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LETTER

Placing bounds on extreme temperature response of maize

Christopher J Anderson[1], Bruce A Babcock[2], Yixing Peng[2], Philip W Gassman[3] and Todd D Campbell[3]

[1] Department of Agronomy, Iowa State University, Ames, IA 50011, USA
[2] Department of Economics, Iowa State University, Ames, IA 50011, USA
[3] Center for Agricultural and Rural Development, Iowa State University, Ames, IA 50011, USA

E-mail: cjames@iastate.edu

Abstract

Plant water availability is a key factor that determines maize yield response to excess heat. Lack of available data has limited researchers' ability to estimate this relationship at regional and global scales. Using a new soil moisture data set developed by running a crop growth simulator over historical data we demonstrate how current estimates of maize yield sensitivity to high temperature are misleading. We develop an empirical model relating observed yields to climate variables and soil moisture in a high maize production region in the United States to develop bounds on yield sensitivity to high temperatures. For the portion of the region with a relatively long growing season, yield reduction per °C is 10% for high water availability and 32.5% for low water availability. Where the growing season is shorter, yield reduction per °C is 6% for high water availability and 27% for low water availability. These results indicate the importance of using both water availability and temperature to model crop yield response to explain future climate change on crop yields.

1. Introduction

Knowledge of maize sensitivity to extreme temperature is needed to understand sensitivity of food production to human-caused climate change and the potential for food production adaptation. Despite intense research undertaken to understand this issue current estimates of yield response to high temperature are misleading because they do not consider the effects of plant water availability. Evaluation of extreme temperature yield effect with crop models and crop system models recognize the role of water availability (Challinor *et al* 2007a, Antle 2015, Gustafson *et al* 2014), but differences in underlying model assumptions make it difficult to place bounds on yield response to high temperature, limiting interpretation of variability across model results. Empirical models avoid process uncertainty but rainfall is used as a proxy for plant water availability because of a lack of data (Lobell and Field 2007, Kucharik and Sherbin 2008, Schlenker and Roberts 2009, Hawkins *et al* 2013, Lobell *et al* 2013). In either case, the effects

of plant water availability on the response of maize yield to extreme temperature is poorly bounded. We hypothesize that current estimates of negative effects of high temperature on maize yield need to be conditioned on water availability. By creating new data measuring plant water availability we test this hypothesis using a new empirical model estimated using data from four states in the primary United States maize growing region,

Iowa, Illinois, Minnesota and Wisconsin account for approximately 45% of US maize production, which in turn, accounts for approximately 35% of world production. In this region, *in situ* soil moisture measurement have demonstrated that soil water holding capacity can ameliorate effects of high temperature stress on maize (Dale and Shaw 1965a, 1965b). Extrapolation to regional scale is complicated, however, by soil heterogeneity and sparse *in situ* measurements. Without a regional scale analysis, there remains unresolved disparity in predictions of yield sensitivity to weather (Maltais-Landry and Lobell 2012, Woli *et al* 2014), technology

(Kucharik 2008, Asseng *et al* 2013, Xu *et al* 2013), and climate change (Kucharik and Serbin 2008, Schlenker and Roberts 2009, Hatfield *et al* 2011). We develop regional soil water climatology, overcoming the problems of using rainfall alone as a proxy and scaling up from *in situ*, field-level measurements.

We limit our analysis to dryland maize production to clearly determine the water-dependent bounds of high temperature effect. In this region, rainfall seasonality is variable from one production year to the next, so that the data sample contains both hot-dry and hot-wet growing seasons. Furthermore, rainfall seasonality is changing rapidly in response to human-caused climate change, so that bounds placed on extreme temperature maize yield effect are immediately relevant to adaptation in this region and stability of global maize production. In this region, spring rainfall increase is a remarkably consistent prediction from the first climate model experiments on CO_2 increase (Takle and Zhong 1991, Wetherald and Manabe 1995) through the Coupled Model Intercomparison Project 3 and 5 (Cook *et al* 2008, Maloney *et al* 2014). This appears to be caused by ocean temperature increase when greenhouse gas concentration is increased above pre-industrial levels (Rhein *et al* 2013), which, in turn, increases total atmospheric column water vapor. Because the Gulf of Mexico and North Tropical Atlantic are the evaporative source for as much as 50%–60% of rainfall in March, April, and May (Dirmeyer *et al* 2014), the recent increase of Atlantic sea surface temperature influences rainfall seasonality through increased oceanic total precipitable water and increased influx of water vapor into the US growing region (Bosilovich *et al* 2005, Bosilovich and Chern 2006).

