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Coordinated evaporative demand and precipitation maximize rainfed maize and soybean crop yields in the USA

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Abstract

To understand how climate change affects crop yields, we need to identify the climatic indices that best predict yields. Grain yields are most often predicted using precipitation and temperature in statistical models, assuming linear dependences. However, soil water availability is more influential for plant growth than precipitation and temperature, and there is ecophysiological evidence of intermediate yield maximizing conditions. Using rainfed maize and soybean yields for 1970–2010 across the USA, we tested whether the aridity index, that is, the ratio of precipitation and potential evapotranspiration seasonal totals and a proxy of soil water availability, better predicts yield than growing season precipitation total, average temperature and their interaction. We also tested for non-monotonic responses allowing for intermediate yield-maximizing conditions. The aridity index alone explained 77% and 72% of maize and soybean yield variability, compared with 78% and 73% explained by temperature, precipitation and their interaction. Yield responses were non-monotonic, with yields maximized at intermediate precipitation and temperature as well as at intermediate aridity index of 0.79 for maize and 0.98 for soybean. The yield maximizing precipitation also increased with growing season average temperature, faster in maize than soybean. The intermediate yield maximizing conditions show that rainfed maize and soybean yields could both increase and decrease depending on whether climatic conditions come closer to or deviate from the yield maximizing conditions in the future. In most counties, during 1970–2010, the precipitation and aridity index were lower and temperature higher compared with those maximizing yields, suggesting that climate change will reduce yields.

KEYWORDS
aridity index, *Glycine max*, interaction, precipitation, rainfed cropping, temperature, *Zea mays*

1 | INTRODUCTION

Temperature, precipitation and their interaction are often used to predict crop yields with statistical models (e.g., Lobell & Field, 2007; Luan et al., 2021; Matiu et al., 2017; Ray et al., 2015), explaining approximately a third of crop yield variability globally, with large local variations (Ray et al., 2015). Several aspects of the crop response to precipitation and temperature are mediated by soil water availability (e.g., Hamed et al., 2021; Luan & Vico, 2021; Riha et al., 1996), making soil moisture a better predictor of yields (Proctor et al., 2022). Soil moisture data are unavailable for long periods and over wide geographical areas, limiting robust statistical inference. We can nevertheless capture key aspects of the local soil water balance without information on soil moisture via the balance between water supply and energy-driven demand. This balance can be summarized by the aridity index (AI), here defined as the ratio of precipitation and potential evapotranspiration, both cumulated over the growing season. AI to great extent predicted water partition between evapotranspiration and runoff from field to catchment (Budyko, 1974; Good et al., 2017) and allowed for distinguishing vegetation controlled by water excess or deficit (Famiglietti et al., 2021). It also emerged as one of the two quantities governing the terrestrial water balance, via dimensional analysis of a minimalist stochastic soil water balance (Porporato et al., 2004), and was linked to abrupt changes of a variety ecosystem attributes (Adams et al., 2021; Berdugo et al., 2020). As a proxy of local water availability and by capturing the joint role of precipitation and temperature in conjunction, AI affords a more process-oriented look at the relationship between climatic conditions and crop yields than precipitation, temperature and their interaction. In spite of this potential, AI or some of its modifications have so far mostly been used for crop suitability delineation (van Wart et al., 2013). The few predictions of yield based on AI are limited in geographical scales and ranges of climatic conditions (Bannayan et al., 2010; Karimzadeh Soureshjani, 2021; Yin et al., 2016). As such, the ability of AI to explain yield variability compared with precipitation, temperature and their interaction remains unknown over a wide range of conditions.

The ecophysiological and biogeophysical mechanisms linking crop yield to precipitation and temperature are complex and often non-monotonic. Both insufficient and excessive water availability can be damaging, and crop yields are highest at intermediate precipitation, as confirmed by process-based models and empirical observations covering an extensive range of conditions (e.g., Grassini et al., 2015; Li et al., 2019; Proctor et al., 2022; Wang, Wu, et al., 2020). Indeed, low precipitation can contribute to plant water stress, in turn impairing most plant processes and reducing rainfed crop yields (Farooq et al., 2009; Hsiao, 1973; Lawlor & Tezara, 2009). Excessive precipitation facilitates nutrient leaching, denitrification and pathogen proliferation and is often associated to reduced solar radiation. These can negatively affect crop yields, but the associated yield reduction remains largely unresolved (Li et al., 2019; Rosenzweig et al., 2002). Warmer temperature and high frequency of temperature-related warm extremes monotonically reduced yields of staple cereals in surveys, field warming experiments and global crop model applications (e.g., Asseng et al., 2014; Vogel et al., 2019; Wang, Zhao, et al., 2020; Zhao et al., 2017). Other evidence points to an intermediate temperature that facilitates key plant processes (Wang et al., 2017; Way & Yamori, 2014) and maximizes yields across US counties (Hoffman et al., 2020; Lobell et al., 2011; Schlenker & Roberts, 2009) and globally at the country scale (Proctor et al., 2022). Hence, the net effects of climatic conditions on yields and the accurate representation of yield response to both temperature and precipitation remain uncertain (Barlow et al., 2015; Li et al., 2019; Peng et al., 2020; Wang et al., 2017). Specifically, despite indications of intermediate precipitation and temperature maximizing plant activity and growth, most statistical analyses of yields consider linear dependencies, thus potentially overlooking non-monotonic responses.

Along similar lines, field data, remote sensing algorithms and modelling point to a global 'mesic maximum', that is an intermediate AI that maximizes the biological water use fraction (defined as the ratio of annual transpiration to precipitation; Good et al., 2017). Crop yields are proportional to transpiration because of the monotonically increasing relationships among transpiration, gross primary production and biomass accumulation (Beer et al., 2009; Grassini et al., 2009; Sadras & Connor, 1991; Vico & Porporato, 2015). Based on these relationships, we can expect that crop yields are highest at intermediate AI, in line with the globally emerging mesic maximum (Good et al., 2017). However, the few attempts made to explain yields with AI assumed a linear dependence (Bannayan et al., 2010; Karimzadeh Soureshjani, 2021; Yin et al., 2016). Tests for an intermediate AI that maximizes yields are lacking. Moreover, the AI maximizing yields is not necessarily the same of the mesic maximum because the relationship between transpiration and grain yield is nonlinear (e.g., Purcell et al., 2007; Vico & Porporato, 2015 and references therein).

