Modeling Temperature and Precipitation Influences on Yield Distributions of Canola and Spring Wheat in Saskatchewan

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ABSTRACT

Warmer temperatures and variable rainfall are likely to affect Saskatchewan's production of canola and spring wheat. This study employs moments-based approaches (full- and partial-moments) to estimate the impact of precipitation and temperature changes on canola and spring wheat yield distributions. Environment Canada weather data and Statistics Canada crop yield, planted area, and summer fallow area are employed for 20 crop districts over the 1987-2010 period. Our results show that the average crop yields are positively associated with the growing season degree days (GDD), and pre-growing season precipitation, while negatively affected by extremely high temperatures. Furthermore, the climate measures have asymmetric effects on the higher moments of crop yield distribution.

Keywords: Climate effect, full-moment function, partial-moment function, variance, Pesaran's test

JEL: Q54, Q16

INTRODUCTION

The latest Intergovernmental Panel on Climate Change (IPCC) (2014) report indicates that,

without adaptation measures, global mean temperature increases of 2ºC or more above

preindustrial levels are expected to have negative effects on agricultural crops such as wheat,

corn, and rice in both temperate and tropical regions of the world. Warmer temperatures

associated with decreasing moisture conditions can lead to severe drought and affect yield

potential and impact crop production. Canadian climate model projection studies indicate a

gradual decline in annual precipitation in the prairie province of Saskatchewan (Price et al. 2011)

which is likely to affect agricultural crops (Lemmen and Warren 2004). Not only is unreliable

precipitation likely to be a climate constraining factor, but the reduction in frost days is expected

to influence the crop growing season in Saskatchewan (Grisé 2013).

The aim of this paper is to estimate the effect of precipitation and temperature on crop

yield distributions by a full- and partial-moment-based approach. This study contributes to the

earlier work by Antle (2010, 2013) and Schlenker and Roberts (2009) by treating precipitation

and temperature as separable inputs consistent with the estimation approach by Ortiz-Bobea and

Just (2013), who argue that monthly temperature and precipitation variables have different

production effects on the output distribution. The full- and partial-moments-based approach is

applied to canola and spring wheat yield in the province of Saskatchewan to illustrate its

flexibility to capture the risk and skewness effects of climate and non-climate variables on the

positive and negative yield distributions. Saskatchewan is considered Canada's breadbasket,

having some of the richest soils, and is a major producer of wheat and canola. Wheat and canola

are Saskatchewan's leading crops. In 2014, Saskatchewan's production of spring wheat and canola totalled respectively 9.1 and 7.9 million tonnes or 43% and 48% of Canada's spring wheat and canola production (Statistics Canada, 2015). Saskatchewan is the leading Canadian field crop exporter with $2.2 billion and $2.5 billion, respectively, of non-durum wheat and canola exports in 2014 (Government of Saskatchewan, 2015).

In the next section we present a literature review which is followed by the theoretical framework and data description in the third and fourth sections, respectively. In the fifth and sixth sections the estimation strategy and results are presented. The final section summarizes our conclusions and identifies areas for future research.

LITERATURE REVIEW

Over the past eighty years, there have been multiple econometric modeling approaches adopted in the empirical literature to study the effects of climate change on crop production. One of the earlier Canadian climate studies looked at the impact of weather conditions on wheat yields in western Canada (Hopkins 1935). Most of the earlier climate crop yield studies were by agronomists and meteorologists who analyzed how weather/crop yield effects varied over the crop growth life cycle. The two basic approaches adopted by agronomists included simulation/crop growth models (Jones et al. 2003; Lobell and Ortiz-Monasterio 2007; Qian et al. 2009a; Qian et al. 2009b; Lobell and Burke 2010; Asseng et al. 2011; Wang et al 2011; Özdoğan 2011; Urban et al. 2012; Potgieter et al. 2013) and regression/correlation analyses (Robertson 1974; McCaig 1997; Kutcher et al. 2010; He et al. 2013). Crop growth models required detailed plant physiological data, and in combination with simulated weather data from global circulation models were able to predict how crop yields such as wheat responded to climatic weather conditions.

The economic literature adopted the Just-Pope (2009) production function (Chen et al. 2004; Isik and Devadoss 2006; McCarl et al. 2008; An and Carew 2015) and hedonic models (Deschênes and Greenstone 2007; Mendelsohn and Reinsborough 2007;Wang et al. 2009) to analyse the impact of climate change on agricultural output and profit. Because of unreasonable restrictions in the Just-Pope modelling approach, recent empirical studies have adopted flexible moment-based approaches (Antle 1983; Antle 2010) to analyse the effect of climate on crop output yield distributions (Antle et al. 2013; Tack et al. 2014).

In general, the multiple empirical approaches adopted to study the effects of climate change on agricultural output have provided mixed results attributed partly to model specifications, weather data employed, and country location. In terms of temperature effects, global warming is expected to have a negative impact on global yields of wheat and maize (Lobell and Field 2007), with wheat and maize yields declining, respectively, by 5.5% and 3.8% (Lobell et al. 2011). These temperature yield reduction effects may offset some of the crop yield improvements achieved from technological progress. Employing a regression model that allows for spatial dependence in crop yields across counties, Chen et al. (2013) show that Chinese maize and soybean yields are expected to be adversely affected by higher temperatures by the end of the century with larger yield reductions for soybean than for maize. Flexible regression models employing finer scale weather data reveal that temperature thresholds above 29ºC (maize), 30ºC (soybeans), and 32ºC (cotton) can have harmful effects on crop yields (Schlenker and Roberts 2009). Apart from crop yield reductions, variability of crop yields is likely also to be impacted by warmer temperatures. Urban et al. (2012) find that, without adaptation, U.S. maize yield variability is expected to increase as a result of projected changes in temperature. Schlenker et al. (2006), employing a hedonic approach and a nonlinear transformation of the temperature

variables, conclude that different warming temperature scenarios will result in a 10%-25% decrease in U.S. farmland values.

While quite a number of studies have concentrated on the adverse effects of global warming on crop yields or agricultural profits, a few studies employing cumulative growing season weather variables have examined the combined effects of temperature and precipitation on agricultural output. Climate model projections of future changes in temperature and precipitation suggest that uncertainties in growing season temperatures will have a greater impact on crop production relative to the changes in precipitation (Lobell and Burke 2008). Chen et al. (2004) found increases in precipitation decreased yield variability for U.S. wheat, maize, and cotton, while increasing sorghum production risk. Conversely, higher temperatures decreased cotton and sorghum yield variability but showed mixed results for wheat depending on the functional form employed.

High-latitude countries like Canada are likely to benefit from global warming, especially in the northern regions and the southern and central prairies (Agriculture and Agri-Food Canada 2014). While drier weather is projected to have the greatest impact on the Canadian prairies, in terms of expanding the growing season and the production of higher value crops such as soybeans (Weber and Hauer 2003), the major climate change challenges will be changes in water availability in the summer season, greater frequencies of droughts, and developing crop adaptation strategies (Sauchyn and Kulshreshtha 2008).

Our study employs Statistics Canada (2013) Saskatchewan crop yield and production data for 20 crop districts that differ in soil and climate characteristics. We employ partial-moments functions to test for asymmetric input effects on output and analyze how yield distributions for different crops (canola, spring wheat) respond to pre-growing season

precipitation and monthly temperature and precipitation over the crop growing season. Our estimation procedure corrects for autocorrelation and tests for spatial correlation in weather variables, an issue that has been neglected in many climate change studies. The benefits of this study will help policymakers and scientists develop improved adaptation strategies to lower yield variance and mitigate yield risk of unpredictable weather events.

THEORETICAL FRAMEWORK

Consider a stochastic production function given by $y = g(x, v)$, where y = crop yield, x = non-climate variables, and v = random weather variables that influence crop yield. The production function is described as

$$g(x, v) = f_1(X, \beta) + \epsilon, \tag{1}$$

where X represents observed characteristics for climate and non-climate variables, $f_1(X, \beta) \equiv E[g(x, v)]$ is the mean function, and $\epsilon \equiv g(x, v) - f_1(X, \beta)$ is a random disturbance term with the variance and skewness given as $f_2(X, \beta_2) > 0$, and $f_3(X, \beta_3)$ (Di Falco and Chavas 2009).

