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Do shallow water tables contribute to high and stable maize yields in the US Corn Belt?

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ABSTRACT

Shallow water tables (WT) can buffer against transitory rain-free periods leading to higher and more stable yields in rainfed crops. However, little is known about their influence on regional crop production and its stability. In the present study, we assessed the impact of WT on maize production in the US Corn Belt. Analysis of historical yields and modeling revealed that WT may explain higher than expected yields. At regional level, WT led to higher (6%) and more stable maize production compared with the scenario without WT, especially in years with severe drought (24% production increase). Results highlight the need to account for WT for yield forecasting and for studies investigating the influence of current and future climate on crop production.

1. Introduction

Shallow water table (WT) is defined as a saturated soil layer situated within the upper *ca.* 2 m of the soil profile (Nosetto et al., 2009). WTs are present in flat sedimentary landscapes located in several agricultural areas around the world, including the US Corn Belt (Fan et al., 2013). Seasonal changes in WT depth are influenced by water inputs (*e.g.*, precipitation) and outputs (*e.g.*, evapotranspiration) as well as (sub-)surface lateral flows between areas with different elevation across the landscape (Boling et al., 2004, 2007, 2008; Portela et al., 2009). When water input exceeds water output, WT is expected to raise and potentially lead to waterlogging and flooding (Christianson and Harmel, 2015; Kaur et al., 2017). Conversely, WT depth declines when water output exceeds input (Nosetto et al., 2009; Mercau et al., 2016). Soil properties and artificial drainage also influence WT depth, which, together with the previous factors, make prediction of WT dynamics over time and space difficult (Soylu et al., 2014).

Previous studies have documented contrasting effects of WT on crop yields. A shallow WT can lead to water excess in the topsoil, which can negatively affect seed germination, crop establishment, and/or performance of established crops due to anoxia, root diseases, or indirect effects associated with nutrition status (Florio et al., 2014; Kahlown et al., 2005; McKevlin et al., 1997; Nosetto et al., 2013). Negative effects of WT in the early crop season are well known by farmers in the central and eastern US Corn Belt, who have installed costly sub-surface drainage systems to remove water excess from the upper 0.9–1.2 m of the soil profile (Walker et al., 1982; Helmers et al., 2012; Skaggs et al., 2012). However, presence of WT at the bottom of the soil rootable zone can help buffer against transitory rain-free periods and lead to higher and more stable yields, especially if WT is present during transitory drought periods that coincide with key reproductive stages for yield formation (Dardanelli et al., 2003; Kahlown et al., 2005; Nelson et al., 2011; Christianson and Harmel, 2015; Gao et al., 2017). In natural ecosystems, the water supply from WT that is used for transpiration has been referred to as a “WT subsidy” (Lowry and Loheide, 2010).

Depth to WT varies across sites and years and, even for a specific site-year, it changes during the crop growing season. To illustrate these dynamics, Fig. 1 shows trends in WT depth at Ames, Iowa (USA) during three years with contrasting rainfall amount and distribution through the crop season. There was a sharp decline in WT depth during the growing season in dry years (*e.g.*, 2017), while WT remained relatively stable or even rose in wet years (*e.g.*, 2015). In all years, WT fluctuated within or close to the crop root zone during silking and grain filling, indicating that water supply from the WT was available for crop transpiration.

While the negative effect of WT due to water excess has been long

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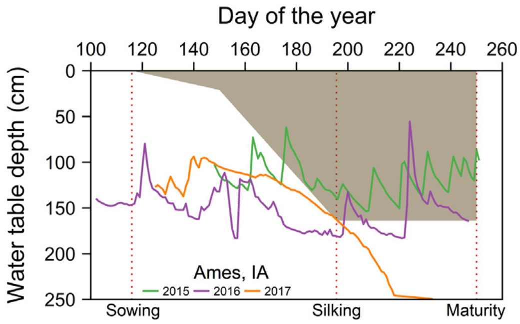

Fig. 1. Water table depth dynamics during maize growing season at Ames, Iowa (IA) in 3 years with contrasting seasonal precipitation (2015, 2016, and 2017). Average dates of sowing, silking, and physiological maturity are shown. Shaded area indicates maize root depth based on data from Ordóñez et al. (2018). Total sowing-to-maturity precipitation was 763 (2015), 499 (2016), and 321 mm (2017). Adapted from Archontoulis et al. (2017).

recognized, there is scarce evidence about the positive influence of WT on crop yields in the US Corn Belt. In a modeling study performed for central Wisconsin, Soylu et al. (2014) found that WT can buffer against water stress, especially in dry years. Based on field data, Archontoulis et al. (2017) estimated that the water subsidy from WT might have contributed to 50% of the attained maize yield at one site in central Iowa. Similarly, Morell et al. (2016) and Grassini et al. (2017) reported higher-than-expected average farm yields for sites in the central and eastern US Corn Belt based on a comparison of observed *versus* forecasted yields using a crop model, attributing this phenomena to the presence of WT. An anecdotal case was a rainfed field in southeastern Nebraska (USA) that took the second place in the 2017 National Corn Growers Association yield contest, which likely benefited from the presence of WT during the entire season.[2] Apart from this fragmented, site-specific evidence, there is a dearth of knowledge on the potential positive effect of WT on regional crop production and its stability in the US Corn Belt, which accounts for *ca.* one third of global maize and soybean production (FAOSTAT, 2017).