Temperatures are increasing and precipitation amounts and patterns are changing in some locations with climate change. Warmer temperature enhances atmospheric vapour pressure deficit (Ficklin & Novick, 2017) and potential evapotranspiration (Monteith, 1965), speeding up soil water depletion (Ficklin & Novick, 2017). The net effect of these changes can be captured directly by the yield maximizing AI, whereas we expect that warming increases the precipitation aat which yield is maximized. Where this intermediate yield maximizing precipitation lies and how it changes with temperature have not been identified for key commodity crops over a large geographical area of a country or continent.

We used time series of yields of maize (*Zea mays*) and soybean (*Glycine max*) during 1970–2010 from 1719 and 1393 counties in the USA, respectively. The counties are dominated by rainfed agriculture and span a wide range of climatic conditions. We summarized the growing season climatic conditions experienced by the crops either with growing season precipitation total, P_{GS}, and average temperature, T_{GS}, or with the aridity index over the same period, AI_{GS}. We hypothesize that (i) AI_{GS} alone explains yield variability equally well to or better than precipitation, temperature and their interaction; (ii) there is an intermediate precipitation that maximizes yield, which increases with temperature; and (iii) there is a yield maximizing AI_{GS}. In the process, we parameterize statistical models that can be used to predict effects of changing climatic conditions on the yields of two dominant commodity crops.

2 | MATERIALS AND METHODS

2.1 | Meteorological and crop yield data

Daily precipitation and minimum, mean and maximum temperatures were obtained from gridded data at 1/8° spatial resolution for 1949–

2010 developed by Maurer et al. (2002). These data cover most of the period for which yield information is available and have a spatial resolution adequate to represent the county conditions.

The soybean and maize yields across the USA are the survey yield data by county available through the US Department of Agriculture (USDA) National Agricultural Statistics Service (USDA NASS, 2020). We focused on the period 1970–2010 because yield data are available for a majority of counties starting in 1970, and year 2010 marks the end of the meteorological dataset. We used the generic yields, that is, yields with no specification of irrigated or rainfed cropping, for all counties in the USA where at least 10 years of data, even if non-consecutive, were available (Supporting information, Figure S1). To avoid confounding effects of irrigation, we limited our analyses to counties dominated by rainfed cropping, as indicated by fraction of irrigated land area <10% (Supporting information, Figure S2). Our conclusions did not change appreciably when setting this threshold to 20% (results not shown).

2.2 | Climatic indices describing the growing season conditions

The growing season was defined as the period between the mean planting and harvesting dates for each county. These dates were obtained from the crop calendar map available at 1/2° spatial resolution (USDA NASS 1997 data, collated and aggregated by Sacks et al., 2010). We aggregated the gridded planting and harvesting dates via the 'raster' package (Hijmans, 2019) in R, version 4.0.2 (R Core Team, 2022), by weighted fraction of area falling within the county boundaries and ignoring the grid cells for which no value was available.

To summarize the growing season conditions, we considered three climatic indices: growing season precipitation total, P_{GS}; growing season temperature average, T_{GS}, calculated based on the daily mean temperature; and growing season aridity index, AI_{GS}, defined as the ratio of precipitation to potential evapotranspiration, PET, both cumulated over the growing season. In the following, we used this definition of AI consistently: when referring to literature in which other definitions are used, for example, based on the inverse of our AI, we translate their conclusions in terms of AI as defined here.

To calculate AI_{GS}, we determined the daily PET for each pixel with the Hargreaves–Samani formula (Hargreaves & Samani, 1985):

$$\mathrm{PET} = 0.0135 k_{Rs} R_a \lambda^{-1} (T_{max} - T_{min})^{0.5} (T + 17.8) \tag{1}$$

where PET is expressed in mm day^{-1}, R_a is the extraterrestrial radiation (MJ m^{-2} day^{-1}), calculated as in Dingman (1994), T_{max}, T_{min} and T are the maximum, minimum and mean daily temperatures (°C), λ is the latent heat of vaporization (2.45 MJ kg^{-1}) and the other terms are empirical coefficients. We selected this PET estimate because it requires no additional data beyond location and standard meteorological data. The empirical radiation adjustment coefficient k_{Rs} was set to 0.16, given that most of the counties are not in coastal regions (Raziei & Pereira, 2013). This value also falls within the range of coefficients that ensure the best match with estimates from the standardized Penman–Monteith for short crops in the region for which most crop yield data are available (Supporting information, Figure S1; Aschonitis et al., 2017).

P_{GS}, T_{GS} and daily PET from Equation (1) were aggregated at the county scale following the same procedure used for the planting and harvesting dates. The county aggregated daily PET was then cumulated over the local growing season, to get PET_{GS} and the growing season AI calculated as $AI_{GS} = P_{GS} / PET_{GS}$. In all the analyses, we considered the actual climatic indices, instead of the anomalies after de-trending, in order to identify the combinations of conditions that gave the highest soybean and maize yields.

The resulting data covered a wide range of climatic conditions. The frequency and spatial distribution of the climatic indices are reported in Supporting information, Figures S3–S7. Few yields were available at combinations of especially high or low precipitation totals and average temperature (Figure S5). To avoid fitting the model for climatic conditions with limited information on yields, we removed the datapoints relative to specific counties and years with climatic conditions outside the 5th and 95th percentiles of P_{GS} and T_{GS} (i.e., P_{GS} outside the range 28.4–75.9 cm and T_{GS} outside the range 15.7–25.3°C for maize; and P_{GS} outside the range 25.7–70.4 cm and T_{GS} outside the range 17.2–25.3°C for soybean). Choosing less conservative thresholds (e.g., 1st and 99th) did not appreciably alter the key conclusions (not shown). The resulting dataset comprised 50,757 maize yield records from 1719 counties and 39,990 soybean yield records from 1393 counties (on average 29.5 years of data per county for maize and 28.7 years per county for soybean). Maize was grown in 99% of the counties for which soybean data were available, and soybean was cultivated in 80% of the counties with yield data for maize (Supporting information, Figure S1).

2.3 | Statistical analyses

Linear mixed effect models were fitted for maize and soybean yields separately. For each crop, we considered in separate models either growing season average temperature (T_{GS}) together with total precipitation (P_{GS}), or aridity index (AI_{GS}) alone, as fixed effects explanatory climatic variables. In all models, we included among the fixed effects also year (t) elapsed from 1969 as a continuous variable to account for technological improvement and long-term effects of climate change. Random effects were county and year as factorial variables, to control for the general impacts from spatial heterogeneity and covariation over the study area within a year, respectively.