Following Antle (2010, 2013), crop district average crop yields follow a distribution $\varphi(Y_{it}|X_{it})$, where Y_{it} equals crop yield in crop district i and period t, and X_{it} represents observed climate and non-climate variables in crop district i and period t. According to Tack et al. (2012), various functional forms of $\varphi()$ are related to different types of moment. Antle (1983) utilized the identity function $\varphi(Y_{it}) = Y_{it}$ and the model conditions the raw moment on explanatory variables. In contrast, Schlenker and Roberts (2006 and 2009) utilized the natural logarithm function $\varphi(Y_{it}) = \ln(Y_{it})$ and this model conditions the natural logarithm moment on X_{it}, while Tack et al. (2012) utilized the higher-power function $\varphi_j(Y_{it}) = Y_{it}^j, j \in N$ and models the higher-order raw moments. In our study, the crop yield's elasticity is our major interest, thus the natural

logarithm function is adopted in this study. The mean function, which is transformed prior to estimating the higher-moment functions, is described as:

$$Ln(Y_{it}) = X_{it}\,\beta + \epsilon_{it}\,, E(\epsilon_{it}|X_{it}) = 0, i = 1, \ldots, N,$$
$$t = 1, \ldots, T, \tag{2}$$

where the moments are assumed to be linear functions of the exogenous variables, while ϵ_{it} is a random error with mean zero. Equation (2) can be very flexible in terms of incorporating quadratic and interaction terms. Employing equation (2), the higher moment function for crop yields is given as:

$$\epsilon_{it}^{j} = X_{it}\beta_j + u_{jit}, E(u_{jit}|X_{it}) = 0, for\ j = 2, 3, \ldots, i = 1, \ldots, N, t$$
$$= 1, \ldots, T, \tag{3}$$

where the errors (u_{jit}) are correlated across all equations and require correction for heteroskedasticity using weighted least squares or a heteroskedastic-consistent estimator (Antle 2010). One advantage of the moments-based model (2) is that it contains a different parameter vector, β_j, for each moment equation. According to Antle (2010), specification of the mean function is important to the properties of the higher-order-moments estimated residuals. However, one disadvantage of equation (3) is that it limits the effects that conditioning variables have on asymmetry related to the negative and positive deviations from the mean (Antle et al. 2013). To address the asymmetric limitations of the full-moments model, Antle (2010, 2013) employed equation (3) to derive the partial-moments model which is described as:

$$|\epsilon_{it}|^{j} = X_{it}\beta_{jn} + u_{jitn}, E(\mu_{jitn}|X_{it}) = 0, for\ j = 2, 3, \ldots, i = 1, \ldots, N, t = 1, \ldots, T\ for\ \epsilon_{it}$$
$$< 0 \tag{4}$$

$$|\epsilon_{it}|^{j} = X_{it}\beta_{jp} + u_{jitp}\,, E(u_{jitp}|X_{it}) = 0, for\ j = 2, 3, \ldots, i = 1, \ldots, N, t = 1, \ldots, T\ \ for\ \epsilon_{it}$$
$$> 0. \tag{5}$$

The empirical model for the full-moments model is described as:

$$\epsilon_{it}^{j} = \beta_{j0} + \beta_{j1}SDA_{it} + \beta_{j2}SFA_{it} + \beta_{j3}TEM_{it} + \beta_{j4}PPRE_{it} + \beta_{j5}PRE_{it} + \beta_{j6}XHT_{it} +$$

$$\beta_{j7}TIM_{it} + u_{jit}, \ j = 2, 3, ..., \tag{6}$$

where ϵ_{it}^{j} is the jth moment function for average crop yield (canola, spring wheat) in crop district i and period t, SDA_{it} equals the seeded area (canola, spring wheat), SFA_{it} is the share of summer fallow area or management measure to conserve soil moisture for the following year's crop, TEM_{it} equals temperature or growing degree days during the growing season (May-September), $PPRE_{it}$ equals precipitation during the pre-growing season (October-April) which captures moisture previously stored in the soil from snowfall, PRE_{it} equals precipitation during the growing season (May-September), XHT_{it} equals the number of excessive heat days during the growing season with temperatures greater than 30ºC, and TIM_{it} is a time trend variable that captures technological (e.g., new varieties adopted) and agronomic management improvements.

DATA DESCRIPTION AND SOURCES

The agriculture sector in Saskatchewan is sensitive to the effects of climate change with the southern region of the province more susceptible to fluctuations in summer precipitation (Grisé 2013). Agriculture production in Saskatchewan has changed over the years with diversified cropping systems and larger planted areas devoted to pulses (peas, lentils) and canola. This has been facilitated in part by the adoption of zero or minimum tillage technological practices. By 2008, about 65% of the seeded area in Saskatchewan was devoted to zero tillage (Nagy and Gray 2012). While the adoption of zero tillage practices offers several environmental and agronomic benefits (e.g., soil conservation), it has contributed partly to the reduction in soil moisture conserving practices, like summer fallow, which declined from 5.9 million ha in 1987 to 1.1 million ha in 2014 (Statistics Canada 2015). In the 1980s, summer fallow as a conservation

practice typically occurred in the drier areas of the province to increase soil water reserves and was used primarily by wheat producers (Williams et al. 1988).

This study is based on a comprehensive field crop data set collected by Statistics Canada (2013) on the total annual crop area seeded/harvested, summer fallow area, yield, and production of all the major crops grown in Canada by province at the crop district level (Figure 1). The time period coverage selected for this study was based on the availability of comparable spring wheat and canola yield, planted area, and summer fallow area data for the 20 crop districts over the 1987-2010 period. Saskatchewan's crop districts are located in three distinct agro-climatic zones (sub-humid, semi-arid, and arid) which correspond to the Black/Gray, Dark Brown, and Brown soils (Mkhabela et al. 2011). Because of lower annual precipitation in the Brown soil zones located primarily in the southwestern part of the province, crop yields tend to be lower than yields in the Black/Gray or Dark Brown soil zones (Table 1). Generally, crop districts in the southern areas of the province experience the warmest winter and summer months, while the northern part of the province receives the highest annual precipitation (Grisé 2013). By 2100, increases in maximum temperature in the semiarid zone of the prairies are projected to increase from 2.5ºC to 4.5ºC, coupled with increases in inter-annual variation in annual precipitation (Price et al. 2011). Saskatchewan's agriculture production vulnerability is attributed to extreme environmental variations from such unpredictable climatic conditions.

Figure 2 shows how canola and spring wheat yield and seeded area have varied over the last twenty-nine years. Crop yields have increased over time which may be attributed to a combination of improved genetics, better agronomic management practices, and favourable climatic conditions. Despite the significant positive spring wheat yield trends, seeded area decline has been much more precipitous than canola. The spring wheat seeded area decrease over

the last three decades has been attributed, in part, to the introduction of new crops like pulses and canola into crop rotations coupled with higher relative commodity prices (Grisé 2013).

The climate of Saskatchewan can be characterized as consisting of long cold winters, warm summers, and insufficient precipitation during the growing season (Williams et al. 1988). Summary weather statistics for the 20 crop districts are shown in Table 2. Weather data from Environment Canada meteorological weather stations included actual daily observations and modeled data (gridded data). The nearest grid points from 10km gridded data were used to fill any missing observations. The weather data for crop districts provided by Agriculture and Agri-Food Canada was for the following weather data categories: daily temperature, minimum temperature, maximum temperature, and daily precipitation (Chipanshi 2013).

Apart from pre-growing season precipitation, cumulative growing season precipitation, and cumulative growing season growing degree days (GDD), intraseasonal weather variables for growing season precipitation and GDD were constructed since studies (e.g., Robertson 1974; Kutcher et al. 2010) have shown that canola and spring wheat phenological crop growth stages respond differently to seasonal weather conditions. Since the development and growth stages of spring wheat follow a monthly pattern, Robertson (1974) considered the monthly averages of weather in measuring the response of Saskatchewan spring wheat to seasonal weather climatic patterns using field-plot experimental conditions. Moisture from growing season precipitation and the amount of rainfall in the months preceding the growing season are the principal climatic factors influencing wheat production in the prairies (Ash et al. 1992; Van Kooten 1992). In our study, GDD is calculated as the sum of positive values of the average [(maximum + minimum)/2] daily air temperatures minus the minimum temperature (5°C) required for growth

(Campbell et al. 1997). Crops like canola and wheat with lower threshold growth temperatures (5ºC) tend to have lower spatial variability throughout the eastern prairies (Ash et al. 1993).

GDD measures the combined effects of temperature and growing season length and provides a useful approach for estimating wheat phenological development (Saiyed et al. 2009). Since GDD does not adequately account for the effects of extreme temperatures, we constructed another weather variable (number of days in the growing season with temperatures > 30ºC) to capture extreme heat days. It is suggested that summer daytime temperatures exceeding 30ºC can adversely affect flowering and reproductive growth of crops in the Canadian prairies (Bueckert and Clarke 2012).

ESTIMATION STRATEGY

As part of our estimation strategy, prior to estimating the full- and partial-moments model we undertook several diagnostic tests. First, we tested for stationarity of the variables in the mean equation employing the Im-Pesaran-Shin (IPS) (2003) unit root test. The IPS test allows for unbalanced panel data where the null hypothesis is that the panels contain a unit root. Table 3 shows the results of the IPS unit root test for canola and spring wheat which indicates that all the variables are stationary or integrated of order zero ((I(0)). This implies that the null hypothesis of a unit root is rejected. Second, we tested for autocorrelation by employing the Woodridge test where the null hypothesis is that there is no first order autocorrelation in the panel data. The F-stat (p-value) in Table 4 indicates the null hypothesis is rejected and therefore the moments-based model is applied to the autocorrelation-transformed data.

Another test undertaken was to determine if the panel data has fixed or random regional effects. The Sargan-Hansen statistics test (Table 5) rejects the null hypothesis that the coefficients from the random effects are consistent with the coefficients from the fixed effects

model. The test result indicates the existence of fixed effects which were used in the estimation of the mean function. We tested for heteroscedasticity prior to estimating the mean function. The modified Wald test results (Table 6) rejected the null hypothesis of groupwise homoscedasticity in the fixed effects regression. Consequently, the heteroskedasticity-consistent standard errors are estimated in the mean equation.

The Pesaran's test employed rejected the null hypothesis of cross-sectional independence (Table 7) which indicates the standard errors in the mean equation are adjusted in estimating for cross-sectional dependence. Furthermore, in the model specification of the mean function, nonlinear quadratic weather terms and interaction weather terms were tried but contributed to multicollinearity (Table 8), and were subsequently deleted. The estimates reported in Tables 9-12 are the parameter elasticities

RESULTS AND DISCUSSION

As discussed in the theoretical framework section, the full-moments model captures how factors have different effects on the major moments of crop yield distribution (i.e., mean, variance, and skewness), while the partial-moments model extends the full-moments approach by allowing the asymmetric effects of factors on the two tails of yield distribution (positive and negative deviations from the mean). It is notable that this study utilized the natural logarithm function (discussed in the theory section above), thus full- and partial-moments discussed in the following section are actually the natural logarithm moments of crop yield. Results of both the full-moments model and partial-moments model are displayed in Tables 9-12, with two model specifications (cumulative vs. intra-seasonal weather effects).