The aim of this study was to explore the positive effect of WT on maize production and its stability across the US Corn Belt. Given the lack of data on spatial and temporal WT dynamics and its influence on crop yield for the US Corn Belt, we used a crop simulation model to provide a first insight on the potential benefit of WT on crop yield and variability. We hypothesized that WT can explain higher than expected maize yield in years with severe water deficit in the US Corn Belt, contributing to higher and more stable production across years.

2. Material and methods

2.1. Study area and site selection

About 30 million ha are annually sown with rainfed maize in USA, producing *ca.* 280 Mt (USDA-NASS, 2005–2016). Here, we focused our analysis on the US Corn Belt, which accounts for 85% of US rainfed maize production. Eight states across the US Corn Belt were selected for our study: Iowa (IA), Illinois (IL), Indiana (IN), Minnesota (MN), Missouri (MO), Ohio (OH), Nebraska (NE), and Kansas (KS). These states account for *ca.* 73% of US rainfed maize production (USDA-NASS, 2017). Fig. 2 shows that WT is present across large areas of these states (except for NE and KS) as it can be inferred from the most recent data on subsurface tile drainage reported by US Census of Agriculture (USDA-NASS, 2012) and consistent with previous studies mapping WT for the same region (Sugg, 2007; Fan and Miguez-Macho, 2011; Kreakie et al., 2012; Fan et al., 2013; SSURGO https://www.nrcs.usda.gov/wps/portal/nrcs/detail/soils/home/?cid=nrcs142p2_053631). For our study, we assumed fraction of maize area with WT to be identical to fraction of cropland with tile drainage because tile drainage is the consequence *and* indicator of persistent WTs.

The US Corn Belt was subdivided into climate zones (CZ), each representing a unique combination of three key variables that influence crop yield and its variability: growing degree days, temperature seasonality, and aridity index (van Wart et al., 2013). Following van Bussel et al. (2015) and Morell et al. (2016), we selected 35 reference weather stations (RWS) from MESONET state-operated networks (http://mrcc.isws.illinois.edu/gismaps/mesonets.htm) to achieve a high coverage of the rainfed maize area across the eight states (Fig. 2). A 100-km 'buffer' zone was created around each RWS, with buffers clipped by CZ and state borders (Fig. 2). Selection of buffers was based on the spatial distribution of rainfed maize harvested area reported by the Spatial Production Allocation Model (SPAM; You et al., 2014, http://mapspam.info/). The selected 35 buffers accounted for 76% of rainfed maize area across the eight selected states and 53% of total US rainfed maize area.

Long-term (2005–2016) daily measured weather data were available for each RWS, including incident solar radiation, maximum and minimum temperature, precipitation, relative humidity, and wind speed. Weather data were screened for erroneous and/or missing data using rigorous quality-control protocols available at: http://www.yieldgap.org/web/guest/methods-weather-data. Missing data (< 1% of total weather data) were filled with the best available alternative weather data source, including adjacent National Weather Station-Cooperative Observer Network stations (NWS-COOP; http://www.nws.noaa.gov/om/coop/) and the NASA-POWER database (https://power.larc.nasa.gov/cgi-bin/cgiwrap/solar/agro.cgi). Dominant agricultural soil types were selected from the gSSURGO database (Soil Survey Staff, 2017). Briefly, gSSURGO map was clipped by the SPAM maize harvested area map to make sure to include only soils where maize production currently takes place. Subsequently, soil types were ranked based upon their share of maize harvested area within each buffer. Finally, for each buffer, soils were iteratively selected starting from the one with largest share of maize harvested area until achieving ≈ 50% of maize area coverage and associated soil properties required for crop modeling were retrieved for each of them (*e.g.*, soil depth, texture, slope). Information about dominant management practice such as sowing date, hybrid maturity, and plant density were retrieved from Morell et al. (2016).

2.2. Simulation of yield potential and assumptions

Yield potential (Yp) is the yield of a crop cultivar in an environment to which it is adapted, with non-limiting water and nutrient supplies, and with pests, weeds, and diseases effectively controlled (Evans, 1993; van Ittersum et al., 2013). Water-limited yield potential (Yw) is influenced by the same factors that define Yp but also determined by the degree of water limitation and soil properties that influence water availability such as rootable soil depth, soil texture, and field slope. In the present study, Yp and Yw were simulated for each buffer using the Hybrid-Maize crop model (Yang et al., 2006, 2017). Hybrid-Maize simulates crop growth and development on a daily basis. It also simulates the crop water balance to determine changes in soil water content over time. Briefly, the active rooting depth is divided into 10-cm layers, and water balance is computed for each layer, from the top to bottom, following a "cascading bucket" approach. For the top layer, water input comes from precipitation while water outputs include canopy interception, transpiration, soil evaporation, surface runoff, and drainage. For the other layers, water input comes from drained water from the layer immediately above it. When a soil layer fills up to field capacity, excess water drains to the next soil layer. Water that drains below the

[2] http://www.agupdate.com/midwestmessenger/business/people_and_industry/nebraska-brothers-second-in-national-corn-yield-contest/article_908a29fa-0135-11e8-8a2c-7762f4a6fa6c.html#utm_source=agupdate.com&utm_campaign=%2Femail-updates%2Fdailyheadlines%2F&utm_medium=email&utm_content=78087D4A730041081FB980BF48BFAA5837715A07.

