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Combined influence of soil moisture and atmospheric evaporative demand is important for accurately predicting US maize yields

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Understanding the response of agriculture to heat and moisture stress is essential to adapt food systems under climate change. Although evidence of crop yield loss with extreme temperature is abundant, disentangling the roles of temperature and moisture in determining yield has proved challenging, largely due to limited soil moisture data and the tight coupling between moisture and temperature at the land surface. Here, using well-resolved observations of soil moisture from the recently launched Soil Moisture Active Passive satellite, we quantify the contribution of imbalances between atmospheric evaporative demand and soil moisture to maize yield damage in the US Midwest. We show that retrospective yield predictions based on the interactions between atmospheric demand and soil moisture significantly outperform those using temperature and precipitation singly or together. The importance of accounting for this water balance is highlighted by the fact that climate simulations uniformly predict increases in atmospheric demand during the growing season but the trend in root-zone soil moisture varies between models, with some models indicating that yield damages associated with increased evaporative demand are moderated by increased water supply. A damage estimate conditioned only on simulated changes in atmospheric demand, as opposed to also accounting for changes in soil moisture, would erroneously indicate approximately twice the damage. This research demonstrates that more accurate predictions of maize yield can be achieved by using soil moisture data and indicates that accurate estimates of how climate change will influence crop yields require explicitly accounting for variations in water availability.

Studies of rainfed agriculture have shown that heat stress is associated with reduced yields[1–7]. Although water is obviously essential for crop growth and development, the relationship between moisture availability and yield remains poorly resolved. Inclusion of precipitation has not, for example, substantially improved statistical yield predictions for maize in the US Midwest relative to models based on temperature alone[4,6,8]. It may be that precipitation is a poor proxy for plant-available soil moisture because of variable runoff, drainage and evaporation[9], as well as the fact that precipitation estimates are generally more uncertain because rainfall is more heterogeneous than temperature variations[10]. Nonlinearities in the relationship between plant-available soil moisture and yield[8,11–18] could also obscure the influence of moisture availability.

A potentially important clue for the role of moisture in mediating yield damage comes from prior findings that maize yield begins to decline by approximately 7% per degree Celsius for air temperature above approximately 30 °C on a given day[6,8]. If reductions in maize yield come from physiological heat stress, which occurs around 35 °C[19], the leaf surface must be substantially warmer than the air. Temperature gradients between a canopy and surrounding air largely depend on available soil moisture, with higher canopy temperatures coinciding with drier soils[20–22] and limited latent cooling. Hence, when atmospheric temperature is below 35 °C, damaging canopy temperatures are likely to be reached only when soil moisture is low. It can be inferred that although heat stress is often accompanied by water stress, these variables are not interchangeable for purposes of predicting yield outcomes.

The inference of moisture-mediated exposure to damage from temperature is consistent with previous studies. Exposure to high temperatures has been found to cause amplified yield damage under conditions of low water availability[13,18,23]. Conversely, well-irrigated fields show little sensitivity to high atmospheric temperature[8,12,15–17]. A further complication is that excess precipitation can cause yield damage through waterlogging, increased pests and fungal pathogens, and loss of nitrogen fertilizer[14,22,24]. Insurance data over the US suggest that maize yield damage associated with excessive precipitation is of the same magnitude as that associated with drought conditions[24]. Damage from excess soil moisture implies that high temperatures may sometimes benefit yields through increasing evaporative demand and reducing soil moisture to more optimal conditions.

On the basis of the foregoing considerations, we propose a statistical model of maize yield based on interactions between the supply and demand of water. Using this model along with observations from the Soil Moisture Active Passive (SMAP) satellite[25], we show that historical variations in US maize yield are better predicted as a function of atmospheric demand and root-zone soil moisture than using standard approaches based on temperature or precipitation (Table 1). Distinguishing the factors controlling moisture balance is important because there is no assurance that historical covariability between higher atmospheric demand and lower soil moisture will hold with respect to future climate change. Coupled Model Intercomparison Project Phase 5 (CMIP5) simulations, for example, give order 100% increases in atmospheric vapour pressure deficit (VPD) during the Midwestern growing season between 1980–2010 and 2070–2100 under Representative Concentration Pathway 8.5

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Table 1 | Correlation between predicted and observed yield anomalies

Variables	r (90% CI)	r_{test}
VPD, SM_r	0.83 (0.82–0.85)	0.64
T, SM_r	0.83 (0.82–0.85)	0.59
SM_r	0.80 (0.78–0.81)	0.62
VPD, *P*	0.79 (0.78–0.81)	0.58
SM_s	0.79 (0.77–0.81)	0.61
T, *P*	0.78 (0.77–0.80)	0.51
VPD	0.78 (0.76–0.79)	0.59
P	0.77 (0.75–0.79)	0.56
T	0.76 (0.74–0.78)	0.52

The correlation (*r*) between predicted and observed yield anomalies with the associated 90% CI (from *n* = 10,000 bootstrap realizations) and the average out-of-sample *r* (r_{test}). Explanatory variables include daily root-zone soil moisture (SM_r), vapour pressure deficit (VPD), maximum temperature (*T*), precipitation (*P*) and near-surface soil moisture (SM_s). See Supplementary Table 1 for an analogous table of root mean square errors.

