Robustness of the Impact of Climate on U.S. Corn Yields

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Abstract

Increasing carbon dioxide and other greenhouse gases are predicted to lead to increased temperatures. In evaluating plans to mitigate climate change, world leaders and policy makers need estimates of the cost of climate change. One potential cost of climate change is the effect that an increase in temperature might have on agricultural yields. We begin with a model first suggested by Schlenker and Roberts (2009) and we are largely successful in replicating their results. We then modify the model to see how it holds up or falls apart as more realistic assumptions are added. These changes include (i) using a time-varying time trend as is common in crop insurance, (ii) using weather data only for critical growth periods, (iii), using climate instead of weather, and (iv) including dummy variables for the Corn Belt region. Using all the estimated models, we predict the effects of a uniform temperature increase by 2℃ .

Key words: corn yield, climate change, food security, Corn Belt, adaptation, mitigation

JEL Codes: Q54, Q18, Q10

Introduction

Most climate scientists predict increasing carbon dioxide and other greenhouse gases will lead to increased temperatures. In evaluating plans to mitigate climate change, world leaders and policy makers need estimates of the cost of climate change. One potential cost of climate change is the effect of increased temperature on agricultural yields. Corn is a major source of calories for much of the world, and the United States is the leading producer and exporter of corn. The impact of climate change on U.S. corn yields is a good measure of the impact on world corn production and a good proxy for the impact on world food security. The Obama administration, under Executive Order 12866, estimated the social cost of one ton of carbon dioxide (CO_2) emitted in 2015 at $54.2; this is a discounted cost with a discount rate of 2.5 percent. This social cost includes the economic impact on agriculture, coastal areas (due to sea level rise), human health, other market sectors (e.g. changes in energy use), non-market amenities (e.g. outdoor recreation), and human settlements and ecosystems.

Previous research made predictions about the impact of climate change on agricultural yields. World food security would be threatened by dramatic drops in yield predicted by current estimates such as Schlenker and Roberts (2009). They predict that by the end of the twenty-first century average corn, soybeans, and cotton yields will drop by 30-46% under the slowest warming scenario (B1) of the Hadley III climate model (Hadley Centre Coupled Model, version 3) and by 63-82% under the most rapid scenario (A1F1). As Hendricks and Peterson (2014) explain, higher temperatures reduce crop yields mainly through heat stress.

Schlenker and Roberts (2009) analyze the yields of corn, soybeans, and cotton, and find that for all three crops the yields increase with temperature up to an optimal level (29°C for corn, 30°C for soybeans, and 32°C for cotton) and that after this temperature the yields decrease sharply. Peng et al. (2004) find that for each 1°C increase in minimum temperature (which is generally at night), rice yields decrease by 10%; interestingly, they do not find a significant relationship between maximum temperature and yield. Other studies such as Deschenes and Greenstone (2007), Brown and Rosenberg (1999) and Mendelsohn, Nordhaus, and Shaw (1994) find less severe effects of climate change on agricultural yields. Deschenes and Greenstone (2007) argue that although an increase in temperature to the predicted level has a negative effect on crop yields, the predicted increase in precipitation has a positive effect on yields, and thus results in an overall small negative effect of climate change on the main crops in the U.S., such as corn and soybeans. Deschenes and Greenstone (2007) use the hedonic method, which is based on land values, to measure the economic impact of climate change on agriculture, and they find that climate change is slightly beneficial to farm profits and crop yields. Kaiser et al. (1993) report that with a mild increase in temperature of 2.5℃ in Southern Minnesota, corn yields are decreased by less than 5%. They also find that adapting to climate change is feasible. There is no consensus in the literature about the direction and magnitude of the impact of climate change on agriculture.