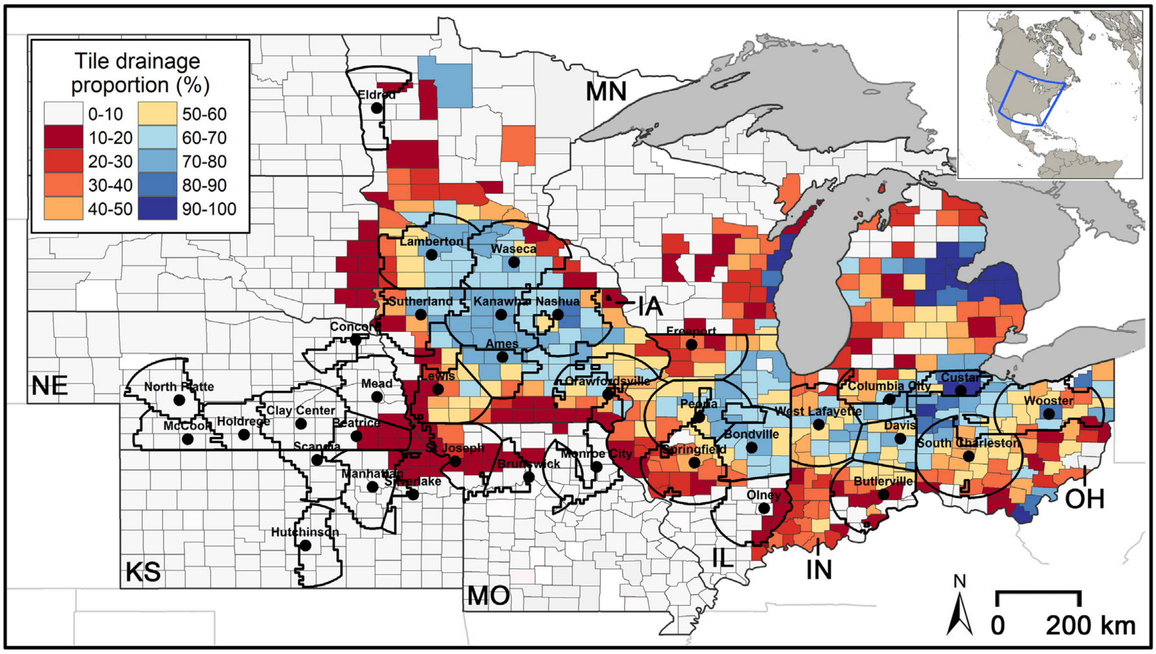

Fig. 2. Proportion of cropland (maize plus soybean harvested area) per county with sub-surface tile drainage across the US Corn Belt. Circles indicate location of meteorological stations (names are shown) used for simulating yield potential in eight states: Iowa (IA), Illinois (IL), Indiana (IN), Minnesota (MN), Missouri (MO), Ohio (OH), Nebraska (NE), and Kansas (KS). Polygons around each station indicate buffer zones. Data were retrieved from the US Agricultural Census 2012 (USDA, 2012).

rootable zone depth is lost as deep drainage. Hybrid-Maize model has been satisfactorily evaluated on its ability to reproduce measured yields across a wide range of environments, ranging from *ca.* 18 Mg ha^{-1} in irrigated conditions to near crop failure in severe drought environments (Grassini et al., 2009; Yang et al., 2017).

Modeling WT dynamics and its influence on crop yields is challenging due to the multitude of factors that are involved and associated high-data requirement (*e.g.*, Zhou et al., 2011; Soylu et al., 2014; Gao et al., 2017). More importantly, existing spatial and temporal WT data are extremely coarse and do not allow a reasonable specification of WT depth for crop modeling (either as an initial condition or as a daily input). Given these constrains, we adopted a simple approach, in which we considered Yp and Yw to represent the attainable yield in fields with and without WT, respectively. In other words, we assumed WT fields to be non-water limited, with WT buffering against water stress during the entire crop season. A similar assumption has been implicitly made in other site-specific modeling studies about WT influence on crop yields by assuming a constant bottom boundary head (Soylu et al., 2014; Boogaard et al., 2013). Because our objective was to estimate the potential positive effect of WT on crop yield and its stability, we assumed no adverse effects of WT on yield due to water excess. We believe this is a reasonable assumption as current drainage systems are efficient at removing water excess from farmer fields early in the season. While we acknowledge that these two assumptions might lead to an overestimation of the real influence of WT on crop yields, our modeling exercise is still useful in providing a first insight on the potential positive impact of WT on maize yield and stability in the US Corn Belt. Similar *in-silico* assessments using crop simulation models have been used for exploring drivers of crop yield gain and climate change impact (Rosenzweig and Parry, 1994; Hammer et al., 2009; Hertel and Lobell, 2014; Lobell, 2014).

