Quantifying the Impacts of Compound Extremes on Agriculture

Iman Haqiqi[1], Danielle S. Grogan[2], Thomas W. Hertel[1,3], and Wolfram Schlenker[4,5]

[1] Department of Agricultural Economics, Purdue University, West Lafayette, IN, USA.
[2] Institute for the Study of Earth, Oceans, and Space, University of New Hampshire, Durham, NH, USA.
[3] Purdue Climate Change Research Center, Purdue University, West Lafayette, IN, USA.
[4] School of International and Public Affairs, Columbia University, New York City, NY, USA.
[5] National Bureau of Economic Research, Cambridge, MA USA.

Correspondence to: Iman Haqiqi (ihaqiqi@purdue.edu)

Abstract. Agricultural production and food prices are affected by hydroclimatic extremes. There has been a large literature measuring the impacts of individual extreme events (heat stress or water stress) on agricultural and human systems. Yet, we lack a comprehensive understanding of the significance and the magnitude of the impacts of compound extremes. This study combines a fine-scale weather product with outputs of a hydrological model to construct functional metrics of individual and compound hydroclimatic extremes for agriculture. Then, a yield response function is estimated with individual and compound metrics focusing on corn in the United States during the 1981-2015 period. Supported by statistical evidence, the findings suggest that metrics of compound hydroclimatic extremes are better predictors of corn yield variations than metrics of individual extremes. The results also confirm that wet heat is more damaging than dry heat for corn. This study shows the average yield damage from heat stress has been up to four times more severe when combined with water stress. **Keywords**. agriculture; climate impacts; water balance model; extreme heat; extreme drought.

1 Introduction

The United States is the world's top food exporter, being the major producer of global calories of the four staple crops corn, soybeans, wheat and, rice, which together account for 75% of the calories humans consume (USDA NASS). Specifically, it produces more than 40% of the world's corn. ~~The United States is the world's top food exporter, producing much of the global population's supply of the staple crops corn, soybeans, and wheat (USDA NASS). In all agricultural production, p~~Precipitation and temperature weather extremes cause variation in crop yields, affecting not only crop growth but also ~~farm revenues and~~ crop ~~markets~~prices and farm revenues. As climate changes, all regions of the planet are experiencing more frequent weather extremes, and often with greater magnitude than in the past (WMO, 2013); the WMO calls 2001-2010 the "decade of climate extremes", and this time frame did not even include the record-breaking year 2012 ~~drought~~ that devastated corn and soybean production across the U.S. (Rippey, 2015). This year was both very hot and very dry in many parts of the corn belt. To understand past and future global food security, it is therefore essential to quantify and build predictive models of the impacts of extreme weather events on staple crop yields.

The focus of this paper is statistical modeling of crop yields, (e.g., Schlenker and Roberts, 2009), which draws heavily on the field of econometrics. While there is also a rich literature of process-based crop yield models (Jones et al., 2017), many of these models still rely on observational data-derived statistical relationships between extreme weather events and yields to capture impacts of extremes. Additionally, recent high-visibility studies on the impact of weather extremes on past and future crop yields rely entirely on statistical econometric modeling (Lobell et al., 2013). The relationship between extreme heat and crop yields has been well-documented, particularly across the United States (US) and for corn, the U.S.'s largest crop by acreage (Schlenker and Roberts, 2009; Urban et al., 2012; Diffenbaugh et al., 2012; Roberts et al., 2013; Lobell et al., 2013; Urban et al., 2015; Wing et al., 2015; Burke and Emerick, 2016). Statistical and process-based crop models also appear to agree on corn yield impacts due to heat (Liu et al., 2016; Tebaldi and Lobell, 2018).

However, there is less agreement and greater uncertainty around the crop yield impacts of hydrologic extremes, due largely to the use of annual or season mean precipitation metrics in statistical models that fail to capture hydrologic extremes (D'Odorico and Porporato, 2004; Lobell and Burke, 2010; Schaffer et al., 2015; Werner and Cannon, 2016). These cumulative indices - monthly mean, or seasonal average precipitation - do not capture extreme events that occur within the season. For example, precipitation amounts from early-season floods and late-season droughts can cancel out when taking the average, effectively smoothing over these extreme events in the data. The computed mean ~~these events~~for this variable can be misleading as crop growth responds to day-to-day variability. While average conditions are important, exposure to extreme water stress can cause permanent unrecoverable damage to plants (Denmead and Shaw, 1960), while too much water can cause yield-damaging floods, waterlogging, or may wash out soil nutrients and fertilizers (Kaur et al., 2018; Schmidt et al., 2011; Urban et al., 2015).

Crops obtain most of their water directly from soil moisture, yet extreme water metrics based on soil moisture have been only minimally explored (Fishman, 2016). Several studies have highlighted the need for irrigation to compensate for soil moisture deficits (Li et al., 2017; McDonald and Girvetz, 2013; Meng et al., 2016; Williams et al., 2016), further pointing to soil moisture as a potentially more important crop water availability metric than precipitation. However, current statistical studies have had limited success in statistically capturing the yield response to soil moisture metrics (Bradford et al., 2017; Peichl et al., 2018; Siebert et al., 2017). There are several potential reasons for this limited success. First, direct measures of soil water availability include complex biophysical and hydrological processes that are difficult to capture in a rather simple statistical model. Another barrier has been the limited availability of daily fine-scale soil moisture data, as well as the inconsistency of soil moisture data with heat information. It has therefore become a standard practice in statistical crop modeling either to focus on a limited geographical area (Rizzo et al., 2018; Wang et al., 2017) or to employ a proxy variable like precipitation, evapotranspiration, or vapor pressure deficit estimates (Comas et al., 2019; Roberts et al., 2013).

A few recent studies have highlighted the importance of mean soil moisture metrics for estimating crop yields in the US (Ortiz-Bobea et al., 2019; Ribeiro et al., 2020). However, Ortiz-Bobea et al. (2019) estimated the average impact of heat stress on corn yields without distinguishing between a hot-dry day (dry heat) and a hot-wet day (wet heat), and similarly, Ribeiro et al., (2020) evaluated the impacts of dry-heat and ignores the impacts of wet-heat stress. These papers do not focus on the interaction or compound effects. Therefore there is currently no robust predictive framework that captures the implications of compound extremes, which~~have been seen~~ appear in the historical climate record and are expected to become more frequent under future climate change conditions (Myhre et al., 2019). It is important to build such a framework because harmful extreme heat can be less harmful when there is sufficient soil moisture (Hauser et al., 2018), indicating that previous estimates of extreme heat impacts on staple crop yields may be biased high.

This paper presents the first statistical predictive crop yield model that directly addresses the gap in our knowledge of crop yield impacts due to compound weather extremes, including both dry-heat and wet-heat. This is accomplished by using high-resolution, daily simulated soil moisture data that is consistent with daily temperature data, applied to corn yield data across the continental United StatesU.S..

We construct various metrics of individual and compound hydroclimatic extremes appropriate for agricultural studies. In agricultural production, water and heat extremes are key determinants of yield variations. They affect agricultural yields, farm revenues, and crop markets. The relationship between extreme heat and crop yields has been well-documented, particularly across the United States (US) and particularly for corn (Schlenker and Roberts, 2009; Urban et al., 2012; Diffenbaugh et al., 2012; Roberts et al., 2013; Lobell et al., 2013; Urban et al., 2015; Wing et al., 2015; Burke and Emerick, 2016). However, the precipitation-based metrics of water conditions used previously are either mean or cumulative measures calculated over the growing season or stages of crop growth. These cumulative indices, monthly mean, or seasonal average metrics do not capture extreme events during the season (e.g. early-season floods and late-season droughts can cancel out when taking the average). The mean variable can be misleading as the plants respond to day to day variability. Furthermore, the mean water index may not represent hydrological extremes (D'Odorico and Porporato, 2004; Lobell and Burke, 2010; Schaffer et al., 2015; Werner and Cannon, 2016). While the average conditions are important, exposure to extreme water stress can cause permanent unrecoverable damage to the plant (Denmead and Shaw, 1960). In addition, too much water can cause flooding, waterlogging, or may wash out soil nutrients and fertilizers (Kaur et al., 2018; Schmidt et al., 2011; Urban et al., 2015). Therefore, it is necessary to introduce metrics of extreme soil moisture stress. This will be even more important in the future, as climate projections are predicting more extreme drought and precipitation events (Myhre et al., 2019). In other words, mean variables can create biases in future climate impact analysis by ignoring the extreme events. It is important to evaluate new metrics of daily water availability to fully understand the impact of water extremes on crop yields, as this will be important in both fundamental understandings of the crop-water system, and in predicting the impacts of future extreme events.

Further, crops obtain their water directly from soil moisture, yet extreme water metrics based on soil moisture have been only minimally explored (Fishman, 2016). Several studies have highlighted the need for irrigation to compensate for soil moisture deficits (Li et al., 2017; McDonald and Girvetz, 2013; Meng et al., 2016; Williams et al., 2016), further pointing to soil moisture as a potentially more important crop water availability metric than precipitation. However, current statistical studies have had limited success in statistically capturing the yield response to soil moisture metrics (Bradford et al., 2017; Peichl et al., 2018; Siebert et al., 2017). There are several potential reasons for the limited success of previous statistical studies in capturing yield response to soil moisture. Direct measures of soil water availability include complex biophysical and hydrological processes that are difficult to capture in a rather simple statistical model. On the other hand, seasonal mean soil moisture is highly correlated to seasonal precipitation. Thus, including an average metric of soil water content may not add value to a statistical model. Another barrier has been limited availability of daily fine-scale soil moisture data and inconsistency of soil moisture data with heat information. It has become a standard practice either to focus on a limited geographical area (Rizzo et al., 2018; Wang et al., 2017) or to employ a proxy variable like precipitation, evapotranspiration, or vapor pressure deficit estimates (Comas et al., 2019; Roberts et al., 2013). The recent work by Ortiz-Bobea et al. is an exception that highlights the importance of mean soil moisture metrics for estimating crop yields in the US (Ortiz-Bobea et al., 2019).

A key unknown is the extent of the benefits of soil moisture in buffering heat damage to yields. Despite existing theoretical frameworks and controlled experiments, we currently lack a comprehensive understanding of the impact of heat on yields while controlling for water (Bradford et al., 2017; Ortiz-Bobea et al., 2019). The problem is that current studies tend to separate the impact of heat from water stress. These studies estimate the average impact of heat stress on corn yields without distinguishing between a hot-dry day (dry heat) and a hot-wet day (wet heat). There is no robust predictive framework that captures the implications of compound extremes in the determination of national crop yields. Also, the current literature is focused mainly on the impacts of dry-heat and ignoring the impacts of wet-heat stress (Ribeiro et al., 2020). The growth effects of heat and soil moisture are mutually interdependent. Beneficial heat is less beneficial without sufficient soil moisture. On the other hand, soil moisture is not beneficial without sufficient heat for plant growth. Harmful heat can be less harmful when there is enough soil moisture (Hauser et al., 2018). While the amount of daily water requirement depends on the biophysical properties of soil and crop, it changes with temperature, solar radiation, humidity, and wind speed. In this framework, daily weather variability, which is expected to change in the future with climate change, can affect both soil moisture supply and demand by altering the abundance and frequency of precipitation and by increasing the water required to compensate evapotranspiration and evaporation. If the temperature is high and there is not enough soil moisture for a long period (drought conditions), this may cause severe damage to crops (Denmead and Shaw, 1960). Therefore, consideration of the daily compound impacts of soil moisture and heat is necessary to capture the impacts on natural supply and plant demand for soil moisture.

In this paper, we investigate the significance of compound heat and water conditions in predicting crop yields, including dry-heat and wet-heat. We focus on corn as the major field crop in the US. We also compare the metrics of compound extremes versus individual extremes (i.e. only heat stress or only water stress). This study also demonstrates the advantages of using soil moisture metrics over current proxy variables in capturing climate-driven variations in heat and moisture availability.

2 Methods

This paper introduces two statistical models of crop yield as a function of heat and soil moisture, effectively building on the regression model methods from Schlenker and Roberts (2009) and Ortiz-Bobea et al. (2019). While both of these studies considered similar metrics for heat, the former is based on precipitation and the latter considers an average soil moisture metric. The current study extends them by introducing easy-to-use metrics of individual and compound extremes based on simulated soil moisture. Here, we introduce two statistical models of crop yield as a function of heat and soil moisture For each model, we Each regression model considers different parameterizations of heat and soil moisture to estimate the impacts of water availability on corn yields in the US. Here, Mmodel 1 assumes that the impacts of heat and water on corn yields are separable. This model considers metrics of individual extremes (heat stress and water availability). Figure 1 visualizes four soil moisture conditions that are unfavorable for crop yield. Both too much water [i] and intense moisture stress [ii] can cause severe damage to crop yields. Similarly, a long period of mild moisture stress [iii] or a short period of severe moisture stress [iv] can also cause significant yield loss. These measures can help to understand the need for artificial drainage or irrigation as shown in panel (b). Within this framework, we investigate which metrics of individual extremes is a better predictor of corn yields. Relaxing the separability assumption, mModel 2 assumes the yield impacts of heat and water are mutually interdependent. Model 2 considers metrics of compound extremes. Technically, we extend the models inSchlenker and Roberts (2009) and Ortiz-Bobea et al. (2019) by assuming the growth effects of heat and water are mutually interdependent. We use detailed soil moisture information available from a physical hydrologic model. Model 1 helps to estimate the marginal impacts of heat stress (individual extreme) as well as the marginal impact of daily soil moisture stress (individual extreme) on crop yields. Model 2 provides a framework to measure the conditional marginal impact of heat and soil moisture (compound extremes) on crop yields.

Here, we introduce two statistical models of crop yield as a function of heat and soil moisture. For each model, we consider different parameterizations of heat and soil moisture to estimate the impacts of water availability on corn yields in the US. Model 1 assumes the impacts of heat and water on corn yields are separable. This model considers metrics of individual extremes (heat stress and water availability). Figure 1 visualizes four soil moisture conditions that are unfavorable for crop yield. Both too much water [i] and intense moisture stress [ii] can cause severe damage to crop yields. Similarly, a long period of mild moisture stress

[iii] or a short period of severe moisture stress [iv] can also cause significant yield loss. These measures can help to understand the need for artificial drainage or irrigation as shown in panel (b). Within this framework, we investigate which metric of individual extremes is a better predictor of corn yields. Relaxing the separability assumption, model 2 assumes the yield impacts of heat and water are mutually interdependent. Model 2 considers metrics of compound extremes.

2.1 Data

In estimating the marginal impact of soil moisture on corn yields, we employ information about soil moisture, temperature, precipitation, and corn yields for counties of the United States for the 1981-2015 period. The data on yield is obtained from USDA-NASS (United States Department of Agriculture-National Agricultural Statistics Service) at the county level. The yield is defined as the corn production (in bushels) divided by harvested area (in acres). Precipitation is defined in millimeters as accumulated rainfall during the growing season (Apr-Sep). It is calculated based on PRISM (Parameter-elevation Regressions on Independent Slopes Model) daily information at 2.5 x 2.5 arcmin grid cells over the continental US for 1981-2015. It is aggregated to each county according to cropland area weights. Compound metrics of heat and soil moisture are also calculated daily at the gridded level. Then we aggregate the metrics to the growing season and county level. Daily soil moisture content and soil moisture fraction are obtained from the Water Balance Model (Grogan, 2016; Wisser et al., 2010) based on daily simulations using PRISM data at 6 x 6 arcmin grid cells for the 1981-2015 period over the continental US. Here, we briefly describe WBM's soil moisture module. However, the model is much more complex and employs a large list of inputs. Full documentation for WBM can be found in Wisser et al. (2010) with updates in Grogan (2016). In WBM, crop-specific soil moisture balance within each grid cell is calculated with an accounting system that tracks a location's water inputs and outputs and is limited by the soil moisture pool's water holding capacity.

We construct our water metrics based on soil moisture conditions shown in Fig. 1 (extreme surplus = A, surplus = B, around normal = C+D, deficit = E, extreme deficit = F). Three types of metrics are constructed for each condition. A simple metric is the number of days during the growing season with each condition. To show the intensity of each condition, the second metric is defined based on cumulative deviation from normal for each condition. Finally, a compound metric is defined as the sum of degree days for each observed soil moisture condition.