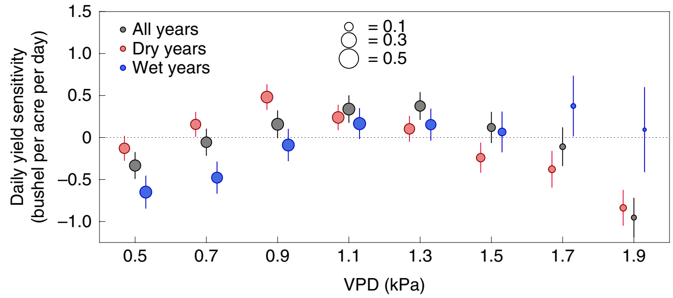

Fig. 1 | Yield sensitivity to VPD. The yield response to daily anomalies in vapour pressure deficit (VPD; equation (3)) fitted to all county-years (black, *n* = 2,552), the driest 40% of county-years (red, *n* = 1,021) and the wettest 40% of county-years (blue, *n* = 1,021). The driest and wettest county-years are selected on the basis of the average May–July root-zone soil moisture. Equal-width bins from 0.4 kPa to 2 kPa are prescribed with bin centres labelled on the *x* axis. The size of the marker symbols indicates the fractional distribution of observations in each analysis (see scale reference on plot), and the vertical bars indicate the 95% CI associated with each response.

(RCP8.5). Corresponding values of root-zone soil moisture, however, change only by order 10%, with different models variously simulating wetter or drier conditions. Yield predictions based only on increased VPD would give twice the damage compared with predictions that also account for relatively stable levels of root-zone soil moisture. Improved monitoring and modelling of soil moisture characteristics therefore appears important for determining how climate change will influence future yield.

A model combining soil moisture and atmospheric evaporative demand

A simple calculation is first presented to illustrate how the response of yield to heat stress depends on soil moisture. We use a standard statistical approach to estimate yield sensitivities whereby the influence of atmospheric demand on yield accrues daily[6,8], but apply the model on three distinct sets of data based on seasonally averaged soil moisture: all of the county-years, the driest 40% of the data, and the wettest 40% of the data. Heat stress is characterized using daily-average VPD, as opposed to temperature, because VPD is suggested to better predict yield loss by more fully capturing water stress[26]. When the results from these three regressions are compared (Fig. 1), high VPDs (>1.3 kPa) are found to be detrimental only in dry years, whereas low VPDs (<0.9 kPa) are detrimental only in wet years. The contrasting responses of yield to high and low VPD differs at the 95% confidence interval (CI). Analyses made unconditionally with respect to soil moisture—that is, using all county-years—would erroneously indicate that both low and high VPDs are invariably detrimental.

The fact that the response of yield to VPD depends on soil moisture indicates that a statistical model of yield should account for both terms. To develop the model, we assume that the response of yield to environmental variables accumulates daily over the growing season. However, rather than modelling yield as a function of one environmental variable, such as temperature[6,8], we employ a two-dimensional dependence whereby interactions of VPD and root-zone soil moisture can be inferred (Fig. 2). As described in detail in the Methods, a model is fit wherein yield varies according to the daily accrued exposure to combinations of soil moisture and VPD. This formulation is agnostic with respect to how and whether supply and demand interact, allowing for inferences to be solely derived from the observations.

Although strong coupling emerges between soil moisture and VPD at the monthly to seasonal timescales over which land equilibrates with the atmosphere[27] (Supplementary Fig. 1), these terms are less correlated at the daily timescales resolved in our analysis[28] (Supplementary Fig. 2), particularly deeper in the column (Supplementary Fig. 3). Exposure to combinations of soil moisture and VPD is better resolved through the analysis of daily variability, as opposed to using monthly or seasonal averages. Process-based crop models[29], of course, also resolve both soil moisture and atmospheric demand but the present approach is complementary in having few enough parameters that the response can be accurately constrained across the US Midwest.

To examine the viability of the model, we first explore a well-instrumented, eddy covariance site in Nebraska[30] where measurements of daily root-zone soil moisture, VPD and carbon fluxes are available. These data are unique among the FLUXNET2015 network for covering more than 3 yr of rainfed maize growth. We verify that imbalances between soil moisture and VPD lead to reduced rates of daily gross primary productivity (GPP, Fig. 2a). In agreement with the physiology of maize[31], a balance between root-zone soil moisture and atmospheric demand gives optimal growing conditions, corresponding to a high-productivity diagonal. Damage accrues when water is in short or over supply relative to demand. We suggest that negative productivity anomalies in the dry-soil and high-demand quadrant of Fig. 2a result from stomatal limitation of photosynthesis. Decreases in leaf water content in maize are associated with stomatal closure[32] that prevents xylem tensions from reaching levels that would cause cavitation[33] but also reduces productivity by restricting CO_2 uptake and, hence, photosynthesis[34].