We simulated annual Yp and Yw for all buffers during the 12-y (2005–2016) time period. Site-specific weather, soil, and management data were used as basis for the crop simulations. As mentioned previously, Yp was simulated for fields with WT assuming no water limitation. For fields without WT, Yw was simulated based on water inputs from precipitation and available soil water at sowing, without any water supply from WT. Available soil water at sowing was dynamically simulated for each site-year by initializing the model at harvest time of previous crop (Morell et al., 2016). Maximum rootable soil depth was set at 1.5 m based on data from field-grown maize reported by previous studies (Dardanelli et al., 1997; Tolk et al., 2016; Ordóñez et al., 2018).

2.3. Data analysis and upscaling

Annual data on average on-farm maize yield (Ya) were retrieved for each of the counties overlapping with the location of the 35 buffers (USDA-NASS; https://www.nass.usda.gov/Quick_Stats/). For each buffer-year, Ya was estimated using a weighted average based on relative proportion of maize area within each county relative to total maize area within the buffer.

We first assessed the influence of WT on maize yield and stability by comparing patterns in Yp, Yw, and Ya during the 12-y time period. The degree of water deficit for a given buffer-year was inferred from the difference between Yp and Yw (large and small in dry and wet years, respectively), as a result of the balance between precipitation and crop water requirements. If WT contributes to buffer against water deficit, Ya is expected to follow the year-to-year trend in Yp (but not in Yw), especially in dry years, in which Ya can even be higher than Yw. In contrast, if influence of WT is negligible because there is no WT and/or precipitation is sufficient to meet crop water requirements, Ya would mimic the year-to-year pattern in Yw.

As a second step to evaluate the influence of WT on crop yields, we plotted Ya for each buffer-year against water deficit during July. Water deficit was calculated as the difference between precipitation and reference grass-based evapotranspiration (ET_O; Allen et al., 1998). The purpose was to compare Ya among buffers with and without WT for the same level of total water deficit in July, using the latter as a proxy to water availability during the period around silking and early grain filling, which is critical for kernel setting in maize (Hall et al., 1982). Sites influenced by WT (Fig. 2) are expected to yield more than sites without WT at the same level of water deficit. Non-linear quantile regression (90th percentile) using the *quantreg* package of R software was used to compare sites with and without WT presence (R Core Team, 2017; Koenker, 2018).

To assess the positive impact of WT on maize production, we estimated maize annual production potential (Pp) for two scenarios: with and without WT. For a given buffer, Pp was estimated as follows:

$$Pp_{i,j} = [Yp_{i,j} \times a_i + Yw_{i,j} \times (1-a_i)] \times A_i \tag{1}$$

where $Pp_{i,j}$ is the production potential for buffer i in year j, a_i is the fraction of maize harvested area in buffer i influenced by WT as derived from Fig. 2, and A_i is the total maize harvested area in the buffer i derived from USDA-NASS (https://www.nass.usda.gov/Quick_Stats/). Estimation of Pp for the scenario without WT assumed $a_i = 0$. Following Morell et al. (2016), Pp was upscaled from buffer to state and region (hereafter called administrative unit for simplicity) based on the relative contribution of each buffer to total maize harvested area in each administrative unit:

$$Pp_{k,j} = \frac{\sum_{i=1}^{q} Pp_{i,j} \times A_i}{A_k} \tag{2}$$

where $Pp_{k,j}$ is the production potential of administrative unit k (state or US Corn Belt) in year j, q is the number of buffers within k, and A_k is the sum of maize harvested area in all buffers within administrative unit k. The same methodology was used to calculate annual actual production (Pa) at buffer, state, and region levels, using the Ya calculated for each buffer. Annual means and inter-annual coefficients of variation (CV) were calculated for Pp at both state and regional levels to compare production and stability between the two WT scenarios. For each state, the difference in Pp between scenarios without and with WT represents the extra Pp due to WT. Potential economic impact was estimated based on this difference and average (2005–2016) maize price of 164 US$ Mg^{-1} (https://www.nass.usda.gov/Quick_Stats/).

3. Results

3.1. Influence of water table on maize yield across locations and years

An important proportion (40%) of total rainfed maize harvested area in the selected eight states coincided with the WT spatial distribution (Fig. 2). This was estimated based on county-level data on maize harvested area and proportion of cropland with tile drainage. Presence of WT was especially remarkable in IA, IL, MN, OH, and IN, accounting for *ca.* half of maize area in these five states, which, in turn, produce 53% of total US maize grain. The total maize area likely to be influenced by WT in the eight states summed up to 7.9 million ha.

