# A case study of field-scale maize irrigation patterns in Western Nebraska: Implications to water managers and recommendations for hyper-resolution land surface modelling

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## Abstract

In many agricultural regions the human use of water from irrigation is often ignored or poorly represented in land surface models and operational forecasts. Because irrigation increases soil moisture, the feedbacks to surface energy balance, rainfall recycling, and atmospheric dynamics are not represented and may lead to reduced model skill. In this work, we describe four plausible and relatively simple irrigation routines that can be coupled to the next generation of hyper-resolution LSMs operating at scales of 1 km or less. The irrigation output from the four routines (crop model, precipitation delayed, evapotranspiration replacement, and vadose zone model irrigation based) are compared against a historical field scale irrigation database (2008-2014) from a 35 $km^2$ study area under maize production and center pivot irrigation in western Nebraska (USA). Here we find the most yield-conservative irrigation routine (crop model) produces seasonal totals of irrigation that compare well against the observed irrigation amounts across a range of wet and dry years but with a low bias of 80 mm $yr^{-1}$. The most aggressive irrigation savings irrigation routine (vadose zone model) indicates a potential irrigation savings of 120 mm $yr^{-1}$ and yield losses of less than 3% against the crop model benchmark and historical averages. The results from the various irrigation routines and associated yield penalties will be valuable for future consideration by local water managers to be informed by the potential value of irrigation savings technologies and irrigation practices. Moreover, the routines offer the hyper-resolution LSM community a range of irrigation routines to better constrain irrigation decision making at critical temporal (daily) and spatial scales (<1 km).

Keywords: Crop model; Irrigation; Irrigation savings technology; Maize; Hydrus

## 1. Introduction

Regional land surface models (LSM) often ignore or do a poor job of representing irrigation physics (Kumar et al., 2015). This is in part due to the difficulty of validating irrigation amount estimates as irrigation datasets are rare, in formats that are difficult to work with on a regional scale (e.g., different reporting formats from one agency to another or in paper records), and have a latency period of months to years making them impractical to use in operational forecasts. The USDA produced Farm and Ranch Irrigation Survey (USDA, 2014) contains survey data on the county level, however data are only reported every five years and irrigation data are given on a pumping volume basis instead of depth per irrigated area as needed by LSMs (Siebert et al., 2010). Another well-known irrigation database, AQUASTAT (FAO, 2008), contains irrigation data at a spatial scale too coarse for investigating important feedbacks like land-atmospheric coupling and lacks information for Europe and North America. There are only a few studies that have used field-level irrigation databases (c.f. Grassini et al. 2011, 2014, 2015), mostly focusing on benchmarking on-farm irrigation in relation to crop production.

With the continual refinement in the spatial resolution of LSMs down to <1 km (Wood et al., 2011) and the coupling to crop models (Kucharik, 2003), reliable irrigation data needs to be incorporated in the calibration and validation of LSMs. Although the presence of irrigation doesn’t necessarily impact soil moisture contribution to the atmosphere, the soil moisture-flux relationship is critical to surface energy balance and atmospheric dynamics. One area of particular importance is the impact of soil moisture on atmospheric processes, such as rainfall recycling (Findell and Eltahir, 1997), the strength of atmospheric coupling (Koster et al., 2004), and planetary boundary layer dynamics (Santanello et al., 2011), all of which impact the skill in operational forecast models. More complicating is that both irrigation timing and volumes are based on human decision making processes and biophysical requirements (Gibson, 2016). For example, the USDA found 24% of producers relied on crop calendars, 16% on crop consultants, and 23% on in-situ probe technology (USDA, 2014). Because irrigation decisions are dependent on both processes, reliable historical irrigation data are critical to understand why and how decisions were made in order to accurately represent the physics in hyper-resolution LSMs and operational forecast models. In the absence of irrigation data, LSMs have typically relied on mass balance approaches (Döll and Siebert, 2002; Wada et al., 2012) where irrigation amounts close the water balance. While a reasonable first approach, this methodology may introduce additional uncertainty into LSMs due to the complexity of representing the human decision making process on water use. The uncertain irrigation schemes affect the time history of soil moisture and thus our ability to properly assess the impacts of human water use on coupled land-atmospheric model physics.

The focus of this study was to investigate historical irrigation use at the critical field scale (~0.8 by 0.8 km) in a study area of 3500 ha in western Nebraska, which resides on the edge of the USA Corn Belt. This critical scale is defined as where human-water decisions are made due to the history of land partitioning and the inherent geometry dictated by this landscape. While a relatively small area, the study site is an ideal location for assessing the sustainability of groundwater pumping for irrigation of crops. The study area is a microcosm of many areas across the globe, where humans rely on groundwater withdrawals for their livelihoods (Mekonnen and Hoekstra, 2011). The study area is at a critical location as it is on the boundary where irrigation supply volumes can no longer economically compensate for the deficit between potential evapotranspiration ($ET_p$) and precipitation ($P$). Of particular concern to impacts on both human and natural ecosystems are the resultant declines in the local water table due to irrigation

(Young et al., 2014). For example, the southern portion of the High Plains Aquifer (HPA) has had significant groundwater depletion over the last 80 years, with up to 50% losses of saturated thickness (Scanlon et al., 2012). In the Northern HPA (Butler et al., 2016), where this study area is located, intense irrigation pumping has led to localized water table declines (specifically in Box Butte County, and widespread throughout the neighboring Upper Republican Natural Resources District) but has yet to be widespread across the region (Young et al., 2013). Given low recharge (Szilagyi and Jozsa, 2013; Gibson, 2015; Wang et al. 2016) relative to irrigation pumping, rising global food and water demands (FAO, 2009), and concomitant effects of climate change (Kumar, 2012), the sustainability of this study area and the overall HPA system in support of long-term irrigation agriculture is uncertain (Butler et al., 2016). The study presented here is an important first step in assessing water saving technologies to continue to make irrigation agriculture sustainable for its critical need in meeting rising global food demands.

Here, we benchmark relatively long-term (2008-2014) and field-specific flow-meter measured irrigation amounts within the study area against a range of irrigation strategies. The data includes information on 55 fields (~65 ha) producing maize under center pivot irrigation. Datasets at this critical LSM scale are rare due to privacy concerns and as a result are often aggregated to county and seasonal totals (USDA, 2014; USDA-NASS, 2014) making assessment of the irrigation depths over a given area difficult to ascertain. This study therefore fills a critical data need in the development and testing of the next generation of hyper-resolution LSMs and operational weather forecast models (Kumar et al., 2015). The next generation of LSMs will be essential for better assessing the impacts of irrigation on the surface energy balance as well as evaluating the long-term sustainability of groundwater resources in agricultural areas. We note that irrigation is a key component of global food security, accounting for ~40% of global food production and ~20% of all arable land (Molden, 2007; Schultz et al., 2005). No doubt irrigation will continue to expand in the future.