2.2 Data processing

Major metrics used in this study are listed in Table 1. To derive the metrics listed in this table, the climate and soil moisture data are processed. The heat metrics are based on the concept of growing degree days. Following D'Agostino and Schlenker (2015), the daily distribution of temperatures is approximated assuming a cosine function between the daily minimum and maximum temperature. Let $\bar{t} = \operatorname{acos}\left(\frac{2b - T_{max} - T_{min}}{T_{max} - T_{min}}\right)$, then degree days (dday) at each day is defined using

$$dday(b) = \begin{cases} \frac{(T_{max}+T_{min})}{2} - b & if\ b \leq T_{min} \\ \frac{\bar{t}}{\pi}\left[\frac{(T_{max}+T_{min})}{2} - b\right] + \frac{(T_{max}-T_{min})}{2\pi} sin(\bar{t}) & if\ T_{min} < b \leq T_{max} \\ 0 & if\ T_{max} < b \end{cases} \quad (1)$$

where b is the base for calculating degree days and can take the base values as well as critical values. This study considers a piecewise-linear function to aggregate the degree days. The major assumption is that plant growth is approximately linear between two bounds. Degree days between two bounds is simply degree days above the smaller bound minus degree days above the larger bound. Degree days are initially calculated for each day at each 2.5 x 2.5 arcmin grid cell during the growing season (Apr-Sep). Then they are aggregated for the whole growing season from the first day of April through the last day of September. Finally, they are aggregated to the county level using cropland area weights. We employ the Crop Data Layer from the US Department of Agriculture to exclude grid cells with no cropland and to aggregate the grid cell information to the county level (Boryan et al., 2012; USDA-NASS, 2017).

The soil moisture metrics are constructed as the deviation from normal. Normal levels are defined as seasonal mean volumetric soil moisture over the 1981-2015 period. The water available to plants depends on volumetric soil moisture as well as soil type. To operationalize the soil moisture metric, this study considers the soil moisture deviation from normal. Soil moisture deviation is defined as daily soil moisture minus the normal soil moisture levels. Figure S1 shows the difference between normal soil moisture content, water available to plants, and unavailable water. The soil moisture level is considered extreme if it is below/above a threshold. The threshold is obtained by testing the impacts of 5-mm intervals of soil moisture deviation from normal.

Figure 1 visualizes soil moisture conditions as the basis for the construction of the soil moisture metrics (on the figure: extreme surplus = A, surplus = B, around normal = C+D, deficit = E, extreme deficit = F). Three types of metrics are constructed for each condition. The simplest metric is the number of days during the growing season with each condition. To show the intensity of each condition, the second metric is defined based on cumulative deviation from normal for each condition. Finally, a compound metric is defined as the sum of degree days for each observed soil moisture condition. In Table 1, SMavg is calculated as the seasonal mean of soil moisture content (in mm for the 1000 mm topsoil) from the first day of April through the last day of September for each grid cell for each year. This metric shows the average soil moisture conditions. Then, NDD and NDS represent the number of days when the daily volumetric soil moisture content is more than 25 mm below normal levels or is more than 25 mm below normal levels, respectively. Further, CMS and CMD show the cumulative soil moisture surplus (above normal) and deficit (below normal) while CEMS and CEMD show the cumulative extreme soil moisture surplus (25+ mm above normal) and deficit (25+ mm below normal), respectively. These are metrics of extreme soil moisture conditions. Finally, CMN represents a cumulative metric of soil moisture index around normal. ~~We construct our water metrics based on soil moisture conditions shown in Fig. 1 (extreme surplus = A, surplus = B, around normal = C+D, deficit = E, extreme deficit = F). Three types of metrics are constructed for each condition. A simple metric is the number of days during the growing season with each condition. To show the intensity of each condition, the second metric is defined based on cumulative deviation from normal for each condition. Finally, a compound metric is defined as the sum of degree days for each observed soil moisture condition.~~

2.~~2~~ 3 Model (1) individual extremes

Model 1 is a basic model that uses individual extremes, following a similar approach as Schlenker and Roberts (2009). Model 1 assumes that the effects of heat on corn yields are cumulative over the growing season and separable from water. In other words, the end-of-season yield is the integral of daily heat impacts over the growing season. This relationship can be demonstrated via Eq. (2):

$$y_{it} = \int_{\underline{h}}^{\overline{h}} g(h)\varphi_{it}(h)dh + z_{it}\boldsymbol{\delta} + c_i + \epsilon_{it} \tag{2}$$

Where y_{it} *is crop yield,* $g(h)$ is a function showing yield as a function of heat, $\varphi_{it}(h)$ is the time distribution of heat (h) over the growing season in location i and year t, while the heat ranges between the lower bound $\underline{h}$ and the upper bound $\overline{h}$; metrics of water availability (e.g., precipitation or soil moisture) and other control factors are denoted as z_{it}, and c_i is a time-invariant fixed effect

All other unobserved variables are in the ϵ_{it} term. The fixed effect variable (also termed the unobserved individual effect) allows us to control for other biophysical or economic characteristics of each location which are not varying over time and can potentially explain the yield differences between counties. Note that this form of equation with fixed effects and unobserved variables is a standard econometric method. We evaluate the accuracy of this model, compared to historical data, using first cumulative precipitation, then mean soil moisture as the water availability metric z_{it}.

For Model (1), different representations of water variables are considered. In Model (1-a), z_{it} includes cumulative precipitation from the first day of April to the last day of September and its square term; this will evaluate the standard way yields have been estimated in previous studies. In Model (1-b), z_{it} is the seasonal mean soil moisture index and its square term, used to evaluate the use of soil moisture instead of precipitation. Model (1-c) includes the number of days with low soil moisture as well as the number of days with high soil moisture, evaluating the importance of extreme soil moisture events (Fig. 1). In Model (1-d), z_{it} includes metrics of soil moisture below or above normal levels, evaluating the importance of extreme soil moisture intensity (Fig. 1). For Model (1), assumes a piece-wise linear form for $g(h)$. It includes degree days above 29˚C as a metric of extreme heat as well as degree days from 10 to 29˚C as a metric of beneficial heat. Look at the Supplementary Information for more details about each model.

2.~~3~~ 4 Model (2) compound extremes

Here, a new statistical model is introduced to focus on the compound metrics of available water and heat as the major indicators of plant growth to evaluate if including the conditional marginal impact of heat and water on yields provides improved yield estimates. Model 2 is:

$$y_{it} = \int_{\underline{m}}^{\overline{m}} \int_{\underline{h}}^{\overline{h}} g(h,m)\varphi(h,m)dhdm + c_i + \epsilon_{it} \quad (3)$$

where y_{it} is the crop yield, $g(h,m)$ is the yield response function to each combination of soil moisture level, m, and heat, h; $\varphi(h,m)$ is the distribution of soil moisture and heat; $\overline{m}$ and $\underline{m}$ are upper and lower thresholds of soil moisture; $\overline{h}$ and $\underline{h}$ are maximum and minimum heat; c_i is a time-invariant county fixed effect; and ϵ_{it} is the residual. Here, the model does not separate the impact of heat from water. In other words, the marginal impact of heat depends on water; and the marginal impact of water depends on heat.

Two approaches are employed to estimate the impacts of compound extremes within this model. First, we construct a binning estimator based on daily interaction on heat and soil moisture in the model (2-a). We define several intervals of soil moisture (SM) represented by daily dummy variables and we interact these dummy variables with the daily excess heat index of 29ºC. Also, we take 25 mm intervals for soil moisture deviation from normal. In other words, we split the degree days into degree days conditional to soil moisture conditions. This includes dday29˚C & SM 75+ mm below normal (extreme deficit), dday29˚C & SM 25-75 mm below normal (deficit), dday29˚C & SM 0-25 mm around normal (normal), dday29˚C & SM 25-75 mm above normal (surplus), and dday29˚C & SM 75+ mm above normal (extreme surplus). We estimate a coefficient for each combination of excess heat and soil moisture; ie., we estimate a model with metrics of degree days while controlling for soil moisture. Second, we estimate a model with metrics of soil moisture while controlling for temperature in the model (2-b). We define an index of soil moisture when the temperature is above the threshold and an index of soil moisture when the temperature is below the threshold. If H is the average daily temperature, and H^* is the temperature threshold, the metrics are the index of normal soil moisture (*SM* 0-25+ mm around normal) when $H > H^*$, the index of normal soil moisture when $H < H^*$, the index of moisture deficit (*SM* 25+ mm below normal) when $H > H^*$, index of moisture deficit when $H < H^*$, the index of moisture surplus (*SM* 25+ mm above normal) when $H > H^*$, and the index of moisture surplus when $H < H^*$. Look at the Supplementary Information for more details about each model.

2.4 Estimation strategy

For Model (1), we build on Schlenker and Roberts (2009) by including different representations of water variables. In Model (1-a), z_{it} includes cumulative precipitation from the first day of April to the last day of September and its square term; this will evaluate the standard way yields have been estimated in previous studies. In Model (1-b), z_{it} is the seasonal mean soil moisture index and its square term, used to evaluate the use of soil moisture instead of precipitation. Model (1-c) includes the number of days with low soil moisture as well as the number of days with high soil moisture, evaluating the importance of extreme soil moisture events (Fig. 1). In Model (1-d), z_{it} includes metrics of soil moisture below or above normal levels, evaluating the importance of extreme soil moisture intensity (Fig. 1). For Model (1), we assume a piece-wise linear form for $g(h)$. We include degree days above 29˚C as a metric of extreme heat as well as degree days from 10 to 29˚C as a metric of beneficial heat. Considering the exposure to each temperature interval to capture the marginal impact of heat and water on crop yields, we estimate the following for model (1-a):

$$y_{it} = \alpha D_{it}^{10-29} + \beta D_{it}^{29} + \delta_a P_{it} + \delta'_a P_{it}^2 + \lambda_s t + \lambda'_s t^2 + c_i + \varepsilon_{it} \tag{7}$$

where i is an index for counties, t is the index of time, s is the index for states, y_{it} is the log corn yields, D_{it} represents growing degree day variables, P shows cumulative precipitation over the growing season, t shows the time trend variable (t = year – 1950), c_i is a time-invariant county fixed effect, ε is the residual, and $\alpha, \beta, \delta, \lambda$ are the regression parameters showing the marginal impacts. The subscript a is used to show the water coefficients (δ) are related to metrics in Model (1-a). To evaluate the importance of soil moisture metrics in Model (1-b), we estimate the following:

$$y_{it} = \alpha D_{it}^{10-29} + \beta D_{it}^{29} + \delta_b M_{it} + \delta'_b M_{it}^2 + \lambda_s t + \lambda'_s t^2 + c_i + \varepsilon_{it} \tag{8}$$

where the variables are defined as Model (1-a) except for the water availability metric. Here M shows the seasonal mean soil moisture index calculated as average daily root zone soil moisture from the first day of April to the end of September. The subscript b is used for δ to distinguish the water coefficients in Model (1-b). For Model (1-c) we estimate the following model:

$$y_{it} = \alpha D_{it}^{10-29} + \beta D_{it}^{29} + \delta_c N_{it}^{def} + \delta'_c N_{it}^{sur} + \lambda_s t + \lambda'_s t^2 + c_i + \varepsilon_{it} \tag{9}$$

where we replace seasonal mean or cumulative metrics with two new metrics to control the impacts of water extremes on corn yields. Here, N^{def} is the number of days that soil moisture is under 25 mm below normal levels (deficit); and N^{sur} is the number of days that soil moisture is higher than 25 mm above normal levels. The rest of the variables are defined as Model (1-a). The subscript c shows δ_c is specific to Model (1-c). Finally, we estimate the following equation for Model (1-d):

$$y_{it} = \alpha D_{it}^{10-29} + \beta D_{it}^{29} + \delta_d M_{it}^{pos} + \delta'_d M_{it}^{neg} + \lambda_s t + \lambda'_s t^2 + c_i + \varepsilon_{it} \tag{10}$$

where M^{pos} is a cumulative measure of positive soil moisture deviations compared to the normal levels (equivalent to A+B+C in Fig. 1). And M^{neg} is the cumulative measure of negative soil moisture deviations compared to the normal levels (equivalent to D+E+F in Fig. 1). The subscript d distinguished estimated δ from previous models.

We assume the errors are serially correlated due to unobservable and systematic measurement errors, and we consider clustering US counties by the state which has been a standard approach in the literature (Blanc and Schlenker, 2017; Hsiang, 2016; Lobell and Burke, 2010). In this study, the models are estimated using a panel fixed-effect approach. A panel fixed-effect approach is a statistical method for analyzing two-dimensional (e.g. time and location) panel data. This method is helpful for analyzing those data collected for the same locations over time with a relatively short time span (Wooldridge, 2016). As our data set contains information for counties over time, a panel data analysis is appropriate. In addition, a fixed-effect model is appropriate as there are unique biophysical and economic attributes of counties that can explain yield differences across counties and are not changing over time. When we conduct a statistical test (Hausman test), it rejects the random effects model in favor of the fixed effect models we use. The panel consists of 35 years (1981-2015) for all US counties with corn production. For purposes of model comparison, we provide adjusted R^2, Akaike's information criterion (AIC), and Bayesian information criterion (BIC).

For Model (2), we consider the daily interaction of heat and soil moisture as the compound metric. The interaction term is defined when the marginal impact of an explanatory variable depends on the magnitude of yet another explanatory variable (Wooldridge, 2016). Here, the marginal impact of heat on yield depends on water availability; also, the marginal impact of water on yield depends on heat. This is called conditional marginal impact. A key empirical challenge arises when estimating the model with daily interaction of heat and soil moisture. A simple multiplicative interaction of soil moisture variable and heat variables will be problematic (Hainmueller et al., 2019). It implies a linear interaction effect that changes at a constant rate with heat. However, as will be shown below, soil moisture has a non-linear marginal effect. We take two approaches here to calculate the conditional marginal impact of heat on corn yields to address the challenges of aggregating daily soil moisture to seasonal water availability metrics.

First, we construct a binning estimator based on daily interaction on heat and soil moisture in model (2-a). We define several intervals of soil moisture (SM) represented by daily dummy variables and we interact these dummy variables with the daily excess heat index of 29ºC. Also, we take 25 mm intervals for soil moisture deviation from normal. In other words, we split the degree days into degree days conditional to soil moisture conditions. This includes dday29˚C & SM 75+ mm below normal (extreme deficit), dday29˚C & SM 25-75 mm below normal (deficit), dday29˚C & SM 0-25 mm around normal (normal), dday29˚C & SM 25-75 mm above normal (surplus), and dday29˚C & SM 75+ mm above normal (extreme surplus). We estimate a coefficient for each combination of excess heat and soil moisture; ie., we estimate a model with metrics of degree days while controlling for soil moisture. The model provides the conditional marginal impact of excess heat as:

$$y_{it} = \alpha D_{it}^{10-29} + \left\{ \sum_m \beta_m D_{mit}^{29} \right\} + \delta M_{it} + \delta' M_{it}^2 + \lambda_s t + \lambda'_s t^2 + c_i + \varepsilon_{it} \qquad (11)$$

where i is the county index, t is the time index, m is an index of soil moisture condition (high, low, normal), s is an index for states, y is average corn yields, D represents conditional growing degree day variables, M shows the seasonal mean soil moisture content, T stands for the time trend variable, c_i is a time-invariant county fixed effect. Here, β is indexed by m; i.e., the marginal impact of heat is conditional to soil moisture conditions. $\alpha, \beta, \delta, \lambda$ are the regression parameters showing the marginal impacts.

Second, we estimate a model with metrics of soil moisture while controlling for temperature in model (2-b). We define an index of soil moisture when the temperature is above the threshold and an index of soil moisture when the temperature is below the threshold. In this model, the soil moisture is separated by a temperature threshold H^*.

$$y_{it} = \alpha D_{it}^{10-29} + \beta D_{it}^{29} + \left\{ \sum_m \delta_m M_{mit}\big|_{H<H^*} + \delta'_m M_{mit}\big|_{H>H^*} \right\} + \lambda_s t + \lambda'_s t^2 + c_i + \varepsilon_{it} \qquad (12)$$

where i is the county index, t is the time index, m is an index of soil moisture condition, s is an index for states, y shows average corn yields, D represents growing degree day variables, M shows conditional seasonal mean soil moisture, T stands for the time trend variable, H is the average daily temperature, H^* is the temperature threshold, and c_i is a time-invariant county fixed effect. Here, we define δ and δ' to test whether the marginal impact of soil moisture depends on heat. The soil moisture metrics are calculated from daily gridded data and aggregated to county and growing season. This includes the index of normal soil moisture (*SM* 0-25+ mm around normal) when $H > H^*$, the index of normal soil moisture when $H < H^*$, the index of moisture deficit (*SM* 25+ mm below normal) when $H > H^*$, index of moisture deficit when $H < H^*$, the index of moisture surplus (*SM* 25+ mm above normal) when $H > H^*$, and the index of moisture surplus when $H < H^*$. $\alpha, \beta, \delta, \lambda$ are the regression parameters showing the marginal impacts.