The study period (2005–2016) portrayed inter-annual variation in weather in the US Corn Belt as indicated by the range of cumulative precipitation and growing-degree days (GDD) shown for four representative locations in the US Corn Belt in Fig. 3. For example, total accumulated GDD at Ames, IA ranged from 1681°Cd in 2009 to 2030 °Cd in 2012 (mean: 1880°Cd), while total in-season precipitation ranged from 261 mm in 2012 to 998 mm in 2010 (mean: 597 mm). All locations were exposed to wet and drought years, providing an interesting range of environmental conditions for evaluating the influence of WT on maize yields.

Magnitude of the difference between Yp and Yw depended on the degree of water deficit at each buffer-year as illustrated for four selected buffers in Fig. 4. Differences between Yp and Yw indicated that water limitation was small at Ames, moderate at Springfield and Waseca, and large at Concord. Drought and high temperatures in 2012 led to low Yw due to widespread crop water stress and shortened grain-filling duration. In contrast, cool temperatures and above-average precipitation in 2010 resulted in high Yw (and almost identical to Yp). In buffers without WT and with severe water limitation (*e.g.*, Concord), trends in Ya mimicked inter-annual variation in Yw, with CVs (28% and 24%, respectively) clearly above the CV for Yp (11%) (Fig. 4). In contrast, Ya followed the inter-annual variation in Yp in buffers with WT and moderate water limitation (Springfield and Waseca), with CVs for Ya remarkably similar to those for Yp and much smaller than for Yw. Indeed, in these two buffers, Ya was relatively stable across years and, in some cases, higher than simulated Yw (*e.g.*, 2012 season). Except for a few years (2013 and 2016), trends in Yp, Yw, and Ya were similar at Ames, which was expected given the similarity in Yp and Yw across years. To summarize, these findings suggest that WT can potentially buffer against rain-free periods, especially in site-years with severe water limitation (*i.e.*, Yp > Yw). In site-years with sufficient and well-distributed precipitation (*i.e.*, Yp ≈ Yw), WT will have a negligible influence on crop yields or even negative due to water excess.

Relationship between Ya and water deficit in July, for the same level of water availability in July, indicated that sites with WT exhibited higher Ya as compared with those without WT (Fig. 5). This yield difference was statistically significant in the range of water deficit from −75 to −175 mm (difference: 3.1 Mg ha^{-1}; *T*-test, $p < 0.01$). In contrast, the yield difference was not discernable below and above this range because WT was absent (dominant) in a majority of the buffers located in very dry (wet) environments. Fitted models indicated an upper yield plateau at 12.8 and 11 Mg ha^{-1} for buffers with and without WT, respectively. To summarize, higher Ya in buffers with WT suggests that crops may have benefited from additional water supply from the WT for crop transpiration.

3.2. Influence of water table on maize production and its stability

By definition, Pa is expected to be lower than Pp because it is impossible (and not economically profitable) for the whole population of farmers to eliminate every single yield-limiting factor in time and space (Cassman, 1999; Lobell et al., 2009). Previous studies indicate that ≈ 80% of simulated yield potential represents an upper limit for average yields for crop systems where farmers have access to production inputs, markets, and extension services, as it is the case of farmers in the US Corn Belt (Lobell et al., 2009; Grassini et al., 2011). However, for the scenario without WT, our analysis showed that Pa was higher than 80% of Pp in 43% of the state-year cases, and even higher than Pp in six cases (Fig. 6a). In general, these cases corresponded to years with below-average precipitation, in which the model did not account for the water supply from WT as shown in Fig. 4. In contrast, estimates of Pp considering the influence of WT (i.e., scenario with WT) were more reasonable, with Pa averaging *ca.* 80% of Pp and no cases with Pp < Pa (Fig. 6b). There were still few (four) cases with Pp ≈ Pa, which we attributed to uncertainty in the WT coverage inferred from Fig. 2, as well as uncertainties in weather, soil, and management data, and difficulties of the model to reproduce specific G x E x M interactions.

Our scenario assessment indicated that, on average, WT accounted for 40 Mt (6%) of regional rainfed maize Pp (Fig. 7, Table 1). Differences in year-to-year variability in state and regional production between the two WT scenarios suggest that WT helped stabilize regional maize production across years, as indicated by the difference in CVs between the scenarios with and without WT (CVs = 9 *versus* 14%). Contribution of WT to regional Pp ranged from *nil* in states with small WT area (NE, KS, and MO) up to *ca.* 10% in those states with large portions of cropland with WT (IL, MN, and OH), reducing inter-annual yield variation in all states but one (KS). The positive influence of WT in the 2012 drought year could have accounted for 24% of regional Pp, ranging from 13% to 44% of Pp in states with extensive presence of WT (IA, MN, IN, OH, and IL) (Fig. 7). To summarize, our model assessment provided an upper limit for the potential impact of WT on maize production in the US Corn Belt, indicating a positive effect on rainfed maize Pp and its stability in the eastern and central portion of the region, especially in years with below-average precipitation.