The primary objective of this study is to benchmark historical irrigation amounts in the study area using different plausible physically based irrigation triggering routines. In the methods sections we will summarize the four identified irrigation triggering routines- 1. crop model (CM), 2. Precipitation delayed (PD), 3. Evapotranspiration replacement (ET), and 4. Vadose zone model where irrigation is triggered by simulated pressure head (H). In the results section we will assess the impacts of annual variations in precipitation on irrigation, and soil texture differences in the study area. In the discussion, we will provide a general framework for including plausible irrigation schemes in LSMs, as well as discuss any expected changes in irrigation behaviors as producers adopt various technologies into practice. The framework and irrigation schemes provide LSMs a practical guideline for estimating irrigation depths and timing as well as a strategy for investigating technology adoption scenarios.

## 2. Methods

### 2.1 Description of study area and historical data

The study area is located in western Nebraska where the South Platte River enters the state (Fig. 1). The site encompasses 55 fields with an average area of 65 ha under irrigated maize production (3500 ha total area). Overhead sprinkler irrigation from center-pivots using water from the underlying HPA is the most common form of irrigation in this area as well as throughout Nebraska, and the USA, as it is a cost effective and more efficient option than flood irrigation. The study area is semi-arid where annual crop referenced (maize) evapotranspiration ($ET_c$) is significantly higher than precipitation ($P$) (HPRCC, 2016). The 7-year (2008-2014) average annual $P$ is 440 mm/yr and average annual $ET_c$ is 820 (mm/yr), as measured by the High Plains Regional Climate Center weather station (HPRCC, 2016) located within 10 km of the study area near Brule, NE.

Data obtained from SSURGO (Soil Survey Staff, 2016) indicates that soil texture in the area falls within 2 USDA textural classes: sandy loam and loam (Fig. 2). Historical land management data for the area are available from the South Platte Natural Resource District (SPNRD, 2015). The SPNRD dataset includes field-specific information from the period of 2008-2014 on crop type, irrigation pumping volumes, and irrigated area. Detailed descriptions and quality control of NRD databases can be found in Grassini et al. (2014) and Farmaha et al. (2016). The above datasets provide the needed meteorological forcing, model parameters, and calibration datasets for running and evaluating the suite of irrigation modeling routines described below.

### 2.2 Irrigation modeling routines

In the following sections we will describe four identified irrigation triggering routines, including crop model (CM), precipitation delayed (PD), evapotranspiration replacement (ET), and Hydrus 1-D (H). The four irrigation triggering routines represent the upper limit of irrigation requirements in which no plant water stress occurs (CM), and the lower irrigation limit needed to ensure minimal yield loss against a crop model benchmark (H). Moreover, the four routines can be easily coupled or implemented into LSMs where PD is the simplest routine, and H the most complex. We also note the difference between the historical irrigation practices and lower bound of simulated irrigation provides a potential irrigation savings value in the study area. This irrigation savings value will be important for evaluating the economics of new irrigation technologies as well as providing critical information to policy makers and local stakeholders on the sustainable management of the HPA (Butler et al., 2016). Table 1 provides of summary of key needed inputs and list of tunable parameters for each routine.

### 2.2.1 Crop model irrigation (CM)

A crop model, Hybrid Maize (HM) (Yang et al., 2013) was utilized to estimate irrigation requirements and yield potential under an idealized scenario of crop growth with no water stress. Model performance has been extensively validated against measured yield in crops that received near-optimal management across the Corn Belt (Grassini et al, 2009, 2011). However, it has not been rigorously tested for seasonal irrigation totals, which is one key outcome of this study. Details on the model can be found in Yang et al. (2013) and a brief description of the model is given here. Inputs to this model include meteorological data, soil texture, crop biophysical parameters, sowing date, and plant density. The datasets are described above in section 2.1. Soil water dynamics over the root zone are simulated through a bucket model approach with 10 cm thick layers. Drainage between soil layers occurs when soil moisture exceeds field capacity. Irrigation application is triggered when actual ET ($ET_a$) is less than crop referenced potential evapotranspiration ($ET_c$), ensuring no water stress occurs throughout the entire growing season. Irrigation depth is determined by the deficit of soil moisture defined by the current moisture level subtracted from 95% of field capacity within the managed root zone. Maximum water application per irrigation event was set to 19.5 mm. When the depth-weighted unsaturated hydraulic conductivity ($K_r$) of the root zone is greater than or equal to $ET_c$, $ET_a$ is equal to $ET_c$. Otherwise $ET_a$ is equal to depth-weighted $K_r$ of the root zone.

### 2.2.2 Precipitation delayed irrigation (PD)

Water application in an idealized land management operation would consider all components of the water balance within the decision making process. However, in practice, precipitation is often the only component considered due to 1) the difficulty of accurately measuring the other water balance components and 2) the relative economic return is minimal when considering the perceived potential of crop yield loss versus savings due to reduced pumping/irrigation. With this in mind, producers often develop "rules of thumb" to irrigate up to a target total amount water equal to irrigation plus in-season rainfall (in the study area, 1 May to 30 September). Using these basic rules of thumb and local crop calendar requirements, we suggest the following routine based off of precipitation data alone. However, we note that this is not a recommendation for producer adoption, but instead represents a simplified method of irrigation management for modeling purposes. In addition, the applicability of this method to other regions should be possible with complimentarily datasets (i.e. $P$ and $ET_c$). Recommendations obtained from the SPNRD indicate that maize requires approximately 650 mm of total water (precipitation plus irrigation, $P$+$I$) per growing season (http://www.spnrd.org/index.html). Field observations indicate that irrigation often starts around mid-June and concludes around mid-September, leading to a 100-day irrigation season. Average irrigation application in the absence of precipitation would be 6.5 mm/day or 19.5 mm per 3 day period. This irrigation depth is consistent with producer interviews and local expert knowledge. Three day periods are critical to consider as this is often the time required to perform a single 360$^{o}$ rotation of a center-pivot (i.e. dictated by soil infiltration rates and well pumping capacity). In this routine, if rainfall is greater than 6.5 mm/day, then irrigation for one day is met, and thus a 1 day delay is set. Likewise, for a rainfall event of 13 mm/day, then two days of irrigation are met and irrigation is delayed 2 days, and so on for larger rain events. For simplicity, rain events and irrigation delays are rounded to the nearest day and up to a maximum of 7 days' delay. For rainfall events greater than 45.5 mm/day, we assume a maximum delay of 7 days due to deep drainage and runoff losses incurring during the event.

### 2.2.3 ET replacement irrigation (ET)

The primary purpose of irrigation is to ensure $ET_a$ is able to adequately keep up with $ET_c$ over the growing season as $ET_a$ is linearly correlated with yield (Passioura, 1977). Proper management allows a deficit between applied water and $ET_a$ in order to allow for adequate infiltration after rainfall. This deficit was assumed to be 6.5 mm for this routine based on the average daily crop water requirement discussed above. In this algorithm whenever the deficit was greater than 6.5 mm during the irrigation season (15 June to 30 September) an irrigation event of 19.5 mm was triggered for the next day. Again, an irrigation event of 19.5 mm was used as it represents a 3 day period, over which the center-pivot operates.

Estimating $ET_c$ is necessary in order to track the deficit between applied water and $ET_a$. While estimating $ET_c$ is complex given the variability of micrometeorological variables from one field to another, in practical applications, crop coefficients are often used to surmise the differences in crop biophysical relationships and the effect of soil (Shuttleworth, 1993). These coefficients are often published from local services like the state climate office or HPRCC in Nebraska.