This model framework and soil moisture data allow us to evaluate the extent to which temperature and moisture effects could be confounded when using empirical models that do not include soil moisture as a predictor. We are not aware of another empirical yield analysis that uses soil moisture at a regional scale. We develop an empirical model to evaluate yield effects by phenological phase, because it is unreasonable to expect the yield effect of extreme temperature to be the same at all stages of crop development even though this is an assumption commonly made in empirical yield equations. We then use the empirical model to estimate upper and low yield bounds under high temperature that correspond to water availability being high and low. We use soil water data generated from a crop growth simulator because available datasets specify a static green up period that may not reveal the true underlying relationship between observed yields and soil moisture. Our results provide insight into the reliability and relevance of predictions of severe future yield shortfalls from climate change and how the effects of plant water availability can be used to improve evaluation of adaptation options.

2. Methods

We use EPIC model version 1102-64 (Izaurralde *et al* 2006) to simulate soil moisture from 1980 to 2012. We apply EPIC to 48 084 points from the 1997 Natural Resources Inventory across western Minnesota through central Illinois (figure 1). This approach includes effects from crop rotation, management practices, and variability of soil characteristics with demonstrated capability to simulate effects of soil management (Chung *et al* 1999, Feng *et al* 2006). To run EPIC, we use daily maximum and minimum temperature and precipitation gridded to 1/8 degree (Maurer *et al* 2002), and we assign to each EPIC point the weather from the nearest grid point. The data on 1/8 degree grid will have fewer extremely high values of temperature and precipitation by the nature of interpolation. EPIC crop growth will be insensitive to error in daily rainfall, because it responds to soil moisture which itself responds to cumulative rainfall. If EPIC crop growth is more aggressive because excessive temperature occurs less frequently in the gridded data compared to station data, it could result in slightly drier soil moisture during extended periods (multiple days) of excessive heat. This is difficult to confirm because soil moisture measurements are sparse and because extended periods of excessive heat often happen simultaneously with lack of rainfall and sometimes soil moisture that is already low.

Maize production and planted acres data are collected from the US Department of Agriculture's National Agricultural Statistics Service (http://quickstats.nass.usda.gov). County-level maize yield is constructed as production divided by planted acres. Weather data are aggregated for May–June (planting and early vegetative growth) and July–August (pollination and grain fill). Daily temperature, precipitation, and root zone water content for each field are averaged for both time intervals. The root zone is variable and defined for each NRI point as the soil layer depth into which the crop growth model may extend roots. The area-weighted average of weather variables over all grids is used to obtain county-level data.

We develop an empirical yield model based upon maize phenological stage. Input variables (table 1) are separated for the vegetative growth stage (May–June) and pollination through grain-fill stages (July–August). While planting dates have changed in this region (Sacks and Kucharik 2011), the timing of flowering, silking, and black layer are not substantially different over the period of analysis (1980–2012), so that the broad phenological stages we use are stable during this analysis. We use multivariate splines with two knots to predict log yield. We use two knots to be consistent with past studies based upon quadratic models while (1) retaining flexibility for more complicated curves, such as asymmetry associated with high temperature, and (2) having a relatively small number of parameters for estimation.

The formal model structure when yield depends on a single climate variable is:

$$\ln Y_{i,t} = \alpha_i + \beta_{0*}\text{Year}_t$$
$$+ \sum_j \Big(\beta_{V,1}^j \min\Big(0, V_{i,t}^j - V_{\text{low}}^j\Big)$$
$$+ \beta_{V,2}^j V_{i,t}^j + \beta_{V,3}^j \max\Big(0, V_{i,t}^j - V_{\text{high}}^j\Big)\Big)$$
$$+ \varepsilon_{i,t}, \tag{1}$$

where V is the environmental variable (temperature, precipitation, soil moisture), V_{low} and V_{high} are the two knot values for the climate variable, i is the county index, t is the time index, and j is the period index (either May–June or July–August). Additional climate variables are accounted for by duplicating the terms in parentheses on the right hand side of equation (1). All climate variables are expressed as deviations from means. Bayesian estimation is used for model parameters following the methods developed by Yu and Babcock (2011).