2.5 Decomposition method

To show the significance of weather variation for crop yields, we estimate the historical impacts of heat and water. In a general form, we can decompose the impacts by taking the total derivative from the yield function. The general form is:

$$dy = \underbrace{\frac{\partial y}{\partial h} dh}_{\text{heat impacts}} + \underbrace{\frac{\partial y}{\partial m} dm}_{\text{water impacts}} \tag{13}$$

where dy shows the deviation of crop yields from the trend, dh is the deviation of heat from thehistorical mean; and dm is the deviation of soil moisture from normal levels. We apply this to Model (2-a) while the trend is estimated assuming no variation in heat and water availability. We predict the overall variation in yields using the estimated coefficients of Model (2-a):

$$d\hat{y} = \frac{\partial y}{\partial D^{10-29}} dD^{10-29} + \sum_m \frac{\partial y}{\partial D^{29}_m} dD^{29}_m + \frac{\partial y}{\partial M} dM + \frac{\partial y}{\partial M^2} dM^2 \tag{14}$$

where d shows the differential, $d\hat{y}$ is the predicted variation of crop yields, and partial derivatives are the estimated coefficients. Then, we re-predict the yields using the estimated coefficients of Model (2-a) for normal soil moisture. Thus, the predicted variation in crop yields is driven only by the variation in observed heat.

$$d\hat{y}^{heat} = \frac{\partial y}{\partial D^{10-29}} dD^{10-29} + \frac{\partial y}{\partial D^{29}_{nl}} dD^{29} \tag{15}$$

Finally, the difference between (14) and (15) shows the predicted impact of variation in water.

$$d\hat{y}^{water} = d\hat{y} - d\hat{y}^{heat} \tag{16}$$

Note that the deviations are calculated for each year.

3 Results

The overall simulation results from WBM are illustrated in Fig. 2-4, showing gridded historical mean for the cultivated continental US, average annual variations for the cultivated continental US, and bivariate distribution of soil moisture and heat for the corn growing grid cells. To illustrate the spatial heterogeneity, Fig. 2 shows the growing season mean soil moisture content (in mm in 1000 mm topsoil) as calculated based on daily root-zone soil moisture level from Apr-Sep for 1981-2015 at 2.5 x 2.5 arcmin grids excluding non-cultivated area. Average growing season soil moisture is heterogeneous across the Continental US, with distinct regional patterns (see Fig. 2). For the corn belt, the soil moisture level is relatively high compared to other regions. The mean of volumetric soil moisture ranges from below 50 mm in southern California to above 250 mm in the Corn Belt and around Mississippi.

To compare the variation of simulated soil moisture and precipitation, Fig. 3 illustrates the weighted average soil moisture and precipitation over the cultivated US for 1981-2015. In general, variation in soil moisture average is higher than in that of precipitation (Fig. 3), showing how this new water metric is different from previous approaches. One interesting finding is that for some years the mean precipitation and the mean soil moisture move in opposite directions. For example, in 1990 the mean precipitation is declined by around 5% while the mean soil moisture is increased by around 13%.

To show the dynamics of soil moisture and heat, Fig. 4 shows their bivariate distribution by month based on daily information for all the cultivated grid cells in the US Corn Belt for 1981-2015. Heat and soil moisture combinations vary through the growing season (Fig. 4) The data shows significant month-to-month variation, with the second half of the season facing hotter and dryer days. Also, July has the highest variation in soil moisture deviation with a high probability of compound extremes as the distribution moves toward the lower right.

Below, we describe the regression results from each individual model, and compare their performance to identify which metrics are important to include in the statistical estimate of corn yields. The central finding is that metrics of soil moisture extremes are statistically significant, and models including intensity, duration, and severity metrics (as illustrated in Fig. 1) better capture both mean and variation in U.S. corn yields. This point is illustrated in Fig. 5, which compares Model 1a to Model 2a: each model estimates the percentage change in corn yields assuming additional 10 degree-days above 29˚C and no change in mean soil moisture. The figure shows that Model (1) would significantly underestimate the damage for conditions with extreme water surplus or extreme water deficit.

3.1 Model (1): predicting yield responses to individual extremes

The results from Model (1-a) show a strong relationship between corn yields and heat and precipitation (Table 2 column 1-a). The marginal impact of a degree-day within 10-29˚C is significantly positive while that from an additional degree day above 29˚C is strongly negative, confirming the seminal findings of Schlenker and Roberts (2009).

The results from Model (1-b), excluding precipitation, shows the marginal relationship with soil moisture is also significant (Table 2 column 1-b). This confirms the findings of Ortiz-Bobea et al. (2019). It shows that the marginal relationship with soil moisture is increasing up to ~92 mm in 1000 mm topsoil and decreasing for higher values.

In Model (1-c), we consider the number of days that soil moisture is either too high or too low. The model with metrics of soil moisture extremes further improves the fit, revealing a negative marginal relationship associated with the number of days with low/high soil moisture. Regarding Model (1-c), the coefficient on the number of days with low moisture is also significant and negative. Our estimation sample shows 26 days of high soil moisture and 27 days of low soil moisture on average. The implication is that eliminating 25 days of high soil moisture and 25 days of low soil moisture can improve the corn yields by up to 12.6%.

Model (1-d) shows the estimated coefficients when considering surplus and deficit (soil moisture deviation from normal) instead of average seasonal soil moisture. Here, we consider two thresholds for low and high soil moisture. Returning to Fig. 1, we evaluate the area of all blue bars and the area of all red bars. It shows that the marginal impact of the moisture deficit (cumulative negative soil moisture deviation) is significant and positive. This indicates the positive contribution of additional soil moisture when the soil moisture levels are below normal. On the other hand, the marginal impact of additional soil moisture in a wet period – i.e., a positive soil moisture deviation -- is negative. In other words, this measure captures the fact that plants will benefit from reductions in soil moisture when the soil moisture levels are above normal. This is an indicator of the value of sub-surface drainage for agriculture. Note that the Model (1-d) decreases the marginal relationship with extreme heat (dday29˚C). However, this effect is not statistically different from that produced by the first model.

The coefficient of the deficit in Model (1-d) is significant and positive. On the other hand, the coefficient of the extreme deficit is also significant and positive. The estimation sample shows this metric is around 2300 mm on average. It indicates that reducing the deficit by 2300 mm and reducing the surplus by the same amount can improve the corn yield by up to 21.2% on average. Note the mean soil moisture can stay unchanged in this scenario.

3.2 Model (2): predicting yield responses to compound extremes

In Model (2-a) we introduce heat-soil moisture interactions to test whether soil moisture availability changes the marginal impact of heat on yields (estimation results are in Table 3). We find that the average marginal impacts of dday29˚Cs (heat stress) are all significant. The coefficient on dday29˚C combined with the extreme deficit is -0.0082. The coefficient of ddays29˚C (heat stress) combined with extreme water surplus is -0.0140. These figures are significantly different compared to Model (1).

We estimate a model with soil moisture while controlling for temperature (2-b). The results are presented in Table 4. The coefficient of degree days from 10˚C to 29˚C is significant and positive. This is not significantly different from previous models (1-a, 1-b, 1-c, 1-d, and 2-a). The coefficient on degree days above 29˚C is significant and negative. It is close to the estimated values from Model (2-a) but slightly lower than Model (1). This indicates that the average damage from extreme heat index (dday29˚C) is around 25% lower than Model (1). The estimated parameters show the yield response to changes in soil water content. Comparing the parameter values can show the difference in yield response to soil moisture in hot weather and moderate weather. The coefficient on normal soil moisture conditional to hot weather is 0.00012. The coefficient on normal soil moisture conditional to moderate weather is 0.00003. This indicates that the yield response to water is up to four times higher in hot weather. The marginal impact on soil moisture deficit index is 0.00009 in hot weather and is 0.00002 in moderate weather. This also supports the finding that water is up to four times more beneficial to corn yields in hot weather. Also, the results show that the damage from excess water is up to two times larger in hot weather.

3.3 Model comparison

A comparison of model performance metrics is given in Table 5, along with a description of the water metric and the extreme metric used in each model. We find that for Model 1b-d and Model 2a-d the coefficients on the soil moisture metrics are significant and with expected signs. Comparing the models' performance suggests that Model (1-b), with mean soil moisture, performs better than the Model (1-a), with cumulative precipitation. Also, Model (1-d), with the extreme soil moisture metrics, outperforms both previous models (with cumulative precipitation or with mean soil moisture). The best corn yield predictor is from Models (2-a) and (2-b), considering compound extremes through the daily interaction of heat and soil moisture. We find that using a seasonally averaged soil moisture metric is insufficient for capturing yield extremes; i.e., the temporal resolution of the soil moisture metric is important for estimating corn yield variability. Figure 6 illustrates the difference by comparing the modeled impacts of average soil moisture (Model 1-b) on corn yields (Panel a) to the impacts considering the deviation from normal soil moisture (Model 1-d) estimated for a sandy soil type (Panel b) and a clay soil type (Panel c). In other words, when parametrizing the soil moisture as a deviation from normal, we get a specific piece-wise linear yield response to water depending on soil types (and normal levels of soil moisture), the extremes of which are completely missed by the model that only uses mean soil moisture. We find that *the average corn yield damage from excess heat is up to four times more severe when combined with water stress.* This damage can only be estimated when including soil moisture and metrics of extreme water stress (e.g., Models 2a-d).

3.4 Decomposing the variation in US corn yields

We have decomposed the changes in the US corn yields from 1981 to 2015 to understand the relative roles of soil moisture and heat in interannual corn yield variation. Figure 7 illustrates a decomposition based on our findings while aggregated for the whole US. With no climate variation, the US corn yield is expected to have a smooth positive trend as shown in green color. The deviation from the trend occurs due to changes in water and heat stressors. The blue bars are showing the expected changes in US corn yields due to changes in the water stress while the orange bars are demonstrating the expected yield changes due to changes in heat stress. While there have been years in which the stressors have moved together (e.g. 2011 and 2012), for several years water and heat have offset each other's benefit or damage. For example, in 1992 the damage from heat is partially offset by benefits from water. Or in 2010, the damage from water stress is partially offset by benefits from heat.

3.5 Robustness checks

The Supplementary Material provides several robustness checks. The goal is to investigate whether different assumptions can improve the predictive power of Model (1) such that it outperforms Model (2). We answer three questions. First, are the estimation results from Model (1) different from those using alternative water metrics from WBM output? Second, are the estimates in Model (1) different from those obtained using a model considering growth stages? And third, do the main findings change if we alter the geographical scope of the study?

For the first robustness question, alternative water metrics, we re-estimate Model (1) using daily evapotranspiration (which is related to the water requirements of plants) and soil moisture fraction. Overall, the findings remain robust to alternative soil moisture metrics from WBM including the mean of soil moisture fraction (soil moisture content divided by field capacity), the seasonal mean of evapotranspiration as well as within season standard deviation of them. We also look at the results using an alternative interpolation of WBM data to PRISM resolution (nearest neighbor versus bilinear interpolations). We reject the null hypothesis that the coefficient on yield response to heat is different between these two metrics. Also, we reject the null hypothesis that the prediction power across these models is higher than Model (2).

To test the second robustness question, time separability, we re-estimate Model (1-b) for two-month intervals (Apr-May, Jun-Jul, Aug-Sep), and the findings remain robust. We find that considering bi-monthly variables does not change the yield response to heat. Although this alternative formulation does improve the predictive power of Model (1-b) a little bit, the performance is not better than the original Models (2-a) and (2-b) with compound extremes.

To test the sensitivity of our findings to geographical area, we re-estimate the models for Eastern US and Western US. We find that the estimated coefficients of Models (1-a) and (1-b) are not robust to the geographical choice, while those of Model (2) remain robust.

4 Discussion

In this paper, we have identified new water availability metrics that improve the predictive power of statistical corn yield models. While predictive power is an important outcome of this analysis, the insights gained from incrementally adding higher temporal-resolution metrics of water extremes to the models are also valuable for understanding the drivers of corn yield variability, and for revealing the resolution of water availability data required to capture future extremes under climate change scenarios. Statistical crop models have been used to both elucidate drivers of crop yield trends and variability, and to evaluate potential climate change impacts on crop production in the future (e.g., Lobell and Burke, 2010; Diffenbaugh et al. 2012). However, these models typically use seasonally averaged water availability metrics (e.g., total growing season precipitation), and utilize precipitation more often than soil moisture. Generally, if the location of the study does not expect a significant change in the within-season distribution of the soil moisture, a mean soil moisture index will work. However, if there is an expected change in this distribution, using the mean variable will create biased yield projections. Because climate models project significant changes in the frequency and intensity of both extreme precipitation and temperature (Bevacqua et al., 2019; Manning et al., 2019; Myhre et al., 2019; Poschlod et al., 2020; Potopová et al., 2020; Wehner, 2019; Zscheischler et al., 2018), the results presented here show that the mean metrics of water availability – especially mean precipitation - are not sufficient to capture the impacts on yields. It is necessary to consider the metrics of extreme events as illustrated in Fig. 1. As we find that the coefficient on extreme heat is significantly different when considering soil moisture. it is possible that previous climate impact studies have over- or under-estimated the yield impacts. Further, farm management practices can alter soil moisture – and therefore yields – independent of precipitation. Supplemental irrigation, as well as no-till farming, cover cropping, and soil conservation, can increase soil moisture. These adaptations may occur in places predicted to face higher mean precipitation coupled with more extreme water events. The results of these management practices cannot be captured by statistical models looking at precipitation metrics alone. Such precipitation-based studies could potentially lead to over-estimation yield damages under future climate extremes by not accounting for human adaptations designed to conserve soil moisture.

Applying this framework to climate impact studies will face a key challenge – namely projecting the future compound extremes with the high temporal resolution of Model 2. It requires collaboration between hydrologists, climate scientists, and statisticians (Zscheischler et al., 2020). For future yield projections, we need reliable future projections of daily temperature (maximum and minimum) and soil moisture. Unfortunately, to the best of our knowledge, available data sets including predictions of future soil moisture have a relatively coarse spatial and temporal resolution, and rely on climate model projections with known difficulties representing daily temporal resolution events (Hempel et al., 2013). Further research is required to improve the ability of climate models and impact models in projecting the bivariate distribution of heat-moisture (Sarhadi et al., 2018).

5 Conclusions

This study serves to bridge the gap between statistical studies of climate impacts on crops and their biophysical counterparts by recognizing the central role of soil moisture – which is not a simple linear transformation of precipitation – in understanding crop yields. We employ a fine-scale, high temporal resolution dataset to investigate the conditional marginal value of soil moisture and heat in US corn yields for the 1981-2015 period employing a statistical framework. The major contribution of this study is showing that the coefficient on extreme heat (dday29˚C) is significantly different while considering daily interactions with soil moisture, emphasizing the importance of compound hydroclimatic conditions.

Our first key finding is that seasonal mean soil moisture performs better than average precipitation in statistically predicting corn yield. While the majority of current empirical studies employ precipitation as a proxy of water availability for crops, we show that the precipitation coefficient may not be always an appropriate measure of water availability. This study suggests that soil moisture content should be used in estimating crop yields instead of cumulative rainfall for locations with high runoff, drainage, or irrigation (e.g. Western and Central US).

Also, the metrics of soil moisture extremes can explain a portion of the damages to corn yield. On average, farmers can improve corn yields by up to 24% only by avoiding extreme water stress. We also find that the coefficient of excess soil moisture is negative. This is in line with the current agronomic literature (Torbert et al., 1993; Urban et al., 2015) which points out that high soil moisture content can result in nutrient loss through excess water flows. In addition, at high humidity, the plants may have difficulty remaining cool at high temperatures. There is also a risk of waterlogging soils. With a few notable exceptions (e.g., rice), most crops do not grow well in inundated conditions as the plant roots need oxygen, so the direct impact of excess water stress is because of the anoxic conditions.

Finally, the marginal impact of heat index on crop yields depends on the soil moisture level. We show the average yield damage from heat stress is up to four times more severe when combined with water stress; and therefore the value of water in maintaining crop yield is up to four times larger on hot days.

Code availability. The codes are available at DOI:10.4231/Q07D-J369.

Data availability. The historical weather data (PRISM) is available at http://www.prism.oregonstate.edu. The input data for estimations are available at DOI:10.4231/0M14-EY38.

Author contribution. All authors contributed to conceptualization, methodology, formal analysis, and writing- review & editing. IH and DSG collected model input, performed the simulations, and contributed to the investigation, resources, software, and validation. IH contributed to writing the original draft and visualization. TWH contributed to supervision and funding acquisition.

Competing interests. The authors declare that they have no conflicts of interest.