4. Discussion

Our assessment extends previous site-specific evidence about the

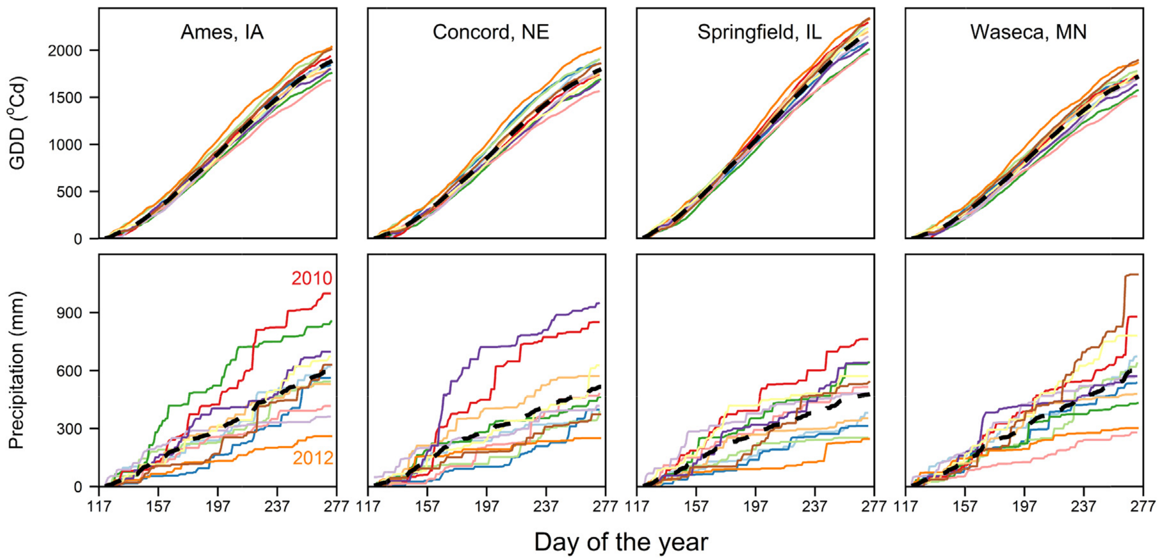

Fig. 3. Cumulative growing-degree days (GDD, T_{base} and T_{max} = 8 °C and 30 °C, respectively) and precipitation for the period between May 1st and Sep 30th, which roughly coincides with maize emergence and physiological maturity, respectively, at four locations. Each colored line corresponds to a year within the (2005–2016) time interval. Dashed line indicates the long-term (25-y) average. Years with extremely high and low precipitation are indicated for Ames IA. Weather data were retrieved from meteorological stations operated by MESONET state networks (http://mrcc.isws.illinois.edu/gismaps/mesonets.htm).