In the temperature-precipitation models, we initially included as fixed effects, beyond t, the factors T_{GS}, P_{GS}, P_{GS}^2, T_{GS}^2 and all possible two-way interactions between them, with either maize or soybean yield per hectare, county and year as response variable, that is,

$$\text{Yield} = \beta_0 + \beta_t t + \beta_P P_{GS} + \beta_T T_{GS} + \beta_{P2} P_{GS}^2 + \beta_{T2} T_{GS}^2 + \beta_{PT} P_{GS} T_{GS} + \beta_{P2T} P_{GS}^2 T_{GS} + \beta_{PT2} P_{GS} T_{GS}^2 + \beta_{P2T2} P_{GS}^2 T_{GS}^2. \quad (2)$$

Here, β_0 is the model global intercept, β_t, β_T and β_P are slopes describing the linear dependences on time, temperature and precipitation, respectively, and β_{P2} and β_{T2} capture the quadratic response of yield to precipitation and temperature, respectively. The interaction of temperature and precipitation is represented by the slopes β_{PT}, β_{P2T}, β_{PT2} and β_{P2T2}. We compared the performance of this most complex model with seven reduced-complexity model variants. All these model variants retain t, T_{GS}, P_{GS} and the interaction $T_{GS} \times P_{GS}$ but include just some of the other terms, namely, the quadratic dependences and their interactions (see Supporting information, Section S3 for the list of model variants considered). The $T_{GS} \times P_{GS}$ interaction was retained in all model variants because physiological evidence and analyses of field and survey data show that the effects of low precipitation causing water stress are exacerbated under high temperature (e.g., Cohen et al., 2021; Luan et al., 2021; Matiu et al., 2017; Suzuki et al., 2014) and those of excessive precipitation under cooler temperatures (Li et al., 2019). In the following, for each crop, we retained the best performing model variant, that is, the model with the lowest value of the Akaike information criterion (AIC). For maize, the best performing model variant (Table S1) had the following structure of fixed effects:

$$\text{Yield} = \beta_0 + \beta_t t + \beta_P P_{GS} + \beta_T T_{GS} + \beta_{P2} P_{GS}^2 + \beta_{T2} T_{GS}^2 + \beta_{PT} P_{GS} T_{GS} + \beta_{P2T} P_{GS}^2 T_{GS} + \beta_{PT2} P_{GS} T_{GS}^2. \quad (3)$$

For soybean, the best performing model variant was (Table S1)

$$\text{Yield} = \beta_0 + \beta_t t + \beta_P P_{GS} + \beta_T T_{GS} + \beta_{P2} P_{GS}^2 + \beta_{T2} T_{GS}^2 + \beta_{PT} P_{GS} T_{GS}. \quad (4)$$

Conversely, only one model was considered with AI_{GS} as climatic explanatory variable. This included linear and quadratic dependencies on AI_{GS}. The fixed effect part of model was

$$\text{Yield} = \gamma_0 + \gamma_t t + \gamma_A AI_{GS} + \gamma_{A2} AI_{GS}^2, \quad (5)$$

where γ_0 is the model global intercept, γ_t and γ_A describe the linear dependences on t and AI_{GS}, respectively, and γ_{A2} is the quadratic dependence on AI_{GS}.

The precipitation and temperature corresponding to the absolute maximum yield were determined by solving the system obtained by setting to zero the first derivatives with respect to P_{GS} and T_{GS} of Equation (3) for maize and Equation (4) for soybean. The dependence of the yield maximizing precipitation on temperature ($P_{GS}^*(T_{GS})$) was instead determined as the precipitation at which the first derivative with respect to P_{GS} of Equation (3) for maize and Equation (4) for soybean equals 0. For maize, this led to

$$P_{GS}^*(T_{GS}) = -\left(\beta_P + \beta_{PT} T_{GS} + \beta_{PT2} T_{GS}^2\right) / [2(\beta_{P2} + \beta_{P2T} T_{GS})]. \quad (6)$$

Whereas, for soybean, P_{GS}^* was obtained as

$$P_{GS}^*(T_{GS}) = -(\beta_P + \beta_{PT} T_{GS}) / (2\beta_{P2}). \quad (7)$$

Similarly, the yield maximizing aridity index, AI_{GS}^*, corresponds to the position of the vertex of the parabola in Equation (5), that is,

$$AI_{GS}^* = -\gamma_A / (2\gamma_{A2}). \quad (8)$$

We determined the confidence intervals of $P_{GS}^*(T_{GS})$ and AI_{GS}^* by creating pseudo-replicates of the dataset via 2000 bootstraps with resampling and estimating the linear mixed effect model coefficients of the models in Equations (3)–(5) and the yield maximizing conditions (Equations 6–8) for each pseudo-replicate.

The R statements of the final models (Equations 3–5) are reported in the Supporting information, Section S4. We fitted the models with a restricted maximum likelihood approach using the 'lme4' package version 1.1.23 (Bates et al., 2015) in R version 4.0.2 (R Core Team, 2022). Linear model assumptions, including homoscedasticity and normality of errors, were visually checked in the residual plots. All the assumptions were satisfied. The correlations between precipitation and temperature were low (Figure S3), indicating no issue with collinearity. We quantified the performance of the selected models via the fraction of variance explained by the fixed effects alone (marginal coefficient of determination R^2) and the total fraction of variance explained (conditional R^2), determined following Nakagawa and Schielzeth (2013), as well as the root-mean-square error, normalized by the yield range (NRMSE).

3 | RESULTS

3.1 | Growing season precipitation and temperature as predictors of yield

Precipitation, temperature and their interactions explained 78% and 73% of the yield variability for maize and soybean, respectively (conditional R^2, Table 1). As expected, the temperature and precipitation interaction was significant (Table 1). There were also negative quadratic dependences on P_{GS} and T_{GS}, that is, yield was maximized at intermediate P_{GS} and T_{GS}.

The absolute highest yields were achieved at intermediate precipitation and temperature, specifically at P_{GS} of 63.4 cm and T_{GS} of 17.9°C for maize and at P_{GS} of 58.6 cm and T_{GS} of 20.0°C for soybean, when estimated based on the fixed effects only (dots in Figures 1–3). Yields improved over time, giving 0.10 and 0.03 ton ha^{-1} annual yield increases in maize and soybean, respectively (Table 1).

