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# Drought tolerant maize hybrids have higher yields and lower water use under drought conditions at a regional scale

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ABSTRACT

Drought is an enduring abiotic constraint to stable and consistent maize productivity under climate change, especially for low rainfall regions with limited irrigation. One adaptation for severe drought is using drought-tolerant (DT) hybrids. Here, we characterize differences between conventional and DT hybrids in terms of yield and water-use efficiency under drought conditions at a regional scale of the Texas High Plains (THP). Using a validated version of APSIM-Maize, we simulated yields of conventional and DT hybrids across 11 water regimes and 25 counties in THP from 1984 to 2018. When irrigation amounts were constrained to 90%, 80%, 70%, 60% and 50% of total irrigation used for the baseline scenario (BS; a simulated scenario of conventional hybrid under full irrigation), DT hybrids showed lower yield penalties under drought stress relative to conventional hybrids. This improved total production by 19%, 24%, 26%, 26%, and 21% for each of the above irrigation levels. When the yield-target was set as 90%, 80%, 70%, and 60% of BS, total regional irrigation applied to DT hybrid could be saved more than that to the conventional hybrid, and therefore reduced more 17%, 16%, 15%, and 15% of BS irrigation, respectively. We showed that DT hybrids had greater yield gain and water savings through improved water productivity under deficit irrigation, highlighting the potential of deficit irrigation for increasing yield for the adoption of DT hybrid. Our quantitative evaluation of the yield advantage and water saving potential associated with DT hybrids also highlighted the regional benefits associated with adoption of drought adaptive hybrids.

## 1. Introduction

With the intensification of the global water cycle borne by climate change, global agri-food systems are becoming increasingly challenged by extreme climatic events (Senapati et al., 2018; Harrison, 2021a). At the same time, global population growth is burgeoning, and the total global food demand is expected to increase by 35–56% between 2010 and 2050 (Michiel et al., 2021). These apparently contradictory trends suggest that crop production must be sustainably increased to reduce hunger and alleviate poverty (Asseng et al., 2018; Godfray et al., 2010) without degrading natural capital, causing loss of biodiversity, increasing greenhouse gas emissions (Harrison et al. 2021b). Given that around one-third of crop yield variability is underpinned by climate variation (Müller et al., 2017; Ray et al., 2015), food security under climate change largely depends on the resilience of crop yields to climatic variability (Kahiluoto et al., 2019) and thus the consistency of crop production from one year to the next (Ibrahim et al. 2018; Liu et al. 2020). Of all abiotic stresses, drought is the most predominant constraint to crop productivity worldwide (Li et al., 2019; Lobell et al., 2014; Prodhan et al., 2022), significantly reducing cereal production by 10% during 1964–2007 (Dai, 2013; Lesk et al., 2016). Consequently, there is an urgent need to derive effective, profitable, and sustainable adaptations to enable consistently high production under drought.

Maize (*Zea mays* L.) plays an essential role in global food security, contributing some 39% of global cereal production in 2020 (FAO, 2021). As the world's largest maize producer, the United States (US) typically supplies ~40% of global maize production. However, maize is highly sensitive to drought stress (Harrison et al. 2014; Ali et al., 2016; Tardieu, 2020). The US has experienced significant increases in the frequency and intensity of extreme drought and sensitivity to drought in recent 20 years (1995–2018) (Lobell et al., 2014; Lobell et al., 2020). The continuing climate change threatens maize production at both national

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and global scales. A moderate, severe, extreme and exceptional drought event would lead to 64.3%, 69.9%, 73.6%, and 78.1% yield loss risk in US maize production, respectively (Leng, 2021). Some observational evidence from crop yield and insurance data has shown that extreme drought can reduce maize yield up to − 37% (−32 ± 2% on average) in the US relative to the expected yield from the long-term trend from 1981 to 2016 (Li et al., 2019). In 2012, severe drought decreased grain yield by 21% compared with the previous 5 years with an average country yield of 7.7 Mg $ha^{-1}$ (Boyer et al., 2013). To adapt the increasing drought events, farmers have already adapted irrigation as an agronomic practice. However, restrictions on the practice and expansion of irrigated agriculture continue, due to the reduced availability of freshwater resources and increasing water scarcity (Steward et al., 2013; Tolk et al., 2016; Zhang et al., 2018). Improving crop tolerance to drought has the potential to offset yield losses and sustain maize productivity under climate change in vulnerable regions (Tesfaye et al., 2018). Avoidance of drought, through selecting crop types with lifecycles that enable drought avoidance is one form of adaptation (Harrison et al. 2014), while breeding of drought-tolerant (DT) maize hybrids is another effective way to maintain the yield with less crop water requirements, particularly in semiarid regions (Cooper et al., 2014; Mounce et al., 2016; Martey et al., 2020).

Drought tolerance is a complicated and multifaceted physiological mechanism (Senapati et al., 2018). Compared with conventional hybrids, DT hybrids generally present a yield benefit and/or improved yield stability in water-limited environments (Cattivelli et al., 2008; Sammons et al., 2014; Simtowe, et al., 2019). Drought tolerance in maize is likely to entail the selection of plants with a reduced leaf area (especially in the upper part of the plant), short thick stems, small tassels, erect leaves, delayed senescence, lower root biomass, and deeper root systems with less lateral branching (Ribaut et al., 2009). In addition, DT maize hybrids have higher water productivity and lower water requirement with greater rainfall and soil water use efficiency (Ao et al., 2020; Hao et al., 2015a; Hao et al., 2015b), especially during the reproductive period (Zhao et al., 2018a). In 2012, DT maize hybrids were planted in only 2% of US maize acreage. By 2016, ~22% of U.S. maize acres were drought-tolerant, indicating the growing in adoption and popularity of DT hybrids over just five years (McFadden et al., 2018).

