results are provided in this Appendix. Results in Table A1 support those in Table 4, but are statistically weaker. They add no additional information beyond what is already available in Table 4. The important information in Table A1 relates to the estimated coefficients on the explanatory variables. These differ across soil zones and this information might be useful for bootstrapping the relationship between crop yield and growing degree days.

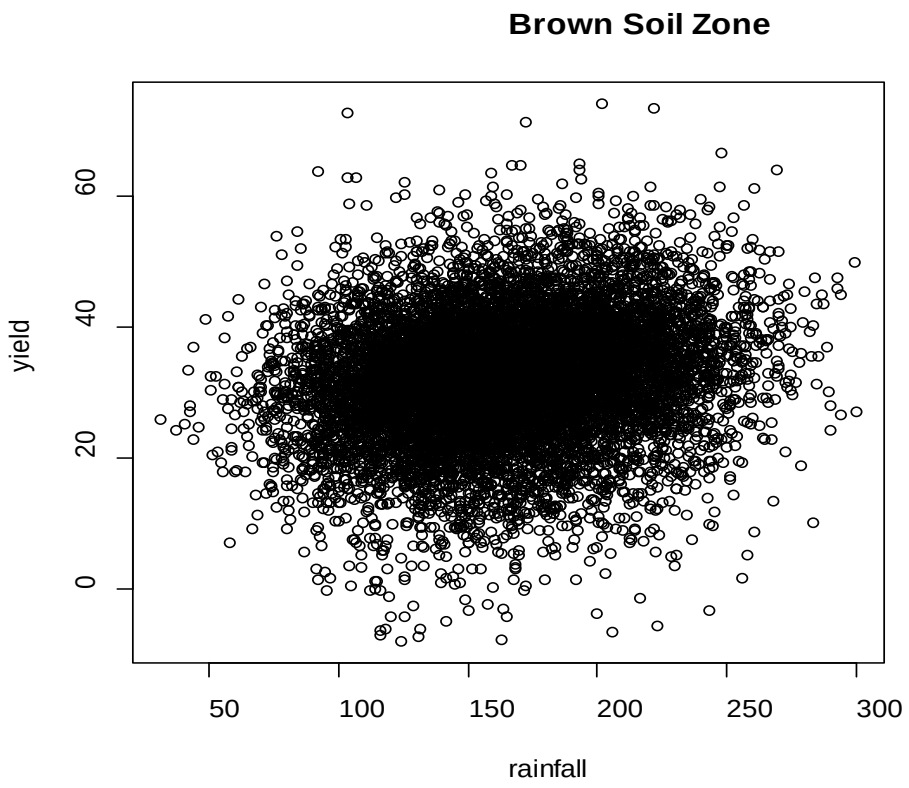
Table A1: Regression Results for Winter Wheat Yield Outcomes by Soil Zone

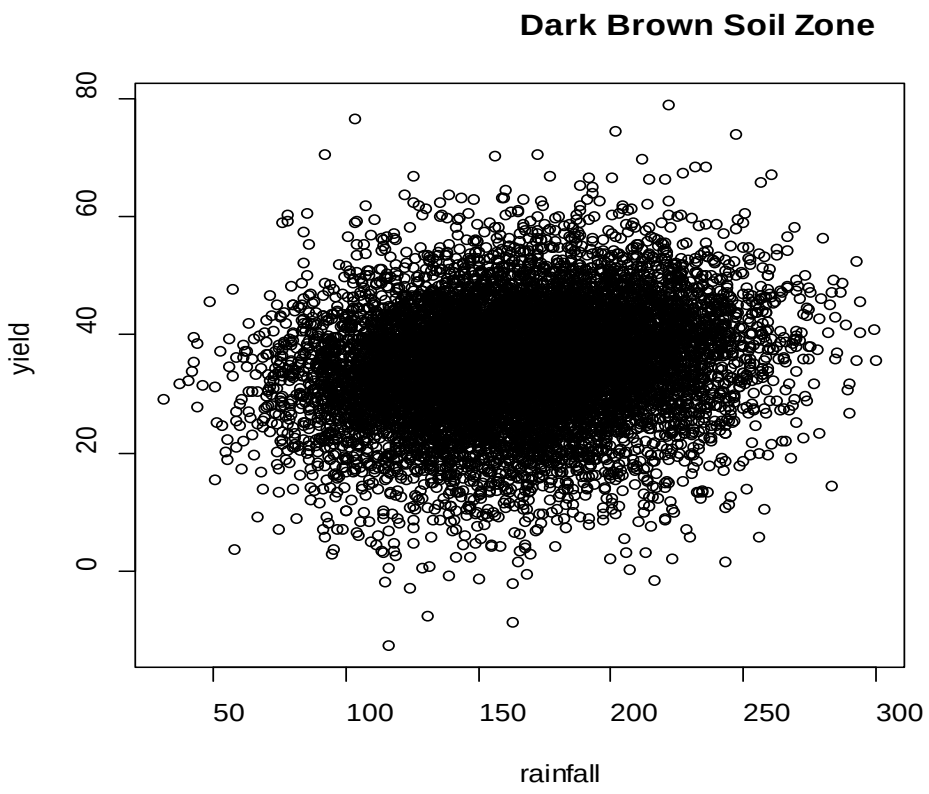
	Black		Dark Brown		Brown	
Variable	Estimated Coefficient[a]	Standard Error	Estimated Coefficient[a]	Standard Error	Estimated Coefficient[a]	Standard Error
April precipitation	0.0716**	0.0281	0.1837***	0.0358	0.1183**	0.0489
May precipitation	0.0544***	0.0156	0.0902***	0.0177	0.0566**	0.0241
June precipitation	0.0146	0.0113	0.0283*	0.0161	0.0325*	0.0176
July precipitation	-0.0242*	0.0122	-0.0028	0.0172	0.0042	0.0211
August precipitation	-0.0127	0.0118	-0.0063	0.0156	-0.0059	0.0201
GDD (April to August)	0.0244**	0.0110	-0.0063	0.0086	0.0171	0.0115
GDD squared	-1.15E-05**	4.50E-06	7.23E-07	3.69E-06	-7.22E-06*	4.38E-06
Snow (Nov to March)	-0.0034	0.0149	-0.0480***	0.0177	-0.0097	0.0215
Constant	20.7963***	7.1262	35.4169***	5.1220	15.2687**	7.7079
Standard error of the residuals		5.8992		4.8262		6.3339