In maize, the yield sensitivity to a change in precipitation depended on temperature. An increase in precipitation increased yields at low temperature but had no effect at high temperature

TABLE 1 Model coefficient estimates, standard errors (SE) and *p* values for the best performing precipitation and temperature model, selected based on the AIC criterion, for maize (Equation 3) and soybean (Equation 4). Effects significant at $p \le 0.05$ are highlighted in bold. Marginal and conditional R^2 represent the variation explained respectively by the fixed factors alone and by the entire model, including fixed and random effects (Nakagawa & Schielzeth, 2013). NRMSE is the root-mean-square error, normalized by the range of yields included in the dataset.

	Maize			Soybean		
Predictors	**Estimates**	**SE**	***p***	**Estimates**	**SE**	***p***
β_0 (ton ha^{-1})	−2.990	1.849	0.106	−9.880	$3.320 * 10^{-1}$	**<0.001**
β_t (ton ha^{-1} yr^{-1})	$1.031 * 10^{-1}$	$6.524 * 10^{-3}$	**<0.001**	$2.626 * 10^{-2}$	$1.864 * 10^{-3}$	**<0.001**
β_P (ton ha^{-1} cm^{-1})	$1.247 * 10^{-2}$	$4.324 * 10^{-2}$	0.773	$2.791 * 10^{-2}$	$2.355 * 10^{-2}$	**<0.001**
β_T (ton ha^{-1}°C^{-1})	$4.439 * 10^{-1}$	$1.674 * 10^{-1}$	**0.008**	1.089	$2.947 * 10^{-2}$	**<0.001**
β_{P2} (ton ha^{-1} cm^{-2})	$-2.709 * 10^{-3}$	$2.892 * 10^{-4}$	**<0.001**	$-3.374 * 10^{-4}$	$1.392 * 10^{-5}$	**<0.001**
β_{T2} (ton ha^{-1}°C^{-2})	$-1.159 * 10^{-2}$	$3.915 * 10^{-3}$	**0.003**	$-2.801 * 10^{-2}$	$6.729 * 10^{-4}$	**<0.001**
β_{PT} (ton ha^{-1}°C^{-1} cm^{-1})	$1.814 * 10^{-2}$	$3.366 * 10^{-3}$	**<0.001**	$5.801 * 10^{-4}$	$9.346 * 10^{-5}$	**<0.001**
β_{P2T} (ton ha^{-1}°C^{-1} cm^{-2})	$1.013 * 10^{-4}$	$1.397 * 10^{-5}$	**<0.001**	-	-	-
β_{PT2} (ton ha^{-1}°C^{-2} cm^{-1})	$-6.981 * 10^{-4}$	$7.295 * 10^{-5}$	**<0.001**	-	-	-
Observations	50,757			39,990		
Marginal R^2	0.467			0.363		
Conditional R^2	0.782			0.725		
NRSME	0.0787			0.0756		
AIC	150,264			28,310		

Abbreviations: AIC, Akaike information criterion; NRMSE, root mean square error, normalized by the yield range.

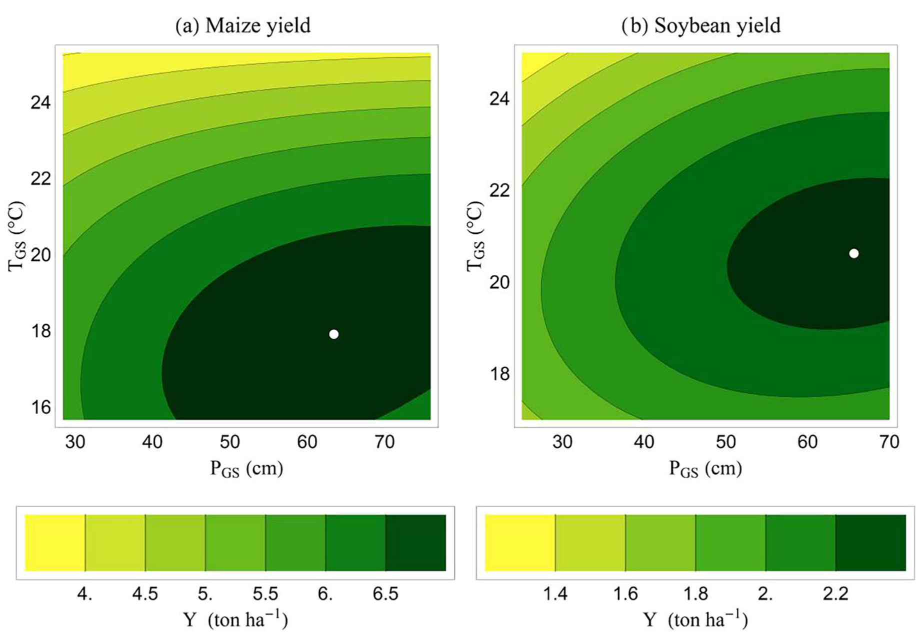

FIGURE 1 Crop yield Y as a function of growing season precipitation and temperature based on the fixed effects of the best performing model for (a) maize (Equation 3) and (b) soybean (Equation 4). The model coefficients are summarized in Table 1. Elapsed years from the beginning of the records were set to the intermediate year within the period 1970–2010, that is, t = 1989–1969 = 20 years. The white dots denote the conditions at which yield is at its absolute highest, as determined by simultaneously setting to zero the partial derivatives of Equation 3 or 4 with respect to P_{GS} and T_{GS}. The ranges of climatic conditions correspond to the 5th and 95th percentiles of observations (Figure S5).

(Figure 2a). In contrast, soybean yields increased with precipitation for P_{GS} below approximately 55 cm and decreased at higher P_{GS} irrespective of temperature (Figure 2b). Also the sensitivity of yield to temperature depended on the climatic conditions (Figure 2c,d).

The yield maximizing precipitation, P_{GS}*, increased with temperature in both crops and was higher in maize than soybean (Figure 3). In addition, yield maximizing precipitation increased faster with temperature in maize than soybean.