The incremental effect of change in a predictor on ln(yield) is the percent yield change (PYC; units are % yield change per unit change in the predictor).

$$\text{PYC}_V^j$$
$$= \begin{cases} \text{PYC}_{V,\text{low}}^j = \beta_{V,1}^j + \beta_{V,2}^j & \text{if } V_{i,t}^j < V_{\text{low}}^j, \\ \text{PYC}_{V,\text{mid}}^j = \beta_{V,2}^j & \text{if } V_{low}^j < V_{i,t}^j < V_{\text{high}}^j, \\ \text{PYC}_{V,\text{high}}^j = \beta_{V,2}^j + \beta_{V,3}^j & \text{if } V_{i,t}^j > V_{\text{high}}^j. \end{cases} \tag{2}$$

Figure 2 illustrates the fit and interpretation of the two-knot spline yield response function for hypothetical precipitation and yield data. (Recall equation (1)
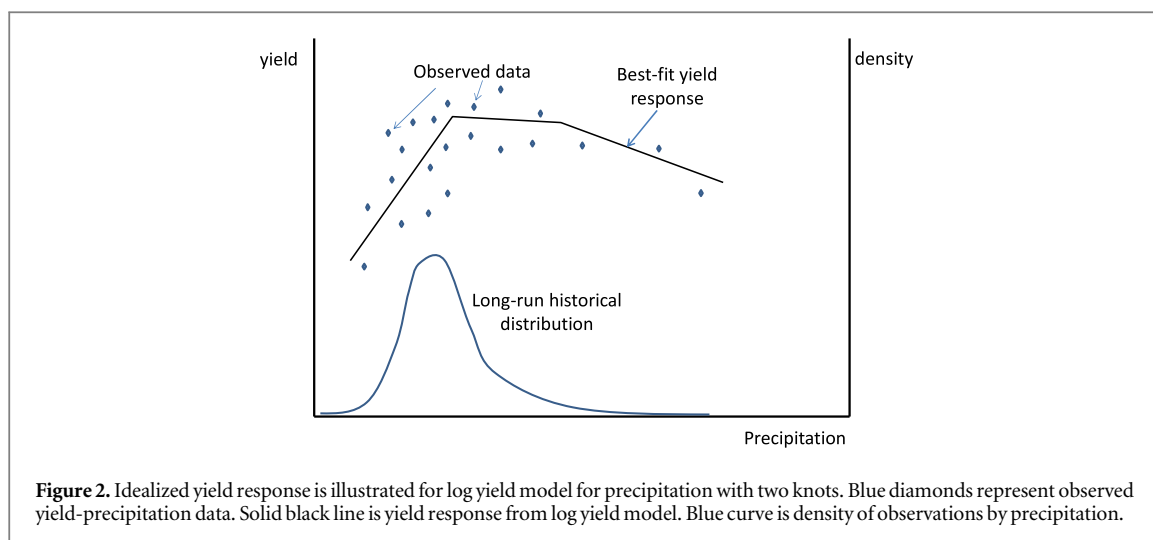
Table 1. Names and descriptions for each variable in the dry-hot, two-knot spline model (subscripts low and high distinguish the two know values in the text).

Variable name	Variable description
Year	Calendar year of yield report
May–June T	May through June average temperature (°C)
July–August T	July through August average temperature (°C)
May–June R	May through June average daily rainfall (mm)
July–August R	July through August average daily rainfall (mm)
1st May SM	Simulated soil moisture on 1st May (mm)
1st July SM	Simulated soil moisture on 1st July (mm)