Although many studies have reported the benefit of DT maize hybrids under drought stress at the field scale, the quantitative potential yield benefits and water-saving from DT hybrids at a regional scale are mostly unknown. Increasingly, biophysical systems models are deployed mechanistically explain complex interactions between crop growth with management and environment ( Harrison et al., 2012; Cooper et al., 2014; Jin et al., 2019; Tofa et al., 2021). The Texas High Plains (THP) is a typical semiarid region. Maize is a major irrigated crop in the region and irrigation is accessed from the Ogallala Aquifer where maize alone accounts for as high as 90% of total groundwater withdrawals (Pathak et al., 2022). Here, we calibrated and validated the Agricultural Production Systems Simulator (APSIM), a comprehensive model developed to simulate biophysical processes in agricultural systems (Keating et al., 2003), using data obtained from the field of experimental data with two maize hybrids differing in drought tolerance under different water regimes in the THP. The objectives were to (1) estimate the contribution of DT hybrids to yield improvement under drought stresses and (2) evaluate the amount of water saving to achieve the target yield in the THP.

## 2. Materials and methods

### 2.1. Field experimental dataset

Two maize hybrids differing in DT characteristics (33D53AM, conventional hybrid; P1151AM, DT hybrid) were grown under irrigated conditions at two research stations in the THP (Fig. 1): the Texas A&M AgriLife Research Station near Etter, Texas (35° 52′ N, 101° 58′ W; elevation 1114 m above mean sea level) in 2014 and at Bushland, Texas (35° 13′ N, 102° 04′ W; elevation 1161 m above mean sea level) in 2015. The soil is classified as a Sherm silty clay loam soil (fine, mixed, mesic Torrertic Paleustolls) at Etter and a Pullman silty clay loam soil (fine, mixed, superactive, thermic Torrertic Paleustolls). The 30-yr (1981–2010) average amount of rainfall is 334 mm at Etter and 396 mm at Bushland during the maize growing season (May–October), respectively.

The field experiment was designed as a split-plot design with four replications, and irrigation treatments were the main plots and hybrids were the subplots. Two irrigation treatments were employed in both years: 100% ($I_{100}$) and 50% ($I_{50}$) of the expected water requirement ($ET_c$) in 2014 and 2015. $ET_c$ was determined by the reference evapotranspiration ($ET_0$) and crop coefficient ($k$). $ET_0$ was calculated according to the FAO Penman-Monteith equation (Allen et al., 1998) and $k$ for maize was previously determined using a lysimeter from TXHPET. Based on $ET_c$ and plant-available soil water (PAW) at the root zone, irrigation scheduling was determined on daily basis for $I_{100}$ (Marek et al., 2011). For $I_{50}$ treatments, irrigation frequency was the same as that of $I_{100}$ but the irrigation amount was 50% of that of $I_{100}$. In 2014, a center pivot irrigation system with a low elevation spray application method was used, while water was applied by furrow irrigation.

Maize was planted on May 15, 2014 and June 4, 2015, with planting density 74,000 plants $ha^{-1}$. Before planting, 290 kg $ha^{-1}$ of N, 109 kg $ha^{-1}$ of $P_2O_5$, and 11 kg $ha^{-1}$ of S were applied. Detailed information on the experiment was described in Zhao et al. (2018a).

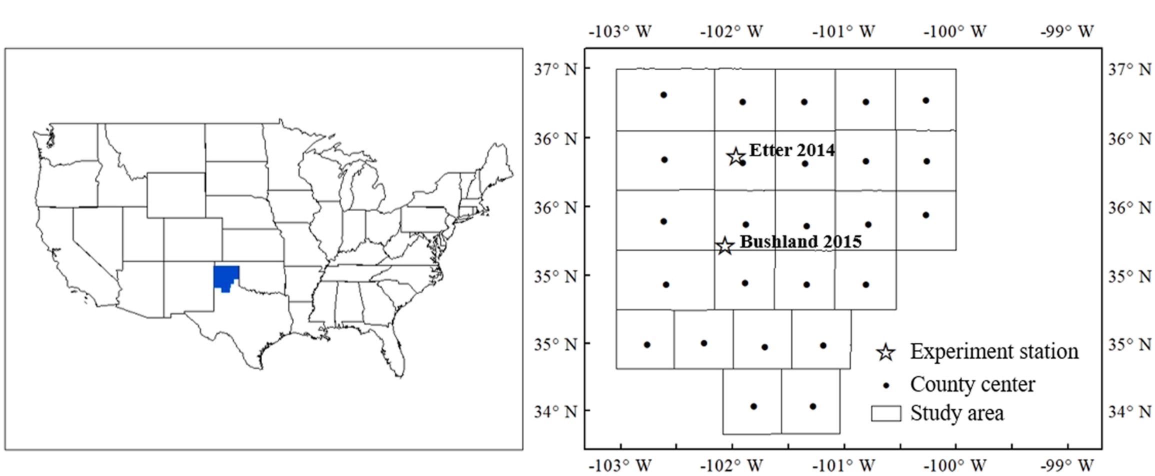


Fig. 1. Study area and location of experiment stations in the T Texas High Plains (THP).

### 2.2. Climate, soil, crop, and irrigation data

Climate data including daily maximum and minimum temperatures, precipitation, and solar radiations from 1984 to 2018 was obtained from NASA's Prediction of Worldwide Energy Resources (NASA/POWER; https://power.larc.nasa.gov). The data are assembled from a range of products derived from satellite imagery, ground observations, windsondes, modeling, and data assimilation, and are available for a global 1°× 1° coordinate grid (White et al., 2008; White et al., 2011).

The soil data used in this study include the soil bulk density (BD), saturated volumetric water content (SAT), drained upper limit (DUL), and 15 bar lower limit (LL15) of water content in different soil layers. LL15, DUL, and SAT describes the water characteristics of the soil. LL15 is approximately the driest water content achievable by plant extraction, DUL is the content of water retained after gravitational flow and is also referred to as "field capacity" (https://www.apsim.info/). These data used for model calibration and validation were collected from the field experiment. The regional soil data used for subsequent simulation were obtained from Soil Survey Staff, Natural Resources Conservation Service, United States Department of Agriculture (https://websoilsurvey.nrcs.usda.gov/).