(i) Full-Moments Model

Full-moment function (mean, variance, skewness) results for canola and spring wheat are shown in Tables 9 (model 1) and 10 (model 2) for two alternative weather variable definitions. In model 1, weather pertains to the cumulative growing season, while weather in model 2 pertains to intraseasonal weather events. The full-moment results have a good fit and include significant climate variables, except the third order full-moment functions for canola and spring wheat (Table 9). The odd order full-moment functions often have a bad fit (Antle et al. 2013). As shown in Table 9, higher growing degree days or heat units during the growing season increases the average yield of both canola and spring wheat, with a larger effect on canola yields. Specifically, a 10% increase in GDD enhances the mean yield of canola and spring wheat by 4.3% and 3.4%, respectively. Increasing GDD reduces canola yield variability but with little significant effect on the variance of spring wheat yield. Our results are in agreement with an earlier study, which reported that higher mean temperature increases winter wheat yield in the Pacific Northwest with an elasticity effect of 0.45 at the sample mean (Antle et al. 2013). Our results indicate the temperature stress variable (the number of days with growing season temperatures greater than 30ºC) reduces both canola and spring wheat average yield and increases spring wheat yield variability. A 20% increase in the number of days with extremely high temperature (about three additional days) decreases average yields by 0.6% for canola (8 kg/ha) and spring wheat (11.7 kg/ha).

Pre-growing season precipitation increases both canola and spring wheat average yields (with elasticity effects of 0.10 and 0.12, respectively) and lowers their yield variance. These results are consistent with the findings of an earlier study (William et al. 1988) that found conserved soil moisture in the winter season was correlated with wheat yield in the Canadian prairies. Precipitation during the pre-growing season has a significant positive effect on the

skewness of spring wheat yield but this is not the case for canola yield. Therefore, increases in pre-growing season precipitation reduce downside risk vulnerability for spring wheat yield and helps avoid crop failure.

Effects of the crop seeded or planted area differs for canola and spring wheat yield. An increase in canola seeded area lowers yield since more marginal land is cultivated as canola seeded area expanded over the years. The positive effect of spring wheat seeded area on average yield is consistent with results from previous Canadian studies for Ontario soybeans (Cabas et al 2010). The share of summer fallow in total cropped area is significant and negatively affects the mean and variance of canola yield but positively influences yield skewness. The combination of adopting soil conservation technologies, diversified rotational cropping systems, and new cultivars appears to have displaced summer fallow as a moisture conserving measure since the mid-1960s (Smith and Young 2000). Mearns (1988), employing a similar technology variable (ratio of fallowed area to total sown area), found it impacts year to year variability of wheat yields in the U.S. Great Plains.

The time trend variable as a measure of technical improvements from improved crop genetics, fertilization, and management practices statistically increases the mean yields of both crops and lowers yield variance of canola with little significant effect on spring wheat yield variance. The increases in canola yield may be consistent with the rapid number of herbicide-tolerant canola varieties adopted in the prairies since the mid-1990s (Canola Council of Canada, 2015).

Table 10 shows the full-moment functions with a more detailed specification of weather variables to coincide with major stages of the crop growth cycle during the growing season. Overall, September GDD increases the average yield and reduces the yield variance for both

canola and spring wheat; conversely, higher July GDD decreases the mean yield and increases the yield fluctuation for both crops; June GDD has a mixed effect on the mean of canola (positive) and spring wheat yield (negative); the positive effect of May and August GDD on the average yield is only significant for canola and spring wheat, respectively. In elasticity terms, a 10% increase of September GDD enhances the mean yield of canola and spring wheat by 2.8% and 3.3%, respectively. The negative effects of July GDD on crop yields are relatively large, with elasticity effects of 0.92 and 0.54 for canola and spring wheat, respectively. Our study results correspond to the observations from a previous study which showed that high temperatures in the month of July adversely affect the flowering period and consequently impact canola seed quality (Kutcher et al. 2010). For wheat, the month of July is associated with the flowering period stage of growth or kernel development (Robertson 1974). Increases in June GDD bolster the mean yield of canola by 2.1%, while decreasing the average yield of spring wheat by 3.0%. Meanwhile, GDD in June has a positive effect on the yield variability with a negative effect on the skewness of spring wheat output. May GDD significantly increases the average yield of canola (elasticity of 0.23) with a modest positive effect on the skewness (elasticity of 0.03) of wheat output. In contrast, the effects of August GDD are significant only on the mean yield (elasticity of 0.33) and variability of spring wheat, but not for canola.

Extreme weather conditions, where the cumulative number of days in the growing season exceeded 30ºC, affect negatively and significantly both canola and spring wheat yields. This result is consistent with a previous Mexican study where they found a similarly defined heat stress variable negatively affected mean wheat yields (Nalley et al. 2010). Warmer temperatures affect the growth pattern of wheat during the growing season because as temperature increases

there is a consequential reduction of soil moisture available for plant crop growth (Van Kooten 1992)

Precipitation in the early part of the growing season affects the mean, variance, and skewness differently for both canola and spring wheat. In general, positive effects of precipitation during pre-growing (October-April) and growing seasons (May-September) on the average crop yields have been confirmed. A 10% increase in pre-growing season precipitation increases the average yield of canola and spring wheat by 0.7% and 0.9%, respectively. May precipitation increases the average yield (elasticity of 0.09) and skewness for both crops, while decreasing their yield variance. June precipitation increases the average yield of both canola and spring wheat but has little significant effect on the variance or skewness. Wheat experiences rapid development growth in June, which is the month with the highest precipitation, and is generally in the stem elongation and head emergence stage of growth by the end of June (Robertson 1974).

The positive effect of July precipitation on canola in mitigating yield loss is in agreement with the results of an earlier Saskatchewan study (Kutcher et al. 2010). Van Kooten (1992) found similar results to our study where the months of May and June precipitation positively affected spring wheat yield in southwestern Saskatchewan. September precipitation only has a significant positive effect on the variance and skewness of canola yield.

(ii) Partial-Moments Model

The second and third partial-moment functions for model 1 and model 2 are shown in Tables 11 and 12. The partial-moment functions are defined in absolute terms (parameter signs are opposite to full-moments for the odd order negative moments) and are based on deviations above (positive) and below (negative) the mean (Antle 2010). Likelihood ratio test statistics show

symmetry restrictions are rejected for both second and third partial-moment functions. This result shows that, unlike the full-moment functions, the partial-moment functions provide a better specification for estimating higher-order moments. The partial-moment function results (Table 11) differ with respect to climate and non-climate effects on canola and spring wheat yield distributions. In general, the impacts of climate changes such as cumulative growing season GDD and extreme temperatures on the yield distribution of canola are only significant in the positive partial moments. The temperature stress (> 30ºC) variable increases the positive variability and skewness of canola and the negative variability of spring wheat yield, while cumulative GDD during the growing season reduces the positive variance and skewness of canola yield. For spring wheat yield, pre-growing season precipitation and temperature stress variable also have asymmetric effects on two tails of the yield distribution, but unlike canola, the impacts are only significant on the deviation below the mean yield (negative moments). Pre-growing season precipitation reduces the negative second and third order partial-moment functions for spring wheat. Increasing the number of extremely high temperature days increases the yield variability of spring wheat, especially significantly at the deviation below the mean level. Combining the results from both full-moments and partial-moments function estimation indicates that increased GDD during the crop growing season reduces the overall fluctuation of canola yield (full-moments) while such a significant impact originates from decreasing the variance of the deviation above the mean level of the yield distribution. In addition, the correlation between the extreme high temperature and the overall variance of canola yield is not significant but such a relationship is confirmed on the upper tail of the distribution.

The partial-moment function results with intraseasonal weather variables to coincide with the crop growth stages are shown in Table 12. Overall, the partial-moment functions present

similar results as the full-moment functions, but the effects of climate on the negative tail of both crop yield distributions is more significant and with a larger magnitude than the positive tail. Temperature variance effects on yield distributions are more significant in the earlier part of the canola growing season when compared to spring wheat. GDD in May reduces the variability of both the positive and negative tail of yield distribution for canola, and the effect on the negative tail is slightly larger. Conversely, GDD in June and July increases the second positive and negative moments of spring wheat yield distributions. GDD in September reduces the variance of spring wheat yield distribution on both tails, and this is similarly the case for canola yield, but only significant on the negative tail. May precipitation reduces the negative variance for both crop (canola, spring wheat) yield distributions, and also reduces the positive variance of spring wheat yield. Precipitation in the pre-growing season decreases the variability of spring wheat yield on the negative tail. Unlike spring wheat, temperature stress parameters are significant weather factors affecting the variance of canola yield distributions. Regarding the effects of weather parameters on the skewness of yield distribution, May GDD has a negative effect on the positive skewness of canola yield as well as on the negative skewness of spring wheat yield. Unlike canola, GDD in June and July increases both the positive and negative skewness of spring wheat, while GDD in September decreases the skewness of spring wheat in both positive and negative tails. Similarly, May precipitation decreases the negative skewness of both canola and spring wheat yield, while pre-growing season precipitation reduces the negative skewness of spring wheat yield.