predicts log yield rather than yield.) The parameters of the yield response function are the two knots and the three line slopes and are determined as the best fit subject to the restriction that the lines intersect at two knots. PYC is slope divided by yield level within each segment (percent change in yield per mm of precipitation). In figure 2, when precipitation is low, slope is positive with low yield values, so that PYC is high. In the second segment, yield response is small and yield is high, so that PYC is close to zero. Finally, when precipitation is high, slope is negative with relatively high yield values, so that PYC is relatively small and negative. The interpretation is that yield response is large and positive as precipitation increases from below average to average, small as precipitation increases from average to an extreme, and slightly downward above an extreme. In figure 2, mean and median precipitation fall in the first segment of yield response to demonstrate that the three segments of the yield response curve need not correspond to low, average, and high values for climate variables or biophysical
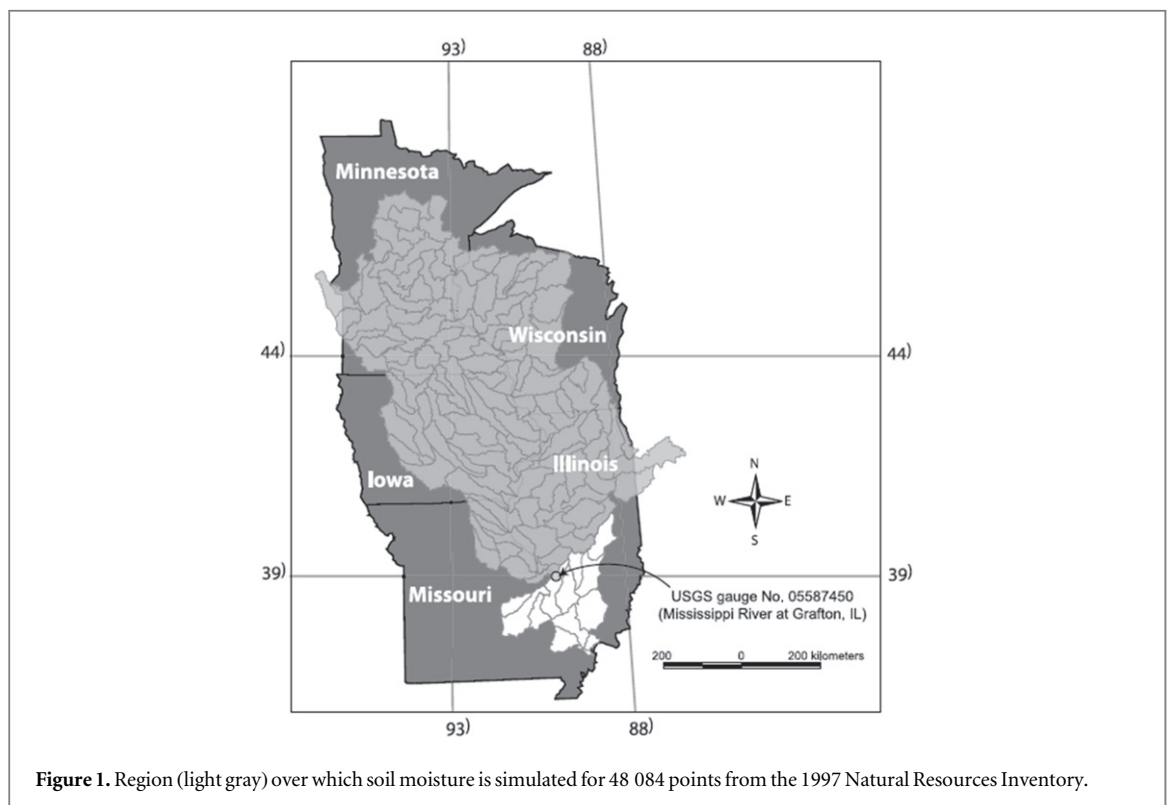
Figure 1. Region (light gray) over which soil moisture is simulated for 48 084 points from the 1997 Natural Resources Inventory.

Figure 2. Idealized yield response is illustrated for log yield model for precipitation with two knots. Blue diamonds represent observed yield-precipitation data. Solid black line is yield response from log yield model. Blue curve is density of observations by precipitation.

thresholds. When yield response depends on the interaction between climate variables, the yield response curve for a single climate variable is calculated conditional on the level of the other climate variables.