The crop data were obtained from the field experiment in two maize hybrids, P1151AM and 33D53AM, including phenology (sowing, emergence, flowering, and maturity dates), yields, and biomass. Furthermore, the management practices (e.g. sowing density, fertilizer, and irrigation) were recorded. These data were used for modifying the APSIM-Maize model.

Irrigated areas of maize at the county level were obtained from the National Agricultural Statistic Service of the United States Department of Agriculture (USDA-NASS, https://quickstats.nass.usda.gov). We collected the annual irrigated areas from 1981 to 2018 and then calculated the multi-year averaged value as the irrigated areas of each county in the THP.

### 2.3. APSIM-Maize calibration and validation

The APSIM model (http://www.apsim.info/apsim/) is a cropping systems software platform capable of simulating a range of crops grown under various climatic, edaphic, and management conditions (Gaydon et al., 2017; Holzworth et al., 2014). APSIM has been proven as an effective research and decision tool worldwide, including in the Midwestern US (Archontoulis et al., 2014).

Field observations in 2014 and 2015 for the two hybrids, including phenology, aboveground biomass, yield, and management practices were used for the APSIM-Maize calibration and validation based on the method of cross-validation (Refaeilzadeh et al., 2009). Crop parameters calibrated for each hybrid in APSIM-Maize are listed in Table 1. The soil properties used as initial soil parameters in APSIM-Maize were listed in Table 2. The depth of the soil profile used in APSIM-maize is 150 cm.

To evaluate the performance of the calibrated APSIM-Maize model, statistical indices of the correlation coefficient ($R^2$), root mean square error (RMSE), and normalized root mean squared errors (NRMSE) (Loague and Green, 1991) were calculated from the observed and simulated variables, which were also relative to the 1:1 line.

**Table 1**
Genetic coefficients of maize in the APSIM model used for calibration.

| Parameter type | Parameter name | Description |
|---|---|---|
| Phenology parameters | tt_emerg_to_endjuv | Accumulated thermal time from emergence to end of juvenile (°C·d) |
| | tt_flower_to_maturity | Accumulated thermal time from flowering to maturity (°C·d) |
| Grain parameters | potKernelWt | Kernel weight (g/pot) |
| | grainNFillRate | Grain nitrogen fill rate (mg/grain/d) |
| Water uptake parameters | x_sw_demand_ratio | Water availability |

**Table 2**
Soil layer parameters used in APSIM-Maize.

| Soil depth (m) | The soil bulk density (BD, g/cm$^3$) | Saturated volumetric water content (SAT, cm$^3$/cm$^3$) | Drained upper limit of water content (DUL, cm$^3$/ cm$^3$) | 15 bar lower limit of water content (LL15, cm$^3$/cm$^3$) |
|---|---|---|---|---|
| 0–0.05 | 1.209 | 0.326 | 0.261 | 0.131 |
| 0.05–0.15 | 1.209 | 0.319 | 0.255 | 0.125 |
| 0.15–0.20 | 1.209 | 0.318 | 0.255 | 0.125 |
| 0.20–0.30 | 1.209 | 0.420 | 0.345 | 0.187 |
| 0.30–0.60 | 1.291 | 0.487 | 0.348 | 0.201 |
| 0.60–0.90 | 1.382 | 0.455 | 0.332 | 0.188 |
| 0.90–1.20 | 1.492 | 0.415 | 0.289 | 0.153 |
| 1.20–1.50 | 1.523 | 0.404 | 0.284 | 0.151 |

The calibration was performed using the DEoptim package in R (Mullen et al., 2011), which is minimizing a user-defined cost function, in this case, the model was fitting a specific date on which the crop reached the days to flowering (FloweringDAS) and to maturity (MaturityDAS). The prior distribution of the parameters (i.e. constraints on parameter values (Table 3)) was assigned based on the recommendation by Habekotté (1997) and followed a uniform distribution.

To avoid the effect of irrigation methods, we used different irrigation efficiencies in simulations based on irrigation methods according to literature when calibrating the model. We set irrigation efficiencies as 0.75 for simulation with sprinkling-irrigation (Brouwer et al., 1989) in 2014 and 0.90 for simulation with furrow-irrigation (Rajan et al., 2015) in 2015, respectively.

### 2.4. Scenario analysis

To estimate the contribution of DT hybrid to yield increase, we simulated yields of two hybrids under the same management practices in the model (Table 4). We simulated the yield of two hybrids with water fully satisfied (the Irrigation Module in APSIM was set to Automatic Irrigation) first. And then we set up irrigation schedules for the Operations Schedule Module of model based on the irrigation dates and amounts under automatic irrigation conditions (Fig. 2). Maize yield under each irrigation treatment was simulated by decreasing the irrigation amount from 100% to 50% (step by 5%) based on evapotranspiration requirement. The maize plants will experience more drought stress as irrigation level is decreased in this irrigated region. Noting that, for these two hybrids, the irrigated amounts and dates for meeting the full water satisfaction were different under automatic irrigation. This has resulted in different irrigation schedules for two hybrids in the next simulations.

