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Crop yield response to economic, site and climatic variables

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Abstract This paper examines the effects of climatic and non-climatic factors on the mean and variance of corn, soybean and winter wheat yield in southwestern Ontario, Canada over a period of 26 years. Average crop yields increase at a decreasing rate with the quantity of inputs used, and decrease with the area planted to the crop. Climate variables have a major impact on mean yield with the length of the growing season being the primary determinant across all three crops. Increases in the variability of temperature and precipitation decrease mean yield and increase its variance. Yield variance is poorly explained by both seasonal and monthly climate variable models. Projections of future climate change suggest that average crop yield will increase with warmer temperatures and a longer growing season which is only partially offset by forecast increases in the variability of temperature and rainfall. The projections would also depend on future technological developments, which have generated significant increases in yield over time despite changing annual weather conditions.

1 Introduction

Climate change could have significant impacts on agriculture but the first step in assessing potential costs and adaptation strategies is to determine the effect of

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climate variability on crop yields. Such predictions can be based on crop biophysical simulation models, such as CERES or EPIC (see Rosenzweig et al. 2001). An alternative is to use regression models with actual crop yield or profit as the dependent variable and climatic measures as explanatory variables (Waggoner 1979; Granger 1980; Dixon et al. 1994; Segerson and Dixon 1999). Regression models have the potential flexibility to integrate both physiological determinants of yield, such as climate, but also socio-economic factors. For example, Kaufmann and Snell (1997) estimated a hybrid regression model integrating physical and social determinants of corn yield in a way that is consistent with crop physiology and economic behaviour. They found that climatic variables account for 19% of the variation in corn yield for counties in the US Midwest while social variables accounted for 74% of the variation. Including adaptive capacity in yield models explicitly has reduced the effect of climate change on crop yield from that suggested by crop model simulations (Mendelsohn and Dinar 1999), while properly accounting for climatic events reduces the projected yield increases suggested by simple yield trend analysis (Lobell and Asner 2003).

The discussion and analysis on climate change effects on crop yield has tended to focus on the effects of predicted increases in average values of climate variables on average crop yields (Adams et al. 1999). Rather than focus on the mean, others have suggested that the greatest challenge facing the agricultural industry will arise from an increase in the frequency and intensity of extreme events resulting from climate change (CCAF 2002). There are several important questions that the agricultural industry will therefore have to answer: What is the relative influence of climatic and non-climatic factors on crop yield? How sensitive is the inter-annual average crop yield to climate variability? How sensitive is inter-annual crop yield variability to climate variability?

The purpose of this paper is to estimate the effects of weather and climate variability on average yield and the variance of yield for corn, soybeans and winter wheat in the Canadian province of Ontario. In 2006, these three crops generated over $1.2 billion in market receipts in Ontario and annually represent at least half of all cropland planted in the province. The yield performance of these crops is fundamental to the success of farmers growing them and to the intensive livestock sector within the province relying on the output for feed. While several studies have examined the influence of weather on yield for these crops in the US Midwest region and generally found negative impacts from greater warming (Philips et al. 1996; Lobell and Asner 2003), no studies have been conducted on these crops within a more northern climate. Climatic change could alter favourably yield distribution for these vital crops but the direction and size of the effect is unknown. Indeed, Mendelsohn and Reinsborough (2007) estimated farmland values as a function of climate variables and found Canadian farms would benefit from higher precipitation but not warmer temperatures while US farms would be harmed from greater heat.

The next section of the paper presents the stochastic production function model used as the basis for the estimation of both the mean and variance of crop yield. The three major categories of explanatory variables (economic, site characteristics, and climatic measures) are then described. The fourth section presents the regression results and simulates the estimated functions under alternative climate change forecasts. The paper concludes with a discussion of the implications of those results.

2 Regression model of mean and variance of yield

In order to determine the effects of weather and socio-economic variables on both the average and variability of crop yield, a stochastic production function approach of the type suggested by Just and Pope (1978, 1979) is developed. The basic concept decomposes the production function into a deterministic one related to the output level and a second related to the variability of that output. The approach allows for estimation of the impacts of an input variable, such as climate, on expected output and its variance.

The general form of the Just and Pope production function is:

$$y = f(X, \beta) + \mu = f(X, \beta) + h(X, \alpha)^{0.5}\varepsilon \qquad (1)$$

where y is output or crop yield, X is a vector of explanatory variables, $f(.)$ is the mean function (or deterministic component of production) relating X to average yield with β as the associated vector of estimated parameters, μ is a heteroscedastic disturbance term with a mean of zero; $h(X, \alpha)$ is the variance function (or stochastic component of output) that relates X to the standard deviation of yield with α as the corresponding vector of estimated parameters, and ε is a random error with zero mean and variance σ^2. With this formulation, inputs such as climate can independently influence mean yield ($E(y) = f(X, \beta)$) and yield variance ($Var(y) = \mathrm{Var}(\mu) = h(X, \alpha)\sigma^2$).

The stochastic production function given by Eq. 1 can be estimated using maximum likelihood estimation (MLE) or a three-step estimation procedure involving feasible generalized least squares (FGLS) under heteroscedastic disturbances. Most empirical studies have used the FGLS approach but MLE is more efficient and unbiased than FLGS estimation in the case of small samples (Saha et al. 1997). Given the large sample in this study, the three stage estimation procedure as described in Judge et al. (1985) is used.