Here, $ET_c$ (mm/day) was estimated following the single crop coefficient method outlined in Allen et al. (1998):

$$ET_c = ET_r K_c \tag{1}$$

where $ET_r$ (mm/day) is reference crop $ET_p$ calculated from micro-meteorological variables, and $K_c$ is a dimensionless empirical constant that encompasses crop development as well as the average effect of soil on evaporation rates. Daily $ET_r$ data were determined from the HPRCC weather station data. $K_c$ values were calculated as a function of growing degree day accumulation (*GDD*) from the HPRCC data (HPRCC, 2016). A single day calculation of growing degrees ($GDD_{daily}$) is defined as:

$$GDD_{\mathrm{daily}} = \frac{T_{\max} + T_{\min}}{2} - T_{base} \qquad (2)$$

where $T_{\max}$ is the daily maximum temperature (°C) (with a maximum of 30°C), $T_{\min}$ is the daily minimum temperature (°C), and $T_{\mathrm{base}}$ is 10°C. The *GDD* method is preferred as it more accurately represents a proxy for crop development, as opposed to a fixed number of days after sowing.

### 2.2.4 Hydrus-1D irrigation (H)

A physically based vadose zone model, HYDRUS-1D (H1D) (Šimůnek et al., 2013) was used to simulate irrigation requirements based on predefined soil pressure head trigger points in the root zone. In order to carry out necessary seasonal dynamics for annual crops (i.e. dynamic root growth, root distribution), we coupled the HM and H1D models using Matlab. We note that soil pressure triggered irrigation events based on more than one soil pressure value, flexible irrigation timeframes, and dynamic root growth with a specified distribution are unavailable in the standard H1D code. Here we use Matlab to link together a series of one day simulations (totaling 7 years), where model outputs (pressure head at depth, flux rates, actual evapotranspiration, etc.) at the end of the day were used to make a decision about irrigation for the following day.

H1D simulates soil water dynamics and water flow by a numerical approximation to the 1D Richards equation:

$$\frac{\partial \theta}{\partial t} = \left(\frac{\partial}{\partial z}\right)\left[K(\theta)\left(\frac{\partial h}{\partial z}+1\right)\right] - S \qquad (3)$$

where $\theta$ is volumetric water content ($cm^3/cm^3$), $t$ is time (day), $z$ is the spatial location (cm), $K(h)$ is unsaturated hydraulic conductivity (cm/day), $h$ is pressure head (cm), and $S$ is a sink term describing evapotranspiration (1/day). The soil profile simulated is 6 m deep with 1 cm node discretization.  Free drainage is set for the lower boundary condition, as local depth to groundwater is on average 15 m (Korus et al., 2013)

The H1D model requires $ET_c$ be partitioned into potential evaporation and potential transpiration. This is accomplished using Beer's law:

$$T_\mathrm{p} = ET_\mathrm{c}\left(1 - e^{-k*LAI}\right) \qquad (4)$$

$$E_\mathrm{p} = ET_\mathrm{c} - T_\mathrm{p} \qquad (5)$$

where $T_p$ is potential transpiration (cm/day), $E_p$ is potential evaporation (cm/day), $k$ is the light extinction coefficient (set here to 0.55 (Yang et al., 2013)), and $LAI$ ($m^2/m^2$) is the leaf area index.  For each year's growing season we simulated a daily $LAI$ time series using HM. This same seasonal dynamic was used for all simulations. In addition, HM was used to estimate date of silking for each simulated year. Water stress is minimized during silking periods as this is the most critical grain filling period for yield. Most producers will heavily water in this period to ensure yield. In order to accurately represent the irrigation behavior, we forced irrigation events every three days, one week before and after the silking date. In the case where a simulated day occurred during the growing season, root depth ($Zr$, cm) and root distribution ($Zr_{RD}$, dimensionless) parameters were calculated on a daily basis based off of a pre-determined $GDD$

accumulation after planting date for each growing season. This process was carried out following the equations outlined in the HM user manual (Yang et al., 2013):

$$Zr = \frac{GDD}{GDD_{\text{Silking}}} Zr_{\max} \tag{6}$$

$$Zr_{RD} = \exp(-VDC\, Z_L / Zr) \tag{7}$$

where $GDD_{silking}$ is growing degree days at silking, $ZR_{max}$ is a biophysical parameter representing the maximum depth the root zone can reach (cm) and set to 150 cm here (Yang et al., 2013), *VDC* is a vertical distribution coefficient set to 3 here, and $Z_L$ is the current depth in the root zone (cm).

Irrigation events and depths for the following day were calculated by investigating the average soil pressure heads at 30, 60, and 90 cm during the historical irrigation period from June 15 through September 30. Prior to the silking date, the average soil pressure head at 30 and 60 cm is computed and compared against a preset irrigation trigger value set to -500 cm based off of the dominant soil types in the area (Fig. 2). Following the silking date, the average soil pressure is computed at 30, 60, and 90 cm with the same trigger point of -500 cm of pressure. This algorithm is based on best practice irrigation recommendations summarized in Irmak et al. (2014). In practice, producers vary the irrigation pressure trigger point based upon farmer risk aversion and soil type. Given that yield is the primary economic driver over energy costs for pumping water, this trigger point is often set at conservative values. When the pressure head at the considered depths exceeds the trigger point, an irrigation event of 19.5 mm is set for the following day. The irrigation event is added to any precipitation that may arrive randomly on that day as well.

In order to numerically advance the models through time, we set up a series of 1 day simulations and logical statements. If the model date occurred outside of the growing season (October 1 to April 30), no changes were made to precipitation and bare surface was simulated. If the model day was after planting (1 May) and before the start of the historical irrigation season (15 June), only the root zone depth and root distribution parameters were updated. For model dates during the irrigation season (15 June to 30 September), the root zone depth, root distribution, and irrigation amounts were changed for the following day. Using this routine, the model was run continuously at 1 day intervals for the entire study period (1 January 2008 to 31 December 2014).

### 2.3 Rainfall variability across the study site

Daily precipitation data for the years 2008-2014 were available from 7 gauges within a radius of 35 km of the study site. In order to help assess the effect of precipitation variability on irrigation application, all 7 time series along with the average precipitation time series were used within the four irrigation routines described above. In addition, all irrigation routines that considered soil type were repeated for the two dominant soil types in the study area, i.e., sandy-loam and loam.

## 3. Results

### 3.1 Precipitation variability and $ET_c$

As expected, significant gauge-to-gauge variability was observed within the 7 rain gauge time series within each growing season with a mean of 320 mm and a CV of 35% (Fig. 3). In general, as precipitation totals increased, the range of seasonal precipitation totals observed by the 7 gauges increased as well (slope = 0.246 mm $yr^{-1}$, $R^2 = 0.38$). There was no consistent year-to-year spatial precipitation gradient, and no gauge consistently reported high or low totals. We hypothesize that this natural variability in rainfall is a large contributor of the irrigation variability we see at the field level. This hypothesis was beyond the scope of the current paper but suggest future research in this area (c.f. Gibson 2016). In terms of growing season $ET_c$, the HPRCC reported an average of 815 mm, and was within 10% of county-level values estimated by Sharma and Irmak (2012).