CONCLUSIONS

Global warming is expected to affect the productivity of Saskatchewan agriculture and influence how agricultural producers adapt to the adverse effects. This study employed a flexible

moments-based approach over the 1987-2010 period to analyze how canola and spring wheat yield distributions respond to changes in precipitation and temperature.

Results obtained from the full-moment functions with alternative specification of the weather variables show different effects of non-climate and climate variables with the latter dissimilarities particularly distinct. For specifications with alternative weather variables, the non-climate variables for both canola and spring wheat have roughly similar results in terms of the statistical significance, directional effect, and size of coefficients. Full-moment functions show that the model where climate variables are disaggregated provides detailed insights about GDD and precipitation effects on the yield distribution that are not captured in the model with weather variables cumulated over the growing season.

The incorporation of the monthly GDD and monthly precipitation during the growing season in the full-moment function discerns the effects throughout the crop growth cycle. For canola, GDD has both positive and negative effects, respectively, on the mean in May, June, and September and on the variance in May and September. However, the effect of July GDD lowers the mean and increases the variance which offsets the positive outcomes in the other months of the growing season. Similarly, the effect on variance is positive and by far larger than the decreasing effect in May and September. Changing weather patterns and more frequent occurrences of hot weather in July likely have a strong negative effect on average canola yields, while increasing its variance.

The disaggregation of GDD on average spring wheat yield and risk provided even more discerning weather insights than for canola output. The aggregated effect of GDD suggested an increase in the average wheat yield and a decrease in variance as the number of GDD increases during the growing season. By contrast, the model specification with five monthly GDD figures

shows no discernable effect of GDD in May, but hot weather in June and July hurts the average spring wheat yield and increases its variance. Only after the initial plant growth has been completed, does warm weather contribute to an increase of average yield, while lowering its variance as indicated by the GDD effect in August and September.

The partial-moment functions provide further insights into the non-climate and climate change variables. Specifically, the effects are made with respect to the average canola and spring wheat yields with the emphasis on the upside and downside influence. Overall, the model with aggregate climate variables explains canola yield better than spring wheat yield.

Among the climate change variables, the number of growing degree days has the only sizable significant effect and reduces the positive variance and skewness of canola yield. The effect of hot weather has a similar directional effect, but of very small magnitude. For spring wheat, pre-growing season precipitation reduces the positive yield variance, while hot weather increases the positive yield variance by a small amount, which is twice the size of a similar effect on canola yields.

Clearly the partial-moment functions of the canola and wheat models that include disaggregated climate change variables provide far more insights than the version with aggregated climate change measures. GDD reduces the positive and negative variance of canola yield by similar amounts when such days occur in May. In subsequent months of the growing season, only the GDD in September reduces the negative variance and skewness of canola yield. Growing season precipitation reduces the negative variance of canola yield if it rains in May, but has the opposite (although minimal) effect in September. The number of exceedingly hot days and the time trend has similar effects on canola as in the model with aggregated climate variables.

The weather effects on spring wheat are far more acute. The monthly GDD in June and July increases both variances, but the negative variance is effected far more than the positive variance, especially in July, showing asymmetrical effects and consequences for wheat yields. However, GDD in September reduces both variances, especially the negative variance and skewness. In terms of precipitation, May precipitation decreases both variances and the reduction of negative variance is particularly large given the critical role of moisture in this stage of crop growth. In addition, pre-growing season precipitation also reduces the negative variance.

In summary, results of the current study are focused on canola and spring wheat produced in Saskatchewan, Canada. Despite the regional nature of data used in the study, results contribute to the global literature on the effects of climate change. First, the study results support the use of highly disaggregated temperature and precipitation data. Second, the application of the full-moment and partial-moment functions to discern the effects on average yields and their variance suggests the use of the partial-moment function in future studies. The specific outcomes of this study also suggest considerably stronger effects of changing temperatures than precipitation, supporting findings of Lobell and Burke (2008). The effects of higher temperatures measured by the monthly GDD broaden insights of earlier studies of other regions suggesting a decrease in wheat yields (Lobell and Field 2007; Lobell et al. 2011), while also confirming results of earlier studies focused on Saskatchewan, but using a different methodological approach (Kutcher et al. 2010). The current study finds that pre-growing season precipitation and precipitation in the early stages of plant growth are particularly relevant, supporting previous studies showing general effect of precipitation on wheat yield variability reduction in other regions (Chen et al. 2004) and specific field experimental studies on spring wheat in the Canadian prairies (He et al. 2013).

REFERENCES

Agriculture and Agri-Food Canada. 2014. Impact of Climate Change on Canadian Agriculture. http://www.agr.gc.ca/eng/science-and-innovation/agricultural-practices/climate/future-outlook/impact-of-climate-change-on-canadian-agriculture/?id=1329321987305 (accessed August 26, 2015)

An, H., and R. Carew. 2015. Effect of climate change and use of improved varieties on barley and canola yield in Manitoba. Canadian Journal of Plant Science. 95 (1): 127-139

Antle, J. M. 1983. Testing the stochastic structure of production: A Flexible Moment-Based Approach. Journal of Business & Economic Statistics. 1(3): 192-201.

Antle, J. 2010. Asymmetry, partial moments and production risk. American Journal of Agricultural Economics. 92: 1294-1309.

Antle, J., J. E. Mu, and J. Abatzoglou. 2013. Climate and the spatial-temporal distribution of winter wheat yields: Evidence from U.S. Pacific Northwest. Selected paper prepared for presentation at the Agricultural & Applied Economics Association's 2013 AAEA & CAES Joint Annual Meeting, Washington, DC, August 4-6.

Ash, G.H.B., C. F. Shaykewich, and R. L. Raddatz. 1992. Moisture risk assessment for spring wheat on the Eastern Prairies: A water-use simulation model. Climatotological Bulletin. 26(2):65-78.

Ash, G.H.B., C. F. Shaykewich, and R. L. Raddatz. 1993. The biologically important thermal character of the eastern Prairie climate. Climatotological Bulletin. 27(1):3-20.

Asseng, S., I. Foster and N. C. Turner. 2011. The impact of temperature variability on wheat yields. Global Change Biology. 17: 997-1012.

Bueckert, R.A., and J.M. Clarke. 2013. Annual crop adaptation to abiotic stress on the Canadian prairies: Six case studies. Review Article. Canadian Journal of Plant Science. 93:375-385.

Cabas, J., A. Weersink, and E. Olale. 2010. Crop yield response to economic, site and climatic variables. Climatic Change. 101: 599-616.

Campbell, C.A., F. Selles, R.P. Zentner, B.G. McConkey, S.A. Brandt, and R.C. McKenzie. 1997. Regression model for predicting yield of hard red spring wheat grown on stubble in the semiarid prairie. Canadian Journal of Plant Science. 77:43-52

Canola Council of Canada. 2015. Estimated acreage of herbicide tolerant canola, 1995-2010. http://www.canolacouncil.org/markets-stats/statistics/estimated-acreage-and-percentage/ (accessed April 2, 2015)

Chen, C-C., B. A. McCarl, and D. E. Schimmelpfennig. 2004. Yield variability as influenced by climate: A Statistical investigation. Climatic Change. 66: 239-261.

Chen, S., X. Chen, and J. Xu. 2013. Impacts of climate change on corn and soybean yields in China. Selected Paper prepared for presentation at the Agricultural & Applied Economics Association's 2013 AAEA & CAES Joint Annual Meeting, Washington, DC, August 4-6.

Chipanshi, A. 2013. Weather Data Tabulation Request. Agriculture and Agri-Food Canada, National Agro-Climate Information Service, Regina, Saskatchewan.

Deschênes, O., **and M. Greenstone. 2007**. The economic impacts of climate change: Evidence from agricultural output and random fluctuations in weather. American Economic Review. 97(1): 354-385.

Di Falco, S. and J-P. Chavas. 2009. On crop biodiversity, risk exposure, and food security in the highlands of Ethiopia. American Journal of Agricultural Economics. 91(3): 599-611.

Government of Saskatchewan. 2015. Agricultural Statistics. Available online at http://www.agriculture.gov.sk.ca/Default.aspx?DN=7b598e42-c53c-485d-b0dd-e15a36e2785b (accessed March 23, 2015)

Grisé, J. 2013. Effect of Climate Change on Farmers' Choice of Crops: An Econometric Analysis. Unpublished Msc Thesis. Department of Bioresource Policy, Business and Economics, University of Saskatchewan, Saskatoon, Saskatchewan.

He, Y., Y. Wei, R. DePauw, B. Qian, R. Lemke, A. Singh, R. Cuthbert, B. McConkey, and H. Wang. 2013. Spring wheat yield in the semiarid Canadian prairies: Effects of precipitation timing and soil texture over recent 30 years. Field Crops Research. 149(1): 329-337.

Hopkins, J. W. 1935. Weather and wheat yields in western Canada. I. Influence of rainfall and temperature during the growing season on plot yields. Canadian Journal of Research. 12(3): 306-334.

Im, K. S., M. H. Pesaran, and Y. Shin. 2003. Testing for unit roots in heterogenous panels. Journal of Econometrics. 115: 53-74.

Isik, M., and S. Devadoss. 2006. An analysis of the impact of climate change on crop yields and yield variability. Applied Economics. 38 (7): 835-844.

IPCC (Intergovernmental Panel on Climate Change) Report. 2014. Climate Change 2014: Impacts, Adaptation, and Vulnerability. Cambridge University Press. Cambridge, United Kingdom.