The first stage of the estimation procedure regresses y on $f(X,\ \beta)$ with the resulting least squares residuals, $\widehat{\mu}(\widehat{\mu} = y - f(X, \widehat{\beta}))$, as a consistent estimator of μ. The σ^2 is unobservable, but the second stage uses the least square residuals from the first stage to estimate the marginal effects of explanatory variables on the variance of production (α). In the second stage, $\widehat{\mu}^2$ is regressed on its asymptotic expectation $h(X,\ \alpha)$ with $h()$ assumed to be an exponential function, $\ln \sigma_i^2 = Z_i^{'}\alpha$. The third and final stage uses the predicted error terms from the second stage as weights for generating the FGLS estimates for the mean yield equation. The resulting estimator of β in this final step is consistent and asymptotically efficient under a broad range of conditions and the whole procedure corrects for the heteroscedastic disturbance term (Just and Pope 1978).

The data on crop yields (y) and its explanatory factors (X) are over time at the county level for 8 counties as will be discussed further in Section 3. The independent variables vary across counties and time but there may also be other unobservable, therefore omitted variables that are county specific or time specific that affect changes in crop yield and mask the true relationship between the dependent variable and independent variables. The panel nature of the data can be estimated using either a fixed effects model, which controls for omitted variables that differ between counties but are constant over time, or a random effects model, which considers that some omitted variables may be constant over time but vary between cases. A Breusch and Pagan test and a Hausman specification test was used to determine which approach should be used. On the basis of these tests, the null hypothesis of no correlation between county specific effects and independent variables was rejected, and so a fixed effects model with county dummy variables is used in the regression of the three crop yield equations.

3 Data

3.1 Dependent variable

The base dependent variable for the analysis is yield in tonnes per acre for corn, soybeans and winter wheat. Yield data were collected from 1981 to 2006 for the counties of Essex, Kent, Elgin, Huron, Perth, Haldimand-Norfolk, Middlesex and Lambton, which are sub-units within the province of Ontario. The basis for the selection of these counties is data availability and the importance of the field crops in this region of Ontario over the period of study.

While there are regional differences in yield for the three crops, county crop yield averages tend to follow provincial trends. Provincial average corn yield has increased dramatically from less than 2 tonnes/acre in 1960 to more than 3.8 tonnes/acre in 2006 with another record yield level achieved in the last growing season of 2008 of just under 4 tonnes/acre. Winter wheat yield also increased and doubled from approximately 1 tonne/acre in 1960 to approximately 2.2 tonnes/acre in 2006. Although there is a strong upward trend in both corn and wheat yield, there are still significant year-to-year variations, especially in the latter half of the study period. In contrast, average soybean yield in the province has only increased by 0.5% annually over the last four decades with more low yielding periods than the other two crops.

3.2 Explanatory variables

The yield response models have three major categories of explanatory variables: (1) economic variables, (1) site characteristics, and (2) climate measures.

Output to input price ratios have been included in several studies as an economic variable to explain yield including Rickard and Fox (1999), Segerson and Dixon (1999), and Dixon et al. (1994). The inclusion of such a variable suggests a supply function is estimated rather than a production function in which input levels would be included as explanatory variables. Actual input levels by crop are difficult to determine so input use is measured here using the approach of Kaufmann and Snell (1997). The change in input use (*Input Change*) can be determined by re-arranging the profit maximising input level condition which is where marginal value product ($P_{crop}{}^{*}(\Delta y/\Delta Q_{input})$ is equal to the input price (P_{input});

$$\begin{aligned} Input\,change &= \Delta Q_{input} = Q_{input,t} - Q_{input,t-1} \\ &= \left(P_{crop,t-1}\left(y_{crop,t} - y_{crop,t-1}\right)\right) / P_{input,t}\right) \end{aligned} \tag{2}$$

where $Q_{input,t}$ is the quantity of purchased inputs per acre in period t, $P_{crop,t-1}$ is the price per unit of crop lagged one year, $P_{input,t}$ is the price index for input purchased in the current period, and $y_{crop,t}$ is crop yield in the current period. Crop price is proxied by actual prices in the previous year at the provincial level and input prices are measured by the index of prices paid by Eastern Canadian farmers. The change in the use of inputs is expected to have a positive effect on average crop yield but the effect is assumed to increase at a decreasing rate reflecting the assumption of diminishing marginal returns. Thus, a quadratic term on the change in input use is assumed to have a negative effect.

Site characteristics are partially captured by the percentage change in acres planted to a crop from one period to the next (*Area Change*). It is assumed that an increase in area will result in a decrease in average yield and an increase in yield variation since as more land is brought into production of a given crop, the comparative advantage of that incremental land will decline and so will crop yield. It is assumed that the effect is non-linear and that increases in area decrease yield at a decreasing rate since the quality of the marginal land planted declines with more area. The lower-quality land will also be subject to greater yield variation. Other potential site variables such as soil quality and location were correlated with the county dummy variable (*County Dummies*) and so were not used. A time-trend variable (*Time Trend*) is also added to represent the effect of technological progress, such as new crop varieties and improved cropping practices, during the sample period.

The major climatic variables included in previous studies are average temperature and precipitation for alternative units of time ranging from a month to a year. For example, Granger (1980) used total seasonal precipitation (April to November), total precipitation in four months (May, June, July and August) and monthly mean daily maximum and minimum temperatures to explain yield of several California crops. Adams et al. (2003) also used monthly average maximum daily temperatures and monthly precipitation but in a quadratic functional form thereby permitting climate changes to have a non-monotonic effect on crop yield (i.e., a potential increase in yields under warming in cooler locations and a decrease in yields under warming in warmer locations as temperatures increases). Hansen (1991) estimated a corn yield function by using climate and weather variables for July because growing conditions in July are strategic due to corn pollination occurring during that month. Various interactions between variables were included to account for changes in the marginal impacts of weather with respect to climate. Rickard and Fox (1999) found mean monthly precipitation from April to September was positively related to yields of corn, barley, and winter wheat. Chen et al. (2004) also included monthly average temperature and rainfall, and found crop specific differences in the climatic impacts on yield level and variability. For example, in the case of corn and sorghum, precipitation and temperature were found to have opposite effects on yield levels and variability. Chang (2002) also included seasonal average monthly temperature and the seasonal mean of monthly average precipitation but also added the variation of these measures from their 20-year seasonal average to capture the effect of an extreme event on yield.