### 3.2 Historical field scale irrigation

Average seasonal irrigation over the 2008-2014 period was 380 mm with a CV of 23%. Distributions of irrigation amounts are provided in the box and whisker plots given in Fig. 4. Normal distributions and non-normal distributions with both negative and positive skewing were observed (D'Agostino-Pearson test, $p<0.05$). Growing season precipitation plus irrigation averaged 700 mm (Fig. 5) with a CV of 5%. The highest seasonal irrigation average occurred during the growing season of 2012 (580 mm) due to an extremely dry growing season with only 80 mm of rainfall. We found that soil texture was not a significant factor affecting irrigation application at the field scale in this region. This finding was consistent with results from central Nebraska (Gibson 2016). After grouping the fields by soil type (loam and sandy-loam), we found that the mean irrigation for all years were not statistically different from each other (Student's t-test, $p = 0.73$). This indicates that soil type did not factor into the irrigation decision making process.

### 3.3 Comparison of historical seasonal irrigation amounts with four irrigation routines

Results of the comparison between the historical irrigation (2008-2014) and the four irrigation routines are summarized in Fig. 6. Both the CM and PD routines reproduce the trend of the historical irrigation amounts but with a low offset (similar slopes). CM irrigation water requirements were on average, 80 mm lower (20% of total) relative to historical irrigation. For PD, the average seasonal difference was 40 mm lower (10% of total). For ET and H, simulated irrigation amounts were 80 mm (20% of total) and 120 mm (30% of total) lower than the historical average, respectively. We also note the slopes of the observed irrigations and the CM and PD for the given years were in general similar. However, it is obvious from Fig. 6 that the slopes of ET and H were different from the observations, which results in larger deviations in drier years and thus a potential for greater irrigation savings. The implications to water management will be discussed in the next section.

### 3.4 Irrigation sensitivity to rainfall

All irrigation routines responded to differences in the eight rainfall time series, and this response is represented as vertical error bars in Fig 6. The difference between the highest and lowest irrigation amount for each growing season was on average 75 mm, or 20% of average irrigation totals. The largest difference in irrigation totals occurred in 2008 for all irrigation routines with an average of 130 mm between all 4 routines, and the smallest difference occurred in 2012 at an average of 27 mm due to uniformly low precipitation. The analysis illustrates the variation in irrigation amounts depends on which rainfall gauge is used to make a decision. Given that producers often have fields distributed across a region the uncertainty in local rainfall directly propagates into variations in irrigation amounts (Gibson 2016). Future research efforts should investigate the effect of spatial rainfall variability on producer decision making but this was beyond the scope of the current study.

### 3.5 Soil texture impact on irrigation routines

We found that the two dominant soil textures in the study area did not have a significant impact on irrigation amounts under CM and H. Both ET and PD do not have a soil component considered in their routine and as such are not impacted by soil texture. In the case of CM, average irrigation was within 1% for all years. For H, the irrigation average of the sandy loam soil was 10% less than the average of the loam soil. Soil hydraulic parameters used for both soil textures were determined using ROSETTA (Schaap et al., 2001) and are presented in table 2.

### 3.6 Simulated yield under irrigation routines

Following the simulated irrigation for the routines of PD, ET, and H, the ($P$+$I$) time series were reinserted back into the crop model for all years to estimate yield impacts (Fig. 7). The crop model yielded an average 14.6 Mg/ha over the study period. The yield gap (i.e., difference between yield potential and actual yield) of US irrigated maize represents approximately 15% of the potential (Grassini et al., 2013, http://www.yieldgap.org/), suggesting an average actual yield of 12.4 Mg/ha for the study area, which is within 5% of historical reported yield. For the three routines and for all years, simulated yields were on average within 3% of the simulated yield based on the CM. The results indicate that the various irrigation scheduling strategies did not have a large impact on yield while reducing irrigation amounts substantially; hence, they may be a sound economic decision for producers.

### 3.7 Simulated growing season irrigation application

Daily time series of simulated irrigation application can be seen in Fig. 8. Data for observed sub-growing season irrigation application is unavailable. Irrigation application tends to begin later in the growing season for the two routines that consider soil (CM and H). This is likely due to the routines first allowing soil moisture to be depleted before irrigation is triggered, thus creating the reduced pumping and irrigation savings. The amount of soil moisture storage is typically near field capacity but in exceptionally dry years (2012) this storage is reduced and thus will lead to less of a delay at the start of the growing season.

## 4. Discussion

### 4.1 Temporal variability of applied irrigation

Historically, the study area has had a consistent amount of total seasonal water (P+I) from year to year. The percent of irrigation to applied water (I/(P+I)) was on average 55%, and notably in 2012 this was as high as 88%. The relative weight of irrigation to precipitation highlights the importance for constraining irrigation amounts for proper water balance closure within the study area, as well as in other areas with intense irrigation application. Given the high seasonal rates of irrigation to precipitation, no doubt the soil moisture will be adversely affected when compared to a rainfed area. More importantly, the impacts to the local surface energy balance (Santanello et. al, 2011), rainfall recycling, and skill in observational forecasts may be diminished without proper accounting for irrigation. For example, regional mesoscale modelling illustrated that up to 40% of East African annual rainfall can be attributed to irrigation across India (de Vrese et al., 2016). With the suggested findings here on reduced irrigation needs (up to

115 mm or 30%), the potential changes to precipitation patterns across the HPA due to adoption of irrigation scheduling technology should be further investigated.

The study area is currently under ground water appropriation, with a historical increase in depth to groundwater of 1.2 m over the period of 1971 to 2013 (SPNRD, 2013; Young, 2013). Precipitation pattern changes in the area induced by global warming are believed to lead to less frequent but more intense storms with an increase in total precipitation (Dai et al., 2011). However, the timing of precipitation is of equal concern to totals, as more infrequent rain events may still lead to increased pumping with the same seasonal totals. The scenario of changing precipitation amounts and timing is not unique to the study area but a more general pattern of the region, highlighting the need for explicit treatment of irrigation depths and timing to fully understand the complex feedbacks that exist beneath the land surface and atmosphere. The irrigation routines suggested in this work can be used as a first assessment of the likely irrigation amounts due to different observed scheduling practices (USDA 2014).

### 4.2 Spatial variability of applied irrigation

The rainfall sensitivity analysis demonstrated the affects and uncertainty for each of the four irrigation routines investigated. Lower rainfall years had lower spatial variability and as a result simulated irrigation for each routine led to similar values. However, this behavior was not consistent with the observed irrigation data, in which the lowest rainfall year (2012) had the largest standard deviation (168 mm) for applied irrigation. The results are likely due to two reasons: 1) producers give up irrigation at some point during the growing season as their crop parishes in the extreme heat and drought conditions and 2) differences in well-to-well pumping capacity become more apparent with increased pumping demand. Although no direct work has been done to confirm differences in pumping capacity or inefficiencies in the study area, the general effect has been explored through modeling in other areas (Foster et al., 2014). With respect to LSMs, these two factors represent significant deviations away from water balance closure approaches, making it challenging to include realistic irrigation values in dry years. Therefore, additional studies and datasets similar to what is presented here are critical for the calibration and validation of the next generation of hyper-resolution LSMs.