### 2.5. Data analysis

For comparing the different growing responses of conventional hybrid and DT hybrid to water regimes, and analyzing the water consumption difference in regional production under drought stress, we calculated the crop water productivity ($WP_C$) which indicates the total above-ground biomass accumulating of per unit water consumption along the whole growing season, and irrigation water productivity ($WP_I$) which reflects the total above-ground biomass accumulating of per unit

**Table 3**
Constraints on parameter values used in parameter calibration.

| Parameter name | The lower limit | The upper limit |
|---|---|---|
| tt_emerg_to_endjuv | 200 | 500 |
| tt_flower_to_maturity | 600 | 1200 |
| potKernelWt | 200 | 800 |
| grainNFillRate | 0.05 | 0.3 |
| x_sw_demand_ratio | 0.1/ 0.5 | 0.8/ 1.5 |

**Table 4**
Management practices used for scenario analysis.

| Management | Value |
|---|---|
| Sowing date | 19-May |
| Sowing density (plants·ha$^{-1}$) | 74000 |
| Sowing depth (m) | 0.05 |
| Row spacing (m) | 0.76 |
| Amount of urea_N at sowing (kg·ha$^{-1}$) | 290 |

irrigation water consumption. $WP_C$ and $WP_I$ were computed using Eq. (1) and Eq. (2), respectively.

$$WP_C = \frac{Biomass}{Precipitation + Irrigation} \tag{1}$$

$$WP_I = \frac{Biomass}{Irrigation} \tag{2}$$

where, $WP_C$ is the crop water productivity, kg·ha$^{-1}$·mm$^{-1}$; *Biomass* is total above-ground biomass, kg·ha$^{-1}$; *Precipitation* is accumulated precipitation during the maize growing season, mm; *Irrigation* is accumulated irrigation during the maize growing season, mm; and $WP_I$ represents irrigation water productivity, kg·ha$^{-1}$·mm$^{-1}$.

We compared conventional and DT hybrids from two aspects (as shown in Fig. 2): 1) under the same irrigation levels, how much yield could be increased; 2) at the same yield-target, how much irrigation water could be saved? We defined the simulation scenario of 33D53AM with full irrigation as the baseline scenario (BS). Yield decrease (YD) across five irrigation levels with irrigated water reaching 90% ($I_{90\%}$), 80% ($I_{80\%}$), 70% ($I_{70\%}$), 60% ($I_{60\%}$), and 50% ($I_{50\%}$) of the irrigation amount under BS were then computed. YD compared with the yield of BS was calculated using Eq. (3).

$$YD_z = \frac{Yield_{BS} - Yield_z}{Yield_{BS}} \times 100\% \tag{3}$$

Where, $YD_z$ is the yield decrease relative to BS yield (%); $Yield_{BS}$ is the grain yield dry weight of BS, kg·ha$^{-1}$; $Yield_z$ is the grain yield dry weight under irrigation level with irrigation reached $z$ of BS, kg·ha$^{-1}$; $z$ is the proportion of the irrigation amount relative to that applied in BS (90%, 80%, 70%, 60%, and 50%).

We calculated the water saving (WS) in irrigation when the yield target was 90% ($Y_{90\%}$), 80% ($Y_{80\%}$), 70% ($Y_{70\%}$), and 60% ($Y_{60\%}$) of the BS yield using Eq. (4).

$$WS_q = \frac{Irrigation_{BS} - Irrigation_q}{Irrigation_{BS}} \times 100\% \tag{4}$$

$WS_q$ represents irrigation water saving compared with irrigation of BS, %; $Irrigation_{BS}$ is the irrigation of BS, mm; $Irrigation_q$ is the irrigation in the yield-target that reached $q$ of BS, mm; $q$ is the proportion of yield of each yield target relative to BS (90%, 80%, 70%, and 60%).

We quantified the total production decrease (TPD; Eq. 5) and total water savings irrigation (TWS; Eq. 6) of the two hybrids. The differences in TPD and TWS between two hybrids provide insights into the different responses of hybrids to drought stress. We used these differences between the two hybrids as the contribution of the DT hybrid to total production improvement (TPI) under each irrigation level with drought stress (Eq. 7) and total irrigation water saving (TWS) in each yield target (Eq. 8).

$$TPD_z = \frac{TP_{BS} - TP_z}{TP_{BS}} \times 100\% = \frac{\sum_{i=0}^{n} s_i \times Yield_{BSi} - \sum_{i=0}^{n} s_i \times Yield_{zi}}{\sum_{i=0}^{n} s_i \times Yield_{BSi}} \times 100\% \tag{5}$$

$$TWS_q = \frac{TI_{BS} - TI_q}{TI_{BS}} \times 100\% = \frac{\sum_{i=0}^{n} s_i \times Irrigation_{BSi} - \sum_{i=0}^{n} s_i \times Irrigation_{qi}}{\sum_{i=0}^{n} s_i \times Irrigation_{BSi}} \times 100\% \tag{6}$$

$$CDTH_{TPIz} = TPD_{z\_P1151AM} - TPD_{z\_33D53AM} \tag{7}$$

$$CDTH_{TWSq} = TWS_{q\_P1151AM} - TWS_{q\_33D53AM} \tag{8}$$

Where $TPD_z$ was the total production decrease compared with BS in THP, %; $TP_{BS}$ is the total production of BS, kg; $TP_z$ is the total production when irrigation reached $z$ relative to BS, kg; $s_i$ is irrigated maize planted area in county $i$, ha; $TWS_q$ is total water saving compared with BS, %; $TI_{BS}$ is total irrigation water of BS, mm; $TI_q$ is total irrigation in the yield-target $q$ relative to BS, mm; $i$ is the serial number of counties in THP, here was 1–25; $CDTH_{TPIz}$ and $CDTH_{TWSq}$ are the contributions of DT hybrid to total production improvement, and total irrigation water saving, %.