Dixon et al. (1994) and Kaufmann and Snell (1997) modified the traditional inclusion of temperature and precipitation in the crop yield response functions and developed corn yield models that included weather related factors by phenological stages of crop development instead of monthly values.[1] Since the development stage of a crop during a particular month varies by location and year due to the variability of weather events and planting dates, the use of monthly data provides only a rough approximation of the weather effects on yields (Dixon et al. 1994).

Several studies using cross-sectional data to explain crop yield or land value have also used climatic variables. Segerson and Dixon (1999) included 30-year average monthly temperatures and precipitation levels (January, April, July, and October) and not the levels of these variables that are observed for the actual crop season as would be done with most conventional yield response studies. Squared terms were included for the climatic variables. The precipitation variables were, in general, significant with January and April precipitation having a negative effect on corn and soybean yield and a positive effect on wheat yield. July precipitation was positively related to the yield of corn and winter wheat. Reinsborough (2003) and Weber and Hauer (2003) examined the relationship between climate and agricultural land value in Canada using data from the 1996 Census of Canada. Their empirical cross-sectional Ricardian models included monthly temperature and precipitation for January, April, July and October, squared values for those climatic variables in the case of Reinsborough's research and interactions in the Weber and Hauser study.

In this study, three models will be estimated to explain the average and variance of yield for corn, soybeans and winter wheat. In the first model, only the economic and site characteristics are used as independent variables and no climatic measures. Thus,

$$\begin{aligned} y = f\Big(&Input\,Change, (Input\,Change)^2, Area\,Change, (Area\,Change)^2, \\ &(Input\,Change)^* (Area\,Change), Time\,Trend, County\,Dummies\Big) \end{aligned} \tag{3}$$

In the second and third models, two specifications of climatic variables are used in addition to the same economic and site variables used in model 1 given by (3). Model 2 uses summary measures of climate over the whole season. One is the length of the growing season (*Grow Days*) measured in days, starting when the mean daily temperature is greater than or equal to 5°C for five consecutive days subsequent to March 1. *Grow Days* are hypothesized to increase mean yields at a decreasing rate. Mean temperature for the growing season (*Temp*) in Celsius degrees is expected to have a positive effect on yields, as is precipitation for the growing season (*Precip*) measured in mm. The variation in seasonal temperature is captured by the coefficient of variation for temperature (*Temp CV*) measured as the standard deviation of the monthly mean temperatures expressed as a percentage of the annual mean of those temperatures. Similarly, the CV for precipitation (*Precip CV*) is measured as the standard deviation of the monthly precipitation estimates expressed as a percentage of the annual mean of those estimates. These two variables have been included to capture the effects of extreme events on average crop yield. An increase in the CV represents an increase in the proportionate variability of these two weather variables

[1]The phenological stages of development considered by Kaufmann and Snell (1997) were sowing to germination, germination to seedling emergence, seedling emergence to the end of the juvenile stage, end of the juvenile stage to tassel initiation, tassel initiation to silking, silking to the beginning of the grain filling period, and effective grain filling period to physiological maturity.

and it is assumed to decrease the level of crop yields and increase yield variation. In all cases, quadratic terms have been included to account for the non-linear response of temperature and precipitation on the mean and variance of yield. An interaction variable between total growing season precipitation and mean growing season temperature is also included for all crops. Model 2 can thus be summarized as

$$y = f\Big(Model\ 1\ X, Grow\ Days, (Grow\ Days)^2, Temp, (Temp)^2, Precip, (Precip)^2,$$
$$Temp\ CV, (Temp\ CV)^2, Precip\ CV, (Precip\ CV)^2, Temp^{*}\ Precip\Big) \quad (4)$$

where *Model 1 X* are the economic and site characteristics listed in Eq. 3.

Table 1 Mean and standard deviation of dependent and explanatory variables

Variable	Mean	Standard deviation
Crop yield (tonnes/acre)		
Corn	2.982	0.507
Soybeans	1.001	0.175
Winter wheat	1.747	0.361
Explanatory variables		
Input change (index)		
Corn	0.077	0.601
Soybean	0.043	0.472
Winter wheat	0.003	0.526
Crop area change (percent)		
Corn	−1.02	11.66
Soybeans	8.75	23.04
Winter wheat	24.71	100.30
Seasonal climatic variables		
Grow days	214.31	13.03
Temperature (°C)	15.43	1.31
Temperature CV (percent)	35.89	4.84
Precipitation (mm)	602.34	133.62
Precipitation CV (percent)	43.93	13.29
Monthly climatic variable		
Temperature (°C)		
April	7.33	2.03
May	13.62	2.34
June	18.91	1.71
July	21.43	1.62
August	20.31	1.82
September	16.33	1.70
October	9.95	1.64
Precipitation (mm)		
April	82.49	28.09
May	87.19	37.49
June	79.20	39.57
July	91.10	48.30
August	79.45	32.67
September	99.93	58.85
October	85.78	41.21

Model 3 uses monthly weather variables (April to October) instead of the seasonal summary measures employed in Model 2 (Eq. 4). The climatic variables for these months include mean monthly minimum temperatures and total precipitation levels within the month. Squared values for temperature and precipitation variables are included to allow for non-monotonicity. A positive coefficient for the linear term and a negative coefficient for the quadratic term would suggest that an intermediate value has the greatest positive effect on yield.