With regard to soil texture differences in the study area, observed irrigation data indicated no difference between fields in these two texture classes. Similar behavior was seen from the irrigation routine simulations that showed 10% difference for H and 1% difference for CM. We note that given the similar soil texture classes (and thus soil hydraulic parameters) this result is not unexpected. In practice, we are finding that producers are beginning to adopt precision irrigation techniques (Hedley and Yule, 2009; Hedley et al., 2013). Here, small scale features within a field (e.g. sandy or gravelly areas, underperforming parts of the field, water ways, pivot roads, etc.) can be better managed with the new technology. Therefore, managing fields following 1 dominant soil type (i.e. irrigation-pressure trigger point) may be highly inefficient (Kranz et al., 2014). More refined and consistent soil texture data across arbitrary political boundaries (Chaney et al., 2016) are needed to better account for differences in irrigation water application on the sub-field scale, especially in areas with increasing adoption of precision agriculture technology.

### 4.3 Potential for reduced pumping

The four irrigation routines presented represent different levels of allowable water stress to develop in the maize. The CM routine is the lowest risk approach with respect to yield and represents the modeled upper limit of required irrigation to maintain a stress free management scenario. It is hypothesized that any irrigation application above this represents irrigation application due to risk aversion, and will not appreciably increase yield. Comparisons between 2008-2014 indicate that the slope of the applied irrigation from observed irrigation are indistinguishable, but with a bias of ~80 mm $yr^{-1}$ more observed irrigation. This indicates that producers are averaging an additional 3-4 irrigation cycles beyond what the CM indicates. The differences in irrigation totals from the other three irrigation routines are the result of increasing allowable water deficit in the routines. A reduction of 115 mm or 30% of irrigation was observed for H when compared to the historical average. We note this hypothetical scenario requires perfect management, with full trust of the technology, and may not be achievable in practical applications. However, we anticipate that a 50-75 mm reduction over a short technology adoption period (2-4 years) is feasible, particularly in areas with strong university extension programs and/or producer to producer knowledge exchange (Irmak et al. 2012). In addition, these hypothetical reduced pumping numbers may be useful to local, state, and federal policy makers about future water management decisions and investment in cost-sharing technology programs.

### 4.4 Assessment of center-pivot irrigation routines in hyper-resolution land surface models

The four irrigation routines although biased (i.e. contain an offset), capture year-to-year variation in irrigation in Western Nebraska. Given the widespread use of center-pivots we expect the irrigation routines to capture year-to-year variation for the HPA and into parts of the eastern USA. We note that the magnitude of the offset is likely related to local producer behavior and influenced by social norms and risk aversion. Gibson (2016) provides a fuller assessment of irrigation behavior throughout central Nebraska. We note that it is unclear how these routines would behave in areas with center-pivot outside the USA (i.e. Brazil, South Africa, and Australia), where energy costs for pumping may be more restricting and drive human-decisions on irrigation. Assessment of these routines in those areas would require further validation.

We believe the routines combined with a reasonable offset correction could be easily incorporated into future hyper-resolution LSMs with the above routine descriptions and readily available LSM model output or datasets (see Table 1). Clearly, accurate and local precipitation is critical in driving these irrigation routines and capturing producer behavior. This topic deserves more research, particularly and the opportunity to combine low cost in-situ gauges with radar and remote sensing products. Additionally, we note the four routines could be run offline in order to provide reasonable guesses of applied irrigation for a given irrigation season. This may be beneficial in representing processes not explicitly considered in LSMs (Kumar et al. 2015), or making future assessments and recommendations about water availability for managers. Finally, the four routines provide reasonable irrigation bounds and more importantly predictions about decreases in irrigation as technology is introduced and adopted in novel areas.

## 5. Conclusions

In this work we describe four plausible and relatively simple irrigation routines that could be coupled to the next generation of hyper-resolution LSMs operating at scales of 1 km or less. The crop model irrigation outputs reproduce the year-to-year variability of the observed irrigation amounts with a low bias of 80 mm $yr^{-1}$. Predictions from the vadose zone model indicate potential irrigation savings of up to 120 mm $yr^{-1}$ for maize. In addition, daily precipitation variability across the study area was found to introduce significant variability in daily irrigation decision making depending on which value was considered. Future work could focus on providing accurate realtime 1 km daily precipitation products through a combination of in-situ low cost gauges, radar, and satellite remote sensing. Accurate and realtime precipitation remains a critical weakness in these rural and vast landscapes. Given the clustering of irrigation fields in Western Nebraska, the number of in-situ gauges needed could be significantly reduced to provide high density networks in key areas. Findings from the work may be useful to local water managers and stakeholders in evaluating potential water saving technologies. In addition, the simple routines could be coupled to future hyper-resolution land surface models that seek to understand the degree of land surface atmospheric coupling and consequences to operational forecasts. This understanding is essential as society continually recognizes the importance of human activities on the global water cycle and invests more resources to understand the water-food-energy nexus.

## 6. Data Availability

Meteorological data used in this paper was provided by HPRCC (2016, http://www.hprcc.unl.edu/). Irrigation flow meter data was obtained from the SPRND and is not widely available for public use. Yearly summary reports are available from SPNRD (http://www.spnrd.org/). Soil data was obtained from SSURGO (Soil survey staff, 2016, http://websoilsurvey.sc.egov.usda.gov/App/HomePage.htm). Data and model subroutines can also be requested from the corresponding author.

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## Figures and Tables

Fig. 1: Study area located in western Nebraska with a 1km grid (white lines) overlain on the study site. Black lines show individual field locations where irrigation volumes/depths are obtained from the SPNRD.

Fig. 2: Area-weighted soil texture of all fields plotted on the USDA soil texture triangle, falling primarily in the sandy loam and loam textures. Data downloaded from NRCS Web Soil Survey.

Fig. 3: Cumulative in-season precipitation depths measured at 7 rain gauges and crop referenced evapotranspiration ($ET_c$) calculated from a weatherstation <10km away. Precipitation variability tends to increase with incresing seasonal totals.

Fig. 4: Box and whisker plots of historical irrigation depths for all sites. Upper and lower boundaries of boxes indicated 75th and 25$^{th}$ percentile, respectively. Horizontal line within boxes is the median value. Whiskers are maximum and minimum values. Asterisks indicate that irrigation distribution deviates from a normal distribution (D'Agostino-Pearson test, $p<0.01$).

Fig. 5: Observed growing season totals for precipitation (P), irrigation (I), and P+I. The dashed line represents the historical average for P+I.