A Control model (see supplemental material) is estimated with only temperature and precipitation variables, similar to past analyses for this region. A dry-hot model is estimated by adding soil moisture variables and interaction terms. There are three interaction terms in the dry-hot model: product of (1) July–August temperature above its high knot and July–August rainfall below its low knot, (2) July–August temperature above its high knot and 1st July soil moisture below its low knot, and (3) July–August rainfall below its low know and 1st July soil moisture below its low knot. We refrain from using stepwise regression to find the subset of predictors that seem to best explain log yield. With our two-knot spline model a statistically insignificant coefficient has a sound agronomic interpretation. For example, in figure 2 the slope parameter between the two knots is close to zero. It would be poor judgment to reject a two-knot spline in favor of a one-knot spline in this case.
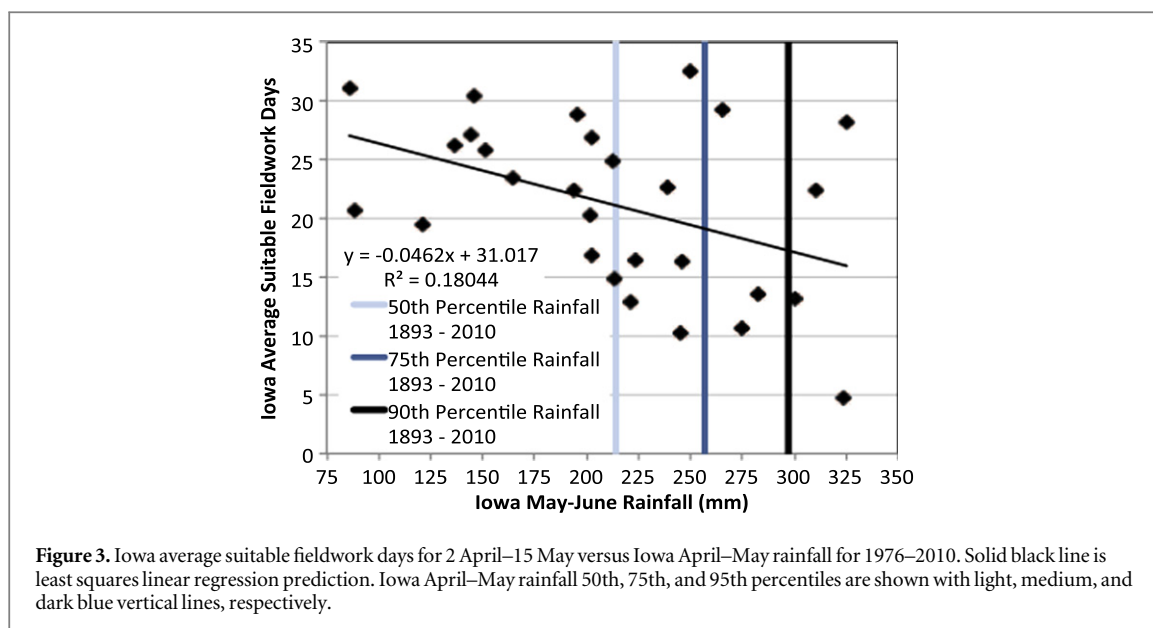
3. Results

3.1. Yield effect of soil moisture

The dry-hot model contains interaction terms for July–August T_{high} with 1st July SM_{low} and July–August R_{low} and 1st July SM_{low} with July–August R_{low}. These three interaction terms allow analysis of whether high moisture can reduce yield losses from high temperature. We interpret May–June rainfall as an immediate water source during planting and vegetative growth, and 1st July soil moisture as the lag water source from previous months' precipitation (not just May–June) during pollination and grain fill. The inherent correlation between precipitation and soil moisture raises the question of whether soil moisture and precipitation effects can be estimated separately. We find that most

coefficients for 1st July soil moisture have a 95% Bayesian probability interval that excludes zero, suggesting effects of precipitation and soil moisture can each be estimated. The value of adjusted-R^2 increases in the dry-hot model by 7% in Iowa, 4% in Illinois, 3% in Wisconsin and 1% in Minnesota. F-test of the null hypothesis that the two models have the same explanatory power is rejected at the 5% level. Thus, we conclude that our data measuring soil moisture has a statistically significant impact on county log yield.

The yield effect of excessive spring rainfall is not well established in literature, so we turn to field data to determine whether the estimated effects have a physical basis. In all states an increase in May–June R when it is below May–June R_{low} increases yield and an increase in May–June R when it is above May–June R_{high} decreases yield. This simply means that more rainfall in May and June increases yield when it is dry but reduces yield when it is already wet. In Iowa, yield loss occurs when planting after 10–14 May. Farnham (2001) estimates a 10% yield loss with a 31st May planting date and a 30% loss when planting is on 15th June. We further evaluate for Iowa the potential for delay in planting by relating state-level 1 April–15 May suitable fieldwork days to May–June rainfall during 1976–2010 (figure 3). Our model uses May–June rainfall, so we analyze it rather than April–May rainfall that would align with the reporting period for suitable days. Negative correlation is clear, and linear regression predicts a reduction of 1.1 fieldwork days for every 25.4 mm increase in May–June rainfall (a higher R^2 of the linear model for rainfall and suitable days is obtained when using April–May rainfall). The estimate for R_{high} is 246 mm, which is 10 mm less than the 75th percentile of May–June precipitation for 1893–2010. For May–June rainfall equal to May–June R_{high}, the linear model predicts a reduction of about a week in suitable fieldwork days. Thus, losses from planting delay caused by excessive rainfall are consistent with yield effects estimated by our model, and it is reasonable for the excessive rainfall effect to exceed

Figure 3. Iowa average suitable fieldwork days for 2 April–15 May versus Iowa April–May rainfall for 1976–2010. Solid black line is least squares linear regression prediction. Iowa April–May rainfall 50th, 75th, and 95th percentiles are shown with light, medium, and dark blue vertical lines, respectively.