The negative productivity anomalies in the wet-soil, low-demand quadrant of Fig. 2a probably also reflect reduced photosynthetic capacity. Some species, such as tomato, respond to sodden conditions by increasing root hydraulic resistance, but this does not appear to be the case for maize[35], where over-supply of water is associated with altered photosynthetic biochemistry, including lower chlorophyll and soluble protein levels, reduced activity of Rubisco and increased potential for photooxidative damage[36]. Waterlogging and associated root-zone anoxia can also lead to water and mineral deficiencies, decreased nitrogen uptake from the soil, and increased exposure to toxic compounds and disease organisms[14,24,37]. Light limitations almost certainly play a role in reducing productivity as well, given the likelihood for wet and cloudy conditions to coincide, although our representation only implicitly includes light variability in that atmospheric temperature and humidity control VPD and are both strong functions of solar radiation.

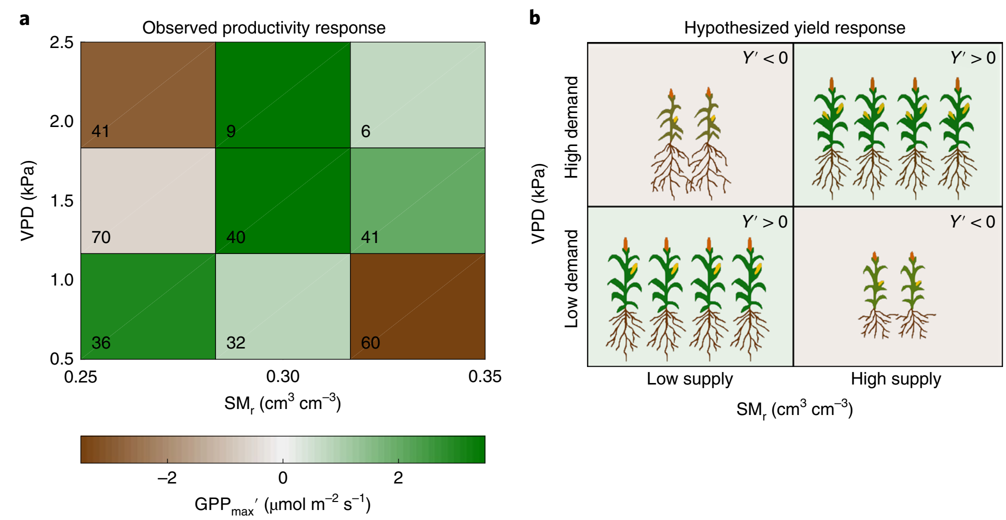

Fig. 2 | Moisture supply and demand drive yield. a, The observed daily response of maize productivity to daily vapour pressure deficit (VPD) and root-zone soil moisture (SM_r) measured at 25 cm. **b**, Hypothesized daily yield sensitivity (Y') to daily VPD and SM_r conditions. In **a**, the colour indicates the average anomaly in daily GPP_{max} (GPP_{max}') and the number indicates the number of days in each bin.

Retrospective yield predictions across the US Midwest

Satellite observations of soil moisture allow us to extend our analysis to the entirety of the US Midwest. Launched in January 2015, SMAP provides soil moisture observations at an unprecedented 9-km and approximately 3-d resolution. Daily average soil moisture is observed at a spatial resolution analogous to county-level maize yields[38] and these outperform other remotely sensed soil moisture data products when compared with in situ soil moisture measurements[39,40]. SMAP observes soil moisture to a depth of approximately 5 cm, which we use as the surface boundary forcing of a simple hydrologic model[41] to estimate root-zone soil moisture. Comparisons of SMAP-derived estimates of root-zone soil moisture against available in situ observations indicate a high degree of association (Supplementary Fig. 4). A more complex land surface model could be used to infer root-zone soil moisture but would entail major assumptions regarding soil characteristics and make connection with the SMAP data less apparent.

Anomalies in Midwestern maize yields[38] are analysed over the SMAP interval from 2015 to 2018. To determine yield anomalies over such a short interval, they are estimated relative to a linear trend fit to historical data since 1998.