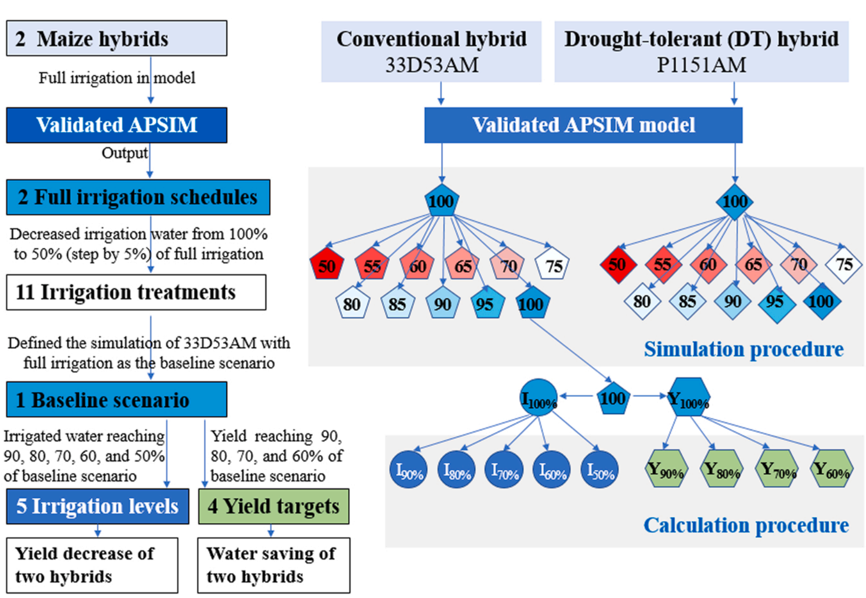


**Fig. 2.** Simulation and calculation flowchart. Text on the left indicates the process used to compute differences between two hybrids in yield decrease caused by irrigation levels and water saving by decreasing yield targets. Figures on the right denote "Simulation procedure" (numbers) which show the percentage of irrigation amount for each irrigation treatment relative to that of full irrigation; letters and numbers in the 'Calculation procedure' represents irrigation levels and yield targets, respectively (e.g. $I_{90\%}$ represents irrigated water in this irrigation level reaching 90% of the baseline scenario; $Y_{90\%}$ represents yield in this yield target reaching 90% of the baseline scenario).

## 3. Results

### 3.1. Model evaluation

As there was no difference in phenology between the hybrids in different water regimes, we used the same parameters in these two hybrids in the simulation of maize development (Fig. 3A). We evaluated model performance in two ways: whether the simulations captured yield differences for different water regimes for each hybrid; and whether the simulations captured yield differences between two hybrids under the same water regime. We found that the model could reflect yield differences between $I_{50}$ and $I_{100}$ for both hybrids (Fig. 3B, left and middle). At $I_{50}$, less yield loss by DT hybrid compared with the conventional hybrid could be well captured in the model (Fig. 3B, the right). We thus concluded that the model could be used to simulate the growth and development of these two maize hybrids under various irrigation treatments.

### 3.2. Simulated yield, crop water productivity ($WP_C$), irrigation water productivity ($WP_I$)

In our simulation of irrigation treatments (from $I_{50}$ to $I_{100}$ full irrigation), total water (irrigation plus precipitation during the simulated growing seasons) applied for maize production was 392, 410, 428, 445, 463, 498, 516, 533, 551, and 569 mm for conventional hybrid, and was 432, 449, 466, 484, 501, 518, 535, 551, 568, 584, and 599 mm for DT hybrid, respectively (Fig. 4). For the conventional and DT hybrid, from low irrigation to full irrigation, the irrigation water amounts ranged from 136 to 282 mm and 143 and 291 mm, respectively.

Yield, $WP_C$ and $WP_I$ in different irrigation treatments were shown in Fig. 5. Yield, $WP_C$ and $WP_I$ of the DT hybrid were significantly higher than that of the conventional hybrid in the same irrigation treatment ($p < 0.01$ by ANOVA). Increasing irrigation from 50% to 100% full irrigation gradually improved yield of conventional and DT hybrid from 2519 to 7111 $kg\cdot ha^{-1}$ and from 4039 to 8287 $kg\cdot ha^{-1}$, respectively (Fig. 5A). For the conventional hybrid, $WP_C$ was improved with increasing irrigation (Fig. 5B), while for the DT hybrid, $WP_C$ under 85% full irrigation was greater than others. This indicates that DT hybrids may have more potential in water saving due to higher $WP_C$ under lower irrigation than conventional hybrid. $WP_I$ decreased with the increasing of irrigation treatments for two hybrids (Fig. 5C). From 50% to 100% full irrigation, the difference between $WP_I$ for the two hybrids narrowed, suggesting that the DT hybrid had greater $WP_I$ improving space than that of conventional hybrid, especially in low irrigation treatments.

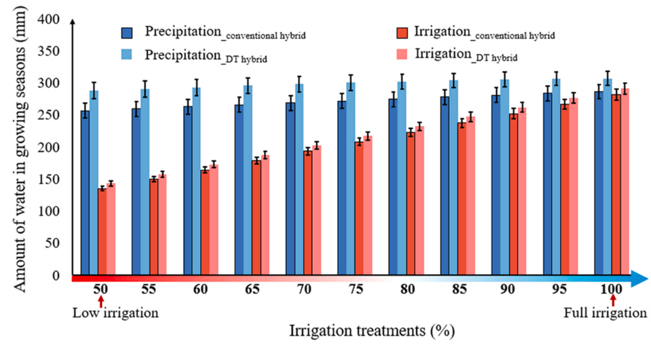


**Fig. 4.** Mean irrigation water and precipitation used in simulated growing seasons from 1984 to 2018.

### 3.3. Differences in yield increase and water savings between hybrids

DT hybrids consistently had greater yields than the conventional hybrid in all water-limited conditions, particularly under low irrigation levels (Fig. 6). When irrigation water was restrained to 90%, 80%, 70%, 60% and 50% of the irrigation under BS, *YD*s of the conventional hybrid were 11%, 24%, 38%, 51% and 64%, while *YD*s of DT hybrid was − 7%, 1%, 12%, 27% and 43%, respectively (Fig. 7A). DT hybrid yielded more than BS (*YD* was −7%) under $I_{90\%}$ which is a slightly limited irrigation condition for the conventional hybrid. For all irrigation levels, DT hybrid yield loss was 18–25% less than that of conventional hybrid. In THP, differences of $YD_z$ between the two hybrids were higher in northwestern counties than that in southeastern counties.