Acknowledgement. This work was supported by the U.S. Department of Energy, Office of Science, Biological and Environmental Research Program, Earth and Environmental Systems Modeling, MultiSector Dynamics, Contract No. DE-SC0016162. The database construction process is done employing high-performance computing solutions of Institute for CyberScience Advanced CyberInfrastructure (ICS-ACI) at Penn State University.

References

Allen, R. G., Pereira, L. S., Raes, D. and Smith, M.: Crop evapotranspiration-Guidelines for computing crop water requirements-FAO Irrigation and drainage paper 56, Fao Rome, 300(9), D05109, 1998.

Bevacqua, E., Maraun, D., Vousdoukas, M. I., Voukouvalas, E., Vrac, M., Mentaschi, L. and Widmann, M.: Higher probability of compound flooding from precipitation and storm surge in Europe under anthropogenic climate change, Sci. Adv., 5(9), eaaw5531, doi:10.1126/sciadv.aaw5531, 2019.

Blanc, E. and Schlenker, W.: The use of panel models in assessments of climate impacts on agriculture, Rev. Environ. Econ. Policy, 11(2), 258–279, 2017.

Boryan, C., Yang, Z. and Di, L.: Deriving 2011 cultivated land cover data sets using usda national agricultural statistics service historic cropland data layers, in 2012 IEEE International Geoscience and Remote Sensing Symposium, pp. 6297–6300, IEEE., 2012.

Bradford, J. B., Schlaepfer, D. R., Lauenroth, W. K., Yackulic, C. B., Duniway, M., Hall, S., Jia, G., Jamiyansharav, K., Munson, S. M., Wilson, S. D. and Tietjen, B.: Future soil moisture and temperature extremes imply expanding suitability for rainfed agriculture in temperate drylands, Sci. Rep., 7(1), 12923, doi:10.1038/s41598-017-13165-x, 2017.

Burke, M. and Emerick, K.: Adaptation to climate change: Evidence from US agriculture, Am. Econ. J. Econ. Policy, 8(3), 106–40, 2016.

Comas, L. H., Trout, T. J., DeJonge, K. C., Zhang, H. and Gleason, S. M.: Water productivity under strategic growth stage-based deficit irrigation in maize, Agric. Water Manag., 212, 433–440, doi:10.1016/j.agwat.2018.07.015, 2019.

Denmead, O. T. and Shaw, R. H.: The Effects of Soil Moisture Stress at Different Stages of Growth on the Development and Yield of Corn 1, Agron. J., 52(5), 272–274, doi:10.2134/agronj1960.00021962005200050010x, 1960.

Diffenbaugh, N. S., Hertel, T. W., Scherer, M. and Verma, M.: Response of corn markets to climate volatility under alternative energy futures, Nat. Clim. Change, 2(7), 514–518, doi:10.1038/nclimate1491, 2012.

Federer, C. A., Vörösmarty, C. and Fekete, B.: Intercomparison of methods for calculating potential evaporation in regional and global water balance models, Water Resour. Res., 32(7), 2315–2321, 1996.

Fischer, G., Nachtergaele, F., Prieler, S., Van Velthuizen, H. T., Verelst, L. and Wiberg, D.: Global agro-ecological zones assessment for agriculture (GAEZ 2008), IIASA Laxenburg Austria FAO Rome Italy, 10, 2008.

Fishman, R.: More uneven distributions overturn benefits of higher precipitation for crop yields, Environ. Res. Lett., 11(2), 024004, 2016.

Grogan, D.: Global and regional assessments of unsustainable groundwater use in irrigated agriculture, Dr. Diss. [online] Available from: https://scholars.unh.edu/dissertation/2, 2016.

Hainmueller, J., Mummolo, J. and Xu, Y.: How much should we trust estimates from multiplicative interaction models? Simple tools to improve empirical practice, Polit. Anal., 27(2), 163–192, 2019.

Hamon, W. R.: Computation of direct runoff amounts from storm rainfall, Int. Assoc. Sci. Hydrol. Publ., 63, 52–62, 1963.

Hauser, M., Thiery, W. and Seneviratne, S. I.: Potential of global land water recycling to mitigate local temperature extremes, Earth Syst. Dyn. Discuss., 1–18, doi:https://doi.org/10.5194/esd-2018-48, 2018.

Hempel, S., Frieler, K., Warszawski, L., Schewe, J. and Piontek, F.: A trend-preserving bias correction–the ISI-MIP approach, 2013.

Hsiang, S.: Climate econometrics, Annu. Rev. Resour. Econ., 8, 43–75, 2016.

Jones, J. W., Antle, J. M., Basso, B., Boote, K. J., Conant, R. T., Foster, I., Godfray, H. C. J., Herrero, M., Howitt, R. E. and Janssen, S.: Brief history of agricultural systems modeling, Agric. Syst., 155, 240–254, 2017.

Kaur, G., Nelson, K. A. and Motavalli, P. P.: Early-Season Soil Waterlogging and N Fertilizer Sources Impacts on Corn N Uptake and Apparent N Recovery Efficiency, Agronomy, 8(7), 102, doi:10.3390/agronomy8070102, 2018.

Li, G., Zhao, B., Dong, S., Zhang, J., Liu, P. and Vyn, T. J.: Impact of controlled release urea on maize yield and nitrogen use efficiency under different water conditions, PLOS ONE, 12(7), e0181774, doi:10.1371/journal.pone.0181774, 2017.

Liu, B., Asseng, S., Müller, C., Ewert, F., Elliott, J., Lobell, D. B., Martre, P., Ruane, A. C., Wallach, D. and Jones, J. W.: Similar estimates of temperature impacts on global wheat yield by three independent methods, Nat. Clim. Change, 6(12), 1130–1136, 2016.

Lobell, D. B. and Burke, M. B.: On the use of statistical models to predict crop yield responses to climate change, Agric. For. Meteorol., 150(11), 1443–1452, doi:10.1016/j.agrformet.2010.07.008, 2010.

Lobell, D. B., Hammer, G. L., McLean, G., Messina, C., Roberts, M. J. and Schlenker, W.: The critical role of extreme heat for maize production in the United States, Nat. Clim. Change, 3(5), 497–501, doi:10.1038/nclimate1832, 2013.

Manning, C., Widmann, M., Bevacqua, E., Loon, A. F. V., Maraun, D. and Vrac, M.: Increased probability of compound long-duration dry and hot events in Europe during summer (1950–2013), Environ. Res. Lett., 14(9), 094006, doi:10.1088/1748-9326/ab23bf, 2019.

McDonald, R. I. and Girvetz, E. H.: Two Challenges for U.S. Irrigation Due to Climate Change: Increasing Irrigated Area in Wet States and Increasing Irrigation Rates in Dry States, PLOS ONE, 8(6), e65589, doi:10.1371/journal.pone.0065589, 2013.

Meng, Q., Chen, X., Lobell, D. B., Cui, Z., Zhang, Y., Yang, H. and Zhang, F.: Growing sensitivity of maize to water scarcity under climate change, Sci. Rep., 6, 19605, doi:10.1038/srep19605, 2016.

Myhre, G., Alterskjær, K., Stjern, C. W., Hodnebrog, Ø., Marelle, L., Samset, B. H., Sillmann, J., Schaller, N., Fischer, E., Schulz, M. and Stohl, A.: Frequency of extreme precipitation increases extensively with event rareness under global warming, Sci. Rep., 9(1), 1–10, doi:10.1038/s41598-019-52277-4, 2019.

Ortiz-Bobea, A., Wang, H., Carrillo, C. M. and Ault, T. R.: Unpacking the climatic drivers of US agricultural yields, Environ. Res. Lett., 14(6), 064003, 2019.

Peichl, M., Thober, S., Meyer, V. and Samaniego, L.: The effect of soil moisture anomalies on maize yield in Germany, Nat. Hazards Earth Syst. Sci., 18(3), 889–906, doi:https://doi.org/10.5194/nhess-18-889-2018, 2018.

Poschlod, B., Zscheischler, J., Sillmann, J., Wood, R. R. and Ludwig, R.: Climate change effects on hydrometeorological compound events over southern Norway, Weather Clim. Extrem., 28, 100253, doi:10.1016/j.wace.2020.100253, 2020.

Potopová, V., Trnka, M., Hamouz, P., Soukup, J. and Castraveț, T.: Statistical modelling of drought-related yield losses using soil moisture-vegetation remote sensing and multiscalar indices in the south-eastern Europe, Agric. Water Manag., 236, 106168, doi:10.1016/j.agwat.2020.106168, 2020.

Rippey, B. R.: The US drought of 2012, Weather Clim. Extrem., 10, 57–64, 2015.

Rizzo, G., Edreira, J. I. R., Archontoulis, S. V., Yang, H. S. and Grassini, P.: Do shallow water tables contribute to high and stable maize yields in the US Corn Belt?, Glob. Food Secur., 18, 27–34, doi:10.1016/j.gfs.2018.07.002, 2018.

Roberts, M. J., Schlenker, W. and Eyer, J.: Agronomic Weather Measures in Econometric Models of Crop Yield with Implications for Climate Change, Am. J. Agric. Econ., 95(2), 236–243, doi:10.1093/ajae/aas047, 2013.

Sarhadi, A., Ausín, M. C., Wiper, M. P., Touma, D. and Diffenbaugh, N. S.: Multidimensional risk in a nonstationary climate: Joint probability of increasingly severe warm and dry conditions, Sci. Adv., 4(11), eaau3487, doi:10.1126/sciadv.aau3487, 2018.

Schlenker, W. and Roberts, M. J.: Nonlinear temperature effects indicate severe damages to US crop yields under climate change, Proc. Natl. Acad. Sci., 106(37), 15594–15598, 2009.

Schmidt, J. P., Sripada, R. P., Beegle, D. B., Rotz, C. A. and Hong, N.: Within-Field Variability in Optimum Nitrogen Rate for Corn Linked to Soil Moisture Availability, Soil Sci. Soc. Am. J., 75(1), 306–316, doi:10.2136/sssaj2010.0184, 2011.

Siebert, S. and Döll, P.: Quantifying blue and green virtual water contents in global crop production as well as potential production losses without irrigation, J. Hydrol., 384(3–4), 198–217, doi:10.1016/j.jhydrol.2009.07.031, 2010.

Siebert, S., Webber, H., Zhao, G. and Ewert, F.: Heat stress is overestimated in climate impact studies for irrigated agriculture, Environ. Res. Lett., 12(5), 054023, doi:10.1088/1748-9326/aa702f, 2017.

Tebaldi, C. and Lobell, D.: Differences, or lack thereof, in wheat and maize yields under three low-warming scenarios, Environ. Res. Lett., 13(6), 065001, 2018.

Torbert, H. A., Hoeft, R. G., Vanden Heuvel, R. M., Mulvaney, R. L. and Hollinger, S. E.: Short-term excess water impact on corn yield and nitrogen recovery, J. Prod. Agric., 6(3), 337–344, 1993.

Urban, D., Roberts, M. J., Schlenker, W. and Lobell, D. B.: Projected temperature changes indicate significant increase in interannual variability of U.S. maize yields, Clim. Change, 112(2), 525–533, doi:10.1007/s10584-012-0428-2, 2012.

Urban, D. W., Roberts, M. J., Schlenker, W. and Lobell, D. B.: The effects of extremely wet planting conditions on maize and soybean yields, Clim. Change, 130(2), 247–260, doi:10.1007/s10584-015-1362-x, 2015.

USDA-NASS: USDA-National Agricultural Statistics Service, Cropland Data Layer, U. S. Dep. Agric. Natl. Agric. Stat. Serv. Mark. Inf. Serv. Off. Wash. DC [online] Available from: http//nassgeodata. gmu. edu/Crop-Scape, 2017.

Wang, R., Bowling, L. C., Cherkauer, K. A., Cibin, R., Her, Y. and Chaubey, I.: Biophysical and hydrological effects of future climate change including trends in CO2, in the St. Joseph River watershed, Eastern Corn Belt, Agric. Water Manag., 180, 280–296, doi:10.1016/j.agwat.2016.09.017, 2017.

Wehner, M.: Estimating the probability of multi-variate extreme weather events, in Workshop on Correlated Extremes, Columbia University., 2019.

Williams, A., Hunter, M. C., Kammerer, M., Kane, D. A., Jordan, N. R., Mortensen, D. A., Smith, R. G., Snapp, S. and Davis, A. S.: Soil Water Holding Capacity Mitigates Downside Risk and Volatility in US Rainfed Maize: Time to Invest in Soil Organic Matter?, PLOS ONE, 11(8), e0160974, doi:10.1371/journal.pone.0160974, 2016.

Wing, I. S., Monier, E., Stern, A. and Mundra, A.: US major crops' uncertain climate change risks and greenhouse gas mitigation benefits, Environ. Res. Lett., 10(11), 115002, 2015.

Wisser, D., Fekete, B. M., Vörösmarty, C. J. and Schumann, A. H.: Reconstructing 20th century global hydrography: a contribution to the Global Terrestrial Network- Hydrology (GTN-H), Hydrol Earth Syst Sci, 14(1), 1–24, doi:10.5194/hess-14-1-2010, 2010.

WMO: The global climate 2001–2010: A decade of climate extremes, WMO-No 1103, 119, 2013.

Wooldridge, J. M.: Introductory econometrics: A modern approach, Nelson Education., 2016.

Zscheischler, J., Westra, S., Van Den Hurk, B. J., Seneviratne, S. I., Ward, P. J., Pitman, A., AghaKouchak, A., Bresch, D. N., Leonard, M. and Wahl, T.: Future climate risk from compound events, Nat. Clim. Change, 8(6), 469–477, 2018.

Zscheischler, J., van den Hurk, B., Ward, P. J. and Westra, S.: Multivariate extremes and compound events, in Climate Extremes and Their Implications for Impact and Risk Assessment, pp. 59–76, Elsevier., 2020.

Table 1. Major variables in each model of the study

	Heat metric (*h*)	Water metric (m)
Model 1: individual extremes		
1-a	dday 10˚C to 29˚C	Precipitation
	dday 29˚C	Square of Precipitation
1-b	dday 10˚C to 29˚C	Seasonal mean soil moisture content (SMavg)
	dday 29˚C	Square of seasonal mean soil moisture content
1-c	dday 10˚C to 29˚C	Number of days with low soil moisture (NDD)
	dday 29˚C	Number of days with high soil moisture (NDS)
1-d	dday 10˚C to 29˚C	Index of soil moisture above normal levels (CMS)
	dday 29˚C	Index of soil moisture below normal levels (CMD)
Model 2: compound extremes		
2-a	dday 10˚C to 29˚C	Seasonal mean soil moisture content
	dday 29˚C & SM 75+mm below normal	Square of seasonal mean soil moisture content
	dday 29˚C & SM 25-75 mm below normal	
	dday 29˚C & SM 0-25 mm around normal	
	dday 29˚C & SM 25-75 mm above normal	
	dday 29˚C & SM 75+ mm above normal	
2-b	dday 10˚C to 29˚C	SM 0-25+ mm around normal (CMN)when T > T*
	dday above 29˚C	SM 0-25+ mm around normal (CMN) when T < T*
		SM 25+ mm above normal (CEMS) when T > T*
		SM 25+ mm above normal (CEMS) when T < T*
		SM 25+ mm below normal (CEMD) when T > T*
		SM 25+ mm below normal (CEMD) when T < T*

Definitions: dday: degree days; SM: soil moisture; SMavg: seasonal mean soil moisture; NDD: number of days when the soil moisture content is more than 25 mm below normal levels; NDS number of days when the soil moisture content is more than 25 mm below normal levels; CMS index of moisture surplus; CMD: index of moisture deficit; CMN: index of normal soil moisture; CEMS index of extreme moisture surplus; CEMD: index of extreme moisture deficit.

Table 2. Corn yield estimation without the interaction of heat and soil moisture in Model 1 (a-d).