Applying our model to end-of-season yields across 2,552 total county-years between 2015 and 2018 gives a sensitivity pattern (Fig. 3a) similar to that of productivity (Fig. 2), consistent with a tight coupling between photosynthesis and yield. Yield sensitivities indicate that 1 d of sodden conditions induces 0.27 bu per acre of yield loss, whereas losses associated with high VPDs and dry conditions account for 0.47 bu per acre of yield loss. The yield sensitivity of sodden conditions is estimated as the average of the eight boxes under the green diagonal in Fig. 3a and the sensitivity of dry conditions is estimated as the average of the six boxes over the green diagonal. Integrating damage between May and July over 2015 to 2018 indicates that approximately half of total yield losses are due to over-saturated conditions (47%) and half to dry conditions (53%). These results may partly reflect SMAP's sampling of unusually wet conditions during 2015 (Supplementary Fig. 5) but are consistent with other recent studies covering a longer time interval[24].

We examine the predictive skill of our yield model using a leave-one-out approach (Table 1 and Supplementary Table 1). If all years are used to parameterize the model using root-zone soil moisture and VPD as explanatory variables, predicted yield anomalies are well correlated with actual yield anomalies ($r=0.83$ with a 90% CI: 0.82–0.85; as listed in Table 1). Training on each combination of 3 yr of data at the county level and testing predictions in the fourth leads to an average correlation across the four resulting out-of-sample tests of 0.64. In contrast, if an analogous model is fitted using maximum daily temperature and precipitation, the r value decreases from 0.78 when trained on 4 yr of data to 0.51 when tested out-of-sample, indicating that VPD and soil moisture provide a stronger basis for predicting the effects of environmental change on yield outcomes.

Implications of soil moisture for future yield

Yield response to increases in VPD will ultimately depend on the availability of root-zone soil moisture, but how the balance between supply and atmospheric demand of moisture will change remains highly uncertain. Relative to a 1980–2010 climatology, the CMIP5 ensemble predicts increases in vapour pressure in 2070–2100 with a range of 0.12 to 1.2 kPa in the US Midwest under the RCP8.5, and changes in root-zone soil moisture that range from −0.04 to 0.01 cm^3 cm^{-3} (Fig. 3a). The increase in VPD reflects an increase in temperature and saturation vapour pressure, but negligible changes in actual vapour pressure, due to stable relative humidity[42]. Increasing VPD will tend to dry near-surface soils, and changes in VPD are strongly anti-correlated with changes in near-surface soil moisture across the 24 CMIP5 models ($r=-0.71$). Root-zone soil moisture is, however, less correlated with VPD across models ($r=-0.52$). This decoupling between the deep soil and atmosphere has been attributed to variations in winter and spring precipitation persisting into the growing season[43].

Increasing VPD by 1.2 kPa for each daily observation reduces the predicted median yield across all county-years by 64 bu per acre per season, or approximately a third of the median yield of 176 bu per acre (Fig. 3b). An increase in root-zone soil moisture of 0.01 cm^3 cm^{-3}, which is the maximum predicted increase across the CMIP5 models, would decrease losses to 54 bu per acre per season. Conversely, a decrease in root-zone soil moisture of 0.04 cm^3 cm^{-3}, which is the maximum predicted decrease across CMIP5 models, would increase losses to 85 bu per acre per season. If median yield loss were instead estimated on the basis of a one-dimensional dependence on VPD (Supplementary Fig. 6), estimated damage would more than double to 131 bu per acre, signifying the importance of including the interactions between soil moisture and evaporative demand.