Available online at http://www.ipcc.ch/report/ar5/wg2/

Jones, J. W., G. Hoogenboom, C. H. Porter, K. J. Boote, W. D. Batchelor, L. A. Hunt, P. W. Wilkens, U. Singh, A. J. Gijsman, and J. T. Ritchie. 2003. The DSSAT Cropping System Model. European Journal of Agronomy. 18:235-265

Just, R. E. and R. D. Pope. 1979. Production function estimation and related risk considerations. American Journal of Agricultural Economics. 61: 276-284.

Kutcher, H. R., J. S. Warland, and S. A. Brandt. 2010. Temperature and precipitation effects on canola yields in Saskatchewan, Canada. Agricultural and Forest Meteorology. 150: 161-165.

Lemmen, D. S. and F. J. Warren. 2004. Climate Change Impacts and Adaptation. A Canadian Perspective. Natural Resources Canada. Ottawa, Ontario.

Lobell, D. B., and C. B. Field. 2007. Global scale climate-crop yield relationships and the impacts of recent warming. Environment Research Letters. 2: 1-7.

Lobell, D. B., and J. I. Ortiz-Monasterio. 2007. Impacts of day versus night temperatures on spring wheat yields: A comparison of empirical and CERES model predictions in three locations. Agronomy Journal. 99: 469-477.

Lobell, D. B., and M. B. Burke. 2008. Why are agricultural impacts of climate change so uncertain? The importance of temperature relative to precipitation. Environmental Research Letters. 3: 1-8.

Lobell, D. B. and M. B. Burke. 2010. On the use of statistical models to predict crop yield responses to climate change. Agricultural and Forest Meteorology. 150: 1443-1452.

Lobell, D. B., W. Schlenker, and J. Costa-Roberts. 2011. Climate trends and global crop production since 1980. Science. 333: 616-620.

Mearns, L. O. 1988. Technological Change, Climate Variability, and Winter Wheat Yields in the Great Plains of the United States. Unpublished Ph.D. Dissertation. University of California, Los Angeles, USA.

McCaig, T. N. 1997. Temperature and precipitation effects on durum wheat grown in southern Saskatchewan for fifty years. Canadian Journal of Plant Science. 77 (2): 215-223.

McCarl, B. A., X. Villavicencio, and X. Wu. 2008. Climate change and future analysis: Is stationarity dying? American Journal of Agricultural Economics. 90(5): 1241-1247.

Mendelsohn, R., and M. Reinsborough. 2007. A Ricardian analysis of US and Canadian farmland. Climatic Change. 81(1): 9-17.

Mkhabela, M. S., P. Bullock, S. Raj, S. Wang, and Y. Yang. 2011. Crop yield forecasting on the Canadian Prairies using MODIS NDVI data. Agricultural and Forest Meteorology. 151(3): 385-393.

Nagy, C. and R. Gray. 2012. Rate of Return to the Research and Development Expenditure on Zero Tillage Technology Development in Western Canada (1960-2010). Department of Bioresource Policy, Business and Economics. University of Saskatchewan, Saskatoon, Saskatchewan.

Nalley, L. L., A. P. Barkley and A. M. Featherstone. 2010. The genetic and economic impact of the CIMMYT wheat breeding program on local producers in the Yaqui Valley, Sonora Mexico. Agricultural Economics. 41: 453-462.

Ortiz-Bobea, A., and R.E. Just. 2013. Modeling the structure of adaptation in climate change impact assessment. American Journal of Agricultural Economics. 95(2): 244-251

Özdoğan, M. 2011. Modeling the impacts of climate change on wheat yields in Northwestern Turkey. Agriculture, Ecosystems and Environment. 141: 1-12.

Potgieter, A., H. Meinke, A. Doherty, V. O. Sadras, G. Hammer, S. Crimp, and D. Rodriguez. 2013. Spatial impact of projected changes in rainfall and temperature on wheat yields in Australia. Climatic Change. 117: 163-179.

Price, D. T., D. W. McKenney, L. A. Joyce, R. M. Siltanen, P. Papadopol, and K. Lawrence. 2011. High-Resolution Interpolation of Climate Scenarios for Canada Derived from General Circulation Model Simulations. Information Report NOR-X-421. National Resources Canada (Northern Forestry Centre) and US Forestry Service. Edmonton, Alberta.

Robertson. G. W. 1974. Wheat yields for 50 years at Swift Current, Saskatchewan in relation to weather. Canadian Journal of Plant Science. 54(4): 625-650.

Qian, B., R. De Jong, R. Warren, A. Chipanshi, and H. Hill. 2009a. Statistical spring wheat yield forecasting for the Canadian prairie provinces. Agricultural and Forest Meteorology. 149: 1022-1031.

Qian, B., R. De Jong, and S. Gameda. 2009b. Multivariate analysis of water-related agroclimatic factors limiting spring wheat yields on the Canadian prairies. European Journal of Agronomy. 30(2): 140-150.

Saiyed, M., P. R. Bullock, H. D. Sapirstein, G. J. Finlay, and C. K. Jarvis. 2009. Thermal time models for estimating wheat phenological development and weather-based relationships to wheat quality. Canadian Journal of Plant Science. 89(3): 429-439.

Sauchyn, D., and S. Kulshreshtha. 2008. Prairies. in From Impacts to Adaptation: Canada in a Changing Climate 2007, edited by D. S. Lemmen, F. J. Warren, J. Lacroix and E. Bush, pp.275-328. Government of Canada, Ottawa, Ontario.

Schlenker, W., and M. J. Roberts. 2006. Nonlinear effects of weather on corn yields. Applied Economic Perspectives and Policy. 28(3): 391-398.

Schlenker, W., and M. J. Roberts. 2009. Nonlinear temperature effects indicate severe damages to U.S. crop yields under climate change. Proceedings of the National Academy of Sciences of the United States of America. 106(37): 15594-15598.

Schlenker, W., W. M. Hanemann, and A. C. Fisher. 2006. The impact of global warming on U.S. agriculture: An Econometric analysis of optimal growing conditions. The Review of Economics and Statistics. 88:1: 113-125.

Smith, E. G., and D. L. Young. 2000. Requiem for Summer Fallow. Choices. First Quarter. pp 24-25.

Statistics Canada. 2013. Estimated areas, yield and production of principal field crops by small area data regions (Census of Agricultural Regions) CANSIM table 001-0071. Available online at

http://www5.statcan.gc.ca/cansim/a26?lang=eng&retrLang=eng&id=0010071&paSer=&pattern=&stByVal=1&p1=1&p2=-1&tabMode=dataTable&csid=(Accessed 20 January 2015)

Statistics Canada. 2015. Estimated areas, yield, production and average farm price of principal field crops. CANSIM table 001-0010. Available online at http://www5.statcan.gc.ca/cansim/a47 (4 March 2015)

Tack, J., A. Harri, and K. Coble, 2012. More than mean effects: Modeling the effect of climate on the higher order moments of crop yields. American Journal of Agricultural Economics. 94(5): 1037-1054.

Tack, J., A. Barkley, and L.L. Nalley. 2014. Heterogeneous effects of warming and drought on selected wheat variety yields. Climatic Change. 125:489-500.

Urban, D., M. J. Roberts, W. Schlenker, and D. B. Lobell. 2012. Projected temperature changes indicate significant increase in interannual variability of U. S. maize yields. A letter. Climatic Change. 112: 525-533.

Van Kooten, G. C. 1992. Economic Effects of Global Warming on Agriculture with some Impact Analyses for Southwestern Saskatchewan. In E. E. Wheaton, V. Wittrock and G. D. V. Williams (eds). Saskatchewan in a Warmer World: Preparing for the Future. Saskatoon: Saskatchewan Research Council. Publication No. E-2900-17-E-92. Pages 159-184.

Wang, J., R. Mendelsohn, A. Dinar, J. Huang, S. Rozelle, and L. Zhang. 2009. The impact of climate change on China's agriculture. Agricultural Economics. 40: 323-337.

Wang, J., E. Wang, and D. L. Liu. 2011. Modelling the impacts of climate change on wheat yield and field water balance over the Murray-Darling Basin in Australia. Theoretical and Applied Climatology 104: 285-300.

Weber, M., and G. Hauer. 2003. A regional analysis of climate change impacts on Canadian agriculture. Canadian Public Policy. 29(2): 163-179.

Williams, G. D. V., R. A. Fautley, K. H. Jones, R. B. Steward, and E. E.Wheaton. 1988. Estimating effects of Climatic change on Agriculture in Saskatchewan. In M. L. Parry, T. R. Carter, and N. T. Konijn (eds). The Impact of Climatic Variations on Agriculture, Vol. 1: Assessments in Cool Temperate and Cold Regions. Pages 219-379. Kluwer Academic Publishers, Dordrecht. The Netherlands.