	(1-a) Log CornYield	(1-b) Log CornYield	(1-c) Log CornYield	(1-d) Log CornYield
Degree Days 10-29°C Apr-Sep	.000336***	.000343***	.0003486***	.0003083***
	(.000087)	(.00008)	(.0000725)	(.0000683)
Degree Days above 29°C Apr-Sep	-.005307***	-.005114***	-.005277***	-.005041***
	(.000673)	(.000691)	(.0006678)	(.0005999)
Precipitation Apr-Sep	.000658**			
	(.000254)			
Precipitation Apr-Sep Square	-5.16e-07**			
	(-9.35e-07)			
Seasonal Mean Soil Moisture Content		.003593***		
		(.000664)		
Seasonal Mean Soil Moisture Content Square		-.000017***		
		(3.000e-06)		
Number of days with SM 25+ mm above normal			-.001838***	
			(.0003816)	
Number of days with SM 25+ mm below normal			-.002089***	
			(.0002817)	
Index of Soil Moisture above Normal (mm)				-.000040***
				(2.800e-06)
Index of Soil Moisture below Normal (mm)				.000044***
				(7.100e-06)
Obs.	69923	69923	69923	69923
R-squared	0.4686	0.4714	0.4795	0.4914
AIC (Akaike's information criterion)	-21238.1	-21612.3	-22696.8	-24303.4
BIC (Bayesian information criterion)	-21201.4	-21575.7	-22660.2	-24266.8

Standard errors are in parenthesis & adjusted for state clusters
*** p<0.01, ** p<0.05, * p<0.1

Notes: Table lists regression coefficients and shows standard errors in brackets. The constant term and coefficients on the interaction of each state and time trends are not reported.

Table 3. Corn yield estimation while splitting heat stress index in Model 2a

	(2-a) Log CornYield
Degree days from 10˚C to 29˚C	.0003083*** (.0000685)
dday29˚C & SM 75+ mm below normal (extreme deficit)	-.0082398*** (.0014372)
dday29˚C & SM 25-75 mm below normal (deficit)	-.0062069*** (.0009793)
dday29˚C & SM 0-25 mm around normal (normal)	-.0037559*** (.0004045)
dday29˚C & SM 25-75 mm above normal (surplus)	-.0055709*** (.0012041)
dday29˚C & SM 75+ mm above normal (extreme surplus)	-.0140295*** (.0019083)
Mean daily soil moisture content (mm)	.0026635*** (.0008153)
Square of mean daily soil moisture content	-.0000161*** (2.600e-06)
Observations	69923
R-squared	.4921
Akaike's Crit	-24401.6
Bayesian Crit	-24328.3

Standard errors are in parenthesis & adjusted for state clusters
*** p<0.01, ** p<0.05, * p<0.1

Notes: Table lists regression coefficients and shows standard errors in brackets. The constant term and coefficients on the interaction of each state and time trends are not reported.

Table 4. Estimation of corn yields while splitting the soil moisture metrics in Model 2b

	(2-b) log CornYield
Degree days from 10˚C to 29˚C	.0003154*** (.0000689)
Degree days above 29˚C	-.004044*** (.0005384)
Index of normal soil moisture when T > T*	.0001199*** (.0000342)
Index of extreme moisture surplus when T > T*	-.0000628*** (.0000151)
Index of extreme moisture deficit when T > T*	.000092*** (.0000234)
Index of extreme moisture deficit when T < T*	.0000209*** (7.100e-06)
Index of extreme moisture surplus when T < T*	-.0000326*** (3.200e-06)
Index of normal soil moisture when T < T*	.000028** (.0000105)
Observations	69923
R-squared	.5006
Akaike's Crit	-25582.4
Bayesian Crit	-25509.2

Standard errors are in parenthesis & adjusted for state clusters
*** p<0.01, ** p<0.05, * p<0.1

Notes: Table lists regression coefficients and shows standard errors in brackets. The constant term and coefficients on the interaction of each state and time trends are not reported.

Table 5: Performance metrics for Models 1(a-d) and 2(a-b).

Model	Water metric	Extreme metric	R-squared	AIC (Akaike's information criterion)	BIC (Bayesian information criterion)
1-a	Avg. precipitation	Precipitation sqr	0.469	-21,238	-21,201
1-b	Avg. soil moisture	Soil moisture sqr	0.471	-21,612	-21,576
1-c	Avg. soil moisture	Number of days with low/high soil moisture	0.480	-22,697	-22,660
1-d	Avg. soil moisture	Avg soil moisture deficit/surplus	0.491	-24,303	-24,267
2-a	Avg. soil moisture	T binned by extreme deficit/surplus	0.492	-24,402	-24,328
2-b	normal soil moisture x T	extreme deficit/surplus x T	0.501	-25,582	-25,509

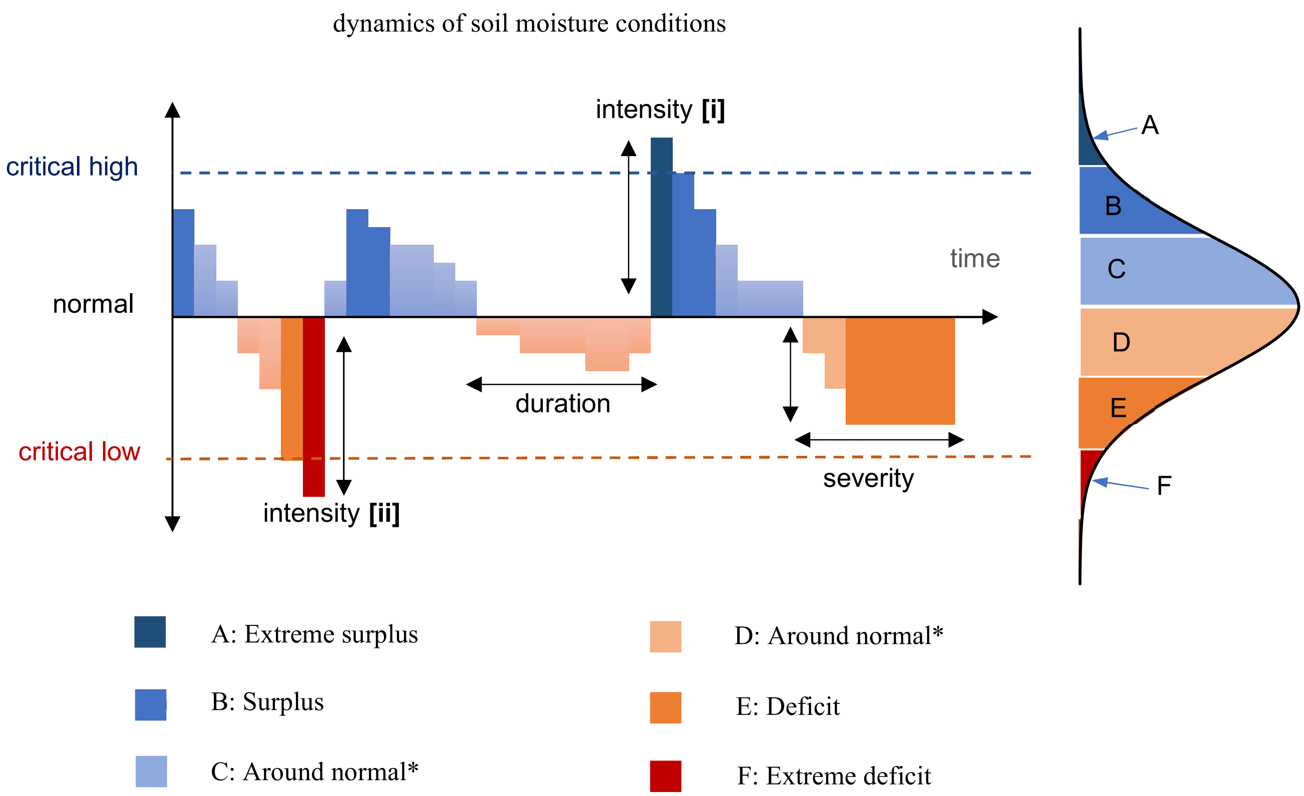


Figure 1. Soil moisture dynamics within a typical growing season. Some soil moisture conditions can be harmful to crops including excess wetness [i], moisture stress intensity[ii], duration of moisture stress [iii], and severity of soil moisture stress [iv].

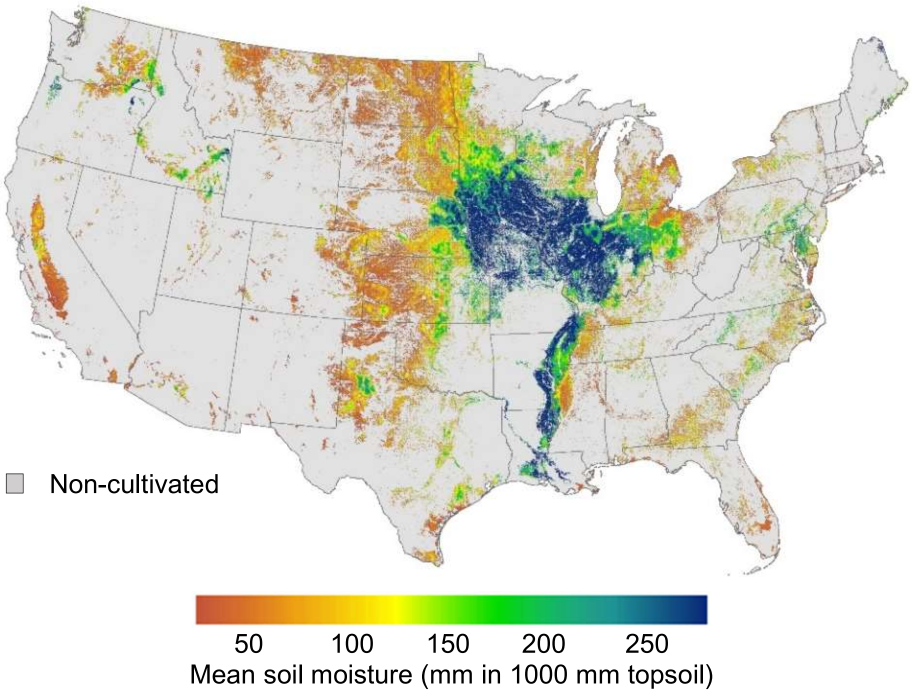


Figure 2. Growing season mean soil moisture content (in mm in 1000 mm topsoil) as calculated based on daily root-zone soil moisture level from Apr-Sep for 1981-2015 at 2.5 x 2.5 arcmin grids excluding non-cultivated area. The soil moisture level is obtained from the Water Balance Model (WBM) and non-cultivated area information is from USDA National Cultivated Layer. This map illustrates the heterogeneity of simulated soil moisture over the Continental US and even within states.

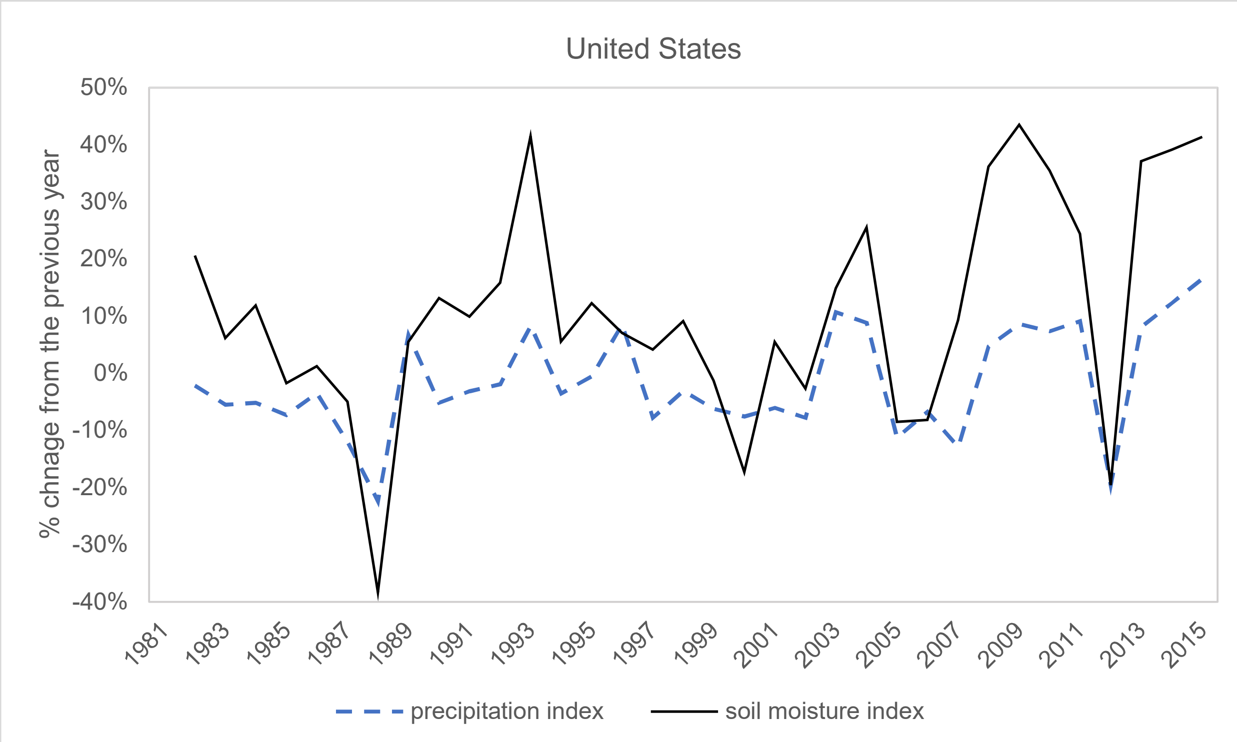
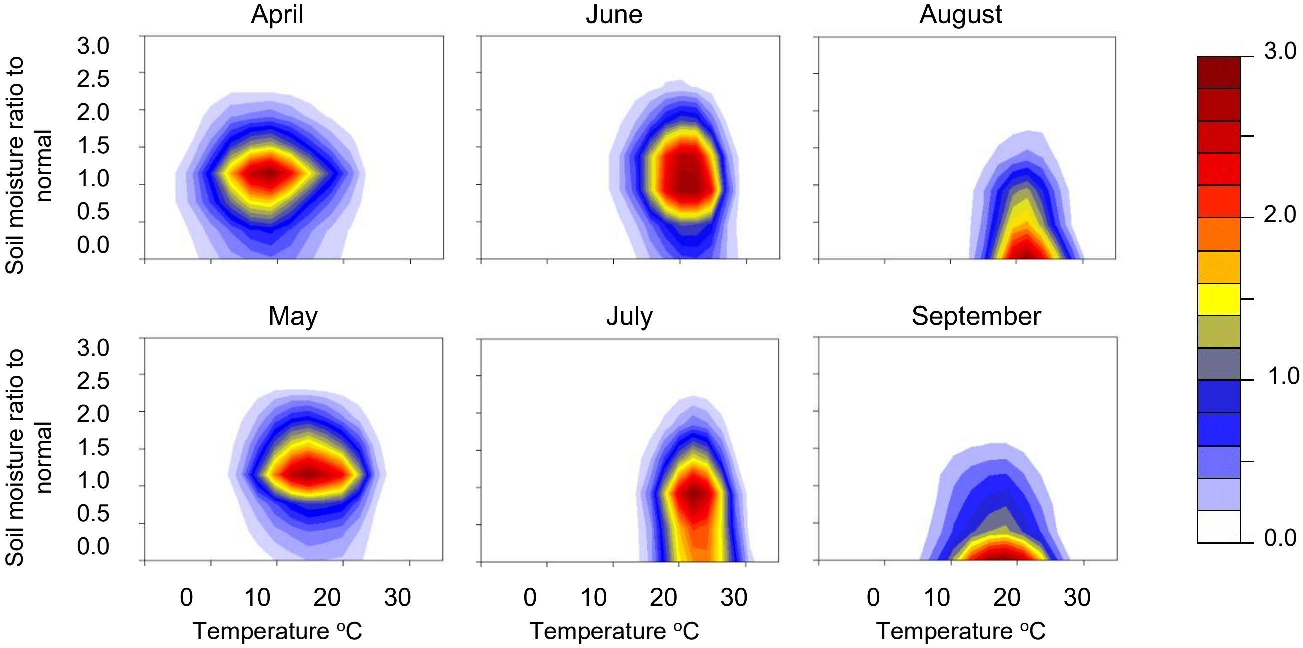


Figure 3. Variations of average precipitation versus average soil moisture over corn areas in the United States. The precipitation is aggregated from PRISM and soil moisture is aggregated from WBM from 2.5 arcmin grid cells weighted by cropland area.