3.2 | Aridity index as predictor of yield

The model based on AI_{GS} and time only (Equation 5) explained 77% and 72% of yield variability of maize and soybean yields (conditional R^2 in Table 2), that is, a proportion of variability comparable with that of the temperature and precipitation models (Equations 3–4; Table 1). Yet, compared with the precipitation and temperature models, the fixed factors of the AI_{GS} model had a lower explanatory power. The

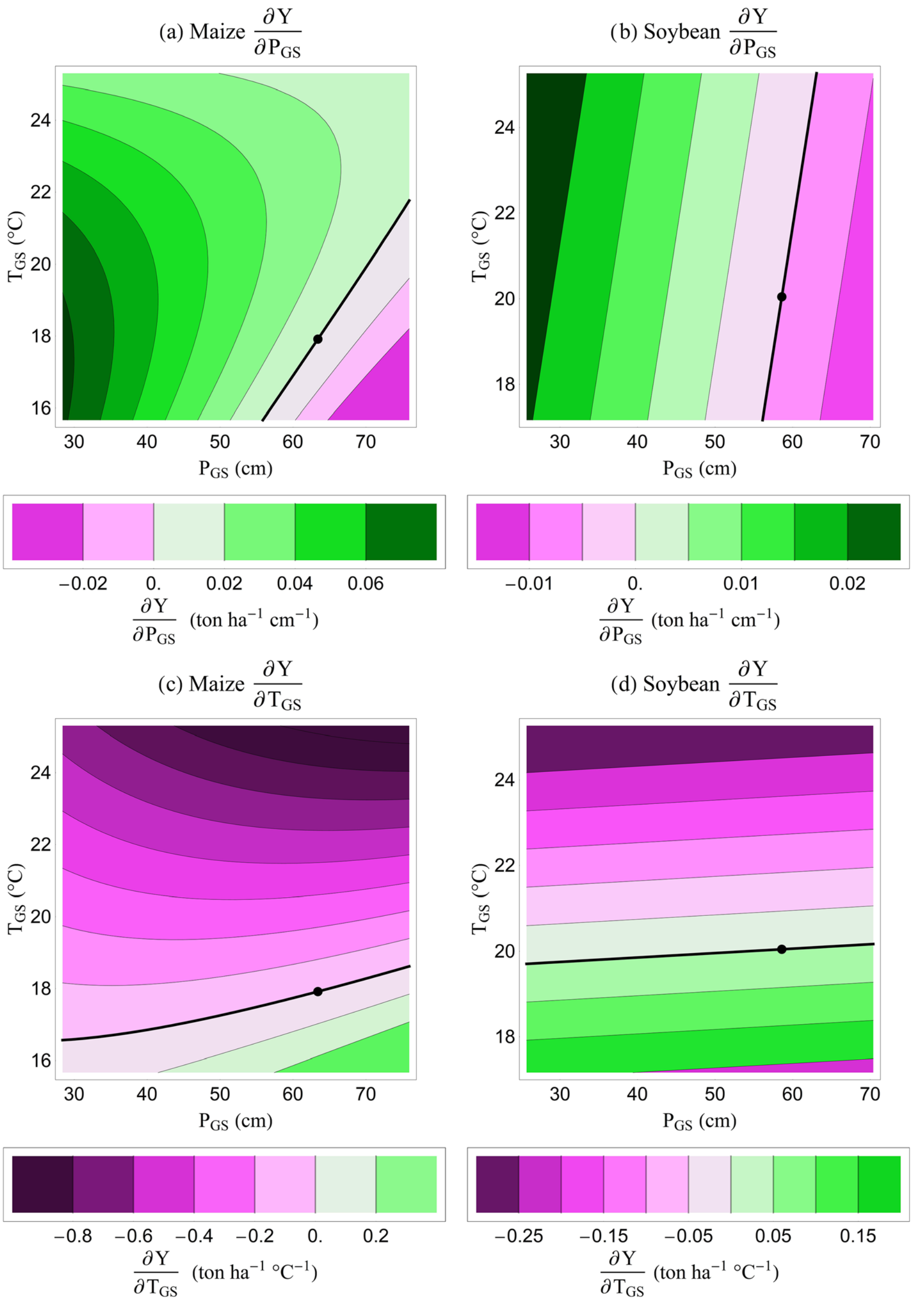

FIGURE 2 Sensitivity of yield Y to unitary change of (a,b) precipitation and (c,d) temperature, as expressed by the derivatives of yield with respect to P_{GS} and T_{GS}, respectively, based on the fixed effects of the best performing model variant, for (a,c) maize (Equation 3) and (b,d) soybean (Equation 4). The model coefficients are summarized in Table 1. The thick black contours denote the conditions at which the derivative equals zero. The black dots correspond to the conditions at which yield is at its absolute highest (i.e., correspond to the white dots in Figure 1). The ranges of climatic conditions considered correspond to the 5th and 95th percentiles of the observations (Figure S5).

AI_{GS} model had marginal R^2 of 0.34 and 0.28 for maize and soybean (Table 2), to be compared with 0.47 and 0.36, respectively, for the precipitation and temperature models (Table 1). The performance was lower also based on the AIC. AIC for the AI_{GS} model was larger than that for the best performing precipitation and temperature model variants by 1669 and 1382 for maize and soybean, respectively (Tables 1 and 2). Similarly, the root mean square error normalized by the yield range (NRMSE) was slightly higher in the AI_{GS} model than in the precipitation and temperature models (+1.3% and +1.4% for maize and soybean, respectively).

Yield depended nonlinearly on AI_{GS} in both crops. The AI_{GS} at which yield was at maximum, AI_{GS}*, was 0.787 for maize and 0.976 for soybean, with bootstrap 5%–95% confidence intervals of 0.763–0.792 and 0.964–0.988, respectively (Figure 4).

3.3 | Comparison of yield-maximizing conditions with 1970–2010 observations

The precipitation totals corresponding to the absolute highest yields (dots in Figure 1) were exceeded only by 14.6% of the values of P_{GS} included in the maize dataset and by 11.6% of those in the soybean dataset. Conversely, the temperatures for the absolute yield maximum were exceeded by 81.2% of the values of T_{GS} in the maize dataset and by 68.4% of those in the soybean dataset.

The faction of observations below the yield maximizing precipitation P_{GS}* increased with recorded T_{GS} and more so for maize than soybean (Figure 5a). In the warmer growing seasons (T_{GS} > 22°C), P_{GS} was lower than P_{GS}* in all or almost all cases for maize. In other words, in most counties and years included in the 1970–2010 dataset,

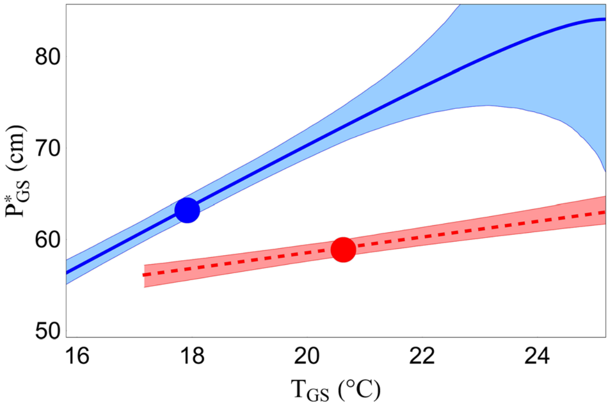

FIGURE 3 Yield maximizing precipitation, P_{GS}*, at different growing season temperatures T_{GS} for maize (blue solid line) and soybean (red dashed line), based on Equations 6 and 7, respectively, and the coefficients in Table 1. The shaded areas correspond to the 5%–95% confidence intervals, obtained via bootstrapping of the data. The dots denote the conditions at which yield is at its absolute highest (i.e., correspond to the white dots in Figure 1). The lines extend to the ranges of average growing season temperature, T_{GS}, covered by the dataset trimmed at the 5th and 95th percentiles.