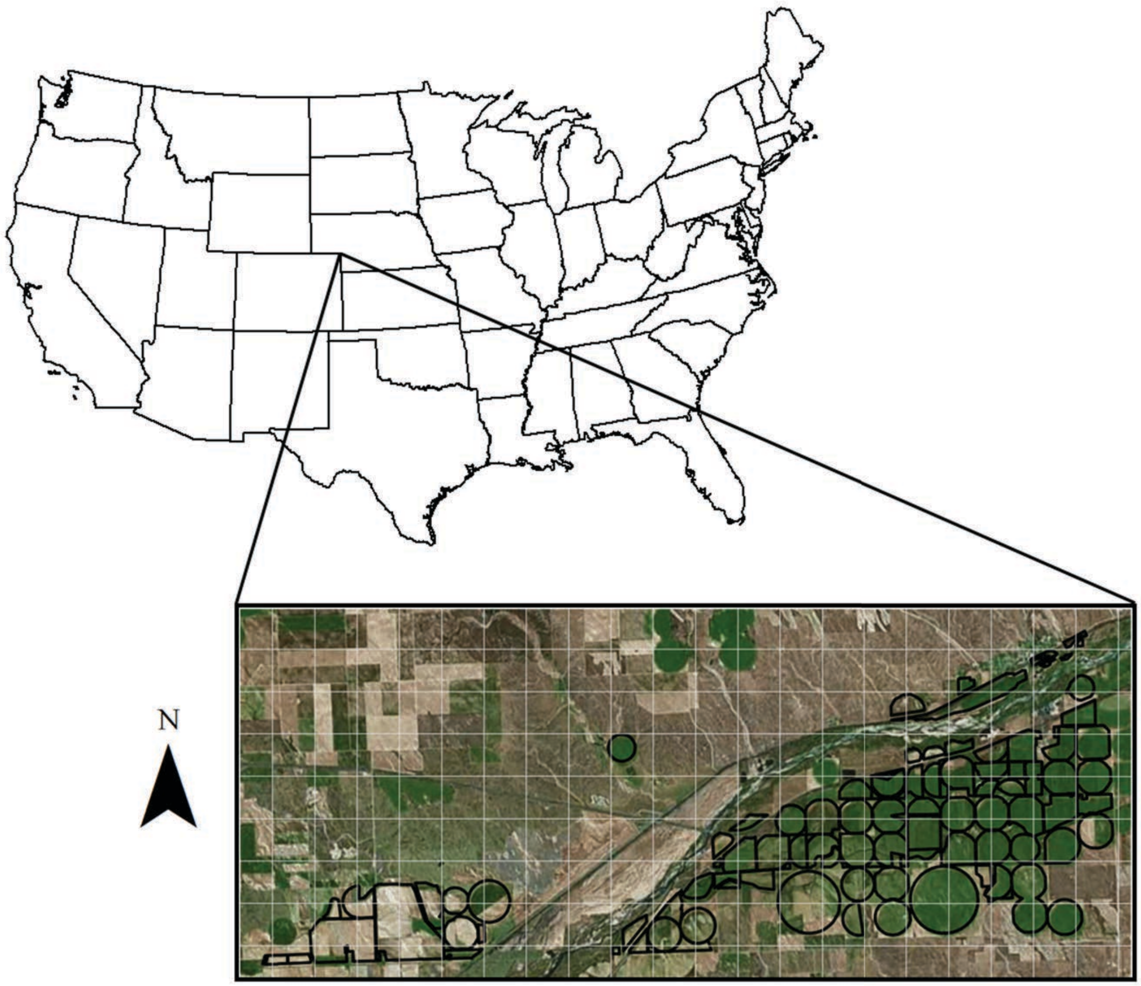
Fig. 6: Historical irrigation vs. the four simulated irrigation routines, for sandy loam (left) and loam (right). Verticle error bars are standard error of the mean from the precipitation sensitivity ananlysis and horizontal error bars are standard error of the mean from observed irrigation.

Fig. 7: Potenital yield simulated by Hybrid-Maize using the 4 irrigation routines: crop model (CM), precipitation delayed (PD), evapotranspiration replacement (ET), and Hydrus-1D (H).

Fig. 8: Example of simulated growing season cumulative P and P+I with daily P values plotted on secondary y-axis for the 4 irrigation routines in a wet (2010) and dry year (2012). Irrigation starts later for routines that track soil moisture thus leading to reduced pumping.

Table 1: Summary of needed inputs and tunable parameters for each irrigation routine.

Table 2: Van Genuchten parameters used in Hydrus-1D simulations.

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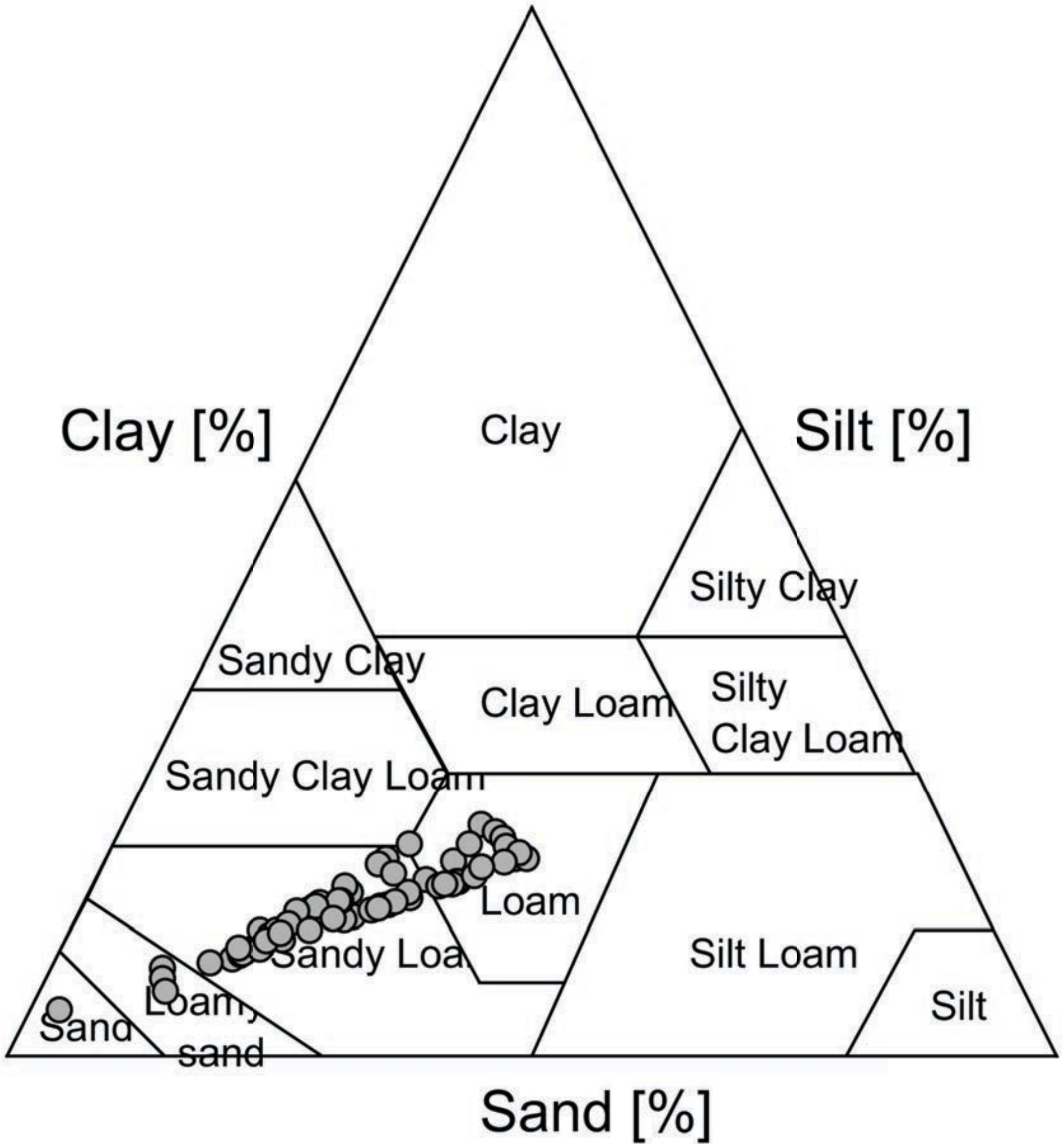