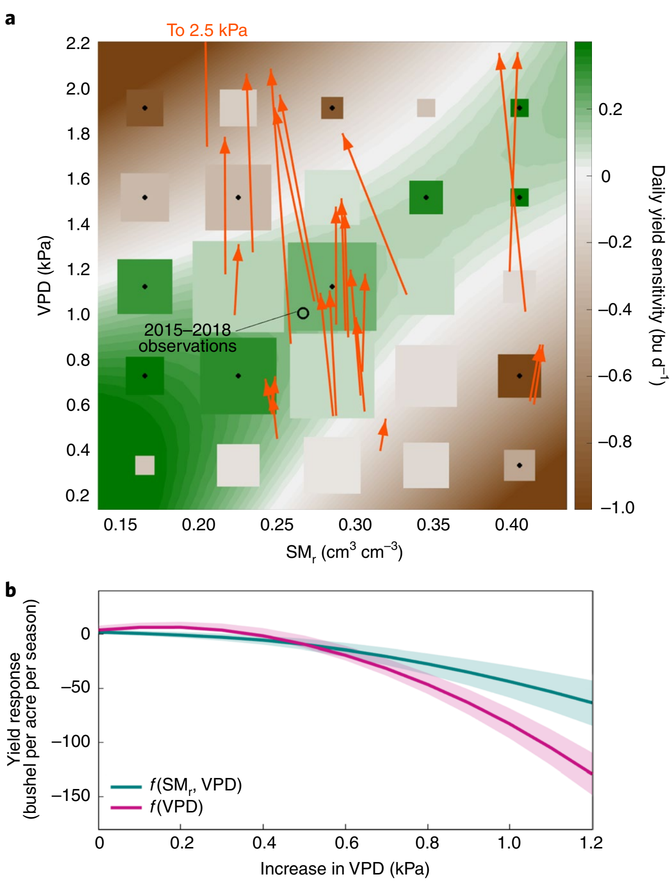

Fig. 3 | Maize yield response to moisture supply and demand in present and future climates. a, Using observations, we estimate the yield response to vapour pressure deficit (VPD) and root-zone soil moisture (SM$_r$). Each square represents inferred daily yield sensitivities (that is, β_h coefficients) that are estimated via observational data and the constraints in equation (4). The size of the square represents the relative number of days within each bin, such that the largest box in the centre represents 12.5% of the data and the smallest box in the upper right corner represents less than 1% of the data (see Supplementary Fig. 13 for the distributions of days in each bin for each year). A black dot within the square indicates that the fit coefficient is significant ($P<0.05$). A polynomial surface fit to these daily yield sensitivities is plotted behind the squares. Residuals of the polynomial fit are shown in Supplementary Fig. 10. Each orange arrow represents the change in SM$_r$ and VPD from 1980–2010 to 2070–2100 from one CMIP5 model (see Supplementary Table 2 for a list of models). For reference, the average of summertime observations (2015–2018) is plotted with an open circle and labelled. **b**, We predict the yield response to elevated VPD by increasing the observed VPD and estimating yields using a fitted polynomial function for VPD (magenta) and a fitted polynomial surface for VPD and SM$_r$ (teal). The shaded CIs represent the 10th to 90th percentile from a distribution of possible median yields estimated by bootstrapping data according to county ($n=10{,}000$ realizations). The polynomial function for VPD is shown in Supplementary Fig. 6, and the polynomial surface for VPD and SM$_r$ is shown above.

Conclusions

Given its importance in determining yield, both with respect to drought[44] and sodden[24] conditions, continued improvement in the representation of root-zone soil moisture in general circulation models appears important for gauging the implication of climate change for food production. This study also implies that adaptation strategies that optimize the root-zone water balance, including plants with deeper roots[45] or crops that better conserve root-zone soil moisture under conditions of high atmospheric demand[46], are especially important for ensuring food security in future climates.

Methods

Data sources. To characterize soil moisture in each county, we utilize the SMAP Level-3 9-km radiometer soil moisture product[25], which has an exact repeat frequency of 8 d and a nominal return frequency of 3 d. To minimize retrieval errors, soil moisture estimates are omitted if the water fraction exceeds 5% of the pixel or if the vegetation density exceeds 5 kg m^{-2}. It is worth noting that ideally soil moisture values estimated over the 9-km footprint would be homogeneous and representative exclusively of croplands. In reality, noise could be introduced by vegetation or other surfaces surrounding croplands that have different dry-down dynamics. Daily average VPD, which is approximated as the average of the maximum and minimum daily VPD, maximum temperature (T), and precipitation accumulation (P) are acquired from the Parameter-elevation Relationships on Independent Slopes Model (PRISM) dataset[47]. The PRISM data are originally derived from weather station measurements. The data were then spatially interpolated to a 4-km grid using an algorithm that accounts for elevation and physiographic factors (for example, coastal proximity and topographic facet orientation)[47]. VPD and temperature measurements used in the PRISM dataset are from instrument height, which is typically 1–2 m above the land surface. Although instrument height measurements are commonly used to model vegetation and yield, we would use leaf-level humidity and temperature values if such measurements were available, as they are more physiologically relevant. If we use data from weather stations instead of PRISM, we find similar relationships between VPD, soil moisture and yield (Supplementary Fig. 7).

County-level maize yield data are from the US Department of Agriculture/National Agricultural Statistics Service[38]. If counties reported non-irrigated maize yields in addition to total yields, the non-irrigated yields are used. Non-irrigated yields are preferentially chosen because we are interested in explaining yield variability in rainfed areas, and the non-irrigated soil moisture conditions are probably more representative of the 9-km SMAP soil moisture observation.

Data from PRISM and SMAP are aggregated to the county scale using county boundary maps obtained from the 2016 US Census Bureau. Specifically, we average over all grid box centres within the county boundary. Our results do not change if we averaged only grid boxes categorized as dominantly 'croplands' or 'cropland mosaics' (Supplementary Fig. 7).

Projections of monthly relative humidity (variable name 'hurs' in CMIP5), temperature ('tas') and multi-level soil moisture ('mrlsl') are obtained from CMIP5 RCP8.5. Models were chosen on the basis of the availability of monthly multi-layer soil moisture and surface-level humidity and temperature. Monthly average VPD is estimated from near-surface relative humidity and temperature. To characterize the plant-available water, root-zone soil moisture is estimated between 0.2 and 1.0 m by linearly interpolating soil moisture between reported levels. Surface soil moisture is defined between 0 and 0.1 m. Soil depth and the number of levels in the soil profile are model dependent (Supplementary Table 2). Averages are calculated over two different intervals, 1980–2010 and 2070–2100 (Fig. 3a).