710 **Figure 4. The bivariate density of heat and soil moisture for 1981-2015 For all the grid cells in the US Corn Belt. The precipitation is aggregated from PRISM and soil moisture is aggregated from WBM based on 2.5 arcmin grid cells.**

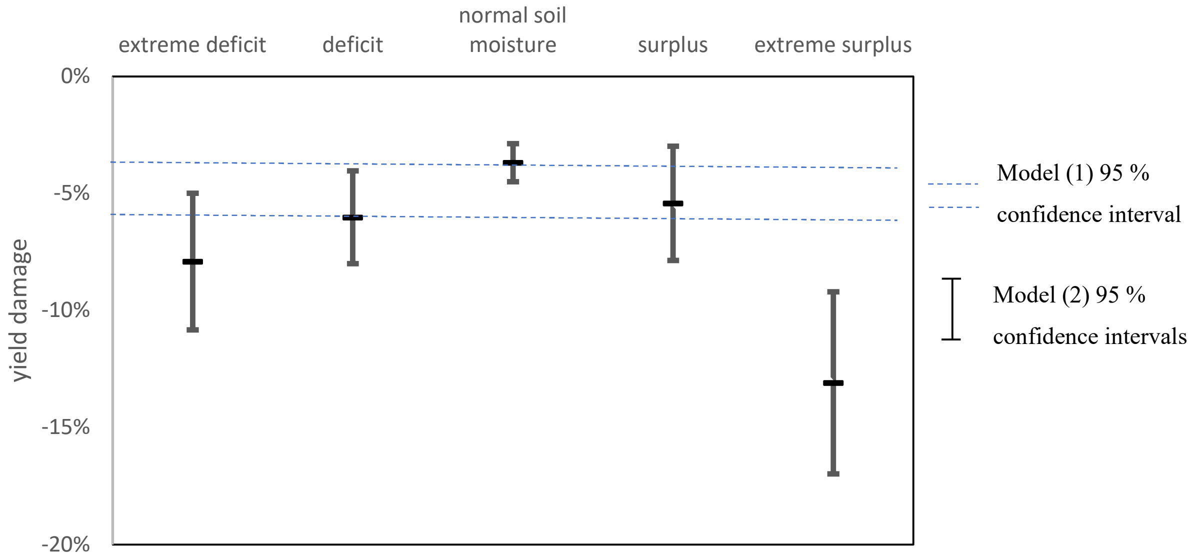


Figure 5. Estimated damage to corn yield from an additional 10 degree-days above 29˚C and no change in seasonal mean soil moisture.

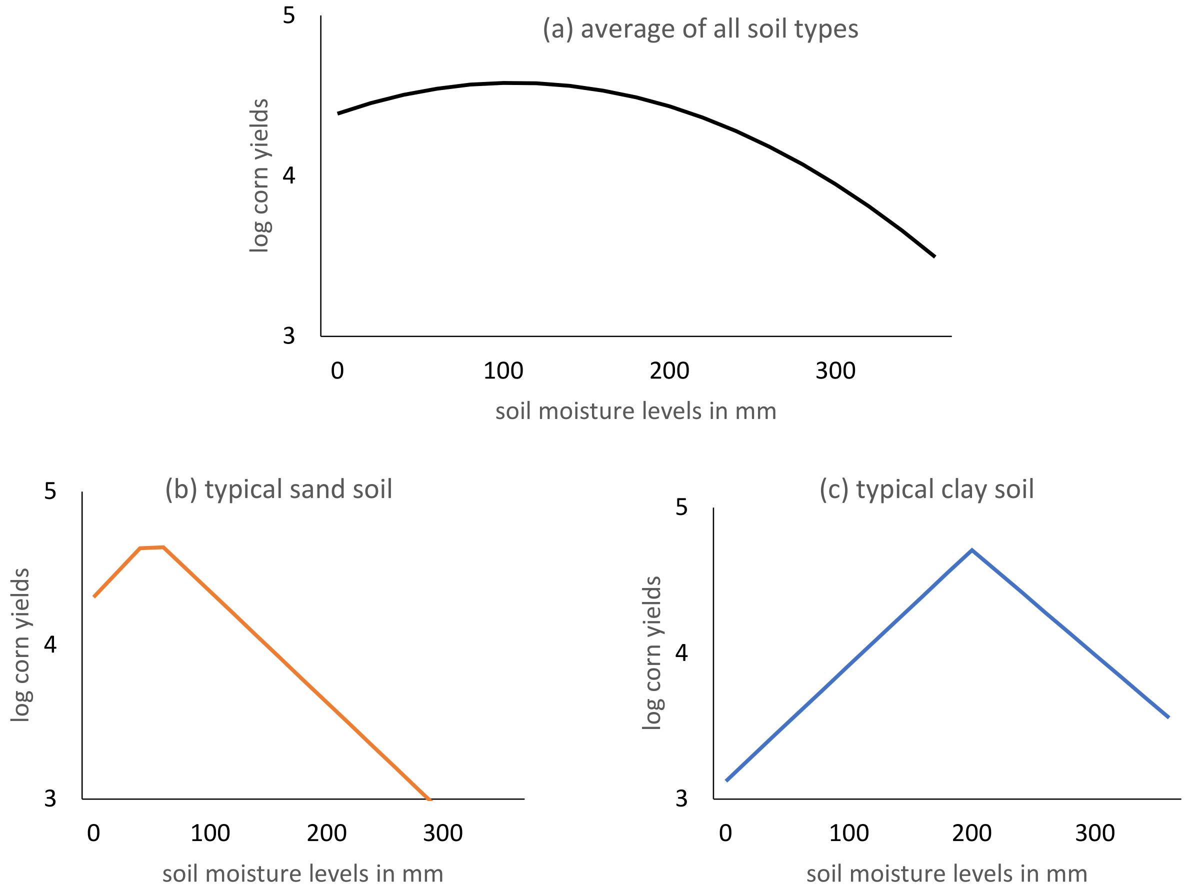


Figure 6. Estimated impact of soil moisture on log corn yields. Including soil moisture in the regression and its square term, as in model 1-b, will give us a quadratic relationship between soil moisture and yields as in panel (a). A piece-wise linear parametrization, as in model 1-d, can provide location-specific piece-wise linear relationship based on soil moisture deviation from normal as in panels (b) and (c). This will cause the maximum of the response curve to be in lower soil moisture levels for sand and in higher soil moisture levels for clay soil texture.

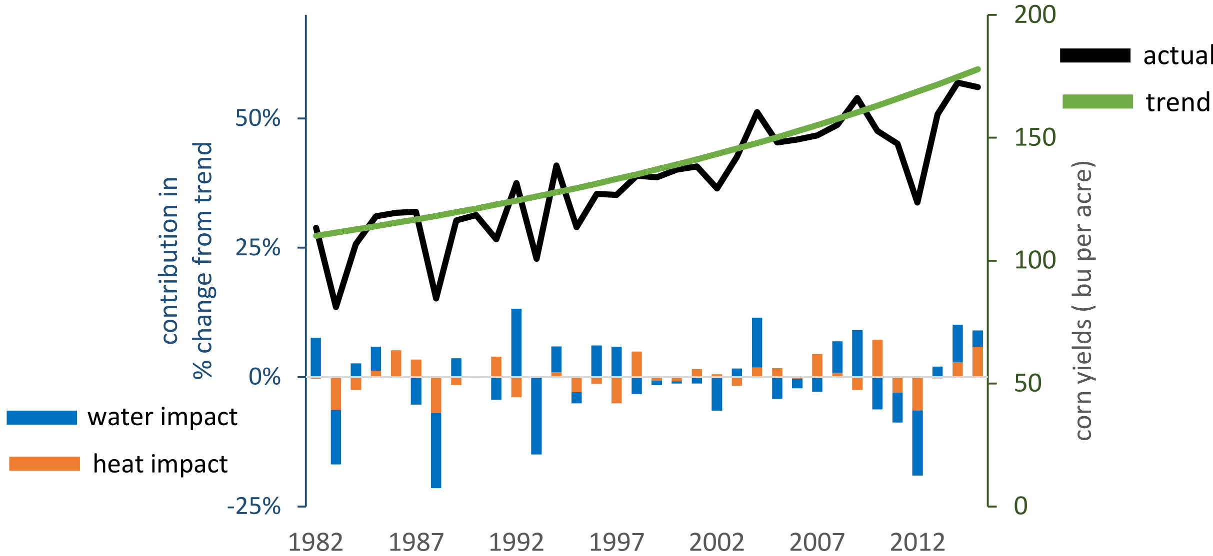


Figure 7. The bars show the "contribution of water" and "contribution of heat" in variation of US corn yields (left axis). The lines
725 illustrate actual yields and trend (right axis).

Supplementary Material

S.1. Overview

This material provides details on the soil moisture module, estimation strategy, decomposition method, and some robustness checks on the results and the model variables. Besides, this material illustrates the correlation between mean volumetric soil moisture and other potential seasonal variables that can be used as indicators of water availability. This includes cumulative precipitation, mean seasonal evapotranspiration, and mean seasonal soil moisture. It also provides some examples to demonstrate the seasonal mean soil moisture shows no linear relationship with the seasonal heat index (degree days above 10˚C). However, it has a positive correlation with evapotranspiration and soil moisture fraction. Then alternative models are introduced controlling for irrigation, growth periods, spatial scope of the study, and other measures of individual and compound extremes.

S.2. Soil moisture in the Water Balance Model

Here, we briefly describe WBM's soil moisture module. However, the model is much more complex and employs a large list of inputs. Full documentation for WBM can be found in Wisser et al. (2010) with updates in Grogan (2016). In WBM, crop-specific soil moisture balance within each grid cell is calculated with an accounting system that tracks a location's water inputs and outputs and is limited by the soil moisture pool's water holding capacity.

$$\frac{\delta W_s}{\delta t} = \begin{cases} g(Ws)(I - PET) \; if \; I < PET \\ I - PET \; if \; PET \le I \; and \; (I - PET) < (W_{cap} - W_s) \\ W_{cap} - W_s \; if \; PET \le I \; and \; (W_{cap} - W_s) \le (I - PET) \end{cases} \qquad \text{(s1)}$$

where W_s is soil moisture, t is time, I is the sum of all water inputs to the soil moisture pool, PET is potential evapotranspiration, and W_{cap} is available water capacity. Water inputs to the soil come in the form of precipitation as rain and as snowmelt. Water intercepted by the canopy reduces precipitation reaching the soil. Here, we use the Hamon method for estimating PET (Federer et al., 1996; Hamon, 1963), and $g(W_s)$ is 1 for all crops, while it is an exponential function of soil moisture depth for non-crop soil areas. Crop-specific potential evapotranspiration values, $PETc$, are calculated following the FAO-recommended crop-modeling methodology (Allen et al., 1998):

$$PET_c = k_c \cdot PET \qquad \text{(s2)}$$

where k_c [-] is a crop-specific, time-varying scalar. Crop scalar values are from Siebert and Döll (2010), and crop maps that identify the area of each rainfed crop type within a grid cell are from the Crop Data Layer (CDL, USDA NASS, 2017). When soil moisture is insufficient for crops to extract water equal to PET_c, actual crop evapotranspiration is limited to available soil water volumes. Available water capacity, W_{cap}, is a function of vegetation-specific rooting depth, a crop-specific depletion factor, soil field capacity, and soil wilting point:

$$W_{cap} = D_c R_c (F - W_p) \qquad \text{(s3)}$$

where D_c is the depletion factor for crop c, R_c is the rooting depth of crop c, F is the soil field capacity, and W_p is the soil wilting point. Here we use the Harmonized World Soil Database (Fischer et al., 2008) as model input for all soil properties. Corn rooting depth is set to 1 meter; and the depletion factor is 0.5, following Siebert and Döll (2010). Once the soil moisture content reaches field capacity, no further water is added to the soil moisture pool; excess inputs move to the groundwater pool via percolation and the river system via runoff.

S.3. Estimation strategy

Considering the exposure to each temperature interval to capture the marginal impact of heat and water on crop yields, we estimate the following for model (1-a):

$$y_{it} = \alpha D_{it}^{10-29} + \beta D_{it}^{29} + \delta_a P_{it} + \delta'_a P_{it}^2 + \lambda_s t + \lambda'_s t^2 + c_i + \varepsilon_{it} \qquad \text{(s4)}$$

where i is an index for counties, t is the index of time, s is the index for states, y_{it} is the log corn yields, D_{it} represents growing degree day variables, P shows cumulative precipitation over the growing season, t shows the time trend variable (t = year – 1950), c_i is a time-invariant county fixed effect, ε is the residual, and α, β, δ, λ are the regression parameters showing the marginal impacts. The subscript a is used to show the water coefficients (δ) are related to metrics in Model (1-a). To evaluate the importance of soil moisture metrics in Model (1-b), we estimate the following:

$$y_{it} = \alpha D_{it}^{10-29} + \beta D_{it}^{29} + \delta_b M_{it} + \delta'_b M_{it}^2 + \lambda_s t + \lambda'_s t^2 + c_i + \varepsilon_{it} \qquad \text{(s5)}$$

where the variables are defined as Model (1-a) except for the water availability metric. Here M shows the seasonal mean soil moisture index calculated as average daily root zone soil moisture from the first day of April to the end of September. The subscript b is used for δ to distinguish the water coefficients in Model (1-b). For Model (1-c) we estimate the following model:

$$y_{it} = \alpha D_{it}^{10-29} + \beta D_{it}^{29} + \delta_c NDD_{it}^{def} + \delta'_c NDS_{it}^{sur} + \lambda_s t + \lambda'_s t^2 + c_i + \varepsilon_{it} \qquad \text{(s6)}$$

where we replace seasonal mean or cumulative metrics with two new metrics to control the impacts of water extremes on corn yields. Here, NDD^{def} is the number of days that soil moisture is under 25 mm below normal levels (deficit); and NDS^{sur} is the number of days that soil moisture is higher than 25 mm above normal levels. The rest of the variables are defined as Model (1-a). The subscript c shows δ_c is specific to Model (1-c). Finally, we estimate the following equation for Model (1-d):

$$y_{it} = \alpha D_{it}^{10-29} + \beta D_{it}^{29} + \delta_d CMS_{it} + \delta'_d CMD_{it} + \lambda_s t + \lambda'_s t^2 + c_i + \varepsilon_{it} \qquad \text{(s7)}$$

where CMS is a cumulative measure of positive soil moisture deviations compared to the normal levels (equivalent to A+B+C in Fig. 1). And CMD is the cumulative measure of negative soil moisture deviations compared to the normal levels (equivalent to D+E+F in Fig. 1). The subscript d distinguished estimated δ from previous models.

We assume the errors are serially correlated due to unobservable and systematic measurement errors, and we consider clustering US counties by the state which has been a standard approach in the literature (Blanc and Schlenker, 2017; Hsiang, 2016; Lobell and Burke, 2010). In this study, the models are estimated using a panel fixed-effect approach. A panel fixed-effect approach is a statistical method for analyzing two-dimensional (e.g. time and location) panel data. This method is helpful for analyzing those data collected for the same locations over time with a relatively short time span (Wooldridge, 2016). As our data set contains information for counties over time, a panel data analysis is appropriate. In addition, a fixed-effect model is appropriate as there are unique biophysical and economic attributes of counties that can explain yield differences across counties and are not changing over time. When we conduct a statistical test (Hausman test), it rejects the random effects model in favor of the fixed effect models we use. The panel consists of 35 years (1981-2015) for all US counties with corn production. For purposes of model comparison, we provide adjusted R^2, Akaike's information criterion (AIC), and Bayesian information criterion (BIC).

For Model (2), we consider the daily interaction of heat and soil moisture as the compound metric. The interaction term is defined when the marginal impact of an explanatory variable depends on the magnitude of yet another explanatory variable (Wooldridge, 2016). Here, the marginal impact of heat on yield depends on water availability; also, the marginal impact of water on yield depends on heat. This is called conditional marginal impact. A key empirical challenge arises when estimating the model with daily interaction of heat and soil moisture. A simple multiplicative interaction of soil moisture variable and heat variables will be problematic (Hainmueller et al., 2019). It implies a linear interaction effect that changes at a constant rate with heat. However, as will be shown below, soil moisture has a non-linear marginal effect. We take two approaches here to calculate the conditional marginal impact of heat on corn yields to address the challenges of aggregating daily soil moisture to seasonal water availability metrics. Model (2-a) provides the conditional marginal impact of excess heat as:

$$y_{it} = \alpha D_{it}^{10-29} + \left\{ \sum_{m} \beta_m D_{mit}^{29} \right\} + \delta M_{it} + \delta' M_{it}^2 + \lambda_s t + \lambda'_s t^2 + c_i + \varepsilon_{it} \qquad \text{(s8)}$$

where i is the county index, t is the time index, m is an index of soil moisture condition (high, low, normal), s is an index for states, y is average corn yields, D represents conditional growing degree day variables, M shows the seasonal mean soil moisture content, T stands for the time trend variable, c_i is a time-invariant county fixed effect. Here, β is indexed by m; i.e., the marginal impact of heat is conditional to soil moisture conditions. α, β, δ, λ are the regression parameters showing the marginal impacts.