Crop Districts and Rural Municipalities in Saskatchewan
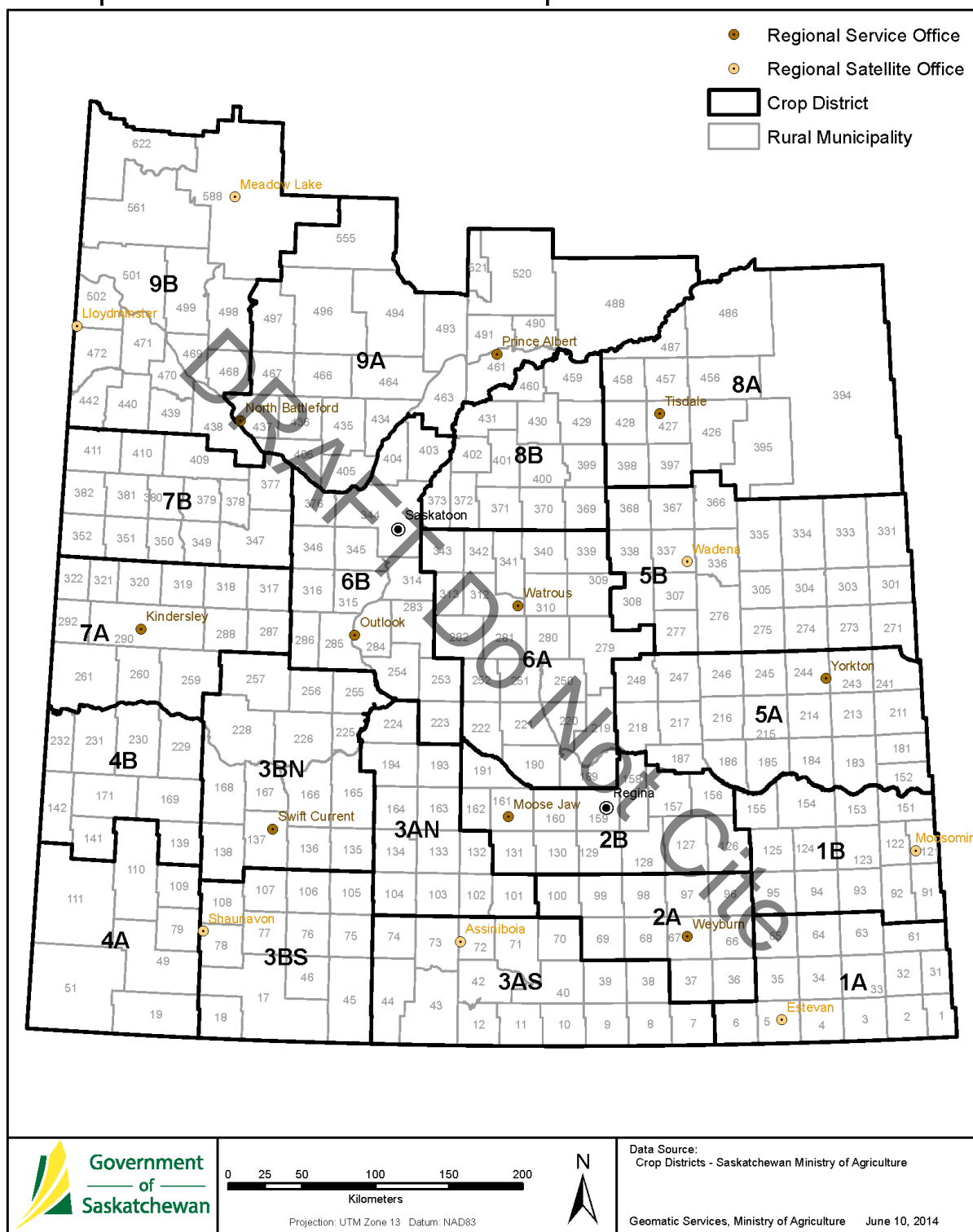
Figure1. Crop districts in Saskatchewan
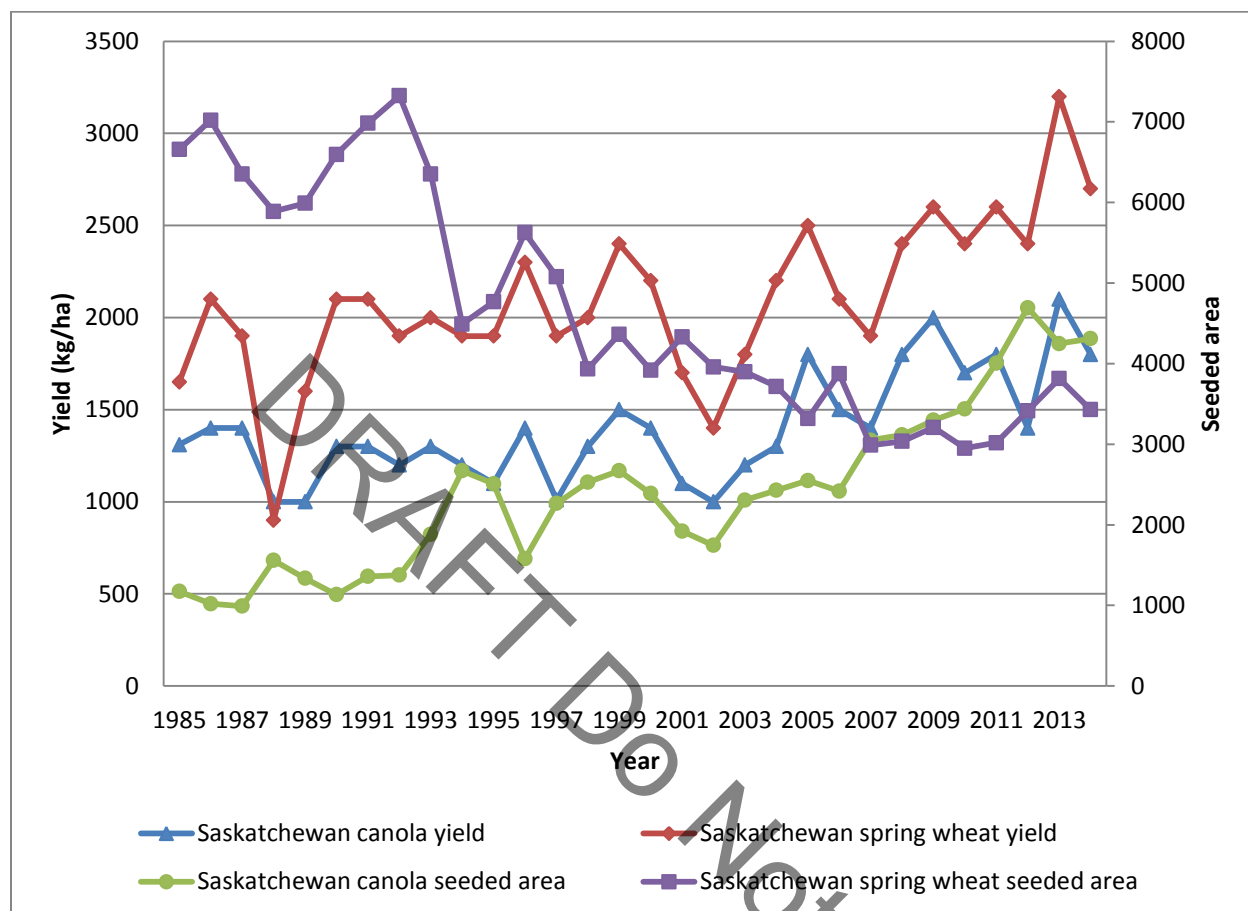
Figure 2. Saskatchewan canola and spring wheat yield and seeded area, 1985-2014

Source: Statistics Canada (2015)

Table 1. Average canola and spring wheat yield (kg/ha) by crop districts (CDs)

CDs	Soil zone	Canola			Spring wheat		
		Mean	Std. Dev.	Freq.	Mean	Std. Dev.	Freq.
1A	Dark Brown	1269.57	329.51	23	1820.83	343.86	24
1B	Black/Gray	1350.00	347.66	24	2062.50	352.40	24
2A	Brown	1237.50	431.19	24	1654.17	378.76	24
2B	Dark Brown	1362.50	373.95	24	2029.17	349.51	24
3A-N	Brown	1304.17	435.87	24	1716.67	382.97	24
3A-S	Brown	1191.30	411.11	23	1804.17	439.84	24
3B-N	Brown	1440.00	388.52	20	1852.17	403.25	24
3B-S	Brown	1220.83	464.36	24	1821.74	458.21	23
4A	Brown	1221.74	334.33	23	1733.33	348.50	23
4B	Brown	1422.73	419.67	22	1849.79	616.92	24
5A	Black/Gray	1354.17	309.25	24	2079.17	337.48	24
5B	Black/Gray	1350.00	310.68	24	2216.67	376.10	24
6A	Dark Brown	1300.00	331.01	24	1904.17	422.70	24
6B	Dark Brown	1400.00	358.74	24	1983.33	523.92	24
7A	Brown	1275.00	437.63	24	1895.65	556.35	23
7B	Dark Brown	1316.67	382.97	24	2012.50	474.86	24
8A	Black/Gray	1391.67	311.96	24	2382.04	593.70	23
8B	Black/Gray	1383.33	317.14	24	2195.83	563.74	24
9A	Black/Gray	1312.50	361.53	24	2143.48	496.19	23
9B	Black/Gray	1370.83	428.83	24	2127.27	625.78	22
Brown Statistic		0.748			1.0752		
P-value		0.768			0.373		

Note: Brown's test suggests that we cannot reject the equality of variances between areas.