When yield targets were set to 90%, 80%, 70% and 60% of the BS yield, *WS*s of the conventional hybrid were 10%, 18%, 26%, and 33%, respectively, and *WS*s of DT hybrid were 27%, 33%, 40%, and 47%, respectively (Fig. 7B). For the same target yield, the DT hybrid saved more water under irrigation, and differences in *WSq* between hybrids decreased with decreasing target yield. In THP, differences in *WSq* between two hybrids were higher in northwestern counties compared with southeastern counties, demonstrating that the northwest THP should be prioritized for further extricating yield advantages of DT hybrids.

### 3.4. Contribution of DT hybrids to the total production increase and irrigation water saving across the Texas High Plains

In the Texas High Plain, irrigated maize was sown across an area of 211933.34 $km^2$ averaged from 1981 to 2017 (Fig. 8A). We calculated the contribution of DT hybrid to total production increase (Fig. 8B) and water saving in irrigation (Fig. 8C) regionally based on irrigated areas of all counties in THP. Under limited irrigation conditions of $I_{90\%}$, $I_{80\%}$,

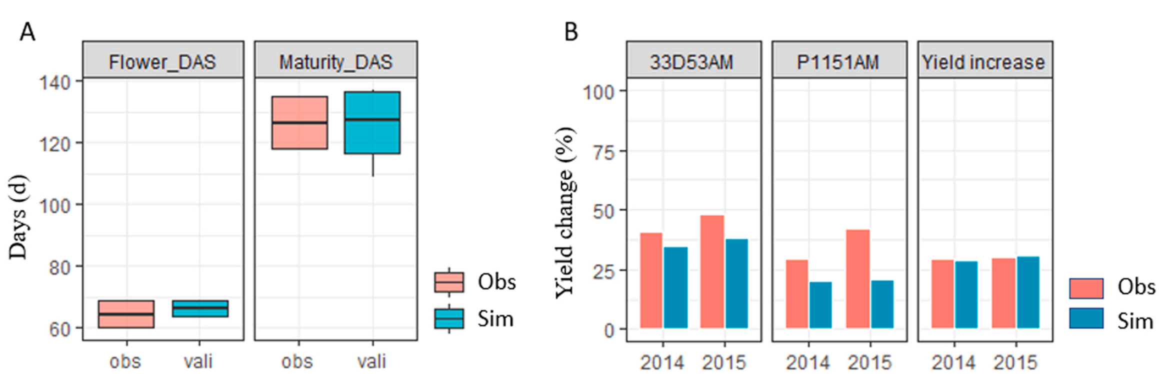


**Fig. 3.** Model evaluation. A, model evaluation of simulated maize growth. B, evaluation of simulated yield; left and middle panels show yield differences between irrigation treatment of $I_{50}$ and $I_{100}$ for the conventional hybrid 33D53AM and DT hybrid P1151AM, respectively, bars show the yield increase percentage of $I_{100}$ compared with $I_{50}$; The right panel shows yield differences between 33D53AM and P1151AM, bars show the yield increase percentage of P1151AM compared with 33D53AM.

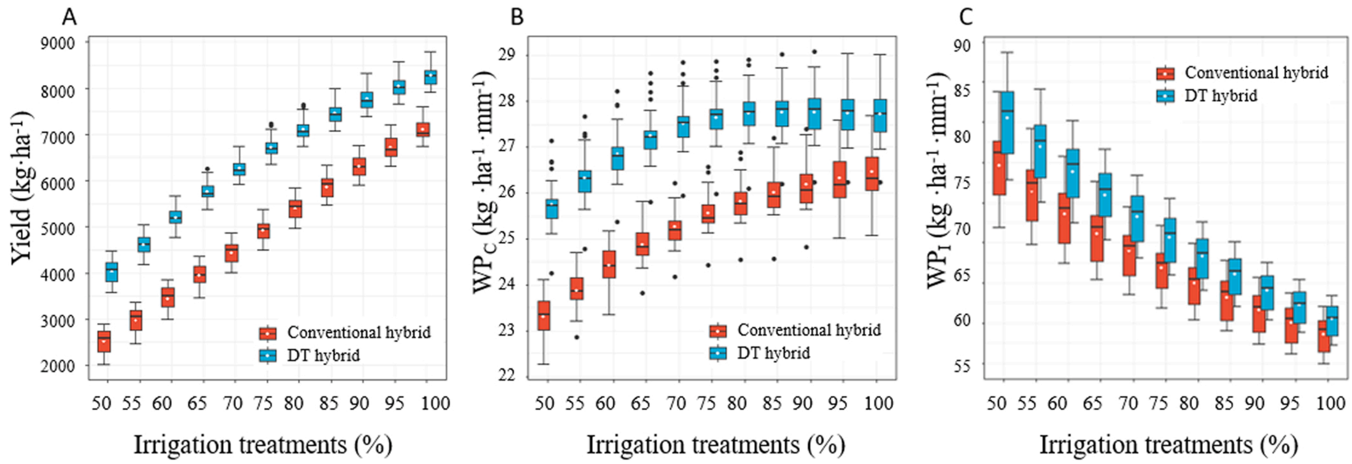


**Fig. 5.** Average simulated yield, crop water productivity ($WP_C$), irrigation water productivity ($WP_I$) for two hybrids across different irrigation treatments.

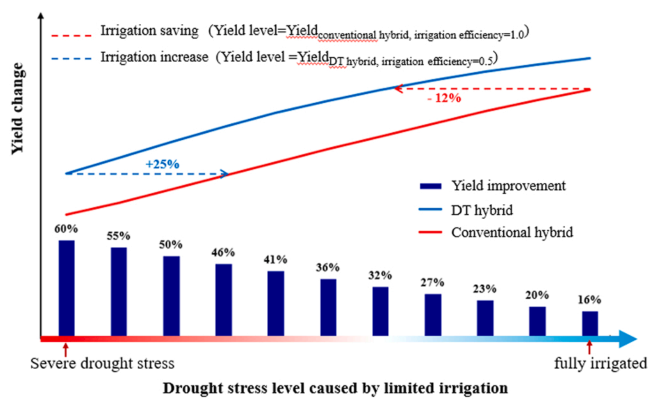


**Fig. 6.** Yield change alone with different drought stress caused by limited irrigation.

$I_{70\%}$, $I_{60\%}$, $I_{50\%}$, contributions of DT hybrid to total production improvement (*CDTH_TPI*) were 19%, 24%, 26%, 26%, and 21%, respectively. For target yields of $Y_{90\%}$, $Y_{80\%}$, $Y_{70\%}$, $Y_{60\%}$, contributions of DT hybrid to total irrigation water saving (*CDTH_TWS*) were 17%, 16%, 15%, and 15%, respectively.