Estimating root-zone soil moisture. The soil moisture estimates from SMAP represent near-surface soil moisture to a depth of approximately 5 cm (ref. [25]). To more accurately characterize plant-available moisture, which has been shown to extend below 5 cm for maize[48], we estimate a root-zone soil moisture at time t_n (SM$_{r,n}$) using an auto-regressive exponential framework where innovations are from the surface[41]

$$\mathrm{SM}_{r,n} = \mathrm{SM}_{r,n-1} + K_n\left(\mathrm{SM}_{s,n} - \mathrm{SM}_{r,n-1}\right) \tag{1}$$

In equation (1), SM$_{r,n-1}$ is the predicted root-zone soil moisture estimate at t_{n-1}, SM$_{s,n}$ is the surface soil moisture retrieved from SMAP at time t_n and K_n is the gain at time t_n estimated as

$$K_n = \frac{K_{n-1}}{K_{n-1} + \mathrm{e}^{\frac{t_n - t_{n-1}}{N}}} \tag{2}$$

In equation (2), N represents the timescale of soil moisture variation in units of days. Although the optimal value of N varies spatially, it has been demonstrated that using an average N does not significantly decrease model accuracy[41,49]. Thus, we assume a spatially uniform $N=8$ d, which is based on calibrations from the Soil Moisture and Ocean Salinity satellite over Nebraska and Oklahoma using near-surface (5–10 cm) and root-zone (25–60 cm) soil moisture measurements[49]. Results and conclusions are not sensitive to the choice of parameter N (Supplementary Fig. 7). We initialize the exponential filter with SM$_{r,1}$ = SM$_{s,1}$ and $K_1 = 1$. The recursive exponential filter smooths the near-surface soil moisture observations, as demonstrated for one SMAP 9-km grid box in Supplementary Fig. 8. We also evaluate this methodology using soil moisture observations at four depths from 24 US Climate Reference Network sites[50,51], finding a high degree of association (Supplementary Fig. 4). This model of root-zone soil moisture is simplified compared to those in land surface and climate models, which represent hydrologic processes in more detail and, thus, have longer soil moisture memory.

A more complex land surface model could be used to infer root-zone soil moisture in this study, but would entail major assumptions regarding soil characteristics, and could make connection with the SMAP data less apparent.

Estimation of yield anomalies. Maize yield anomalies are estimated for 2015 to 2018 in each county as follows: fitting a linear regression to the yield in each county from 1998 to 2014 to determine the long-term trend external to climate variability; and subtracting the predicted yields from the observed yields, respectively. In the first step, we include only counties with over 14 yr of data excluding 2012, which had extremely low yields due to severe drought. We obtain similar results if yield anomalies are estimated relative to the 2015–2018 average (Supplementary Fig. 7).

First, we resolve the univariate yield response to individual climate variables, including daily near-surface soil moisture, root-zone soil moisture, precipitation, VPD and maximum temperature. To facilitate comparisons between the climate variables, we analyse only days with available soil moisture observations (as there are missing data only in soil moisture), and counties that have a minimum of 21 d of available soil moisture observations from May to July. Note that we do not fill missing soil moisture data because preserving the covariance between climate variables is critical to accurately resolve how they interact to affect yield. In total, there are 2,552 county-years that meet these criteria, aggregating across all counties east of 100° W, west of 80° W and north of 35° N and years 2015–2018.

To model the yield response for each climate variable, we assume the effects are cumulative over time during the months of May, June and July, and thus additively substitutable over time[6]. We model yield as a function of exposure time to climate conditions, rather than fitting a parametric yield model to the climatic variable, to avoid prescribing a functional relationship. For each climate variable, we fit a step function to the county-level yield anomalies

$$Y'_c = \sum_{h=1}^{n} \rho_{h,c}\beta_h + f_c + \epsilon_c \quad (3)$$

In equation (3), ρ_h represents the exposure time in units of days to each of n different environmental states measured for each county, c; β_h represents sensitivity to different exposures in units of bushels per acre per day and is held fixed across counties and years; f_c represents county-level fixed effects and ϵ_c represents the error. To account for the fact that soil moisture observations are not necessarily available every day and counties may have more or less missing data, we scale ρ_h assuming that the available data are representative of the whole growing season. Specifically, the value of ρ_h is estimated for each county-year as $N_b/N_o \times N_g$, where N_b is the number of days that fall in the bin, N_o is the total number of days in which soil moisture is observed, and N_g is the total number of days in the growing season ($N_g = 92$ d). The β_h and f_c values are fitted using a linear mixed-effects model without a global intercept. We estimate 95% CIs for β_h coefficients (Fig. 1), and P values for a hypothesis test of whether each parameter is equal to zero (Fig. 3a). To estimate CIs on the correlation coefficients (Table 1), we utilize non-parametric bootstrapping techniques wherein data from individual counties are resampled in 10,000 iterations. These CIs have a slight asymmetry due to the fixed effects[52].