Table 2. Descriptive statistics of climate and non-climate variables for canola and spring wheat

	Canola				Spring wheat			
Variable	Mean	Std	Min	Max	Mean	Std	Min	Max
Yield (kg/ha)	1,322.93	375.85	200.00	2,400.00	1962.96	448.31	400	3200
Non-climate variable								
Seeded area (ha)	111,452.7	99,472.4	100.00	412,100.0	236,090.2	116,613.8	48,100	710,200
Fallow share (%)	23.17	12.31	2.70	56.80	34.71	24.04	2.8	131.7
Climate variable								
GDD in growing season	1,507.81	173.68	1,019.70	2,043.60	1510.46	174.04	1019.7	2043.6
May GDD	184.31	47.70	48.10	331.70	184.97	47.99	48.1	331.7
June GDD	319.71	53.65	196.40	557.50	320.84	53.88	196.4	557.5
July GDD	409.23	50.50	295.10	578.40	409.53	50.28	295.1	578.4
August GDD	381.53	57.87	245.90	532.00	381.93	58.32	245.9	532.0
September GDD	213.12	49.85	107.50	369.50	213.28	49.68	107.5	369.5
Precipitation in growing season (mm)	272.58	87.92	88.60	609.20	272.41	87.69	88.6	609.2
Precipitation in pre-growing season (mm)	122.01	47.36	11.00	355.60	121.96	47.27	11.0	355.6
May Precipitation (mm)	45.99	30.11	1.50	163.80	46.02	30.07	1.5	163.8
June Precipitation (mm)	76.11	40.02	9.00	328.80	76.65	40.36	9.0	328.8
July Precipitation (mm)	63.97	36.70	3.80	216.20	63.81	37.22	3.8	217.4
August Precipitation (mm)	53.31	34.33	0.00	180.20	53.19	34.22	0	180.2
September Precipitation (mm)	33.47	25.78	0.00	196.60	33.02	25.22	0	196.6
Temperature stress, >30 ℃ (no of days)	12.77	9.29	0.00	50.00	12.87	9.25	0	50.0
Number of observations	471				473			

Table 3. Im-Pesaran-Shin (2003) panel unit-root test results for canola and spring wheat yields, climate and non-climate variables

Crop type	Canola		Spring wheat	
Variable	Z-t-tilde-bar statistic	P-value	Z-t-tilde-bar statistic	P-value
Yield	-9.3880	0.0000	-9.8572	0.0000
Seeded area	-2.7081	0.0034	-2.1483	0.0158
Fallow share (%)	-3.6803	0.0001	-3.0709	0.0011
GDD in growing season	-8.2204	0.0000	-8.2204	0.0000
May GDD	-10.6191	0.0000	-10.6191	0.0000
June GDD	-10.6633	0.0000	-10.6633	0.0000
July GDD	-9.8994	0.0000	-9.8994	0.0000
August GDD	-9.6772	0.0000	-9.6672	0.0000
September GDD	-10.2126	0.0000	-10.2126	0.0000
Precipitation in growing season	-10.8896	0.0000	-10.8896	0.0000
Precipitation in pre-growing season	-9.3443	0.0000	-9.3443	0.0000
May Precipitation	-10.9424	0.0000	-10.9424	0.0000
June Precipitation	-11.7218	0.0000	-11.7218	0.0000
July Precipitation	-11.5406	0.0000	-11.5406	0.0000
August Precipitation	-10.2986	0.0000	-10.2986	0.0000
September Precipitation	-10.0503	0.0000	-10.0503	0.0000
Temperature, >30 degrees (no of days)	-10.5947	0.0000	-10.5947	0.0000

Note: Im-Pesaran-Shin allows unbalanced panel data and the Z-t-tilde-bar Statistic is employed because of fixed time period. Cross sectional mean is removed. The null hypothesis is all panels contain unit roots.

Table 4. Test for autocorrelation in the panel data model

Model \ F-stat (P-value)	Canola	Spring wheat
Model 1	9.489 (0.0062)	10.956 (0.0037)
Model 2	11.006 (0.0036)	20.481 (0.0002)

Note: Woodridge test (df1=1, df2=19). The null hypothesis is no first-order autocorrelation exists in the panel data.

Table 5. Test of fixed effect vs random effect in the panel data model

	Canola			Spring wheat		
	Statistic	DF	P-value	Statistic	DF	P-value
Model 1	75.898	7	0.0000	240.644	7	0.0000
Model 2	396.122	15	0.0000	322.500	15	0.0000

Note: Sargan-Hansen statistic is reported. The null hypothesis is that coefficients from random effect are consistent to coefficients from the fixed effect.

Table 6. Modified Wald test of groupwise heteroskedasticity for crop yield

	Canola			Spring wheat		
	Chi.sq Statistic	DF	P-value	Chi.sq Statistic	DF	P-value
Model 1	123.56	20	0.0000	172.73	20	0.0000
Model 2	147.01	20	0.0000	63.48	20	0.0000

Note: the null hypothesis is groupwise homoskedasticity in fixed effects regression model.

Table 7. Pesaran's Test of cross section correlation for crop yield

	Canola		Spring wheat	
	Statistic	P-value	Statistic	P-value
Model 1	17.572	0.0000	20.780	0.0000
Model 2	10.862	0.0000	15.448	0.0000

Note: the null hypothesis is cross-sectional independence.

Table 8. Test for multicollinearity in the panel data model

Model \ Mean VIF	Canola	Spring wheat
Model 1	2.47	2.13
Model 2	2.14	1.96

Note: since all of the variable VIF and mean VIF are all smaller than 10, thus there is no multicollinearity.

Table 9. Full moment functions (1st, 2nd, 3rd) results: canola and spring wheat yield (Model 1)

Variable	Canola			Spring wheat		
	Mean	Variance	Skewness	Mean	Variance	Skewness
Constant	-17.7894***	5.4257**	-3.0847*	-29.5361***	1.8164	-.5007
	(6.3135)	(2.1333)	(1.7648)	(7.0390)	(3.0284)	(2.3858)
			Non-climate variable			
Seeded area (ha)	-.0546***	-.0196***	.0116	.2068***	.0124	-.0106
	(0.0183)	(0.0064)	(0.0072)	(0.0484)	(0.0150)	(0.0135)
Fallow share (%)	-.0053**	-.0022*	.0028*	-.0006	-.0001	.0005
	(0.0023)	(0.0012)	(0.0015)	(0.0009)	(0.0004)	(0.0003)
			Climate variable			
GDD Growing season	.4303**	-.0936**	.0016	.3404**	-.0452	.0374
	(0.1852)	(0.0422)	(0.0512)	(0.1662)	(0.0696)	(0.0420)
Precipitation Growing season	.0290	-.0284	.0549	-.0240	-.0050	.0238
	(0.0481)	(0.0461)	(0.0727)	(0.0428)	(0.0393)	(0.0467)
Precipitation Pre-growing season	.1013***	-.0376**	.0465	.1230***	-.0580***	.0441*
	(0.0306)	(0.0215)	(0.0291)	(0.0281)	(0.0185)	(0.0224)
Temperature stress, >30 degrees C	-.0285***	.0019	.0004	-.0264***	.0025*	-.0013
	(0.0030)	(0.0012)	(0.0014)	(0.0026)	(0.0014)	(0.0012)
Time trend	.0112***	-.0021*	.0012	.0160***	-.0007	-.0000
	(0.0031)	(0.0010)	(0.0008)	(0.0031)	(0.0013)	(0.0010)
District fixed effects	Yes	No	No	Yes	No	No
Observations	471	471	471	473	473	473
R-squared	0.4727			0.5017		
F-stat (P-value)		3.99(0.0076)	0.92(0.5099)		5.09(0.0022)	2.72(0.0390)

Note: Prais-Winsten regression, heteroskedastic panels corrected standard errors (PCSEs) in parentheses for mean equation.

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 10. Full moment functions (1st, 2nd, 3rd) results: canola and spring wheat yield (Model 2)

Variable	Canola			Spring wheat		
	Mean	Variance	Skewness	Mean	Variance	Skewness
Constant	-27.0846***	3.1813	.2858	-21.1265***	1.0876	-.1313
	(6.0328)	(1.8777)	(1.7806)	(6.5038)	(1.7260)	(1.2475)
Non-climate variable						
Seeded area (ha)	-.0481***	-.0152**	.0107	.1755***	-.0124	.0075
	(0.0178)	(0.0062)	(0.0064)	(0.0461)	(0.0103)	(0.0084)
Fallow share (%)	-.0062***	-.0002	.0008	.0001	.0003*	-.0001
	(0.0022)	(0.0007)	(0.0006)	(0.0009)	(0.0002)	(0.0001)
Climate variable						
May GDD	.2306***	-.0854***	.0265	-.0032	-.0372	.0309*
	(0.0576)	(0.0264)	(0.03266)	(0.0503)	(0.0237)	(0.0158)
June GDD	.2092**	.0716	-.0597	-.2966***	.0956**	-.0595*
	(0.1035)	(0.0528)	(0.0567)	(0.0869)	(0.0395)	(0.0320)
July GDD	-.9225***	.2183*	-.1988	-.5374***	.1346**	-.0994*
	(0.1460)	(0.1199)	(0.1232)	(0.1247)	(0.0571)	(0.0518)
August GDD	.0648	-.0160	.0032	.3351***	-.0461*	.0134
	(0.1041)	(0.0321)	(0.0352)	(0.0857)	(0.0252)	(0.0206)
September GDD	.2763***	-.0734**	.0691*	.3264***	-.0583***	.0398**
	(0.0588)	(0.0285)	(0.0337)	(0.0512)	(0.0197)	(0.0155)
May precipitation	.0888***	-.0311**	.0257*	.0875***	-.0275***	.0184**
	(0.0170)	(0.0114)	(0.0141)	(0.0148)	(0.0083)	(0.0066)
June precipitation	.0581**	-.0316	.0401	.0606***	-.0175	.0176
	(0.0232)	(0.0266)	(0.0378)	(0.0198)	(0.0146)	(0.0165)
July precipitation	.0534**	-.0078	.0080	-.0128	.0059	-.0041
	(0.0217)	(0.0107)	(0.0086)	(0.0175)	(0.0072)	(0.0058)
August precipitation	-.0156	.0063	-.0047	-.0154	.0038	-.0043
	(0.0162)	(0.0063)	(0.0069)	(0.0127)	(0.0036)	(0.0029)
September precipitation	.0008	.0080**	.0046*	-.0013	-.0000	.0009
	(0.0125)	(0.0030)	(0.0024)	(0.0105)	(0.0045)	(0.0040)
Precipitation Pre-growing season	.0695**	-.0182	.0195	.0897***	-.0242**	.0173*
	(0.0300)	(0.0160)	(0.0167)	(0.0270)	(0.0104)	(0.0090)
Temperature stress, >30 degrees	-.0191***	-.0002	.0020	-.0171***	.0005	-.0001
	(0.0030)	(0.0016)	(0.0019)	(0.0025)	(0.0011)	(0.0009)
Time trend	.0177***	-.0017*	.0001	.0135**	-.0006	.0002
	(0.0030)	(0.0009)	(0.0008)	(0.0030)	(0.0007)	(0.0005)
District fixed effects	Yes	No	No	Yes	No	No
Observations	471	471	471	473	473	473
R-squared	0.5868			0.5991		
F-stat (P-value)		8.00(0.0000)	1.94(0.0863)		11.88(0.0000)	5.47(0.0004)