Table 2. Total PYC (units of %) for combinations of 1st July soil moisture and July–August rainfall at July–August T_{high}.

1st July soil moisture	July–August rainfall	Iowa	Illinois	Wisconsin
μ	μ	−10.89	−15.57	−6.88
$-\sigma$	μ	−15.52	−21.50	−17.16
μ	$-\sigma$	−21.62	−26.62	−16.80
$-\sigma$	$-\sigma$	−26.25	−32.54	−27.07

Note: μ indicates variable is at its mean level, and $-\sigma$ indicates variable is one standard deviation below its mean.

~3% loss due to crop physiological damage from excessive wetness (Rosenzweig *et al* 2002).

Our primary interest is yield effects of high temperature in July and August when moisture is not available and when it is available. Temperature effect is determined at mean and one standard deviation below mean for July–August rainfall and 1st July soil moisture (table 2). Minnesota is excluded because high temperature effects are essentially absent, and excessive moisture is the dominant predictor of yield loss. As expected, increasing July–August temperature when it is above the second knot (July–August T_{high}) negatively impacts yield. But the yield loss is much lower in all three states when adequate moisture is available. For example, PYC in Iowa drops from 26.25% to 10.89% and from 32.5% to 15.5% in Illinois if both soil moisture and rainfall move from one standard deviation below their mean value to their mean.
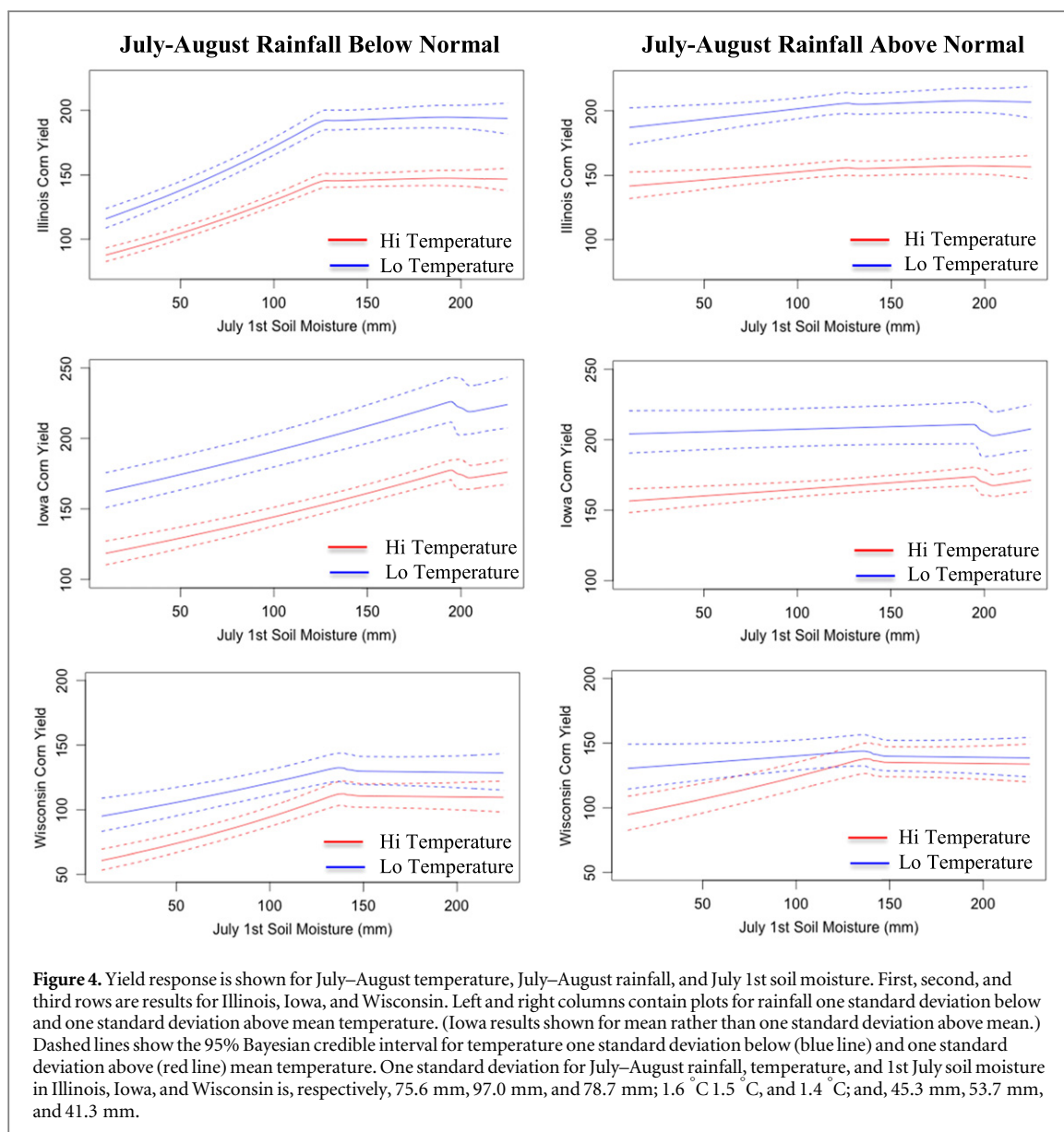
We further examine how climate variables affect predicted yield levels and the degree to which rainfall and soil moisture are fungible. Figure 4 presents predicted yield levels for Illinois (top two charts), Iowa (middle two charts) and Wisconsin. Two soil moisture response curves are shown in each chart corresponding to low July–August temperature (one standard deviation below mean), and high July–August temperature (one standard deviation above mean). The left column of charts is response curves when rainfall in July and August is low (one standard deviation below mean). The right column of charts is when rainfall in July and August is high (one standard deviation above mean)[4]. The dashed lines in each chart represent 95% Bayesian credibility intervals that were estimated by taking 15 000 samples from the posterior distributions of the coefficients.