To illustrate the dependence of heat stress on water availability (Fig. 1), we fit equation (3) to VPD using three sets of data: all of the county-years, the driest 40% of county-years based on seasonally averaged soil moisture, and the wettest 40% of county-years. For visual clarity, we fit the yield response using eight equal-width bins ranging from 0.4 to 2 kPa, although this response function looks similar to the one fitted with five bins (Supplementary Fig. 6).

To compare the yield response to different climate variables, May–July daily observations are binned into five equal-width bins. We use five bins to allow for comparisons between models with interactions, which increase the number of bins by its square (from 5 to 25), as described in the next paragraph. When fitting equation (3), bin edges are defined on the basis of the 1% and 99% quantiles, which we estimate using all days in May to July across all 2,552 county-years for each explanatory variable. Bins range from 0.1 to 0.5 $cm^3 cm^{-3}$ for surface soil moisture, 0.14 to 0.44 $cm^3 cm^{-3}$ for root-zone soil moisture, 0.14 to 2.1 kPa for VPD, 10 to 36 °C for temperature and 0 to 40 mm for precipitation. Data outside bin edges are counted in the edge bin. Five bins and their respective ranges are selected to ensure sufficient data resides within each to allow for sensitivity estimates, but the conclusions of the study are insensitive to the specification of the bin edges and number of bins, provided that the bins adequately span the observational range of data (Supplementary Fig. 7).

To incorporate moisture supply and demand interactions, data are binned conditioned on both supply (root-zone soil moisture or precipitation) and demand (VPD or temperature), resulting in 25 bins in total (for example, 5 soil moisture bins (h) by 5 VPD bins (i))

$$Y'_c = \sum_{h=1}^{n}\sum_{i=1}^{m} \rho_{h,i,c}\beta_{h,i} + f_c + \epsilon_c \quad (4)$$

In this two-dimensional framework, $\rho_{h,i}$ represents an exposure matrix and β_h represents a sensitivity matrix whose product is summed across rows and columns. The range of environmental data is maintained as previously stated. As more soil moisture data become available from SMAP, additional covariates should be explored, such as interactions with solar radiation[13]. Residuals from equation (4) fitted to root-zone soil moisture and VPD are shown in Supplementary Fig. 9.

Underlying our statistical framework is the assumption that moisture availability influences yield variability similarly from May to July. Field-level studies have shown that certain growth stages (for example, tasselling and ear formation) are more sensitive to water stress[1,23], although the general conclusions of this study do not change on the basis of the summertime months selected (Supplementary Table 3).

Extrapolating yield model to future climate conditions. To extrapolate the yield response beyond environmental conditions observed in 2015–2018 (Fig. 3b), we fit polynomial functions to the derived daily yield response (β_h) from equations (3) and (4). Specifically, we fit a quadratic curve to the five VPD coefficients from equation (3), as

$$\beta_h(\mathrm{VPD}) = W_h\left(q_0 + q_1 \times \mathrm{VPD}_h + q_2 \times \mathrm{VPD}_h^2\right) \quad (5)$$

In equation (5), we incorporate unequal weights, W_h, that reflect the fraction of total number of days in each bin summed across the 2,552 county-years, N_h, to the total number of observations summed across all 2,552 county-years, ΣN_h, as $W_h = N_h/\Sigma N_h$. This quadratic fit is shown in Supplementary Fig. 6. To account for the interactions between VPD and soil moisture, we fit a two-dimensional polynomial surface of order two for VPD and root-zone soil moisture to the 25 coefficients in equation (4)

$$\beta_h(\mathrm{VPD}, \mathrm{SM}) = W_h\big(p_0 + p_1 \times \mathrm{SM}_h + p_2 \times \mathrm{VPD}_h + p_3 \times \mathrm{SM}_h^2 + p_4 \times \mathrm{VPD}_h \times \mathrm{SM}_h + p_5 \times \mathrm{VPD}_h^2\big) \quad (6)$$

Weights are similarly based on the number of observations in each of the 25 bins. The weights are important so that coefficients based on a small number of observations are not over-represented in the fit, and explain why, for example, the coefficient in the low soil moisture and low VPD combination differs from the polynomial fit. The polynomial fit with interactions is shown in the background in Fig. 3a and the residuals are shown in Supplementary Fig. 10. These polynomial fits allow us to estimate yield under elevated VPD conditions (Fig. 3b) that extend beyond current observational ranges. To estimate uncertainty in the polynomial fits, we fit polynomials to 10,000 resampled versions of the β_h coefficients in equations (3) and (4) obtained from bootstrapping yield through resampling according to county. Yield response is predicted for an increase in VPD for each county and the median yield is recorded as a function of VPD, with the shaded CIs in Fig. 3b showing the 10th to 90th percentile of the distribution of possible median yields given uncertainties in regression coefficients.