The predictions that are made here using weather assume no adaptation to climate change, i.e, management practices such as planting dates and fertilizer applications remain the same. Predictions have been made based on various climate change scenarios. Schlenker and Roberts (2009) use four scenarios of the Hadley III climate model. Other studies such as Kittel et al. (1995) and Brown and Rosenberg (1999) use scenarios from the general circulation models (GCMs). Thornton et al. (2009) use a combination of two climate models (CERES-Maise and BEANGRO) and two contrasting greenhouse-gas emission scenarios to study the types of response to climate in Eastern Africa. Kaiser et al. (1993) simulate yields using four scenarios for Southern Minnesota: (i) a basis scenario with no climate change, (ii) a scenario with 2.5°C increase in temperature and a 10% increase in precipitation, (iii) a scenario with 2.5°C temperature increase but with a 10% reduction in precipitation, and (iv) a severe warming scenario. We make predictions for a 2°C uniform temperature increase.

In reaching a rational decision about mitigation policies, it is important to provide accurate estimates of the effect of increased temperatures on crop yields. The objectives of this study are to: (i) determine the effect of weather and climate on crop yields, taking into consideration nonlinearities in these relationships; (ii) determine differences in results when different assumptions are made about these relationships; and (iii) predict how crop yields will respond to a uniform 2°C temperature increase.

The climate change literature is recent relative to the crop insurance literature; research on climate change could borrow models—or features of models—developed in the crop insurance literature. The crop insurance literature has documented time trend variables that influence crop yields. Another major difference with the current climate change literature and previous yield models is the inclusion of weather or climate variables spanning the entire growing season. Yield prediction models typically use weather or climate measurements at crops' specific growth stages. In the case of corn, yield is sensitive to weather conditions at the pollination stage. Weather in this growth stage is expected to be a better predictor of yield than conditions over the entire growing season.

Theory

The concern of this study is to determine how an increase in temperature under climate change will influence yields. Although corn is adaptable and grows in a variety of climates, extended periods of high temperature are harmful to corn growth, and extreme temperatures can directly damage plant cells (Lobell and Gourdji 2012; Hendricks and Peterson 2014). In particular, corn yield is sensitive to weather conditions at the stage of pollination (Nielson 2002). It is at this stage that pollen grains are transferred by wind or gravity from the tassel (male flower) to the silks of the corn ear (female flower).

Corn yields are harmed by temperatures above an upper threshold. This threshold is commonly regarded in the agronomy literature to be 30℃ (e.g., McMaster, Gregory and Wilhelm 1997), but Schlenker and Roberts (2009) suggested a threshold of 29℃.

Predicted corn yield loss under climate change can help policy makers assess the agricultural cost of climate change. This is an optimization problem where policy makers and farmers decide between the tradeoffs between a combination of the cost of climate change mitigation and the potential for adaptation. Mitigation consists of reducing human activities that contribute to climate change such as greenhouse gas emissions, while adapting to climate change involves changing planting locations, planting dates, and crop varieties, among other management practices. This optimization problem can be expressed mathematically as:

$$(1) \qquad \max_{\boldsymbol{A},\boldsymbol{X},D} E[\pi] = P(Y)Y(X,D) - C(\boldsymbol{A},\boldsymbol{X})$$

where π is the profit to be maximized, A is the acreage allocation to crops, $\boldsymbol{X}$ are the farming inputs, and D is the planting date, Y is the yield, P is the price and it depends of the yield, and

C is the cost that includes the cost of farming but may also include the cost of mitigation and/or adaptation.

Although researchers tend to focus on increasing temperature, other weather characteristics will change under climate change. As Peng et al. (2004) point out, the interactions between the effects of CO_2 concentrations and the effects of temperature are complex and need to be investigated. The benefits from carbon fertilization and increased precipitations under climate change partially compensate for the negative impact of higher temperature. Adapting to climate change will also play an important role in reducing the potential losses caused by higher temperatures. If the cost of mitigating or the extra cost of adapting to climate change, or both, is less than the potential loss from climate change, then policy makers should choose not to impose the cost of adaptation or mitigation on citizens. If, on the other hand, the potential cost of climate change to current and future generations is greater than the cost of mitigation and adaptation, then an appropriate combination of these solutions should be sought. Kaiser et al. (1993) suggest that adaptation is feasible by changing planting and harvesting dates, and by making other farm-level decisions.