Note: Prais-Winsten regression, heteroskedastic panels corrected standard errors (PCSEs) in parentheses for mean equation.

*** p<0.01, ** p<0.05, * p<0.1

Table 11. Partial Moment Functions (2nd and 3rd): canola and spring wheat (Model 1)

Variable	Canola				Spring wheat			
	Variance_P[a]	Variance_N[b]	Skewness_P	Skewness_N	Variance_P	Variance_N	Skewness_P	Skewness_N
Constant	3.2677**	6.0575	1.8405**	5.0280	1.5528	.0314	.3313	-9.9786
	(1.2420)	(4.7972)	(0.6605)	(5.6136)	(2.0942)	(4.3628)	(0.9187)	(4.1343)
Non-climate variable								
Seeded area (ha)	-.0102**	-.0251*	-.0054**	-.0232	.0014	.0190	.0006	.0174
	(0.0047)	(0.0127)	(0.0025)	(0.0142)	(0.0080)	(0.0264)	(0.0035)	(0.0281)
Fallow share (%)	-.0004	-.0036	-.0002	-.0052	.0003	-.0008	.0001	-.0012
	(0.0006)	(0.0023)	(0.0003)	(0.0030)	(0.0003)	(0.0008)	(0.0001)	(0.0009)
Climate variable								
GDD Growing season	-.1149***	-.0343	-.0579**	.0120	-.0235	-.0571	-.0030	-.0357
	(0.0356)	(0.0968)	(0.0217)	(0.1070)	(0.0542)	(0.0996)	(0.0219)	(0.0792)
Precipitation Growing season	-.0080	-.0344	-.0042	-.0900	.0043	.0079	.0019	-.0217
	(0.0170)	(0.0848)	(0.0092)	(0.1335)	(0.0101)	(0.0746)	(0.0036)	(0.0893)
Precipitation Pre-growing season	-.0047	-.0885	-.0006	-.1133	-.0164	-.1258***	-.0077	-.1332**
	(0.0071)	(0.0565)	(0.0039)	(0.0765)	(0.0109)	(0.0441)	(0.0051)	(0.0538)
Temperature stress, >30 degrees	.0022***	.0013	.0012**	-.0005	.0009	.0053***	.0002	.0035
	(0.0008)	(0.0023)	(0.0004)	(0.0032)	(0.0008)	(0.0027)	(0.0003)	(0.0026)
Time trend	-.0011*	-.0024	-.0007	-.0018	-.0007	.0004	-.0001	.0009
	(0.0006)	(0.0023)	(0.0003)	(0.0028)	(0.0009)	(0.0019)	(0.0004)	(0.0018)
Observations	265	206	265	206	261	212	261	212
F test (P-value)	3.96(0.0079)	2.11(0.0928)	3.47(0.0145)	1.53(0.2161)	5.12(0.0021)	5.29(0.0018)	3.66(0.0115)	2.01(0.1073)
LR test (P-value)	459.04 (0.0000)		882.76 (0.0000)		573.71 (0.0000)		1063.85 (0.0000)	

Note: Clustered robust standard errors in parentheses the mean equations report the Driscoll-Kraay standard errors adjusted for spatial dependence.
[a] Positive residual from the mean equation.
[b] Negative residual from the mean equation.
*** p<0.01, ** p<0.05, * p<0.1;

Table 12. Partial moment functions (2nd and 3rd) : canola and spring wheat (Model 2)

Variable	Canola				Spring wheat			
	Variance_P	Variance_N	Skewness_P	Skewness_N	Variance_P	Variance_N	Skewness_P	Skewness_N
Constant	3.3832**	2.3751	1.5533**	0.1980	-.5245	5.1095**	-.3415	3.0199
	(1.2038)	(3.1266)	(0.6096)	(3.4145)	(1.9224)	(2.3279)	(0.7393)	(1.8805)
Non-climate variable								
Seeded area (ha)								
	-.0040	-.0213**	-.0016	-.0167**	-.0000	-.0464*	-.0003	-.0367
	(0.0044)	(0.0080)	(0.0022)	(0.0798)	(0.0080)	(0.0235)	(0.0028)	(0.0218)
Fallow share (%)	.0005-	-.0005	.0002	-.0007	.0003	.0005	.0001	.0003
	(0.0005)	(0.0010)	(0.0002)	(0.0009)	(0.0002)	(0.0004)	(0.0001)	(0.0004)
Climate variable								
May GDD	-.0634***	-.0894*	-.0314***	-.0749	-.0053	-.0750	-.0003	-.0754*
	(0.0177)	(0.0484)	(0.0090)	(0.0441)	(0.0126)	(0.0533)	(0.0049)	(0.0417)
June GDD	-.0070	.1662	-.0038	.1528	.0422*	.1369*	.0158**	.1145*
	(0.0250)	(0.1056)	(0.0121)	(0.1013)	(0.0227)	(0.0783)	(0.0076)	(0.0595)
July GDD	.0552	.3688	.0216	.3982	.0471**	.2315*	.0140*	.2134*
	(0.0425)	(0.2183)	(0.0175)	(0.2351)	(0.0211)	(0.1137)	(0.0076)	(0.1052)
August GDD	-.0158	-.0871	-.0036	-.0624	-.0240	-.0532	-.0042	-.0033
	(0.0317)	(0.0805)	(0.0132)	(0.0772)	(0.0287)	(0.0803)	(0.0106)	(0.0635)
September GDD	-.0178	-.1110**	.0028	-.1206**	-.0257*	-.0862**	-.0074*	-.0758*
	(0.0164)	(0.0455)	(0.0073)	(0.0553)	(0.0133)	(0.0329)	(0.0042)	(0.0374)
May precipitation	-.0086	-.0477**	-.0022	-.0479*	-.0092*	-.0449***	-.0028	-.0363**
	(0.0068)	(0.0197)	(0.0031)	(0.0241)	(0.0045)	(0.0157)	(0.0016)	(0.0137)
June precipitation	-.0042	-.0546	-.0012	-.0754	-.0041	-.0260	-.0011	-.0328
	(0.0095)	(0.0458)	(0.0043)	(0.0629)	(0.0032)	(0.0283)	(0.0011)	(0.0288)
July precipitation	-.0043	-.0089	-.0045	-.0112	.0021	.0103	.0006	.0087
	(0.0055)	(0.0172)	(0.0027)	(0.0163)	(0.0037)	(0.0131)	(0.0013)	(0.0115)
August precipitation	.0005	.0051	.0004	.0055	-.0026	.0092	-.0008	.0083
	(0.0046)	(0.0117)	(0.0024)	(0.0115)	(0.0033)	(0.0074)	(0.0011)	(0.0058)
September precipitation	.0021	.0140*	-.0009	.0105	-.0004	-.0029	-.0002	-.0034
	(0.0053)	(0.0071)	(0.0033)	(0.0063)	(0.0023)	(0.0071)	(0.0008)	(0.0057)
Precipitation Pre-growing season	-.0023	-.0199	-.0003	-.0251	-.0052	-.0491*	-.0016	-.0419**
	(0.0088)	(0.0333)	(0.0041)	(0.0300)	(0.0072)	(0.0241)	(0.0025)	(0.0196)
Temperature stress, >30 degrees	.0016**	-.0017	.0008*	-.0032	.0001	-.0003	-.0001	-.0009
	(0.0074)	(0.0025)	(0.0004)	(0.0031)	(0.0006)	(0.0017)	(0.0002)	(0.0016)
Time trend	-.0016**	-.0016	-.0007**	-.0006	.0002	-.0025**	.0001	-.0016*
	(0.0006)	(0.0015)	(0.0003)	(0.0015)	(0.0008)	(0.0011)	(0.0003)	(0.0009)
Observations	247	224	247	224	256	217	256	217
F-stat (P-value)	23.68(.0000)	5.7(.0003)	10.10(.0000)	5.22(.0005)	3.98(0.0000)	7.89(0.0000)	3.10(0.0109)	3.19(0.0095)
LR test (P-value)	277.03 (0.0000)		608.12 (0.0000)		404.72 (0.0000)		833.27 (0.0000)	

Note: Clustered robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1.