Second, we estimate a model with metrics of soil moisture while controlling for temperature in model (2-b). We define an index of soil moisture when the temperature is above the threshold and an index of soil moisture when the temperature is below the threshold. In this model, the soil moisture is separated by a temperature threshold H^*.

$$y_{it} = \alpha D_{it}^{10-29} + \beta D_{it}^{29} + \left\{ \sum_{m} \delta_m M_{mit}\big|_{H<H^*} + \delta'_m M_{mit}\big|_{H>H^*} \right\} + \lambda_s t + \lambda'_s t^2 + c_i + \varepsilon_{it} \qquad \text{(s9)}$$

where i is the county index, t is the time index, m is an index of soil moisture condition, s is an index for states, y shows average corn yields, D represents growing degree day variables, M shows conditional seasonal mean soil moisture, T stands for the time trend variable, H is the average daily temperature, H^* is the temperature threshold, and c_i is a time-invariant county fixed effect. Here, we define δ and δ' to test whether the marginal impact of soil moisture depends on heat.

S.4. Decomposition method

To show the significance of weather variation for crop yields, we estimate the historical impacts of heat and water. In a general form, we can decompose the impacts by taking the total derivative from the yield function. The general form is:

$$dy = \underbrace{\frac{\partial y}{\partial h} dh}_{\text{heat impacts}} + \underbrace{\frac{\partial y}{\partial m} dm}_{\text{water impacts}} \qquad \text{(s10)}$$

where dy shows the deviation of crop yields from the trend, dh is the deviation of heat from thehistorical mean; and dm is the deviation of soil moisture from normal levels. We apply this to Model (2-a) while the trend is estimated assuming no variation in heat and water availability. We predict the overall variation in yields using the estimated coefficients of Model (2-a):

$$d\hat{y} = \frac{\partial y}{\partial D^{10-29}} dD^{10-29} + \sum_m \frac{\partial y}{\partial D^{29}_m} dD^{29}_m + \frac{\partial y}{\partial M} dM + \frac{\partial y}{\partial M^2} dM^2 \qquad \text{(s11)}$$

where d shows the differential, $d\hat{y}$ is the predicted variation of crop yields, and partial derivatives are the estimated coefficients. Then, we re-predict the yields using the estimated coefficients of Model (2-a) for normal soil moisture. Thus, the predicted variation in crop yields is driven only by the variation in observed heat.

$$d\hat{y}^{heat} = \frac{\partial y}{\partial D^{10-29}} dD^{10-29} + \frac{\partial y}{\partial D^{29}_{nl}} dD^{29} \qquad \text{(s12)}$$

Finally, the difference between (14) and (15) shows the predicted impact of variation in water.

$$d\hat{y}^{water} = d\hat{y} - d\hat{y}^{heat} \qquad \text{(s13)}$$

Note that the deviations are calculated for each year.

S.5. Correlation of mean seasonal soil moisture and other variables

The soil moisture output from WBM is informed mainly by soil moisture memory, heat, precipitation, and many other time-variant and time-invariant information. In a statistical study, a natural first step is to look at the correlation between these variables. To show that mean soil moisture is a different metric than mean precipitation, we have plotted the annual mean soil moisture versus annual cumulative precipitation in Fig. S2. This figure is a scatter plot for US counties for the growing season from 1981 to 2015. The simple correlation coefficient between them is 0.44. This rejects the hypothesis that soil moisture is highly correlated with precipitation. As mean precipitation has a linear relationship with cumulative precipitation, it shows that mean soil moisture is a different metric than cumulative or mean precipitation.

We have taken two other variables from WBM including soil moisture fraction and evapotranspiration (ET). Also, we have interpolated WBM soil moisture using an alternative method (nearest neighbor method). Here, we plot these variables against the volumetric soil moisture content to illustrate the correlation and differences. As shown in Fig. S3 two interpolations of soil moisture are closely correlated by R= 0.9997. Figures S4 and S5 are the scatter plots of seasonal ET and seasonal mean soil moisture fraction against volumetric soil moisture. The figures show the seasonal variables are not following a simple linear relationship. Figure S6 shows the scatter plot of cumulative growing degree days above 10˚C versus mean soil moisture for US counties for the growing season from 1981 to 2015. This indicates the soil moisture output is not a simple linear transformation of heat data.

S.6. Are the results different with alternative water metrics?

We re-estimate Model (1) with other related metrics of water availability to crops including simulated daily evapotranspiration of rainfed corn (ET) from WBM; daily soil moisture fraction (SMF) from WBM; and soil moisture content from different spatial interpolation of WBM grid cells to PRISM (nearest neighbor method versus original bilinear method).

The soil moisture fraction index considers the volumetric soil moisture content divided by field capacity. We have also considered the within-season standard deviation of ET and SMF. Note that we keep the degree days above 29˚C as an indicator of heat stress and the degree days from 10˚C to 29˚C as an indicator of beneficial heat to corn.

Table S1. reports regression results for these models. Columns 1 and 2 show a significant relationship with the mean of soil moisture fraction, its square term, and its within season standard deviation. Columns 3 and 4 with mean ET and within-season SD of ET also show a significant relationship. Column 5 shows that the other interpolation of soil moisture has a very close marginal coefficient and standard error compared to our original Model (1). The important finding is the marginal relationship for beneficial and harmful heat remains significant and not significantly different from Model (1). Overall, the main findings of the paper remain robust to the choice of alternative seasonal metrics of water availability.

S.7. Are the estimates different when considering the stages of plant growth?

How critical is separating the stages of plant growth in the yield function? We re-estimate the Model (1-b) considering bi-monthly metrics of seasonal soil moisture. Table S3. provides the estimation coefficients, standard errors, AIC, BIC, and R-squares statistics for Model (1-b) for Eastern, Western, and the continental US with bi-monthly mean soil moisture. The results suggest that the coefficients on extreme heat (DD29˚C) are not significantly different from the model with seasonal mean soil moisture.

The results suggest that the marginal impact of mean soil moisture is higher in June-July. This is in line with agronomic literature as it suggests the water stress during pollination and the silking stage is more damaging. These stages are the most critical stage of development for corn. Water stress during this stage can cause higher yield loss than almost any other stage in the crop's development.

The marginal impact of mean soil moisture is not significant in August-September. This suggests that additional soil moisture can have a positive or negative impact on yield. This also makes sense as a high level of moisture can hurt the maturity and drying stage. High soil moisture at the end of the growing season can cause delayed grain maturity and may lead to delay in the harvest.

In Addition, the marginal impact of mean soil moisture in April-May is negative for the whole US and the Western US and significant at 90% confidence interval. This can be a result of the negative impacts of excess soil moisture on germination and early crop developments as a result of flooding and waterlogging.

S.8. Do the main findings change if we alter the geographical scope of the study

In this section, we estimate the main models separately for Eastern and Western US. Those counties with centroids on the left of 100th meridian are considered West. The idea is that water stress is less severe in the Western US as it is mostly irrigated. Table S2. provides the main descriptive statistics to compare these regions. Overall, Western US experiences more excess heat by 82 versus 58 DD29˚C in the East. On average, Eastern US receives 601 mm of cumulative precipitation while it is only 271 mm in the Western US. On the other hand, within-season SD of soil moisture is 39 mm in the East while it is 13 mm in the west. Looking at the number of days with high/low soil moisture, only 11 days in the West soil moisture is not at normal levels, while this is 59 days in the East.

Table S4. shows the estimated coefficients, standard errors, adjusted R-squared, AIC, and BIC statistics for four models for Eastern US. Model (1-a) includes cumulative precipitation. Model (1-b) includes mean soil moisture metrics. The third column, similar to Model (1-d), considers soil moisture extremes. The results suggest that the coefficient on the extreme heat is not significantly different from the estimations for the whole US.

Table S5. shows the estimated coefficients, standard errors, adjusted R-squared, AIC, and BIC statistics for four models for the Western US. The results suggest that the coefficients on the extreme heat are significantly different from the estimations for the whole US and the Eastern US. For example, the coefficient on DD29˚C is -0.0020 in Model (1-a) for the West, while it was estimated -0.0056 in Model (1-a) for the East. This is around 65% lower damage for a given degree day above 29˚C.

We also re-estimate Model (2) for Eastern and Western US. The results of Model (2-a) are presented in Table S6. Column 1 shows the results for the whole US while columns 2 and 3 contain the results for the Western US and Eastern US, respectively. According to column 2, the coefficient on dday29˚C and the extreme deficit is -0.0074 in the Western US which is significantly different from all other estimations for the Western US. These results indicate that, even in the Western US, *the damage from heat stress can be up to four times higher when combined with water stress*. The coefficient on excess heat and the extreme surplus is not significant (note that this is a very rare condition in the West).

The results of model (2-b) for Eastern, Western, and whole US are shown in Table S7. As in column (3) of Table S7, the coefficient on normal soil moisture conditional to hot weather is 0.00010. The coefficient on normal soil moisture conditional to moderate weather is 0.00002. This indicates that yield response to water is up to four times more in hot weather. The marginal impact on soil moisture deficit index is 0.00008 in hot weather and is 0.00002 in moderate weather. This also supports the finding that the yield response to water is up to four times more in hot weather. Also, the results suggest that the damage from excess water is up to two times bigger in hot weather.

915

Table S1. Estimating corn yields using ET and SMF from WBM

	Log CornYield	Log CornYield	Log CornYield	Log CornYield	Log CornYield
Degree days from 10˚C to 29˚C	.0003422***	.0003445***	.0003193***	.0003372***	.0003426***
	(.0000752)	(.0000741)	(.0000801)	(.0000751)	(.0000801)
Degree days above 29˚C	-.005298***	-.005343***	-.005017***	-.004884***	-.005115***
	(.00069)	(.0006681)	(.00064)	(.0006367)	(.0006914)
Mean daily soil moisture fraction	.2533803**	.9821037***			
	(.1107891)	(.2394119)			
Sqr. mean soil moisture fraction	-.1030471	-.777505***			
	(.1166278)	(.2402404)			
SD daily soil moisture fraction		-.509464***			
		(.1156073)			
Mean daily ET[1] (mm)			.4901121***	.6357687***	
			(.0735423)	(.0985801)	
Sqr. mean daily ET[1]			-.086206***	-.118748***	
			(.0234848)	(.0254433)	
SD daily ET[1]				-.2516986**	
				(.0997848)	
Mean moisture content (mm)[2]					.0036395***
					(.0006759)
Sqr. mean daily moisture content[2]					-.000017***
					(3.000e-06)
Observations	69923	69923	69923	69923	69923
R-squared	.4667911	.4712361	.4755177	.4770727	.4713225
Akaike's Crit	-21005.7	-21589.0	-22159.5	-22365.1	-21602.5
Bayesian Crit	-20969.0	-21543.3	-22122.9	-22319.4	-21565.9

Standard errors in parenthesis
*** p<0.01, ** p<0.05, * p<0.1

Notes: 1- ET shows the average daily evapotranspiration. 2- It shows the volumetric soil moisture interpolated from WBM to PRISM grid cells using the nearest neighbor method. Table lists regression coefficients and shows standard errors in brackets.

Table S2. Descriptive statistics of main variables for Eastern and Western US

Variables	East		West	
	Mean	Std. Dev.	Mean	Std. Dev.
Degree days from 10˚C to 29˚C	1877.79	433.54	1612.74	363.57
Degree days above 29˚C	58.01	57.13	82.11	80.29
Cumulative precipitation Apr-Sep (mm)	601.13	153.31	271.69	132.12
Mean daily soil moisture content (mm)	50.49	39.49	15.15	13.17
Number of days with high soil moisture	28.89	30.38	8.69	11.57
Number of days with low soil moisture	30.39	35.46	2.97	7.1
Surplus (sum of positive daily deviation, mm)	2546.95	2177.62	964.98	938.69
Deficit (sum of negative daily deviation, mm)	-2563.43	2200.22	-962.27	699.6
Degree days from 10˚C to 29˚C & low soil moisture	442.94	433.88	29.08	94.27
Degree days from 10˚C to 29˚C & high soil moisture	364	351.68	62.88	90.52
Degree days from 10˚C to 29˚C & normal soil moisture	1067.65	573.28	1462.24	426.27
Degree days above 29˚C & low soil moisture	20.19	32.55	.85	3.22
Degree days above 29˚C & high soil moisture	5.17	9.34	.76	2.41
Degree days above 29˚C & normal soil moisture	32.24	41.87	72.91	72.8
Index of extreme deficit	-1823.19	2339.6	-160.91	597.29
Index of extreme surplus	1942.11	2207.68	482.25	770.15
Index of normal soil moisture	-194.99	516.76	-406.16	434.96
Mean daily evapotranspiration (mm)	.6	.59	.15	.19
Mean daily soil moisture fraction	.71	.18	.68	.2
Mean daily soil moisture content (mm), alternative	50.52	39.41	15.17	13.2
Mean daily soil moisture content (mm), Apr-May	21.82	16.5	6.29	6.75
Mean daily soil moisture content (mm), Jun-Jul	17.7	15.77	5.14	4.53
Mean daily soil moisture content (mm), Aug-Sep	10.98	10.74	3.72	3.27
Observations	62094	62094	7829	7829

Table S3. Corn yield estimation with bi-monthly soil moisture metrics

	US Log CornYield	West Log CornYield	East Log CornYield
Degree days from 10˚C to 29˚C	.0003176***	.0004543***	.0002921***
	(.0000774)	(.0000853)	(.0000838)
Degree days above 29˚C	-.0044571***	-.0023373***	-.0047849***
	(.0006231)	(.0004904)	(.0006742)
Mean daily soil moisture content (mm), Apr-May	-.0029599*	.0045436**	-.0034124**
	(.0015561)	(.002061)	(.0015243)
Square of mean daily soil moisture content (mm), Apr-May	-9.800e-06	-.0000564	-2.600e-06
	(.000022)	(.0000581)	(.0000216)
Mean daily soil moisture content (mm), Jun-Jul	.0141021***	.0148123*	.013605***
	(.0019928)	(.0071408)	(.0020404)
Square of mean daily soil moisture content (mm), Jun-Jul	-.0001589***	-.0005616**	-.0001562***
	(.0000252)	(.0002422)	(.0000258)
Mean daily soil moisture content (mm), Aug-Sep	.0030501*	.007007	.0026044
	(.001805)	(.0049266)	(.0018059)
Square of mean daily soil moisture content (mm), Aug-Sep	-.0000385	-.000213	-.0000351
	(.0000291)	(.0002114)	(.0000294)
Observations	69923	7829	62094
R-squared	.4884616	.2782172	.515591
Akaike's Crit	-23898.8	-3040.6	-22112.9
Bayesian Crit	-23825.6	-2984.8	-22040.6

Standard errors are in parenthesis
*** p<0.01, ** p<0.05, * p<0.1

Notes: Table lists regression coefficients and shows standard errors in brackets.

Table S4. Estimation of Model (1) for the East

	(1-a) Log CornYield	(1-b) Log CornYield	(1-d’) Log CornYield
Degree days from 10˚C to 29˚C	.0003108***	.0003152***	.0003072***
	(.0000936)	(.0000868)	(.0000724)
Degree days above 29˚C	-.0056293***	-.0054707***	-.0052882***
	(.0007259)	(.0007343)	(.0006442)
Cumulative precipitation Apr-Sep (mm)	.0009245***		
	(.0002502)		
Square of cumulative precipitation Apr-Sep	-7.000e-07***		
	(2.000e-07)		
Mean daily soil moisture content (mm)		.00319***	
		(.0006763)	
Square of mean daily soil moisture content		-.0000158***	
		(3.000e-06)	
Index of extreme deficit			.0000379***
			(5.700e-06)
Index of extreme surplus			-.0000381***
			(2.700e-06)
Index of normal soil moisture			.0000292**
			(.0000112)
Observations	62094	62094	62094
R-squared	.4997799	.4989592	.5205428
Akaike's Crit	-20126.6	-20024.8	-22756.9
Bayesian Crit	-20090.4	-19988.6	-22711.8

Standard errors in parenthesis
*** p<0.01, ** p<0.05, * p<0.1

Notes: Table lists regression coefficients and shows standard errors in brackets. Model (1-d’) is slightly different from Model (1-d) considering extreme deficit and extreme surplus metrics.

Table S5. Estimation of the Model (1) for the West

	(1-a) Log CornYield	(1-b) Log CornYield	(1-d') Log CornYield
Degree days from 10˚C to 29˚C	.0004426***	.0004484***	.0004539***
	(.0000829)	(.0000823)	(.0000862)
Degree days above 29˚C	-.0020381***	-.0023744***	-.0022938***
	(.000423)	(.0004911)	(.0004752)
Cumulative precipitation Apr-Sep (mm)	.0005768		
	(.0003372)		
Square of cumulative precipitation Apr-Sep	-3.000e-07		
	(5.000e-07)		
Mean daily soil moisture content (mm)		.0078908**	
		(.0027432)	
Square of mean daily soil moisture content		-.0000848**	
		(.0000326)	
Index of extreme deficit			.0000255
			(.0000271)
Index of extreme surplus			-9.800e-06
			(7.600e-06)
Index of normal soil moisture			.0000762**
			(.0000309)
Observations	7829	7829	7829
R-squared	.2784229	.2768284	.2772401
Akaike's Crit	-3050.8	-3033.5	-3035.9
Bayesian Crit	-3022.9	-3005.6	-3001.1

Standard errors are in parenthesis
*** p<0.01, ** p<0.05, * p<0.1

Notes: Table lists regression coefficients and shows standard errors in brackets. Model (1-d') is slightly different from Model (1-d) considering extreme deficit and extreme surplus metrics.