It is apparent by comparing the slopes of the charts in the left column to the slopes in the right column that the response of yield to 1st July soil moisture is higher when rainfall is low. This indicates that 1st July soil moisture and summer rainfall are substitutes. Figure 4 demonstrates different yield floors corresponding to different levels of water availability. When July–August temperature is high, rainfall in July–August is high, and 1st July soil moisture is high, yield levels in Illinois, Iowa, and Wisconsin, respectively are 150, 170, and 135 bu ac^{-1}. However, when rainfall and soil moisture are low the yield levels are reduced to 120, 135, and 90 bu ac^{-1}.

When the model is used to extrapolate to higher temperature than observed, the yield floors separate further. This occurs because the model identified a different PYC (table 2) under low compared to high water availability. In Illinois the high temperature yield level when water is abundant is 150 bu ac^{-1} (figure 4), and a 1 °C increase in temperature results in a yield level of 126 bu ac^{-1}. In comparison, when water is limiting the high temperature yield level is 120 bu ac^{-1} (figure 4) and a 1 °C increase in temperature decreases yield to 81 bu ac^{-1}. Thus, the yield floor difference within the sample of temperature is 30 bu ac^{-1} (150

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[4] Iowa average July and August rainfall is used because the catastrophic 1993 flood skews results for high July and August rainfall.

Figure 4. Yield response is shown for July–August temperature, July–August rainfall, and July 1st soil moisture. First, second, and third rows are results for Illinois, Iowa, and Wisconsin. Left and right columns contain plots for rainfall one standard deviation below and one standard deviation above mean temperature. (Iowa results shown for mean rather than one standard deviation above mean.) Dashed lines show the 95% Bayesian credible interval for temperature one standard deviation below (blue line) and one standard deviation above (red line) mean temperature. One standard deviation for July–August rainfall, temperature, and 1st July soil moisture in Illinois, Iowa, and Wisconsin is, respectively, 75.6 mm, 97.0 mm, and 78.7 mm; 1.6 °C 1.5 °C, and 1.4 °C; and, 45.3 mm, 53.7 mm, and 41.3 mm.

minus 120) and outside the sample is 45 bu ac^{-1} (126 minus 81). This result shows the importance of considering whether moisture is a limiting factor when determining yield effects of climate change and whether yield loss is measured in percentage terms or in absolute levels.