Climatic variables were obtained from Environment Canada with county measures based on values from a representative weather station located centrally within the county. Trends in temperature and precipitation over the time period mirror the projected changes in the region from climatic change models defined at a smaller spatial scale by McKenney et al. (2006). The mean temperature for the growing season has varied between 14°C and 17°C but is increasing steadily while precipitation from April to October, which has varied between 400 and 800 mm, has been on a downward trend. Summary statistics for all of the variables used in the function regressions are given in Table 1.

4 Results

4.1 Mean yield

The regression coefficients for mean yield from stage three of the Just and Pope stochastic production function estimation procedure are listed for each crop in Table 2 for Model 1 (no climate variables), Table 3 for Model 2 (seasonal climate variables), and Table 4 for Model 3 (monthly climate variables). The regressions fit the data well given that the lowest adjusted R-squared value, which is available from the first stage of the estimation procedure, is 0.74 for Model 1 with corn, 0.60

Table 2 Mean yield—model 1 with no climatic variables (Eq. 3)

Explanatory variables	Corn		Soy		Wheat	
	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat
Intercept	−70.051	−33.50	−15.052	−14.36	−49.444	−29.29
Input change	0.426	26.81	0.174	18.37	0.265	15.93
(Input change)^2	−0.164	−10.30	−0.200	−15.42	−0.115	−4.99
Area change	−0.001	−1.74	0.001	4.66	−0.001	−8.52
(Area change)^2	−0.00008	−2.37	−0.00002	−7.91	0.0000009	2.83
Input chg × area chg	0.009	6.04	−0.002	−7.82	0.0007	3.45
Time trend	0.037	34.88	0.008	15.38	0.026	30.46
County dummies						
Perth	0.048	1.82	0.018	1.40	0.043	1.76
Haldimand	−0.376	−12.82	−0.165	−15.76	−0.530	−23.22
Middlesex	0.047	1.69	−0.031	−2.35	−0.059	−2.44
Lambton	0.031	0.97	−0.009	−0.76	−0.090	−4.69
Elgin	0.006	0.19	−0.031	−3.09	−0.195	−7.43
Kent	0.365	12.13	0.087	5.95	0.012	0.56
Essex	0.074	2.81	−0.019	−1.28	−0.149	−5.47

Table 3 Mean yield—model 2 with seasonal climatic variables (Eq. 4)

Explanatory variables	Corn		Soy		Wheat	
	Coefficient	*t*-stat	Coefficient	*t*-stat	Coefficient	*t*-stat
Intercept	−70.593	−31.62	−16.999	−11.36	−55.927	−28.54
Input change	0.441	32.16	0.199	19.93	0.259	17.94
(Input change)^2	−0.150	−11.48	−0.184	−13.10	−0.129	−8.89
Area change	−0.001	−1.29	0.001	5.03	−0.001	−4.38
(Area change)^2	−0.00005	−1.85	−0.00002	−9.93	2e-07	1.08
Input chg × area chg	0.006	5.49	−0.003	−9.33	0.001	4.05
Time trend	0.035	43.22	0.007	12.67	0.027	37.87
County dummies						
Perth	0.046	1.11	0.006	0.51	0.055	2.33
Haldimand	−0.374	−12.11	−0.170	−13.78	−0.547	−22.97
Middlesex	0.057	2.19	−0.031	−2.08	−0.062	−2.86
Lambton	−0.024	−0.68	−0.041	−2.90	−0.129	−5.85
Elgin	0.031	1.12	−0.053	−4.22	−0.219	−8.86
Kent	0.340	9.59	0.043	2.66	0.027	1.10
Essex	−0.034	−1.04	−0.084	−4.26	−0.149	−5.04
Climatic variables						
Grow days	0.061	5.37	0.027	3.97	0.054	4.81
(Grow days)^2	−0.0001	−4.99	−0.00006	−3.73	−0.0001	−4.61
Temp	−0.312	−3.35	0.020	0.34	−0.157	−3.04
(Temp)^2	0.009	3.37	0.001	0.35	0.003	1.66
Temp CV	−0.012	−7.85	−0.001	−0.64	−0.008	−5.82
Precip	−0.002	−2.96	0.0003	0.59	−0.001	−1.70
(Precip)^2	7e-07	2.32	2e-07	0.84	−4e-07	−2.18
Precip CV	−0.002	−3.07	−0.001	−2.86	−0.001	−3.08
Heat × precip	0.0001	2.67	−0.00002	−1.12	0.0001	3.98

for soybeans, and 0.81 for wheat. The majority of explanatory variables are both statistically significant and consistent with a priori expectations.

The non-climatic factors are all important in explaining average crop yield and have consistent signs across the three crops. The change in input use determined from the profit-maximizing input level condition (Eq. 2) has a statistically significant positive effect on average yield across all models and crops. The impact is particularly evident for corn, which uses more inputs than the other two crops. The positive correlation with input use and corn yield was also found by Kaufmann and Snell (1997) and suggests that changes in relative prices can influence productivity as well as area planted. Reidsma et al. (2007) also found crop yield increases with input intensity implying that management strategies can affect the adaptive capacity to climate change. The quadratic term on the change in input use is negative and statistically significant across all crops and models suggesting the existence of diminishing marginal returns to inputs on crop yield.