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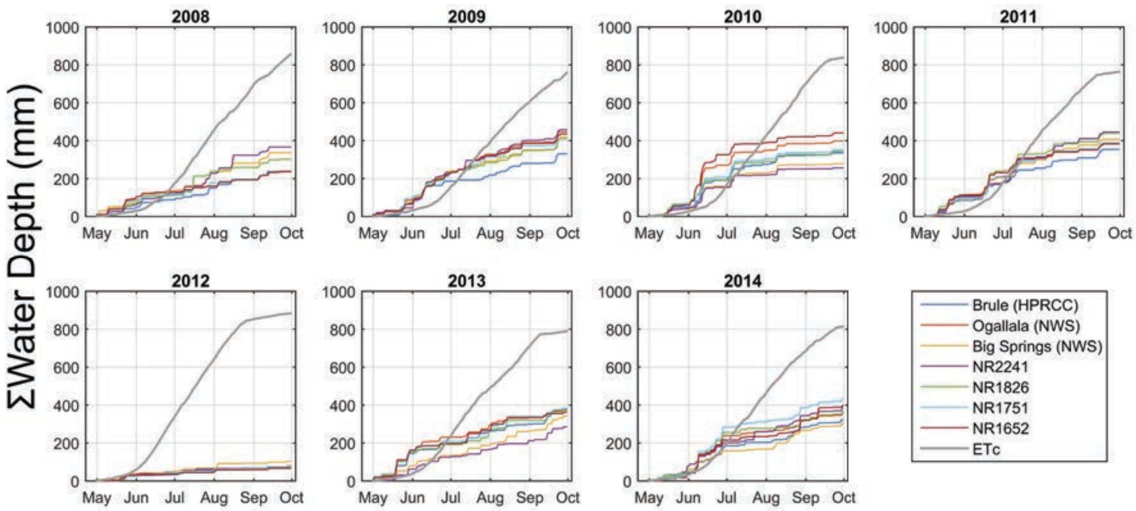


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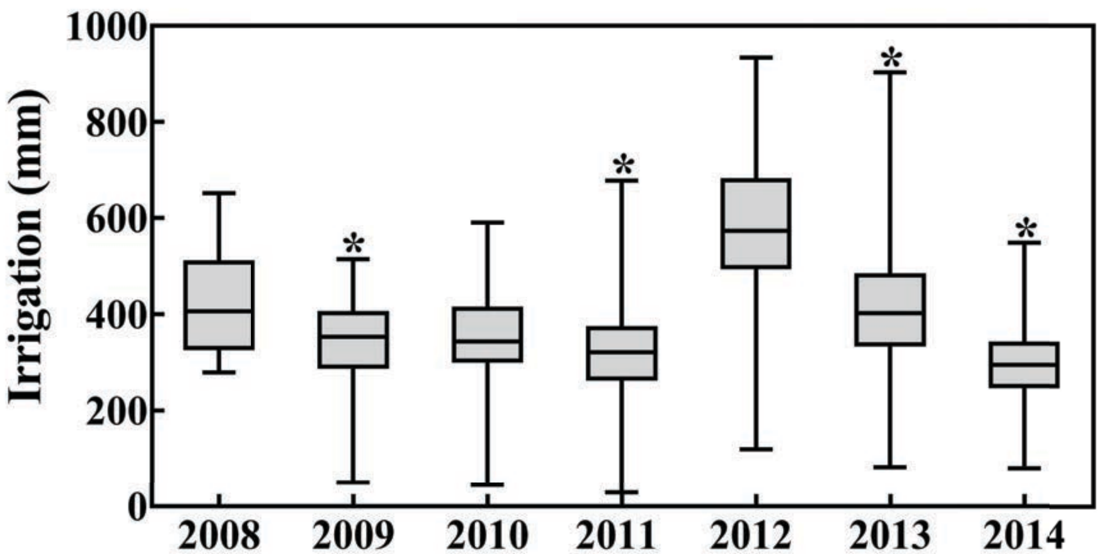


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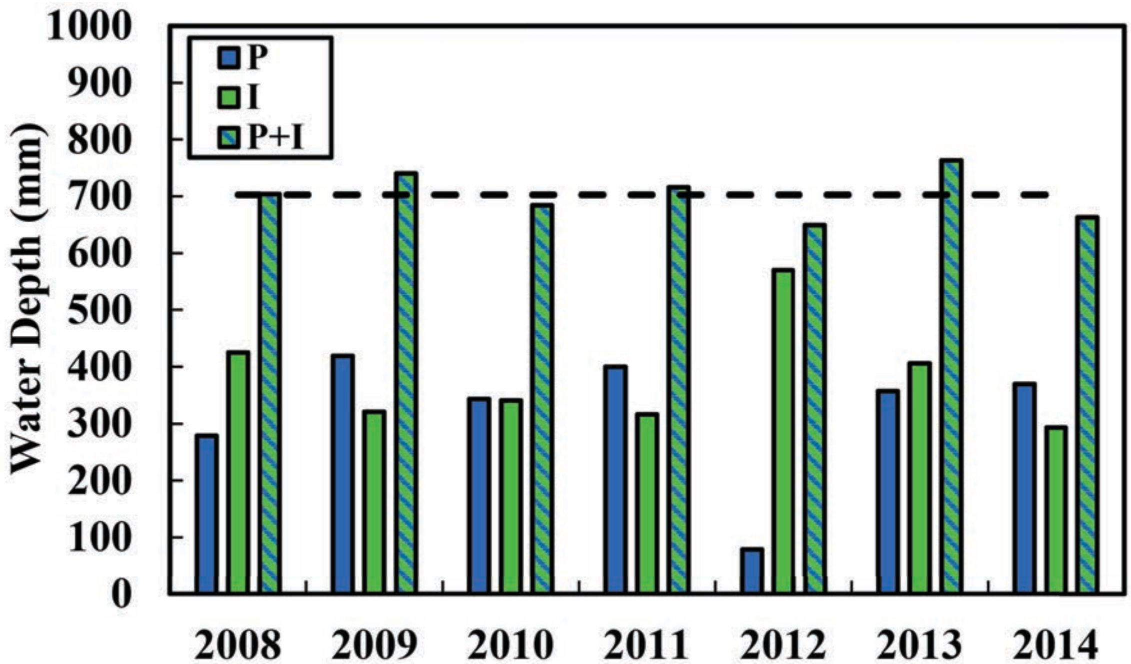