4. Discussion

Our results demonstrate that maize sensitivity to high temperature is dependent on water availability. This effect is regionally important and not a localized effect found in only a subset of fields. Several empirical evaluations of maize yield sensitivity lack interaction between water availability and temperature. While Schlenker and Roberts (2009) argue a small correlation between daily rainfall and temperature suggest non-interaction, we find substantial interaction when aggregating over phenological stage. Additionally,

when aggregate weather data are used, it is common practice to select monthly aggregates through stepwise regression without consideration of interaction terms (Thompson 1986, Kucharik and Serbin 2008). By including interaction terms, we find the percent yield reduction from high temperature is 10–20 percentage points greater under low compared to high plant water availability. Consistent with recent work on maize heat sensitivity in France (Hawkins *et al* 2013), we conclude that temperature sensitivity of maize should be evaluated from the long-standing perspective of agronomists and maize breeders who evaluate temperature-induced stress relative to water availability (e.g., Dale and Shaw 1965b, Challinor *et al* 2007b, Wahid *et al* 2007).

Our results predict in the United States Midwest different maize sensitivity to temperature change compared to past studies. Kucharik and Serbin (2008) use data from 1976–2006 and report for Wisconsin 13% yield reduction per °C increase. Only under low

water availability do we find a similar result. Using data for 1960–2006, Tannura *et al* (2008) report for Illinois and Iowa 2%–5% yield reduction per °C during July and August, so that the effect of back-to-back July and August at 1 °C above average is a yield reduction of 4%–10%. Our model predicts similar yield response only when July–August temperature is relatively cool (below the second knot), which rarely occurs at the same time as low water availability. When we compared the Control model to the dry-hot models, we found similar discrepancies in maize yield sensitivity estimates which suggests that past studies have conflated yield effects of temperature and water availability.

We recognize empirical models can be constructed in many ways. Our results support the use of asymmetric temperature response and dependence on water availability. Soil moisture climatology from reanalysis (Mitchell *et al* 2004, Messinger *et al* 2006) presents a new opportunity to re-evaluate US maize production sensitivity to extreme heat. A question to consider is whether agricultural scientists need to develop soil moisture climatology. Assuming for a moment this is not the case, a common soil moisture source would allow systematic experimentation in yield response variables because the available water would be consistent across models that implement different representation of temperature, preferably with consideration of phenological stage. A variety of perspectives could uncover sensitivity not yet identified. Ultimately, the goal would be convergence that would signal robust estimates on temperature response given water availability.

The value of improved high temperature sensitivity estimates is evident when evaluating adaptation options. For instance, two approaches for adapting to increased frequency of high temperature are (1) implementing irrigation and (2) integrating cultivars from hotter regions. While discussion has emerged on the possibility for developing cultivars to survive yet-to-be-observed temperature thresholds, a breeding development path is not yet clear, so this option is not considered in this discussion. Yield reduction from high temperature under high water availability would provide a conservative estimate of the impact of adopting irrigation, and our results suggest a conservative estimate of reduction in yield loss of 15% in Iowa, 17% in Illinois, and 21% in Wisconsin. Regarding cultivar adaptation, Butler and Huybers (2013) estimate reduced yield loss from integrating heat tolerant cultivars under an assumed uniform warming of 2 °C and finds for Illinois that cultivar adaptation reduces yield loss by 4%–6%. Although our reduced yield loss estimates are made with a similar increase in July–August temperature in Illinois (1.9 °C), the studies can only be directly compared when using empirical models that make heat tolerance dependent on water availability. This is also the only way to estimate empirically the combined effect of these two adaptation options.

5. Conclusions

We have clarified the dependence of maize yield sensitivity to high temperature on available water using a high maize production region in the United States. We have identified bounds for maize yield loss under high temperature. For the portion of the region with relatively long growing season, the reduction per °C is 10% for high water availability and 32.5% for low water availability. In Wisconsin, where the growing season is shorter, yield reduction per °C is 6% for high water availability and 27% for low water availability. High temperature sensitivity is indeterminate in Minnesota where extreme temperature yield effect does not yet exceed excessive water yield effect. We conclude new soil moisture climatology from reanalysis datasets should be evaluated for use in developing robust estimates of high temperature sensitivity based upon water availability.

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