An increase in area planted to a crop is assumed to decrease average yield since more marginal land is brought into production with the negative impact increasing in absolute terms with the area planted. The respective linear and quadratic terms on the change in area were generally statistically significant across the models for corn and winter wheat. The expected negative effect was not found for soybeans which may relate to the development of soybean varieties suited for cooler climates.

Table 4 Mean yield—model 3 with monthly climatic variables

Explanatory variables	Corn		Soy		Wheat	
	Coefficient	*t*-stat	Coefficient	*t*-stat	Coefficient	*t*-stat
Intercept	−75.399	−22.03	−15.667	−10.81	−54.172	−29.23
Input change	0.425	26.45	0.204	21.28	0.270	18.35
(Input change)^2	−0.106	−7.21	−0.142	−13.33	−0.136	−7.69
Area change	0.001	1.26	0.00050	1.79	−0.001	−5.36
(Area change)^2	−0.00002	−0.54	−0.00002	−5.34	9e-07	4.25
Input chg*area chg	0.002	2.02	−0.002	−4.85	−0.0001	−0.94
Time trend	0.039	26.75	0.009	14.13	0.028	32.56
County dummies						
Perth	0.045	1.60	0.004	0.38	0.076	5.32
Haldimand	−0.325	−10.03	−0.222	−18.82	−0.544	−38.19
Middlesex	0.087	3.03	−0.065	−5.65	−0.049	−3.46
Lambton	0.065	01.86	−0.051	−4.11	−0.112	−6.60
Elgin	0.029	0.91	−0.104	−8.99	−0.182	−11.69
Kent	0.283	7.82	0.007	0.41	0.024	1.20
Essex	−0.083	−1.97	−0.088	−4.73	−0.147	−6.11
Climatic variables						
Temp						
April	0.346	5.43	0.0005	0.02	0.128	3.14
May	−0.021	−0.40	−0.057	−2.80	0.316	9.74
June	−0.293	−2.58	0.114	2.43	−0.076	−1.22
July	−0.228	−1.59	−0.118	−2.21	−0.288	−2.87
August	0.007	0.06	−0.108	−2.00	0.073	1.02
September	0.243	2.32	0.086	2.01	0.047	0.80
October	0.120	1.28	0.052	1.41	−0.039	−0.68
(Temp)^2						
April	−0.008	−4.09	−0.0002	−0.32	−0.002	−2.02
May	0.002	1.31	0.002	2.99	−0.011	−11.37
June	0.006	2.12	−0.002	−1.73	0.001	0.72
July	0.006	2.03	0.003	2.65	0.006	2.46
August	−0.002	−0.87	0.002	1.86	−0.003	−1.58
September	−0.008	−2.64	−0.003	−2.62	−0.001	−0.50
October	0.002	0.42	−0.001	−0.44	0.003	1.52
Precip						
April	0.013	5.83	0.001	1.37	−0.003	−2.62
May	−0.008	−4.25	−0.003	−4.19	−0.001	−0.68
June	−0.012	−3.95	0.000	0.40	0.003	1.55
July	0.004	1.18	−0.002	−1.51	−0.003	−1.77
August	0.004	1.11	0.002	1.25	−0.004	−1.71
September	−0.004	−2.27	−0.001	−0.88	0.004	3.61
October	0.002	0.87	0.007	7.28	−0.004	−2.38
(Precip)^2						
April	−0.00002	−1.91	−0.00001	2.88	6e-06	1.20
May	0.00003	5.87	5e-06	2.85	−5e-06	−1.56
June	0.00000	−0.10	−7e-07	−1.15	7e-07	0.37
July	−0.00001	−5.50	−3e-06	−2.88	−2e-06	−0.90
August	−0.00001	−2.23	−2e-06	−1.04	9e-06	3.05
September	0.00001	3.34	1e-06	1.61	−3e-06	−3.53
October	0.00001	2.62	−8e-06	−4.03	−2e-06	−0.71
Temp × precip						
April	−0.0015	−9.44	−0.0004	−5.74	0.0004	3.37

Table 4 (continued)

Explanatory variables	Corn		Soy		Wheat	
	Coefficient	*t*-stat	Coefficient	*t*-stat	Coefficient	*t*-stat
May	0.0001	0.62	0.0006	1.64	0.0001	2.00
June	0.0007	4.24	7e-06	0.11	−0.0002	−1.68
July	0.0000	0.26	0.0001	2.77	0.0002	2.11
August	−0.0001	−0.59	−0.0007	−1.03	0.0001	1.28
September	0.0002	2.20	1e-06	0.03	−0.0002	−2.76
October	−0.0004	−2.13	−0.001	−6.89	0.001	4.10
Temp CV	0.055	3.01	−0.015	−2.56	0.045	3.89
Precip CV	−0.005	−5.58	−0.0003	−0.94	−0.001	−1.49

Soybeans can now be planted in all counties considered whereas production had been primarily limited to the southern counties for the initial years of the data set. The interaction term between the change in planted area and the change in input use is also generally statistically significant and positive as expected for corn and wheat. The result suggests that increases in the area of less productive land planted to a crop can still result in increases in yield provided additional inputs are used.

Technological advances as captured by a time trend variable also increased average yield as expected. The coefficient indicates the increase in tonnes per acre expected annually and the values are consistent with the trends in yields discussed earlier. The county dummy variables are also consistent with expectations. Mean yields are lowest in Haldimand county, which is dominated by lower-yielding sandy soils. Yields for soybeans and wheat are higher in Huron county (the omitted region from the regression) than most other counties but corn yields are lower as compared to the most southern counties. The result is due to the larger difference in relative yield for shorter versus longer growing crop varieties present for corn than for the other two crops. Soil quality will have a larger influence on soybean and wheat yield than the crop variety in this relatively small region.