Table S6. West versus East in corn yield estimation with the interaction of heat and soil moisture (Model 2-a)

	(US) log CornYield	(West) log CornYield	(East) log CornYield
Degree days from 10˚C to 29˚C	.0003083***	.0004344***	.0002963***
	(.0000685)	(.0000847)	(.0000736)
dday29˚C & SM 75+ mm below normal (extreme deficit)	-.0082398***	-.0074467*	-.0082928***
	(.0014372)	(.0035727)	(.0014365)
dday29˚C & SM 25-75 mm below normal (deficit)	-.0062069***	-.0033152*	-.0061966***
	(.0009793)	(.001627)	(.0009797)
dday29˚C & SM 0-25 mm around normal (normal)	-.0037559***	-.0024412***	-.0041335***
	(.0004045)	(.0005053)	(.0004376)
dday29˚C & SM 25-75 mm above normal (surplus)	-.0055709***	-.004754*	-.005625***
	(.0012041)	(.0024763)	(.0011677)
dday29˚C & SM 75+ mm above normal (extreme surplus)	-.0140295***	.0095881	-.0143573***
	(.0019083)	(.0128016)	(.0018101)
Mean daily soil moisture content (mm)	.0026635***	.0080027**	.0025636***
	(.0008153)	(.0028858)	(.0008324)
Square of mean daily soil moisture content	-.0000161***	-.0000844**	-.0000156***
	(2.600e-06)	(.0000326)	(2.600e-06)
Observations	69923	7829	62094
R-squared	.4921263	.2777862	.5149811
Akaike's Crit	-24401.6	-3035.9	-22034.8
Bayesian Crit	-24328.3	-2980.2	-21962.5

Standard errors in parenthesis
*** p<0.01, ** p<0.05, * p<0.1

Notes: Table lists regression coefficients and shows standard errors in brackets.

Table S7. West versus East in estimation of corn yields while splitting the soil moisture indicators (Model 2-b)

	(US) log CornYield	(West) log CornYield	(East) log CornYield
Degree days from 10˚C to 29˚C	.0003154***	.0004451***	.0002983***
	(.0000689)	(.0000919)	(.000074)
Degree days above 29˚C	-.004044***	-.0020707***	-.0044516***
	(.0005384)	(.0005793)	(.0005981)
Index of normal soil moisture when T > T*	.0001199***	.0001805	.0001034***
	(.0000342)	(.0001426)	(.0000358)
Index of extreme moisture surplus when T > T*	-.0000628***	-.0001173	-.0000586***
	(.0000151)	(.0001071)	(.0000149)
Index of extreme moisture deficit when T > T*	.000092***	-.0000526	.0000817***
	(.0000234)	(.0000978)	(.0000229)
Index of extreme moisture deficit when T < T*	.0000209***	.0000287	.0000223***
	(7.100e-06)	(.0000337)	(7.000e-06)
Index of extreme moisture surplus when T < T*	-.0000326***	-5.700e-06	-.0000334***
	(3.200e-06)	(6.500e-06)	(3.200e-06)
Index of normal soil moisture when T < T*	.000028**	.000063**	.0000247**
	(.0000105)	(.0000249)	(.0000102)
Observations	69923	7829	62094
R-squared	.5006312	.2782242	.5262193
Akaike's Crit	-25582.4	-3040.6	-23490.5
Bayesian Crit	-25509.2	-2984.9	-23418.2

Standard errors in parenthesis
*** p<0.01, ** p<0.05, * p<0.1

Notes: Table lists regression coefficients and shows standard errors in brackets.

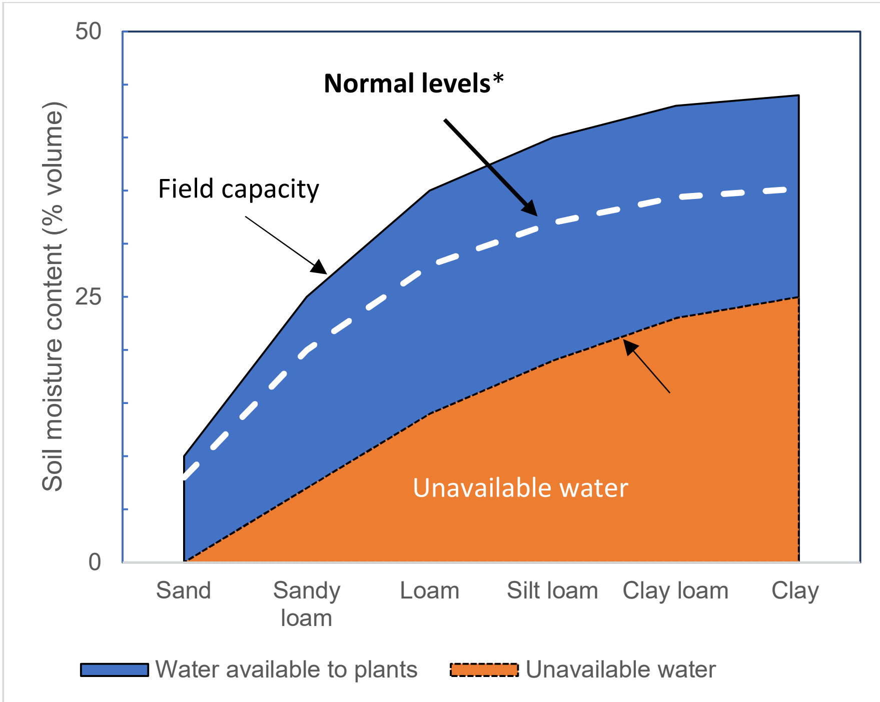


Figure S1. Soil texture affects normal moisture levels. The sandy soil has the lowest normal level while the clay has the highest normal levels.

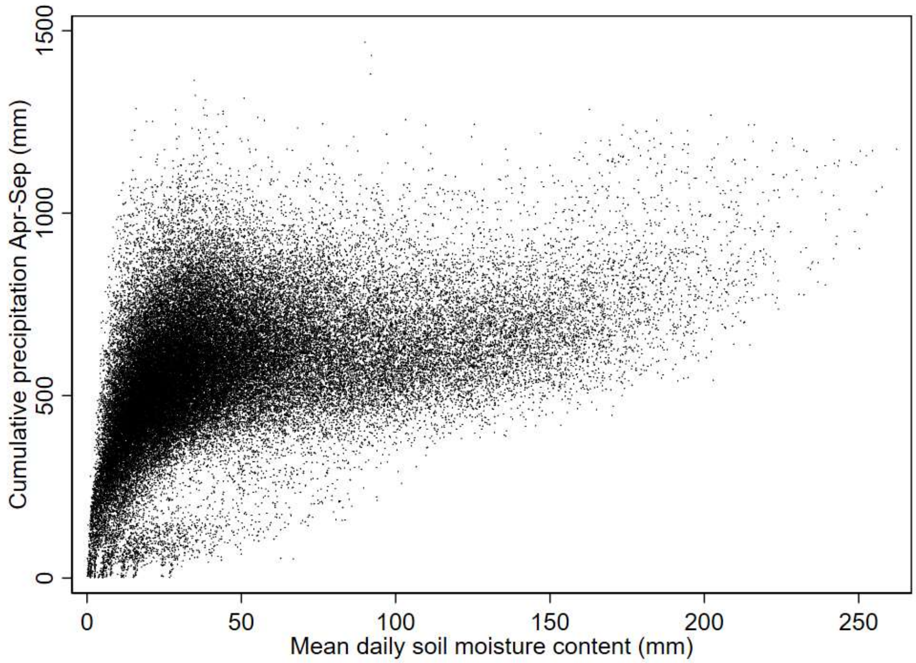


Figure S2. WBM mean soil moisture versus PRISM cumulative precipitation for 1981-2015 by US counties.

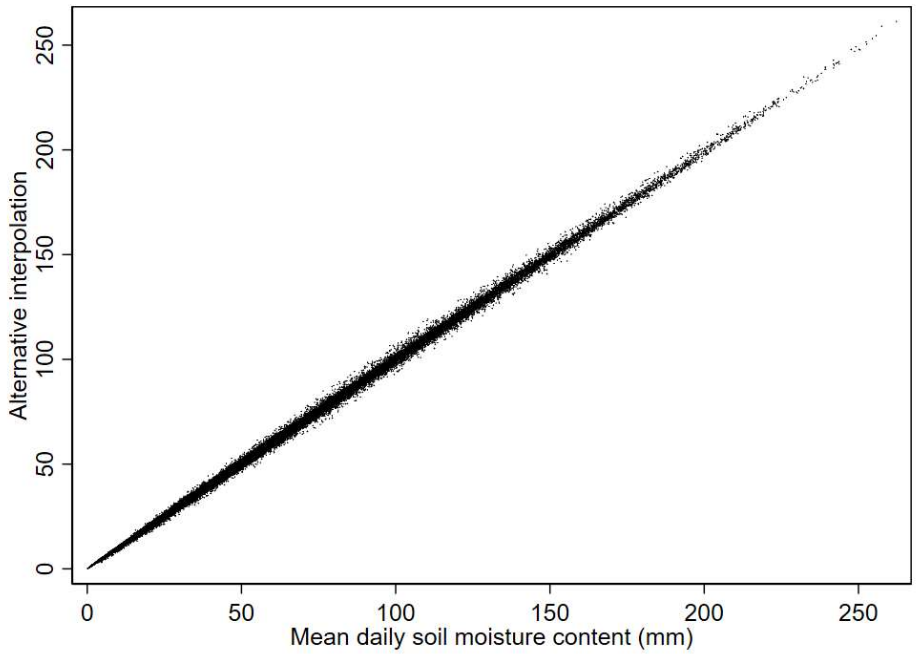


Figure S3. County-level mean seasonal soil moisture based on bilinear interpolation versus alternative interpolation (nearest-neighbor) from WBM 6 arcmin grids to PRISM 2.5 arcmin resolution for the 1981-2015 period.

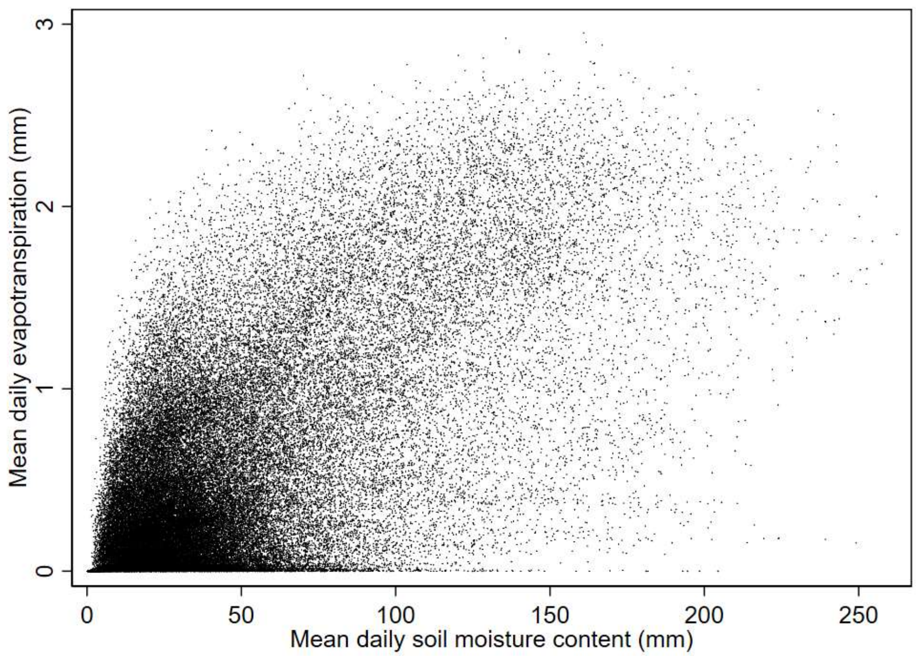


Figure S4. County-level mean soil moisture versus mean ET aggregated from WBM for the 1981-2015 period.

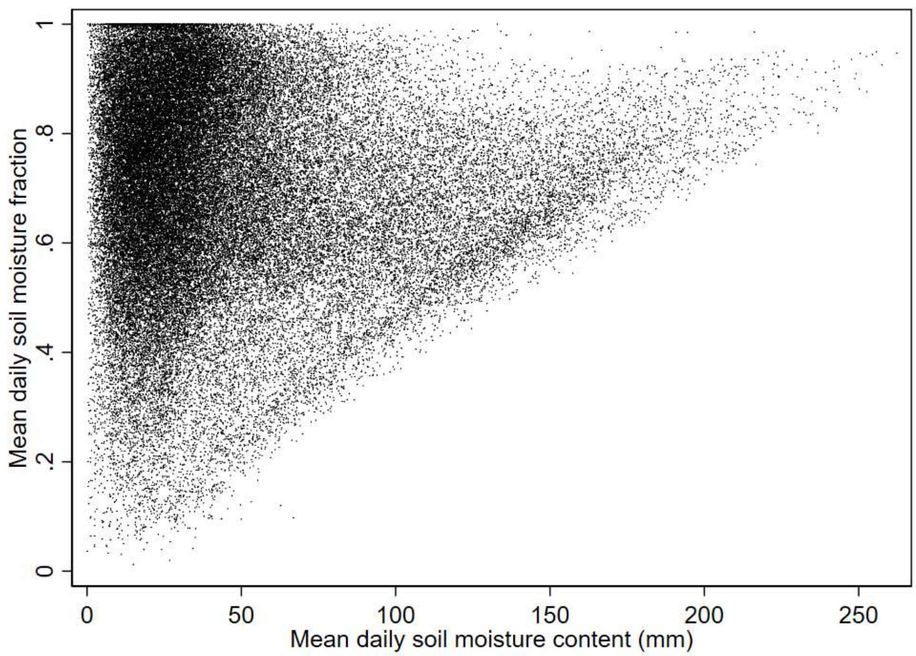


Figure S5. County-level mean volumetric soil moisture content versus mean of soil moisture fraction aggregated from WBM for the 1981-2015 period.

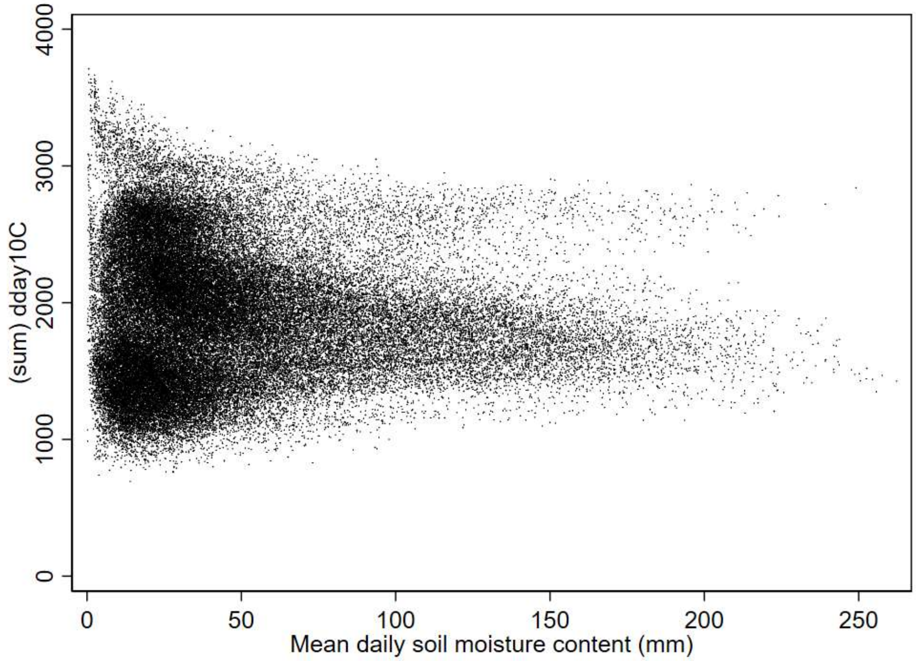


Figure S6. County-level seasonal mean soil moisture versus seasonal heat index aggregated from WBM and PRISM for the 1981-2015 period.