## 4. Discussion

In this study, we quantified the regional contribution of a DT hybrid to yield improvement and water-saving compared with a conventional hybrid. Based on the data from the field experiment of DT hybrid P1151AM and conventional hybrids 33D53AM in the THP, we modified the APSIM model to simulate maize yields in different irrigation treatments. We next analyzed the different yield and irrigation responses of two hybrids to limited irrigation conditions and different yield targets, and calculated the contribution of DT hybrid to total production increase and water saving in irrigation in this region. The limits of process-based crop simulation models (CSMs) can be seen in particular when crops are exposed to extreme weather events and/or to multiple (biotic and abiotic) stresses, which are characteristics of low-input agricultural

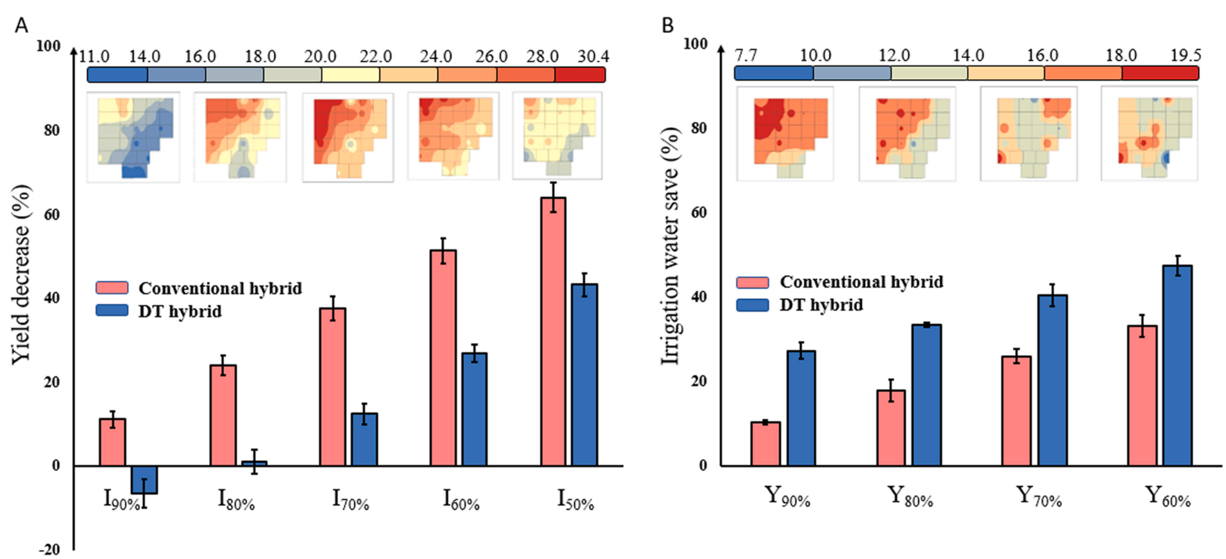


**Fig. 7.** Yield and water savings associated with irrigation levels and target yield of conventional and DT hybrid. A shows yield response to limited irrigation of conventional and DT hybrids, bars show yield decrease (YD) caused by reduced irrigation, while upper maps show the spatial pattern (interpolated by inverse distance weight in ArcGIS version 10.6) for differences of $YD_{90\%}$, $YD_{80\%}$, $YD_{70\%}$, $YD_{60\%}$, $YD_{50\%}$ between two hybrids ($YD_{z\_conventional\ hybrid}$ - $YD_{z\_DT\ hybrid}$); B shows irrigation water saved in response to target yields, bottom bars show irrigation water saving (WS), and upper maps show spatial pattern for differences of $WS_{90\%}$, $WS_{80\%}$, $WS_{70\%}$, $WS_{60\%}$ between two hybrids ($WS_{q\_DT\ hybrid}$ - $WS_{q\_conventional\ hybrid}$).

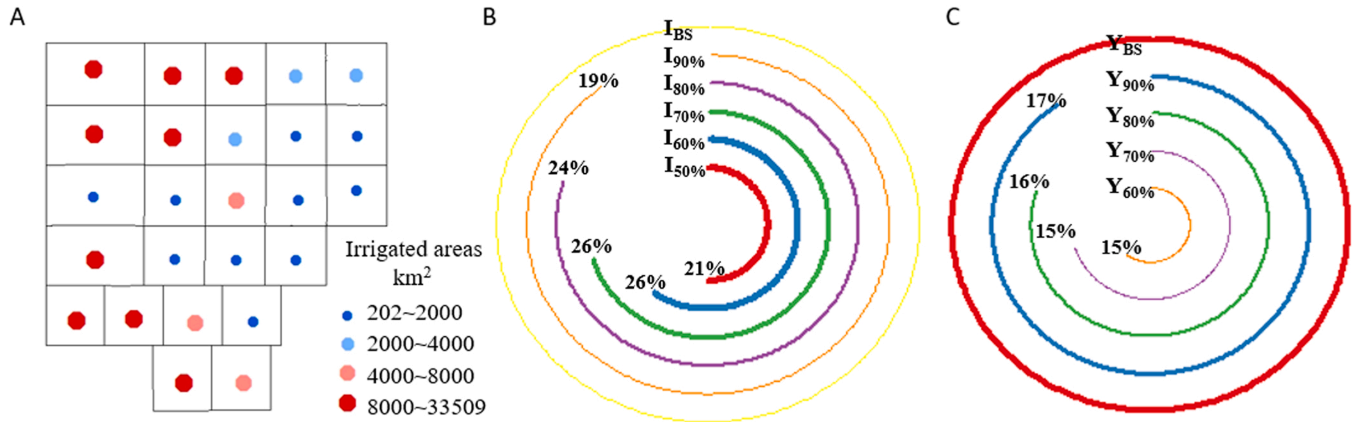


**Fig. 8.** Irrigated areas (A) and the contribution of DT hybrid to total production increase (B) and water savings in irrigation (C) in THP.