While the coefficients on the economic and site variables are generally statistically significant and of the same magnitude across all models, the impact on yield distribution is relatively small. Increases of 10% in input use would increase average yield of all three crops by approximately 0.1%. The small effect is consistent with the finding by Pannell (2006) that the response function for many agricultural inputs is flat around the optimum. Similarly, 10% increases in the area planted to a crop decrease yield by 1% on average across the three crops. The major non-climatic factor influencing the distribution of yield is technological advance. The annual increases suggested by the *Time Trend* coefficient translate into just over 1% annual increases in yield for corn and winter wheat and approximately 0.6% increases for soybeans.

The relatively small effect of the non-climatic variables aside from time suggests climatic variables should have a major effect on yield distribution. Length of the growing season has a statistically significant positive effect on average yield for all three crops but the marginal effect decreases with the number of growing degree days. These linear and quadratic terms on the length of the growing season are statistically significant factors of yield for all crops (see Table 3). The other season climatic variables are also statistically significant for corn and wheat but not for soybeans. The only other seasonal weather variable affecting soybean yield is the variability in precipitation, which has an inverse effect. Similarly, increases in the variability of temperature over the season decreases crop yield but the coefficient is only statistically significant for corn and wheat. The result is consistent with the negative effect found for average temperature over the season. For a given number of growing days, corn and wheat yields are higher for a lower and more evenly dispersed heat pattern. Similarly, total precipitation over the season decreases yield but an increasing rate for corn and wheat. The interaction term between temperature and precipitation is statistically significant for corn and wheat and positive, which is consistent with Philips et al. (1996). Damp and cool or hot and dry conditions inversely affect the yield of those two crops.

The seasonal climate impacts on mean yield are consistent with the results obtained for model 3 in which the climate variables are specified on a monthly basis (see Table 4). While the length of the growing season and its average temperature are major determinants of average yield, the timing of the heat pattern matters. In general, increases in temperature for the spring and fall months increase yield at a decreasing rate while the opposite is true for the summer months. Warmth in the spring allows the crop to be planted sufficiently early to allow for the possibility of full maturity, and warmth in the fall allows the crop to mature and be harvested with less field loss. Conversely, excess temperatures in the hot, summer months can put the crop under heat stress and lower yields. Weber and Hauer (2003) and Mendelsohn and Reinsborough (2007) both estimated Canadian farmland values increase with temperature and precipitation. Their studies, however, were for all of Canada and increases in precipitation are particularly valuable for the semi-arid Prairie regions that have the largest amount of Canadian farmland.

Similar to temperature, the timing of precipitation influences yield. Generally, increases in precipitation at the very beginning of the growing season and during the summer increase yield at a decreasing rate while the opposite effect is found for the months around planting and harvest. Note that for winter wheat, the planting dates are in the fall months and the harvest occurs in July and August so the monthly precipitation impacts are consistent with those for corn and soybean average yield. Segerson and Dixon (1999) found similar results.

4.2 Variance of yield

The regression coefficients for yield variance from stage two of the Just and Pope stochastic production function estimation procedure are listed for each crop in Table 5 for Model 1 (no climate variables), Table 6 for Model 2 (seasonal climate variables), and Table 7 for Model 3 (monthly climate variables). Unlike the regressions for mean yield, the variance models fit the data poorly (adjusted-R^2 values less than 0.1) and few of the explanatory variables are statistically significant.

Inputs were found to generally increase risk at an increasing rate for winter wheat but no conclusions could be drawn with regard to the other crops. The result is consistent with studies that found higher input levels increase the top end of the yield distribution without altering the bottom end and thus increase yield variance (Rajsic and Weersink 2008).

Few climatic variables have a statistically significant impact on yield variance. The distribution of corn yield increases at a decreasing rate with early precipitation but the effect is offset with higher temperatures given the negative sign on the

Table 5 Yield variance—model 1 with no climatic variables

Explanatory variables	Corn		Soy		Wheat	
	Coefficient	*t*-stat	Coefficient	*t*-stat	Coefficient	*t*-stat
Intercept	−104.143	−2.30	−32.279	−0.74	28.435	0.75
Input change	0.321	1.13	−0.441	−1.31	0.432	1.45
(Input change)^2	0.415	1.56	0.090	0.19	0.923	2.35
Area change	0.016	1.07	−0.033	−2.80	0.004	1.63
(Area change)^2	0.000	−0.09	0.000	1.70	0.000	−0.85
Input chg × area chg	−0.019	−0.82	0.044	2.41	0.000	0.02
Time trend	0.050	2.19	0.013	0.60	−0.017	−0.89
County dummies						
Perth	0.173	0.26	1.020	1.71	0.406	0.79
Haldimand	0.639	0.96	0.462	0.78	0.214	0.42
Middlesex	0.517	0.78	0.945	1.59	0.351	0.69
Lambton	0.920	1.39	0.288	0.48	−0.665	−1.30
Elgin	0.700	1.06	0.012	0.02	0.553	1.07
Kent	0.681	1.03	0.874	1.45	−0.175	−0.34
Essex	0.082	0.12	0.879	1.46	0.608	1.16

interaction term for April. While seasonal and monthly temperature do not affect corn yield variance, warmer temperatures in April and during the summer decrease yield variance of soybeans at an increasing rate. A similar effect was noted for winter