Although corn is grown in a variety of climates within the U.S. and in warmer climates such as in Mexico, the Corn Belt region of the U.S. has had a comparative advantage in growing corn. Perhaps in the Corn Belt corn plants respond to temperatures differently than other regions. A different response may be due to soil characteristics or to other climatological properties not reflected in temperature and precipitation measurement.

Weather data and climate data (average of weather) can both be used to estimate the relationship to corn yields. Schlenker and Roberts (2009) implicitly used unexpected weather deviations rather than climate. However, it is perhaps more logical to use climate data because: (i) using climate partially considers potential adaptations, and (ii) the end goal is to predict average yields under climate, not a particular year.

Data

We analyze these relationships for corn in the United States. We use yearly corn yield data by county from the National Agricultural Statistics Service (NASS) of the United States Department of Agriculture (USDA) for the period 1950-2015. The yield is calculated as the total production in the county divided by the total number of harvested acres. The natural logarithm of the yield is also computed. Daily weather was obtained for the period of 1950-2015 from Schlenker (2016). The data contains estimates for daily precipitation, daily maximum temperature, and daily minimum temperature for 4km x 4km grid cells on the contiguous United States. Schlenker and Roberts (2009) made these estimates based on monthly estimates for the 4km x 4km grid cells provided by the PRISM Climate Group at Oregon State University. Schlenker and Roberts also make available a meta-file that links each grid cell to a county. Similar to their work, we select only those cells in a county with cropland in them. We assume that land used for farming has not changed much over the last few decades. There are some legitimate concerns about the smoothing that occurs in gridded data, but we use the gridded data since that is what Schlenker and Roberts (2009) used.

From the minimum and maximum temperatures, we estimate the distribution of temperature throughout the day like Schlenker and Roberts (2009), using a sinusoidal curve suggested by Baskerville and Emin (1969) and later used by Snyder (1985). This sinusoid has a period of one day and an amplitude equal to half of the difference between the maximum temperature and the minimum temperature. This sinusoidal curve allows estimating the amount of time in each day spent within each one-degree interval for each grid. These times are accumulated for each county and for each growing season.

Planting and harvesting dates for corn vary (NASS, USDA 1997), but most planting takes place in mid-April and most corn is harvested around the end of October. We use data that correspond to this corn growing season. The time spent within each one-degree interval is accumulated per year for each grid cell and averaged throughout the county. Similarly, season precipitation totals are averaged for the county.

In order to capture the possible effects of weather in different growth stages, we compute monthly accumulation of temperatures and precipitation. In particular, we compute them for the months of July and August, the time around which pollination takes place. Corn yield is sensitive to weather conditions at the stage of pollination (Nielson 2002).

Procedures

Our approach is to first replicate the Schlenker and Roberts (2009) model and then see how it holds up or falls apart as more realistic assumptions are added. Similar to Schlenker and Roberts we use counties east of the 100° meridian because western states have considerable irrigation. We begin by replicating their work by estimating their model using data from the same period they used, i.e., from 1950-2005. Then we add more recent data (2006-2015) and see how the model holds up. The model assumes temperature effects on yields are cumulative over the entire growing season (March-August for corn). In this model, the natural logarithm of yield for county i in year t is

$$(2) \qquad y_{it} = \int_{\underline{h}}^{\overline{h}} g(h)\varphi_{it}(h)dh + \beta_1 P_{it} + \beta_2 P_{it}^2 + \tau_{i1}t + \tau_{i2}t^2 + C_i + \varepsilon_{it}$$

where y_{it} is the natural logarithm of corn yield for county *i* in year *t*, $\overline{h}$ and $\underline{h}$ are the highest and lowest observed temperatures, $g(h)$ is a nonlinear plant growth function, $\psi_{it}(h)$ is the time distribution of heat over the growing season, P_{it} is the season total precipitation for county *i* in year *t*, C_i is the county fixed effect for county *i*, the terms $\tau_{i1}t$ and $\tau_{i2}t^2$ represent state-specific time trends, and ε_{it} ~ N(0, σ^2) is the random error term.