systems exposed to climate change (Muller and Martre, 2019). In our study, the use of a simulation framework model that could capture drought influence was very important. We conducted this partly by management control and partly by parameterization. Model parameter estimation problem is raised as an optimization problem and optimization algorithms could be used to solve it (Zúñiga et al., 2014); various automated parameterisation approaches with APSIM have been tested (Harrison et al. 2019). Differential evolution (DE) algorithms can improve the efficiency and accuracy in modifying the dynamic crop model and have been applied in parameter optimization before (Zúñiga et al., 2014; Jiang et al., 2018; Li et al., 2021b; Martínez et al., 2021). For our calibration and validation of the crop model, we combined DEoptim and cross-validation in R software to optimize parameters permitting subsequent use of APSIM. These ensured that the APSIM could simulate growth and development of these two hybrids as accurate as possible. Moreover, the water uptake parameters were contained in our modification of the model, which made further sure that the model could reflect differences between the two hybrids in response to drought stress. Thus in our study, the APSIM model could capture the yield gap not only between the high and low irrigation conditions for each hybrid but also between two hybrids in low irrigation conditions. These conclusions were by earlier studies of a variety of applications of the APSIM model in simulating agricultural drought and the production of the crop in this environment (Jin et al., 2016; Jin et al., 2017; Li et al., 2021a).

In semiarid areas, increasing irrigation is generally perceived as a management option for improving the yield and stability of maize production. However, indiscriminately increasing the irrigation was not an appropriate practice to realize the advantage of DT hybrids in yield improvement under drought stress. Differences in yield decrease caused by limited irrigation between these two hybrids reached the maximum (25%) when irrigation was controlled to 70% of BS. This indicated that, compared with the production of conventional hybrid under fully irrigated conditions, applying only 70% of irrigated water would result in the greatest yield increase advantage of DT hybrid and reduce water consumption. This result supports the conclusion from a field study which suggested that limited irrigation can save water and maintain maize yield in the THP (Zhao et al., 2019). From our study, we recommend the limited irrigation level $I_{70\%}$ (70% irrigation of BS) as the best management practice that would realize the greatest contribution of the DT hybrid (26%) to total production improvement under the lowest water consumption. We also showed that DT hybrids performed better than conventional hybrids under more severe drought conditions (Fig. 6). This simulation result is consistent with the previous experiment-based study conclusions (Hao et al., 2015a; Hao et al., 2015b). In general, DT hybrids had higher water use efficiency, which resulted from either greater shoot dry weight or lower reduction in dry weight reduction compared with the conventional hybrid under water stress (Zhao et al., 2018b). Our simulation results show that if there was no irrigation limitation, DT hybrids need more water input compared with conventional hybrids (Fig. 4). This may be a key factor driving the invariance of $WP_C$ under high irrigation treatments (Fig. 5B), potentially limiting the advantage of DT hybrid in high water regimes. Some studies have shown that DT hybrids might contribute to reducing the yield loss caused by heat stress (Chukwudi et al., 2021). Selecting for DT hybrids may increase the output of maize to the greatest extent in the limited irrigation input for arid and semi-arid regions, all of which are warming under climate change.

We conducted our experiment in different locations in 2014 and 2015. The difference between two locations in soil and climate may have contributed to the difference between two hybrids in yield formation. But this environmental difference was not directly considered in our parameterization of the model. In actual maize production, field management practices such as irrigation method and fertilization rates play an important role in fully exerting the yield advantage of DT hybrids. These need to be determined based on more detailed experiment data to quantify the contribution of DT hybrids in yield increase and water saving more accurately in future research. In different climate years (wet or dry), the resource input of water (precipitation and irrigation) to meet the physiological need of maize growth and development is different, it may cause different yield responses for two hybrids and need more research combining field and climate control experiment in the future.

## 5. Conclusions

Under the same watering regime, DT hybrids increase maize yield and water productivity, especially at low irrigation levels. This caused more yield improvement and water-saving potential for DT hybrid. The DT hybrids had greater yield under the same irrigation amount and saving water with the same target yield. When irrigation was constrained to 90%, 80%, 70%, 60%, and 50% of the irrigation required for the baseline scenario (BS), DT hybrid decreased total maize production loss caused by drought stress by 19%, 24%, 26%, 26%, and 21% compared with the conventional hybrid, which means the contribution of DT hybrid to total production improvement under different irrigation levels with drought stress above was 19–26%. When the target yield was set to 90%, 80%, 70%, and 60% of BS, water applied could be reduced by 17%, 16%, 15%, and 15%, which means the contribution of the DT hybrid to total irrigation water saving in these four yield targets were 15–17%, if the conventional hybrid was changed to DT hybrid in production.

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## CRediT authorship contribution statement

Jin Zhao designed research; Zheng'e Su performed research; Qingwu Xue and Thomas H. Marek provided field experiment data; Jin Zhao and Zheng'e Su wrote the first draft of the manuscript; Qingwu Xue, Matthew Tom Harrison and Ke Liu commented on previous versions and contributed to the revisions of the manuscript.

## Code availability

Not applicable.

## Ethics approval

Not applicable.

## Consent to participate

Not applicable.

## Consent for publication

Not applicable.

## Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

## Data availability

The data sets analyzed during the current study are available from the corresponding author on request.

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