Table 6 Yield variance—model 2 with seasonal climatic variables

Explanatory variables	Corn		Soy		Wheat	
	Coefficient	*t*-stat	Coefficient	*t*-stat	Coefficient	*t*-stat
Intercept	−123.289	−1.72	25.093	0.43	−46.961	−0.83
Input change	0.010	0.03	−0.496	−1.44	0.602	1.71
(Input change)^2	0.567	1.89	0.147	0.30	0.969	2.10
Area change	0.014	0.83	−0.019	−1.52	0.008	2.54
(Area change)^2	0.000	−0.10	0.000	−0.02	0.000	−2.39
Input chg × area chg	−0.047	−1.90	0.054	2.94	−0.005	−1.35
Time trend	0.052	1.86	−0.023	−0.96	0.010	0.43
County dummies						
Perth	1.076	1.46	0.325	0.54	−0.417	−0.75
Haldimand	−0.333	−0.44	0.135	0.22	−0.471	−0.82
Middlesex	−1.594	−2.13	0.684	1.12	−0.749	−1.31
Lambton	−0.072	−0.09	−0.127	−0.20	−1.950	−3.18
Elgin	−0.807	−1.08	−0.116	−0.19	−0.355	−0.62
Kent	−0.677	−0.80	−0.167	−0.24	−1.158	−1.77
Essex	−2.396	−2.56	0.278	0.38	−0.555	−0.78
Climatic variables						
Grow days	0.310	0.76	0.125	0.37	−0.011	−0.03
(Grow days)^2	−0.001	−0.79	0.000	−0.40	0.000	0.09
Temp	−1.575	−0.72	−0.621	−0.35	1.154	0.69
(Temp)^2	0.039	0.69	0.029	0.63	−0.002	−0.04
Temp CV	−0.002	−0.04	0.090	2.36	−0.032	−0.88
Precip	−0.025	−0.97	0.000	0.00	0.050	2.49
(Precip)^2	0.000	0.39	0.000	−0.06	0.000	−2.23
Precip CV	0.010	0.64	0.002	0.12	−0.010	−0.81
Temp × precip	0.001	1.14	0.000	0.14	−0.002	−2.07

Table 7 Yield variance—model 3 with monthly climatic variables

Explanatory variables	Corn		Soy		Wheat	
	Coefficient	*t*-stat	Coefficient	*t*-stat	Coefficient	*t*-stat
Intercept	−89.684	−1.33	193.042	2.68	78.058	0.99
Input change	0.385	1.20	−0.062	−0.13	0.023	0.04
(Input change)^2	0.075	0.28	−0.819	−1.39	0.925	1.51
Area change	−0.004	−0.27	−0.018	−1.25	0.003	0.59
(Area change)^2	−0.001	−1.77	−0.00006	−0.03	0.000	−2.81
Input chg × area chg	0.031	1.35	0.016	0.83	−0.009	−1.80
Time trend	0.021	0.75	−0.074	−2.40	−0.052	−1.53
County dummies						
Perth	−0.733	−1.26	−0.508	−0.82	0.247	0.37
Haldimand	0.172	0.28	−0.621	−0.98	−0.564	−0.82
Middlesex	−0.351	−0.60	−0.569	−0.91	−0.139	−0.21
Lambton	0.367	0.56	−1.059	−1.54	−0.002	0.00
Elgin	−0.373	−0.62	−1.066	−1.63	−0.281	−0.40
Kent	0.141	0.19	−0.779	−0.99	−0.365	−0.42
Essex	0.189	0.22	0.120	0.14	0.617	0.66
Climatic variables						
Temp						
April	0.520	0.33	−3.577	−2.24	0.943	0.53
May	−1.396	−1.09	−1.391	−1.04	2.639	1.77
June	3.725	1.53	2.709	1.03	1.001	0.35
July	4.311	1.24	6.161	1.74	−0.397	−0.10
August	−2.072	−0.84	−5.900	−2.14	0.380	0.13
September	−2.486	−1.25	−0.629	−0.30	−1.215	−0.55
October	−0.444	−0.24	−2.249	−1.16	−1.966	−0.90
(Temp)^2						
April	−0.012	−0.26	0.091	1.91	0.002	0.04
May	0.050	1.32	0.012	0.31	−0.086	−1.92
June	−0.085	−1.37	−0.056	−0.83	−0.024	−0.32
July	−0.108	−1.38	−0.131	−1.66	0.012	0.14
August	0.059	1.01	0.165	2.48	−0.023	−0.35
September	0.087	1.51	0.026	0.43	0.042	0.67
October	0.024	0.33	0.005	0.06	0.102	1.17
Precip						
April	0.143	2.90	−0.031	−0.60	0.086	1.47
May	0.025	0.58	−0.034	−0.77	0.038	0.74
June	0.072	1.09	0.056	0.81	0.023	0.29
July	−0.005	−0.09	0.025	0.43	0.081	1.28
August	0.053	0.67	−0.072	−0.85	−0.139	−1.57
September	−0.004	−0.10	0.015	0.37	0.046	1.09
October	0.080	1.64	−0.039	−0.78	−0.036	−0.65
(Precip)^2						
April	−0.0005	−2.58	0.0001	0.55	−0.0001	−0.70
May	−0.0002	−1.66	−0.0002	−1.37	0.0001	0.84
June	−0.0001	−1.49	−0.0001	−2.20	0.00001	0.06
July	0.0000	0.42	−0.0001	−1.36	0.00001	0.19
August	0.0001	1.06	0.0001	0.45	0.0001	0.45
September	0.0000	0.05	−0.0001	−1.29	−0.0001	−1.25
October	−0.0001	−0.85	0.0001	1.58	0.0001	0.58
Temp × precip						
April	−0.008	−2.17	0.002	0.39	−0.008	−1.68

Table 7 (continued)