Schlenker and Roberts (2009) use three specifications for the function *g(h).* In this study we use one of the three specifications: a piece-wise linear function. The county fixed effects control for heterogeneous characteristics of counties, such as soil quality. The time trends capture yield improvements resulting from better production technology such as planting earlier and from improvements in genetics; perhaps these time trends also capture yield increases resulting from increases in CO_2, reductions in ozone, and could be net of reductions due to any global warming that has already taken place.

The integral in equation (2) is approximated numerically and equation (2) becomes

$$(3) \quad y_{it} = \sum_{-5}^{49} g(h+0.5)[\Phi_{it}(h+1) - \Phi_{it}(h)] + \beta_1 P_{it} + \beta_2 P_{it}^2 + \tau_{i1}t + \tau_{i2}t^2 + C_i + \varepsilon_{it}$$

where $\Phi_{it}(h)$ is the cumulative distribution function of heat in county *i* and year *t*.

The specification for *g(h)* is a piecewise linear function with a break point at 29°C, following Schlenker and Roberts (2009). The shape of *g(h)* is similar to that in figure 1. This function has two slopes. In light of the impact of higher temperatures, we are interested in the magnitude of the second slope, i.e., the slope associated with an accumulation of temperatures above 29℃.

We now add alternative assumptions. First we borrow from the crop insurance literature, which has been in existence longer than the climate change literature, the assumption of a time trend that varies. For example, a time trend with two parts would modify Equation (3) to become

$$(4)\quad y_{it} = \sum_{-5}^{49} g(h+0.5)[\Phi_{it}(h+1)-\Phi_{it}(h)] + \beta_1 P_{it} + \beta_2 P_{it}^2 + \tau_{i1}t_1 + \tau_{i2}t_2 + C_i + \varepsilon_{it}$$

where $t_1 = \min(t-1950, t^*-1950)$, $t_2 = \max(0, t-t^*)$, and t^* is the year when the time trend takes a new slope. We use a time trend with seven segment, one segment for each decade in the data period.

The growth of corn goes through many different stages, but the most crucial stage in determining the yield is pollination. Corn yields are very sensitive to weather conditions in this growth stage. It is therefore appropriate to modify equations (3) and (4) to only use the weather corresponding to pollination; in most regions, pollination happens in July.

It is important to note here that by including county fixed effects in the above models one is adjusting for climate and only obtains the effects of weather variations. An alternative approach is to use climate data instead of weather data. Equation (3) then becomes

$$(5)\qquad y_i = \sum_{-5}^{49} g(h+0.5)[\Phi_i(h+1)-\Phi_i(h)] + \beta_1 P_i + \beta_2 P_i^2 + \varepsilon_i$$

where values in equation (5) are averages of values in equation (3) over the 1950-2015 period.

County fixed effects are intercept dummies, and they do not indicate any differences in how different regions of the county may respond differently to temperature or precipitation changes. As one alternative, we include Corn Belt dummy variables for all the variables in the models.

We conduct Davidson and MacKinnon's (1981) J-test of nonnested hypotheses. This test for nonnested models is conducted as follows: (i) run the first model and obtain the predicted values $\hat{y}_0$: (ii) run the second model and obtain predicted values $\hat{y}_1$; (iii) modify the first model by adding $\hat{y}_1$as an explanatory variable, and if the coefficient on $\hat{y}_1$ is significant, we conclude in favor of the second model; (iv) modify the second model by adding $\hat{y}_0$ as an explanatory variable, and if the coefficient on $\hat{y}_0$ is significant, we conclude in favor of the first model.

We conduct misspecification tests for the conditional mean and for the conditional variance. These include a misspecification test for the functional form relating to the time trend (e.g. a linear time trend vs. a quadratic time trend vs. a piecewise linear time trend). We test for a structural change in the response of corn yields to temperature, testing whether yields in the Corn Belt region different slopes in this function. We test for static heteroskedasticity in the model that uses climate data, and for both static and dynamic heteroskedasticity in the model that uses weather data.

Equations (2)-(5) and other regressions are estimated using restricted maximum likelihood. The estimated parameters are used to predict what yields would be under different climate scenarios. One simplistic scenario is a uniform increase of 2℃ from the levels observed over the 1950-2005 period. These predicted yields are then compared to current yields. An average yield reduction is then calculated, weighted by acres harvested.