P_{GS} was lower than the value corresponding to the maximum yield for that county and year, with, on average, very few exceptions in the Northeast for maize and the deep South for soybean (orange and yellow hues in Supporting information, Figure S8).

Similarly, AI_{GS}* corresponds to the 92th and 90th percentiles within the dataset for maize and soybean, respectively. AI_{GS}* was greater than AI_{GS} in most observations, particularly in warmer years and in maize (Figure 5b), with average geographic distribution in line with that of the differences between average P_{GS} and P_{GS}* (Supporting information, Figure S9).

4 | DISCUSSION

Our models explained more than 70% of the observed yield variability (Tables 1 and 2), placing them at the upper end of previous global explorations (e.g., Ray et al., 2015). Growing season precipitation total, P_{GS}, average temperature, T_{GS}, and their interactions performed better than growing season aridity index, AI_{GS}, according to AIC and capacity of the fixed effects to explain yields, but the overall fractions of explained variance and normalized RMSEs were similar. As such, our first hypothesis is only partially supported. AI emerges as a viable alternative to precipitation and temperature to explain yield variability but does not improve predictions, despite being a closer proxy of plant water availability. This lack of improvement in explanatory power could be caused by the direct effect of temperature on crop development and yield formation, which is partially captured by the T_{GS} and T_{GS}^2 terms in the precipitation and temperature models, but not included in the AI model. Nevertheless, the small difference in performance between the P_{GS} and T_{GS} and the AI_{GS} models suggests that reductions in yields when away from the yield maximizing conditions can be primarily ascribed to the effect of water deficit or excess, resulting from the interaction of temperature, evaporative demand and precipitation, rather than a direct effect of temperature on the crops.

Crop yields depended nonlinearly on temperature, precipitation and their interactions, as seen from the model selection (Supporting information, Section S3) and coefficient significances (Table 1), in line with ecophysiological evidence (e.g., Suzuki et al., 2014; Way & Yamori, 2014). Including nonlinear dependences on precipitation and temperature as well as interactions between these conditions appears necessary to explain a large share of yield variability. This is an improvement with respect to statistical modelling in which crop yields were predicted from precipitation and temperature and that included the nonlinear dependencies but did not account for the interactions between temperature- and precipitation-related indices (Lobell & Burke, 2010; Ortiz-Bobea et al., 2021). Conversely, statistical models in which temperature-precipitation interactions have been considered have lacked nonlinear dependencies on precipitation and temperature (Carter et al., 2018; Hawkins et al., 2013; Luan et al., 2021; Urban, Sheffield, & Lobell, 2015). These would not capture the effects of both insufficient and excessive precipitation and temperature, limiting their use to generally dry (wet) or warm (cold) conditions. Moreover, the clear nonlinear dependence of crop yields on temperature is a step forward in effectively summarizing yield responses to temperature, which is needed to improve process-based model predictions (Lobell & Burke, 2010; Wang et al., 2017).

In line with our second hypothesis, yields were maximized at intermediate precipitation (Figure 1), and the yield maximizing precipitation increased with temperature (Figure 3), clearly indicating that warming enhances the needed water supply. This points to the key role of soil water availability, more than temperature directly, in defining yields, in line with recent results (Proctor et al., 2022). Our estimated yield maximizing precipitation ranged from 570 to 840 mm for maize and from 556 to 629 mm for soybean, over the range of temperatures included in the dataset (lines in Figure 3). These yield maximizing precipitation ranges are in broad agreement with other results. The total water supply needed for the highest yield quantified via process-based models in the US Corn Belt ranged between 700 to 1000 mm for maize (Grassini et al., 2009, 2011) and 700 to 750 mm for soybean (Grassini et al., 2015; Sharda et al., 2019). These values are somewhat higher than our estimates, likely because they include also the depletion of soil water storage during the growing season. In the same region, maize yield shifted from being positively to negatively affected by a precipitation increase when April-to-August precipitation reached 650 mm, based on a statistical model (Lobell et al., 2020). This threshold is comparable with the precipitation at which the absolute maximum yield is achieved based on our model results (634 mm; dots in Figures 1a and 3).

Yield depended nonlinearly also on growing season AI for both crops, with the highest yield at intermediate AI_{GS}, as per our third hypothesis. The few previous analyses using AI to explain yields are limited in geographical and climatic range and are all based on linear relationships. They showed yield increased with AI, at the annual scale

TABLE 2 Model coefficient estimates, standard errors (SE) and *p* values for the fitted maize and soybean AI model (Equation 5). Effects significant at $p \leq 0.05$ are highlighted in bold. The marginal and conditional R^2 represent the variation explained respectively by the fixed factors alone and by the entire model, whereas NRMSE is the root-mean-square error, normalized by the range of yields included in the dataset.

	Maize			Soybean		
Predictors	Estimates	SE	*p*	Estimates	SE	*p*
γ_0 (ton ha^{-1})	$6.044 * 10^{-1}$	$1.836 * 10^{-1}$	**0.001**	$3.408 * 10^{-1}$	$5.032 * 10^{-2}$	**<0.001**
γ_t (ton ha^{-1} yr^{-1})	$1.004 * 10^{-1}$	$6.918 * 10^{-3}$	**<0.001**	$2.539 * 10^{-2}$	$1.775 * 10^{-3}$	**<0.001**
γ_A (ton ha^{-1})	9.313	$2.447 * 10^{-1}$	**<0.001**	2.856	$6.491 * 10^{-2}$	**<0.001**
γ_{A2} (ton ha^{-1})	−5.913	$2.060 * 10^{-1}$	**<0.001**	−1.462	$4.174 * 10^{-2}$	**<0.001**
Observations	50,575			39,990		
Marginal R^2	0.342			0.278		
Conditional R^2	0.771			0.720		
NRMSE	0.0797			0.0767		
AIC	151,933			29,692		

Abbreviations: AIC, Akaike information criterion; NRMSE, root mean square error, normalized by the yield range.

in wheat and barley in Iran (Bannayan et al., 2010; Karimzadeh Soureshjani, 2021), during the growing season in soybean and wheat, and within shorter periods in maize and rice in north-eastern China (Yin et al., 2016). Despite not considering these more complex dependences, the ratio of monthly precipitation to temperature—somewhat proportional to AI—explained 34% to 78% of maize and sorghum yield variation depending on month and location across Botswana (Byakatonda et al., 2018). Yet, for the large range of climatic conditions explored here, neglecting the quadratic dependence on AI_{GS} reduces the fraction of explained variance and doubles the NRMSE (not shown).