When extrapolating the yield response, we focus on VPD and root-zone soil moisture because these are physiologically relevant variables[26] that are the most skillful out-of-sample predictors. When applied in the context of climate change, we assume that the joint distribution between VPD and soil moisture is unchanged except for a shift in the mean and that sensitivity to these variables remains fixed. There is the potential, however, for altered sensitivities from increased carbon dioxide concentrations and associated improved water relations[53] that should be explored in future work.

Out-of-sample testing. To test the predictive ability of the yield model in equations (3) and (4), we train the model on 3 yr of data and test it on the remaining year (for example, train using 2015–2017 data, and test on 2018) and average the statistics across all four sets of out-of-sample tests (Table 1 and Supplementary Table 1). The fits for temperature or VPD and root-zone soil moisture or precipitation are shown in Supplementary Figs. 11 and 12.

Eddy covariance analysis. We explore the relationship between daily VPD, soil moisture and GPP using data from the Mead rainfed eddy covariance site in Nebraska[30] (site abbreviation: US-Ne3). Isolating the years with maize (2001, 2003, 2005, 2007, 2009 and 2011), we estimate anomalies in daily maximum GPP (GPP_{max}) during the growing season. We define the growing season by smoothing GPP_{max} with a two-week window and isolating days when the smoothed seasonal cycle of GPP_{max} exceeds 40 $\mu mol\, m^{-2} s^{-1}$. To quantify the influence of soil moisture, measured at 25 cm, and VPD on productivity (Fig. 2a), we average GPP_{max} anomalies on the basis of the daily daytime VPD and soil moisture status, with daytime hours identified by when incoming solar radiation exceeds 50 $W m^{-2}$. In the conditional averaging scheme, we use 3 × 3 bins due to the smaller number of observations at the eddy covariance site relative to county-year yield data.

Reporting Summary. Further information on research design is available in the Nature Research Reporting Summary linked to this article.

Data availability

SMAP science data are available at the NASA National Snow and Ice Data Center Distributed Active Archive Center (https://nsidc.org/data/smap). Meteorological data are available at the PRISM Climate Group at Oregon State University (http://prism.oregonstate.edu). Maize yield data are available at the US Department of Agriculture/National Agriculture Statistics service (https://www.nass.usda.gov). Observations from the US-Ne3 eddy covariance site are available at the AmeriFlux (soil moisture; http://ameriflux.lbl.gov) and FLUXNET2015 (VPD, GPP and solar radiation; http://fluxnet.fluxdata.org/) data repositories.

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A.J.R. and P.H. conceived and drafted the manuscript, A.J.R. performed the analysis, and all authors contributed to the writing and interpretation.

Competing interests
The authors declare no competing interests.

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Study description	We use measurements of soil moisture, vapor pressure deficit, temperature, and precipitation to elucidate the primary climatic drivers of maize yield. To quantify the sensitivity of maize yield to daily climatic conditions, we fit a step function to the estimated yield anomalies, with the fit coefficients indicating the daily yield sensitivity. This statistical framework is flexible in that it allows for nonlinearities in the yield dependence, and can be fit to one climatic variable in isolation or two interacting climatic variables. To fit the yield anomaly model, we used 2,552 county-years of data spanning the U.S. Midwest from 2015 to 2018.
Research sample	All observations used in this study are from publicly available, existing datasets.
Sampling strategy	We analyze 2,552 county-years of data, as these county-years are within our spatial and temporal domain, and meet our inclusion criteria (described in detail in sections below). The county-years are not further sampled.
Data collection	All observations used in this study are from publicly available, existing datasets.
Timing and spatial scale	We use observational data spanning the U.S. Midwest from 2015 to 2018 in May, June, and July. We focus spatially on the U.S. Midwest because this region is intensely farmed with rain-fed maize, and maize yield data is available at the county scale. Prior to determining the drivers of maize yield, we aggregate all climatic data (e.g. soil moisture and vapor pressure deficit) from their native resolution to the county scale to match the yield observations. We focus on 2015-2018 because the Soil Moisture Active Passive satellite was launched in early 2015.
Data exclusions	Counties are excluded from the analysis if there is insufficient yield or soil moisture data, with insufficient data defined as either having less than 15 years of yield observations from 1998 to 2014, excluding 2012, or having less than 21 days of soil moisture observations from May to July.
Reproducibility	To verify reproducibility, we perform out-of-sample tests. Specifically, we train the model on three years of data and test it on the remaining year (e.g. train using 2015-2017 data, and test on 2018). We average the statistics across all four sets of out-of-sample tests (Table 1 and Table S1).
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