Results.

As temperature increases under climate change and hot days become more prevalent, it is believed that crop yields will fall. Partial regression results are summarized in table 1. Model 1 in this table and the subsequent tables is the replication of Schlenker and Roberts (2009), using 1950-2005 data. The replication is mostly successful. Similar to Schlenker and Roberts, we find that the effect of temperature on corn yield is positive until the temperature reaches 29℃. Temperatures above this level are harmful to corn yield, and the downward slope above the 29℃ temperature threshold is steeper than the upward slope below the threshold, as shown in figure 1. In our regression the squared precipitation variable was scaled.

The rest of the models in table 1 are grouped in blocs of four, according to the data used. This grouping is summarized in table 2. Models 2-5 use weather data from the entire growing season, models 6-9 use climate data from the entire growing season, models 10-13 use weather data from July and August, and models 14-17 use climate data from July and August. In each bloc of four models, the first is similar to Schlenker and Roberts (2009), the second is modified by adding varying time trends as opposed to quadratic time trends, the third is the Schlenker and Roberts model modified to include dummy variables for the Corn Belt region, and the forth has the varying time trends and the dummy variables.

After adding the more recent data up to 2015 (model 2), the results do not change much, as seen in table 1. The downward slope of the temperature function changes from -0.0073 to -0.0070. When we change from quadratic time trends to varying linear time trends, results do not differ. In the models that include dummy variables for the Corn Belt region, the coefficients of these dummy variables are significant, meaning that the coefficients of the different regressors are different in the Corn Belt area than in the rest of the country. For example in model 4, the downward temperature slope is -0.0067 for non-Corn Belt counties and -0.0067 plus -0.0017, or -0.0084, for Corn Belt counties. This signifies that the yield response to a preponderance of hotter days more severe in the Corn Belt.

The amount of precipitation throughout the growing season positively influences corn yield. This effect is modeled by a quadratic. In most models the coefficient of the linear term in precipitation is positive and the coefficient of the quadratic term in the precipitation is negative. The marginal effect of precipitation on corn yield diminishes as precipitation increases.

The results from models that use climate data are different than those obtained from modes that use weather data. Note that the models that use weather data include county fixed effects. Models that use climate data cannot include county fixed effects as this they that would remove the effect of climate; these models instead include county random effects. These models are not complete as they lack characteristics that are specific to counties, such as soil characteristics. Future versions of this study will include county-specific characteristics in the climate models.

Switching from using data form all season to using data form July and August only alters the regression results. This is due to the fact that the period from July to August is shorter than the period covering the entire growing season. In addition, July and August have more hot days relative to cold days.

We use estimates of models 2 through 17 to predict the impact on corn yields of a uniform increase by 2℃ from temperate levels observed over the 1950-2015 period. These predicted impacts are presented in table 3. Using the original Schlenker and Roberts, we find that under a 2℃ uniform temperature increase corn yields are predicted to decrease by 14.7 percent on average relative to predicted 2015 yields. This reduction is an average, weighted by acres planted in 2015. To be conservative in this prediction, we use the year 2015 for the time trend when predicting future corn yields. One could argue that the upward trend in yields continues beyond 2015. All the models that use weather data (all season or July-August) predict average yield losses between 14 and 16 percent. The models that use climate data predict average yield losses between 23 and 32 percent. In both cases, losses predicted using July-August data are slightly less severe than those predicted using data from the entire growing season.

Summary and Conclusions.

Changes in assumptions lead to different predictions about the impact of climate change on U.S. corn yields. The Schlenker and Roberts (2009) model holds up to the use of varying time trends, the addition of dummy variables for the Corn Belt region, and the use of July and August data only. But the model falls apart when climate data is used instead of weather data. For a 2℃ uniform temperature increase, the losses predicted by models that use climate data are roughly double those predicted by models that use weather data.