[a] ***, ** and * indicate statistical significance at the 0.01, 0.05 and 0.1 levels of significance, respectively

Plots of Simulated Rainfall and Winter Wheat Crop Yields

In Figure A1, a plot is provided of the randomly generated (simulated) relationship between spring rainfall (precipitation summed over the months April, May and June) and winter wheat crop yields. The R-project software was used to program the simulation program. The Monte Carlo method used to generate the plots is described in the text. Notice that 10,000 iterations are used.


Brown Soil Zone
yield
0
20
40
60
50
100
150
200
250
300
rainfall


Dark Brown Soil Zone
yield
0
20
40
60
80
50
100
150
200
250
300
rainfall

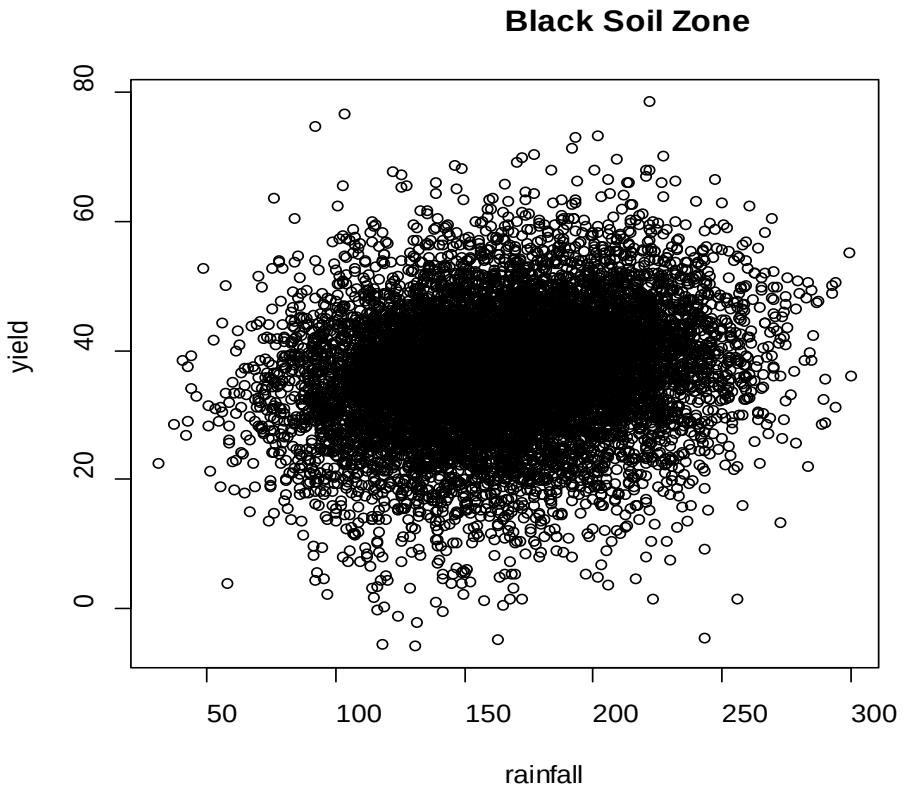


Figure A1: Simulated Relationship between Winter Wheat Crop Yield and Spring Precipitation