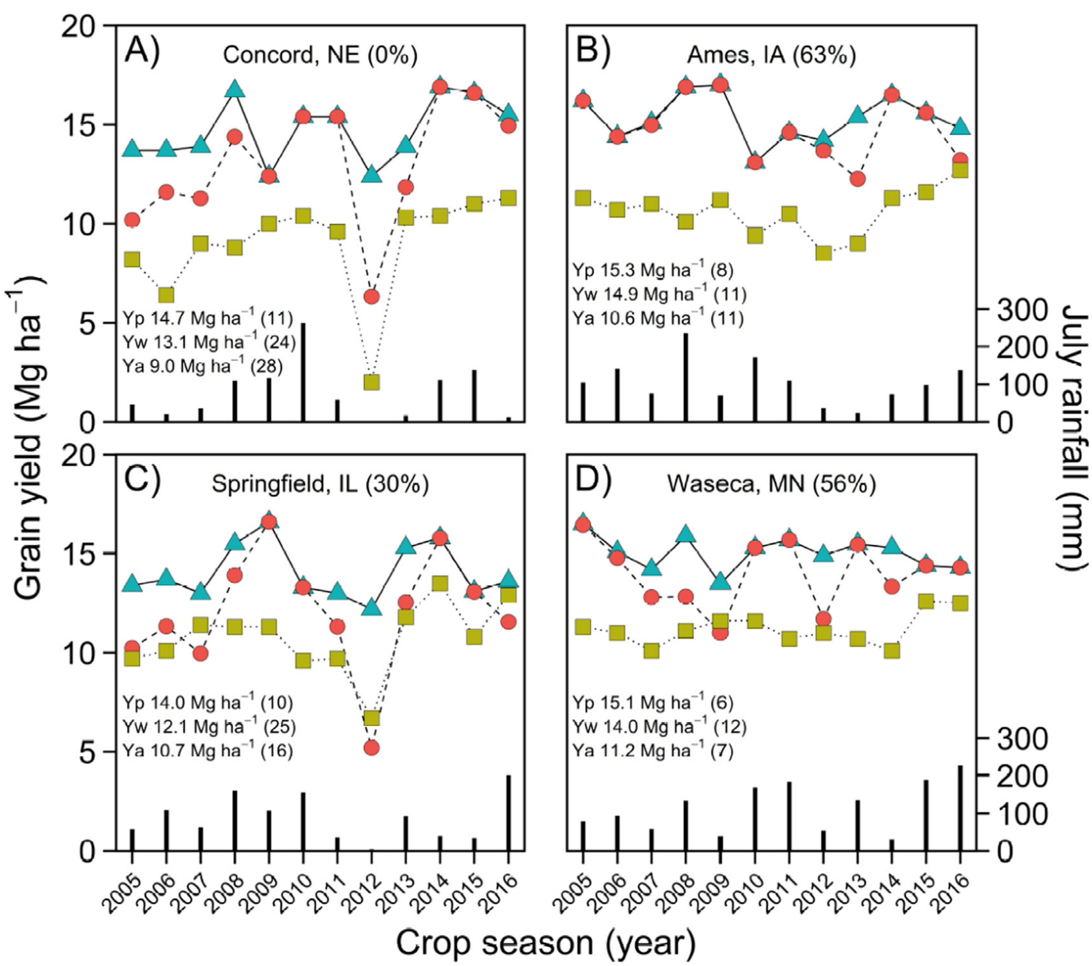

Fig. 4. Simulated annual yield potential without water limitation (Yp, triangles), water-limited yield potential (Yw, circles), and average farmer yield (Ya, squares) for rainfed maize in four buffers with contrasting water table (WT) area coverage. Percentage of maize harvested area with WT is shown at the top of the panels. Bars indicate total precipitation in July; this month coincides with silking and early grain filling stages in maize. Average Yp, Yw, Ya, and their coefficients of variation (parenthetic values, in %) are shown.

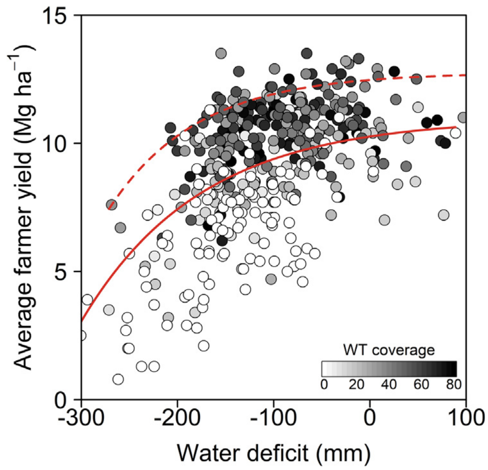

Fig. 5. Average farmer maize yield *versus* water deficit during July, which coincides with the period for kernel setting and early grain filling in maize. Water deficit was estimated as the difference between total precipitation and reference grass-based evapotranspiration. Each datapoint corresponds to a buffer-year combination, considering only 2005–2016 time period and buffers shown in Fig. 2. Gray intensity is proportional to water-table coverage (WT, in %) of maize harvested area in each buffer, with empty circles indicating buffers without presence of WT (*i.e.,* WT coverage ≈ 0). Separate non-linear models were fitted to the 90th percentiles for sites with and without WT (dashed and solid lines, respectively).

positive influence of WT on yields to a regional scale, suggesting that WT plays an important role at increasing and stabilizing regional maize production in the US Corn Belt, especially in years with below-average precipitation. In turn, our analysis also showed that water-limited locations without WT have lower "baseline" productivity and considerably higher yield variation than regions with WT. Perhaps more importantly, this study provides a framework that can be used by future studies to integrate high-quality WT spatial data and better validated crop models as these become available over time. The framework is generic enough to be applied in other cropping systems in the world where WTs are present.

Our approach highlighted data and knowledge gaps that constrain our ability to determine the influence of WT on crop production. We believe that three specific areas of research should receive priority. First, collection of observational data on WT depth and other ancillary variables (weather, soil, and topography) that can ultimately serve as basis to model WT behavior for the entire region at adequate spatial and temporal resolution. Second, field research explicitly focused on understanding the interactions between crops and WT and associated water and nutrient exchanges. Some significant advances have been made on this direction (*e.g.*, Mehring et al., 2015; Portela et al., 2009; Ordóñez et al., 2018) but clearly more work is needed. Third, improvement of current crop models to account for both positive and negative effects of WT on crop growth and yield across the landscape without need of site-year calibration. In principle, some models have the capability to account for the influence of WT on crop and soil processes, but this requires copious amounts of site-year specific data and parameters (*e.g.*, van Diepen et al., 1989; Boling et al., 2007; Soylu et al., 2014; Puntel et al., 2016; Gao et al., 2017). Likewise, most of these models focused on understanding WT-crop interactions at field level, lacking the capability to simulate the influence of WT on crop yield across the landscape, which is ultimately needed to estimate the overall impact at regional and national levels.

Of particular interest is the observation that *ca.* 40% of rainfed maize area in the eight states is subjected to the influence of WT, which has implications not only on yield level and stability, but also on nutrient dynamics and environmental footprint (Ferguson, 2015; Helmers et al., 2012). At the field level, a better understanding (and predictability) of WT depth can help manage risk and fine tune agronomic practices, such as drainage management, fertilizer application, plant density, and irrigation management (Dardanelli et al., 2003; Florio et al., 2014; Gao et al., 2017; Helmers et al., 2012; Mercau et al., 2016). At local and regional level, accounting for the presence of WT seems relevant for proper interpretation of results from yield contests and field trials evaluating agronomic technologies (crop cultivars, management practices, *etc.)*, for increasing accuracy of yield and production forecasts (Morell et al., 2016, Grassini et al., 2017), and for more robust assessments of crop production and environmental footprint in different scenarios of climate change and land use (*e.g.*, Hertel and Lobell, 2014; IPCC, 2014; Lobell, 2014).