The yield loss predictions from all models in this study are larger than they would if we assumed that the time trend continues in the same direction it has been for the past few decades. By not assuming a continued trend, these models ignore the possibility of new inventions such as more heat-resistant corn varieties, or the ability for farmers to learn new farm management practices. In addition, precipitations will likely be higher when temperatures rise, and as our results show precipitations are beneficial to corn yields.

Policy makers need estimates such as these to inform their decisions. Policies that aim to regulate or deregulate the emission of greenhouse gases need to take into consideration the impact of climate change on different sectors of the economy for current and future generations, as well as the cost of mitigation and adaptation to climate change.

This study is still ongoing. The important caveats of this study are that climate change will impact not only mean yields but also the variance of yields, as found in our heteroskedasticity tests, and confirming previous studies (Tack et al. 2012). In addition, the models that use climate data need to be re-estimated and made to include county characteristics such as soil properties.

So far we have assumed that parameters are the same throughout the county, except for the Corn Belt dummy variables that were included. This is a strong assumption and may lead to biased estimates. The United States being such a large country, it is plausible to assume that parameters in these models vary across space rather than using pooled models. To accomplish this, we plan to use a technique called Kriging developed in the geostatistics literature and that has been used by Park et al. (2016) in crop insurance. This technique provides spatially smoothed parameters.

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Table 1. Partial Regression Results for the Logarithm of County Corn Yields (bu/acre)

Model	intercept	cornbelt	tempslope1	cornBeltslope1	tempslope 2	cornBeltslope2	prec	cornBeltPrec	precsq	rnBeltPrec	state19time	state19timesq	state19time1	state19time2	:ate19time	:ate19time	:ate19time	:ate19time	:ate19time	fips19129
1. weather all season (up to 2005)	3.069		0.00021		-0.0073		0.1094		-0.0085		0.0319	-0.0002								0.0888
2. weather, all season	3.177		0.00016		-0.0070		0.1076		-0.0083		0.0301	-0.0002								0.1163
3. weather, all season, varying trend	3.146		0.00017		-0.0071		0.1050		-0.0082				0.0340	0.0328	0.0145	0.0050	0.0225	0.0133	0.0008	0.1056
4. weather, all season, corn belt dummies	3.204		0.00015	0.00008	-0.0067	-0.0017	0.1011	0.1195	-0.0073	-0.0124	0.0300	-0.0002								-0.3186
5. weather, all season, varying trend, corn b	3.157		0.00016	0.00004	-0.0069	-0.0013	0.0980	0.1210	-0.0072	-0.0122			0.0310	0.0340	0.0134	0.0099	0.0173	0.0175	-0.0049	-0.2339
6.climate, all season	2.157		-0.00014		-0.0078		0.6410		-0.0493		0.0309	-0.0002								
7.climate, all season, varying trend	2.740		-0.00016		-0.0086		0.4503		-0.0350				0.0448	0.0323	0.0120	0.0038	0.0318	0.0065	0.0214	
8.climate, all season, corn belt dummies	2.630	-0.8856	-0.00014	0.00087	-0.0069	-0.0162	0.4326	-0.2688	-0.0304	0.0212	0.0301	-0.0002								
9.climate, all season,varying trend, corn bel	3.336	-1.0297	-0.00013	0.00083	-0.0075	-0.0160	0.1649	-0.1755	-0.0101	0.0143			0.0415	0.0332	0.0118	0.0039	0.0318	0.0065	0.0214	
10. weather, JulyAugust	3.705		0.00000		-0.0074		0.1284		-0.0230		0.0309	-0.0002								0.1712
11. weather, JulyAugust,varying trend	3.663		-0.00002		-0.0075		0.1383		-0.0247				0.0375	0.0323	0.0170	0.0008	0.0264	0.0123	0.0049	0.1537
12. weather, JulyAugust,corn belt dummies	3.750		-0.00001	0.00025	-0.0072	-0.0021	0.0994	0.1464	-0.0164	-0.0350	0.0313	-0.0002								-0.2525
13. weather, JulyAugust,varying trend,corn I	3.693		-0.00002	0.00018	-0.0074	-0.0016	0.1100	0.1385	-0.0184	-0.0320			0.0364	0.0331	0.0170	0.0027	0.0235	0.0140	0.0055	-0.1769
14. climate, JulyAugust	2.980		0.00041		-0.0149		0.3091		-0.0590		0.0312	-0.0002								
15. climate, JulyAugust,varying trend	3.145		0.00091		-0.0194		-0.3702		0.0699				0.0468	0.0318	0.0122	0.0038	0.0318	0.0065	0.0214	
16. climate, JulyAugust, corn belt dummies	3.173	-5.2928	0.00016	0.00326	-0.0124	-0.0216	0.2628	1.7430	-0.0364	-0.4331	0.0301	-0.0002								
17. climate, JulyAugust, varying trend, corn I	3.408	-4.9254	0.00070	0.00230	-0.0163	-0.0171	-0.5470	2.4690	0.1189	-0.5886			0.0417	0.0331	0.0118	0.0039	0.0318	0.0065	0.0214	