The estimated yield maximizing aridity index (AI_{GS}*) is 0.79 for maize and 0.98 for soybean (Figure 4), to be compared with the interquartile range of aridity indices maximizing biological water use (0.53 to 0.77, obtained by Good et al., 2017). Hence, both maize yields across the USA and biological water use globally are maximized when PET exceeds precipitation, whereas soybean yields are highest when precipitation nearly balances PET.

AI_{GS}* is greater than the AI maximizing the biological water use for both crops. This suggests that to maximize yields, precipitation needs to meet a larger fraction of potential evapotranspiration in crops compared with vegetation annually and globally, that is, that maize and soybean are on average less water stressed when achieving the maximum yield. The difference between AI_{GS}* and the global mesic maximum is likely even larger than apparent from these figures, because we focused on the growing season only, whereas the mesic maximum in Good et al. (2017) was based on conditions during the entire year. In locations with growing season coinciding with the warmer season (like most of the USA), AI_{GS} is lower than AI calculated over the entire year (like those in Good et al., 2017), except when precipitation occurs mostly during the growing season. There are several possible explanations for the difference between AI_{GS}* and the AI maximizing biological water use. Nonlinear relationships link the grain yield that we assessed here to transpiration, which drives biological water use (Purcell et al., 2007; Vico & Porporato, 2015 and references therein). Unfavourable conditions of short durations, such as water stress, could reduce yield more than indicated by the cumulated actual evapotranspiration to which the biological water use is proportional. Another possible explanation is that crops are generally more anisohydric than other species (Konings & Gentine, 2016), that is, they maintain their stomata open even under water limitation.

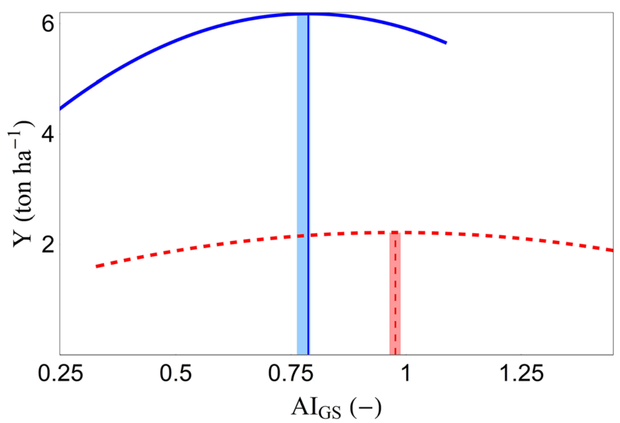

FIGURE 4 Crop yield Y as a function of AI_{GS}, based on the fixed effects of the AI model (Equation 5), for maize (blue solid line) and soybean (red dashed line), extending only over the ranges of AI_{GS} corresponding to P_{GS} and T_{GS} within the 5th to 95th percentiles. Vertical lines correspond to the yield maximizing aridity index, AI_{GS}* as determined by the fixed effect part of the model (Equation 8) and the coefficients in Table 2. The shaded areas extend to the AI_{GS}* 5%–95% estimated by bootstrapping of the data. The confidence interval of the maize is not centered around AI_{GS}* determined via the coefficients in Table 2 because the range of AI_{GS} in the database is skewed towards values lower than AI_{GS}* (Supporting information, Figure S4), affecting the fully random data bootstrapping with replacement. Elapsed years from the beginning of the records were set to an intermediate year within the period 1970–2010, that is, $t = 1989–1969 = 20$ years.

The existence of yield maximizing intermediate growing season precipitation total, average temperature and AI implies that depending on location and year, yields could be constrained by both insufficient and excessive precipitation and by warm and cool conditions and their combinations. Nevertheless, the yield maximizing precipitation corresponded, for both crops, to a precipitation that was higher than most of the observations, in particular in warmer years and counties and for maize (Figure 5). Similarly, the yield maximizing AI_{GS} was higher than observed AI_{GS} in >80% of the cases in the dataset, that is, the precipitation was higher for a set PET, or PET was lower for a set precipitation. Moreover, yield maximizing precipitation totals were within the upper half of the precipitation totals observed within the dataset for soybean but exceed observations for temperatures above 22°C for maize (Figure 5a and Figure S3). Hence, in most counties, rainfed corn and maize production over the period 1970–2010 occurred in conditions where precipitation was often lower and temperature higher than ideal (Figures 5, S8 and S9). Temperature will continue to increase in the USA and globally, whereas projected changes in precipitation amount and pattern differ by region (Liu et al., 2020; Wuebbles et al., 2017). Rising temperatures will exacerbate the occurrence of insufficient precipitation input, while being beneficial in the minority of locations where yields are currently reduced by water excess. Indeed, precipitation above the local norm had a negative effect on maize yield in the northern US states, while the effect was positive in the southern states (Li et al., 2019). In the majority of locations, global warming will be detrimental for yields, unless accompanied by an adequate increase in precipitation or further expansion of irrigation, if locally sustainable. Conversely, growing season potential evapotranspiration is increasing in many agricultural regions but not, for example, in the US Midwest (Basso et al., 2021; Liu et al., 2020). Because of the compounded uncertainties in changes in potential evapotranspiration and precipitation, we cannot speculate on whether climate change will further increase the counties and years with AI_{GS} lower than the yield maximizing value.