5. Conclusions

The present study used an *in-silico* approach to assess the positive influence of WTs on crop production at local and regional scale. Our results showed that shallow WT can buffer against rain-free periods and have a positive effect on potential production and its stability across years. On average, WT accounted for 6% (40 Mt) of regional potential maize production, with this value increasing up to 24% in severe drought years. These findings were consistent with analysis of average farmer yields, showing that sites with WT exhibited higher yields than sites without WT, given the same degree of water deficit during the kernel setting phase. Our analysis gave an indication of the upper limit of the effect of WT as it was assumed that sites with WT were not limited by water supply during the entire growing season and yield losses due to water excess were not considered. We highlighted areas of research where more efforts are needed to improve current knowledge and capability to estimate local and regional impact of WT on crop production and environmental footprint.

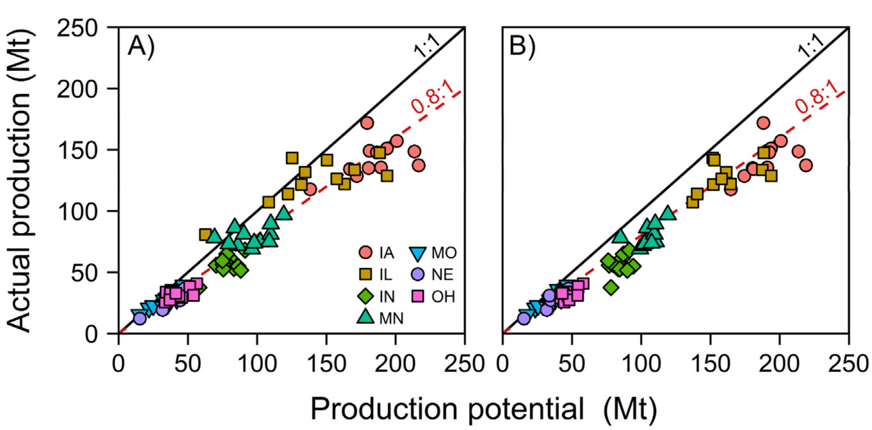

Fig. 6. Comparison between actual and simulated production potential (Pp) for rainfed maize in five US states during the 2005–2016 time period. Each data point represents a state-year. Pp was estimated for two scenarios: (A) without WT and (B) with WT presence. The 1-to-1 (solid) and 80% of Pp line (dashed) are shown. Only states with large portions of cropland with WT presence are shown (MN: Minnesota, IA: Iowa, IL: Illinois; IN: Indiana; OH: Ohio; see Table 1 for WT coverage in each state).

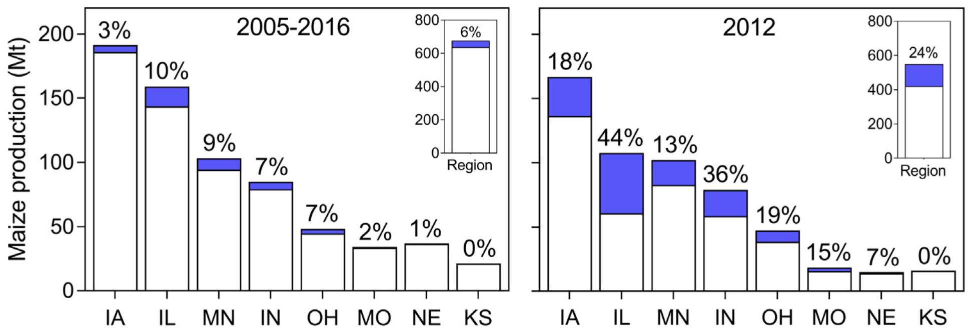

Fig. 7. Simulated annual rainfed maize production potential (Pp) across eight states of the US Corn Belt. Bars represent average Pp across the entire (2005–2016) time period (left) and only for 2012 drought year (right). The entire bar represents Pp, with the solid portion representing extra production potential due to water table (WT), with values on top of the bars indicating fraction (in %) of Pp accounted for by WT. Insets show Pp aggregated for the 8 states.

Table 1
Rainfed maize potential production (Pp, Mt) and inter-annual coefficient of variation (CV, %) for 8 US maize producing states in two scenarios: with and without water table. Fraction of maize harvested area with WT and potential economic impact are shown.

State	WT coverage (%)	Without WT		With WT		Economic impact (million US$)
		Pp (Mt)	CV (%)	Pp (Mt)	CV (%)	
Iowa (IA)	55	185	11	191	8	984
Illinois (IL)	44	143	26	158	15	2460
Minnesota (MN)	47	94	16	103	9	1476
Indiana (IN)	50	79	11	84	7	820
Ohio (OH)	59	44	16	48	12	656
Missouri (MO)	11	33	27	34	24	164
Nebraska (NE)	4	36	26	36	25	69
Kansas (KS)	3	21	24	21	24	*nil*
Total 8 states	40	635	14	675	9	6629

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Declarations of interest

None.

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