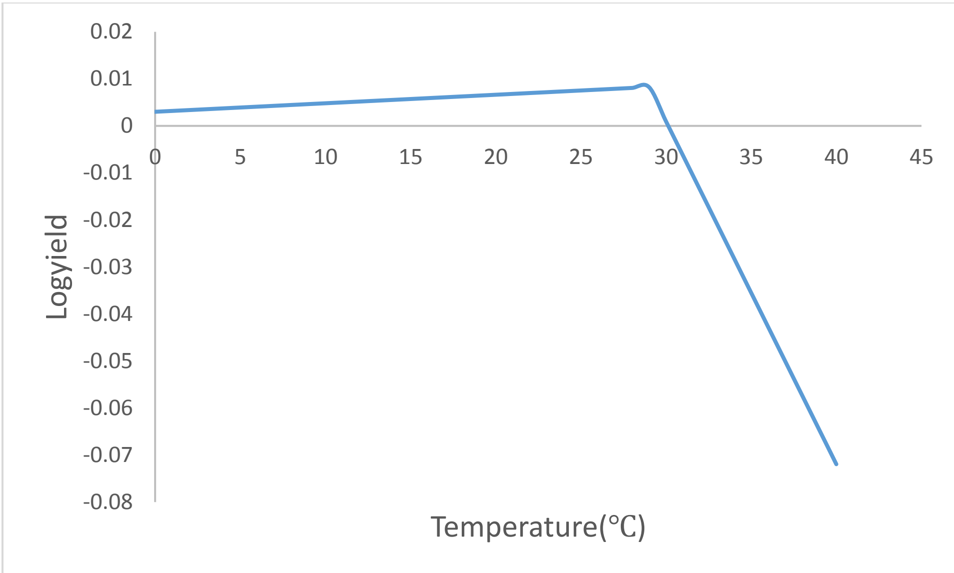
Table 2. Groups of Models According to Data Used

	Weather data	Climate data
All season	Models 2-5	Models 6-9
July and August	Models 10-13	Models 14-17

Table 3. Predicted Yield Losses from Uniform Temperature Increase

Model	Impact of 2℃ Increase
2. weather, all season	-14.7%
3. weather, all season, varying trend	-15.0%
4. weather, all season, corn belt dummies	-15.5%
5. weather, all season, varying trend, corn belt dummies	-15.8%
6. climate, all season	-24.0%
7. climate, all season, varying trend	-26.2%
8. climate, all season, corn belt dummies	-30.6%
9. climate, all season,varying trend, corn belt dummies	-32.1%
10. weather, JulyAugust	-14.3%
11. weather, JulyAugust,varying trend	-14.6%
12. weather, JulyAugust,corn belt dummies	-15.0%
13. weather, JulyAugust,varying trend,corn belt dummies	-15.2%
14. climate, JulyAugust	-23.8%
15. climate, JulyAugust,varying trend	-27.2%
16. climate, JulyAugust, corn belt dummies	-26.4%
17. climate, JulyAugust, varying trend, corn belt dummies	-28.9%

Figure 1. Effect of Temperature on Log Yield[1]



[1] Downward slope= -0.00729.