Within the general patterns described above, some differences emerged between maize and soybean. Precipitation needed to maximize yields was larger in maize than soybean under all temperatures (Figure 3). Despite its C4 photosynthetic pathway, rainfed maize had 11% higher cumulated growing season evapotranspiration than rainfed soybean, according to eddy covariance data (Suyker & Verma, 2009). Hence, larger precipitation totals during the growing season are needed to meet the greater evapotranspiration demand of maize compared with soybean, which is in line with our results. Accordingly, maize received insufficient precipitation to maximize yields more frequently than soybean across most of the USA during 1970–2010 and in all cases when growing season average temperature exceeded 22°C (Figure 5). This pattern places maize at larger risk of yield reduction under global warming. Similarly, AI_{GS}* was lower in maize than soybean likely due to the higher water demands and hence more frequent water limitation of maize compared with soybean. Finally, for maize, yield sensitivity to a change in precipitation was higher at lower temperature and under excess more than shortage of precipitation under those conditions (Figure 2). But when factoring in the yield difference, that is, when normalizing the partial derivatives by yields, maize had a higher relative sensitivity than soybean only at

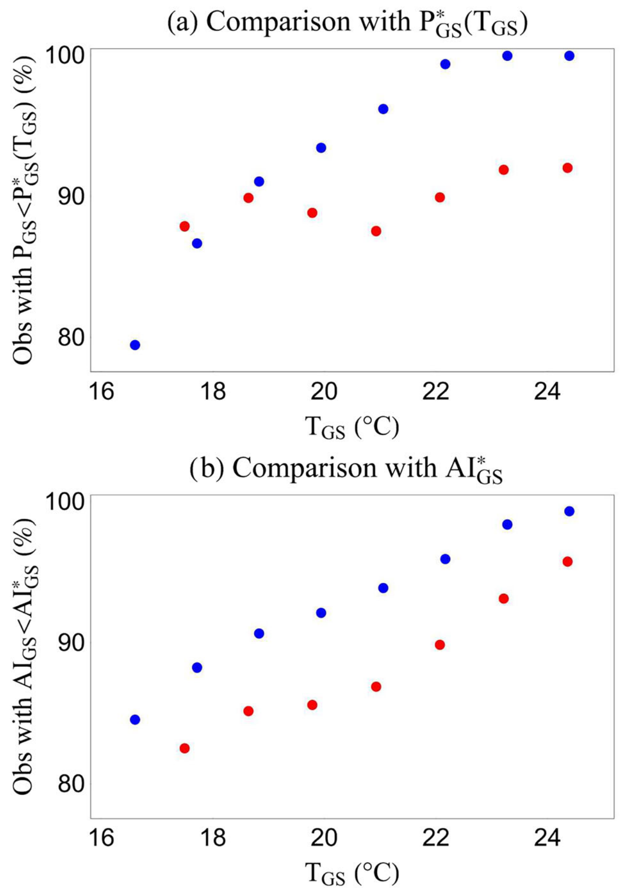

FIGURE 5 Percentage of observations exceeding (a) yield maximizing precipitation, P_{GS}* and (b) yield maximizing aridity index, AI_{GS}*, as a function of growing season average temperature for maize (blue) and soybean (red). Each dot refers to observations falling within ±0.5°C of the temperature indicated on the x-axis.

excess precipitation (not shown), in line with effects of precipitation anomalies on yields across the USA (Nelson & Burchfield, 2021) but in contrast to global country-level data (Proctor et al., 2022).

The explanatory power of our models was high and yield maximizing precipitation estimates were in agreement with other findings, despite considering only the average conditions over the growing season. Crop growth and yield are influenced also by intra-seasonal climatic conditions. Short-term stress conditions can markedly damage crops and reduce yields (e.g., Troy et al., 2015; Vogel et al., 2019), especially at critical developmental stages (Tack et al., 2016) and if co-occurring, for example, heat and water stress (Hamed et al., 2021; Luan et al., 2021). The role of water-mediated damaging short-term conditions is likely reduced at higher precipitation totals, as shown by a model application (Dietzel et al., 2016). Moreover, the effects of growing season conditions can be altered by pre-season soil water storage. A crop model showed that higher pre-season soil water led to overestimated yield losses under water stress and underestimated losses at water excess (Li et al., 2019), by buffering against later water shortage and enhancing water excess. This effect of pre-season soil water content would also hold true for our model results and particularly so for the central USA, where water excess at planting is increasingly frequent (Urban, Roberts, et al., 2015). Higher pre-season soil water storage would reduce yield sensitivity to changes in precipitation at insufficient precipitation and increase that under precipitation excess, all else being the same, potentially calling for a model able to accommodate nonsymmetric responses to precipitation. The relevance of pre-season conditions also depends on crop species, although in complex ways. For example, the longer growing season of maize compared with soybean might reduce the effect of pre-season soil water status on the final yield. At the same time, maize earlier sowing and final deeper roots (Borg & Grimes, 1986; Sacks et al., 2010) might enhance the benefits from off-season recharge where growing season rainfall is limited.

5 | CONCLUSIONS

Crops, in particular if rainfed, depend nonlinearly on precipitation and temperature to achieve their yield potential, all other conditions being equal. The effects of temperature and precipitation are largely mediated by soil water availability, which can be partially described by the aridity index, that is, the ratio between precipitation and potential evapotranspiration. Examining county yield data for rainfed maize and soybean across the USA over 1970–2010, we found that growing season aridity index alone explained yield variability almost equally well as growing season temperature, precipitation and their interactions, but had a lower performance based on the AIC, despite being a proxy of water availability to meet evaporative demands. Yields of both maize and soybean responded nonlinearly to precipitation and temperature, and aridity index, with intermediate conditions leading to the maximum yields. The yield maximizing precipitations increased with temperature for both crops and more so for maize. The yield maximizing aridity index exceeded the global estimates of the mesic maximum, suggesting that crops achieving the highest yield are on average less water stressed than vegetation globally.

Yields can both increase or be reduced by a change in precipitation under warming conditions, depending on whether the co-varying precipitation and temperature shift conditions closer or farther away from the yield maximizing precipitation for the corresponding temperature. However, most of the observations over 1970–2010 across the USA are relative to conditions where precipitation is lower than that maximizing yield for the local temperature and aridity index below the yield maximizing value. Hence, warming could be more damaging than beneficial for US rainfed maize and soybean. Knowledge of the locations where future climatic conditions will move farther away from those that maximize yields allows identifying climate change vulnerability hotspots, where adaptation is most urgent.

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DATA AVAILABILITY STATEMENT

All the data used are freely available online. Daily gridded meteorological data were obtained from https://www.engr.scu.edu/~emaurer/gridded_obs/index_gridded_obs.html (Maurer et al., 2002), yield data from USDA NASS https://quickstats.nass.usda.gov and area equipped with irrigation infrastructure from FAO http://www.fao.org/aquastat/en/geospatial-information/global-maps-irrigated-areas/irrigation-by-country/country/USA (last accessed December, 2020).

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SUPPORTING INFORMATION

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