Explanatory variables	Corn		Soy		Wheat	
	Coefficient	*t*-stat	Coefficient	*t*-stat	Coefficient	*t*-stat
May	0.001	0.52	0.005	1.76	−0.004	−1.44
June	−0.003	−1.02	−0.001	−0.33	−0.001	−0.26
July	0.000	0.02	−0.001	−0.18	−0.004	−1.48
August	−0.004	−0.99	0.003	0.73	0.006	1.44
September	0.0004	0.20	0.0002	−0.11	−0.002	−1.06
October	−0.006	−1.63	0.001	0.28	0.004	0.89
Temp CV	−0.063	−0.15	−1.129	−2.55	0.138	0.27
Precip CV	0.003	0.17	0.012	0.61	0.003	0.16

wheat from May temperatures which is when much of the vegetative growth occurs for this crop. However, much of the yield variance across crops is unexplained by the explanatory variables considered.

4.3 Forecast yields under climate change

The estimated regression coefficients for the mean yield response functions using seasonal climatic variables (Eq. 4 and Table 3) were used to simulate future yields under alternative climate change scenarios. The regression results with the seasonal climatic variables (Model 2) was used to forecast rather than the results with the monthly weather variables (Model 3) given the small difference in forecast ability and to give general predictions stemming from potential climate scenarios. McKenney et al. (2006) have generated forecasts for a number of agroclimatic variables from climate change models at a small spatial scale for Canada and the USA.[2] The general consensus from these forecasts is that the growing season will be longer in southern Ontario with more variability in both temperature and precipitation. In comparison to the average values for this century (2000–2006), forecasts are generated under assumptions on no change, 10% and 25% increase in growing degree days and a 0% and 20% change in the coefficient of variation for temperature and precipitation.

The results of the forecasts are listed in Table 8. The greatest impacts from climate change for corn yield arise from changes in the length of the growing season. For example, a 10% increase in the number of growing degree days is projected to increase corn yield by 12.2% whereas 20% increases in the coefficient of variation in temperature and precipitation decrease average corn yield by 2.6% and 0.6% respectively. Thus, the positive impacts of climate change on corn in Ontario associated with a longer growing season significantly outweigh the detrimental effects of greater variation in heat and rainfall.

Similar forecasts of higher yields under the climate change scenarios were predicted for winter wheat. Weiss et al. (2003) also projected winter wheat yield increases with climate change projections for the sub-humid parts of the Great Plains

[2]Present-day and future climate scenarios for agroclimatic variables described by McKenney et al. (2006) can be obtained from the Natural Resources Canada web site http://cfs.nrcan.gc.ca/subsite/glfc-climate.

Table 8 Predicted percentage changes in crop yield to changes in climatic variables

Crop	% Change in grow days	% Change in temp CV	% Change in precip CV	% Change in both temp and precip CV	
		20	20	0	20
Corn	0	−2.56	−0.63	0.00	−3.19
	10	9.11	11.04	11.67	8.48
	25	26.62	28.55	29.18	25.99
Soybeans	0	−0.67	−0.98	0.00	−1.64
	10	2.67	2.36	3.34	1.69
	25	7.68	7.37	8.34	6.70
Wheat	0	−2.73	−0.50	0.00	−3.23
	10	9.00	11.23	11.73	8.50
	25	26.59	28.81	29.31	26.09

but not for the semi-arid regions. As with corn, the effect of a longer growing season offset the detrimental effect of greater variance in temperature and precipitation.

While the effects of a longer growing season are also positive for soybeans, the magnitude of the impact is approximately one-fourth of that estimated for corn and soybeans. The estimated results are similar to the simulated yield increases from greater warming found by Southworth et al. (2002) for soybeans grown in the upper midwest Great Lakes region that are comparable to southwestern Ontario. In contrast, Southworth et al. (2002) projected decreases in average soybean yield from increases in warming for southern US regions.

5 Summary

This paper examined the effects of climatic and non-climatic factors on the mean and variance of corn, soybean and winter wheat yield for southwestern Ontario, Canada. Average crop yields increase at a decreasing rate with input use suggesting that economic factors can affect yields in addition to growing conditions. The effect, albeit statistically significant, is small in relative terms which may be due to the existence of a flat production function (Pannell 2006). Increases in area planted to a crop result in lower average yields as more marginal land is brought into production. Expected crop yields thus not only influence crop area planted but the reverse is also true. The major non-climatic factor influencing yields is technological advance and the estimated effect is consistent with the approximately annual 1% increase in yields for corn and winter wheat and the 0.6% increase in average soybean yields.

Climate variables have a major effect on crop yield distribution. The major effect on average yield is the length of the growing season while variance of yield, although poorly explained by the models, is largely determined by the variance of temperature and precipitation. In general, increases in temperature for the spring and fall months increase yield at a decreasing rate while the opposite is true for the summer months. Precipitation at the very beginning of the growing season and during the summer increases yield at a decreasing rate but decreases mean yield for months around planting and harvest.

The climate in southwestern Ontario is projected to be warmer but with more variability in temperature and precipitation. The positive impact of a longer growing season offsets the negative effect of greater heat and rainfall variability resulting in higher average yields in the future. The results differ from several US studies that suggest higher temperatures will decrease yields for these major crops (Southworth et al. 2002; Lobell and Asner 2003; Weiss et al. 2003) and for other Canadian studies (Weber and Hauer 2003; Mendelsohn and Reinsborough 2007) in which the semi-arid Prairie regions that suffer from greater heat stress dominate the effects of climate change. The projections depend on future technological developments, which have generated significant increases in yield over time despite changing annual weather conditions.

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