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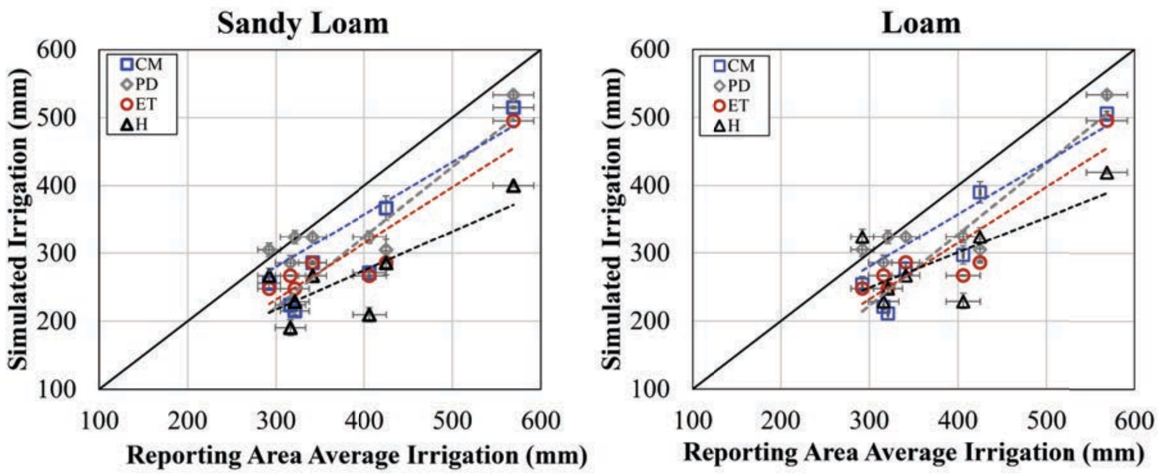


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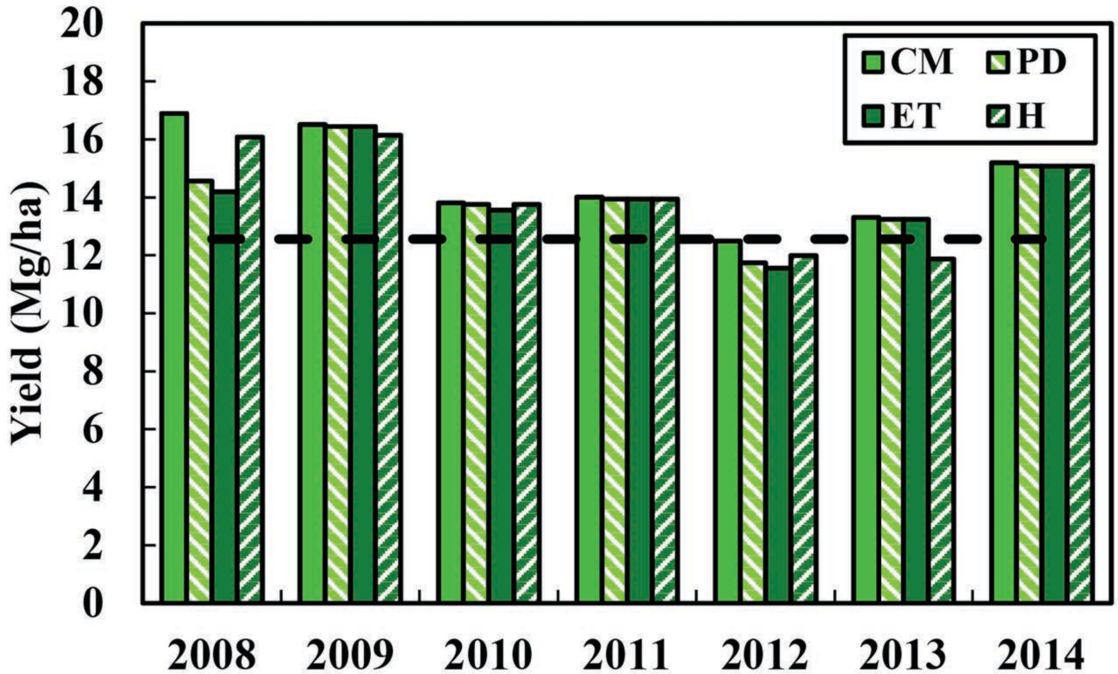


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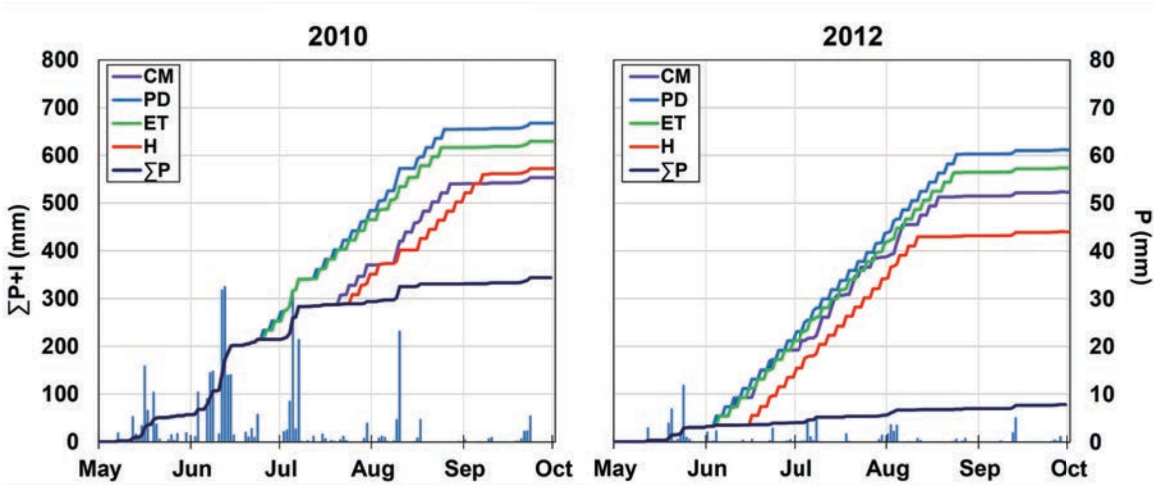


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Table 1: Summary of needed inputs and tunable parameters for each irrigation routine.

| Routine | Needed Inputs | Tunable Parameters |
|---|---|---|
| CM | P, ETr, soils | I intensity (mm/day, growing season ETa/growing season length) |
| PD | P | I intensity |
| ET | P, ETr, kc | I intensity |
| H | P, ETr, kc, soils, zr | I intensity, pressure-irrigation trigger point, root depth irrigation-trigger point(s) |

Table 2: Van Genuchten parameters used in Hydrus-1D simulations.

| Texture | $\theta_r$ (-) | $\theta_s$ (-) | $\alpha$ (1/cm) | $n$ (-) | $K_s$ (cm/day) |
|---|---|---|---|---|---|
| Sandy Loam | 0.048 | 0.385 | 0.0289 | 1.389 | 31.91 |
| Loam | 0.060 | 0.400 | 0.0127 | 1.458 | 10.85 |