Estimation of the effects of climate variability on crop yield in the Midwest USA

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ABSTRACT

Crop yield is strongly affected by climate variability. When applying ecohydrologic models to study climate impacts on crop yield, especially interannual yield responses to climate stresses, the model simulation of plant available soil moisture must be constrained in order to reproduce plant production variation via moisture related bio-climate variables. In this study, the Soil and Water Assessment Tool (SWAT) is used to investigate the relationship between climate variability and crop yield at four sites (Boone, Woodbury, Madison, and Mason) in the Midwestern USA. The model was first calibrated for soil moisture at the plot scale. The calibrated model was then used to extend the observational records between 1991 and 2010 to better capture the effect of climate variability on crop yield over a longer period (1941-2010). We also explored the relative yield reduction due to individual stresses. Our results indicated that annual observed yield from 1991 to 2010 is correlated with drought stress intensity in the early and middle reproductive stage at most sites. The early and middle reproductive periods were thought more critical than other stages, because severe drought stress in those periods is substantially correlated with low observed yields. No significant relationship between crop yield and aeration stress was found at any of the four sites, due to their different impacts under different spatial scales, as well as low frequency of events in the historical record. Long term simulation of yield reduction indicates that drought stress was the dominant factor affecting yield in the historical period when compared with aeration stress both at short and long return periods (high/low probability of exceedance). For a 70 year period, the total yield reduction due to drought stress is 8.1%, 17.5%, 15.2% and 9.7% respectively for Boone, Woodbury, Madison and Mason.

1. INTRODUCTION

Crop yield is of great concern all over the world. The Food and Agriculture Organization of the United Nations (FAO) has predicted that “although the growth of food demands are expected to slow to 1.2 percent a year over the period 2015 to 2030, by 2030, an extra billion tons of cereals will still be needed each year” (FAO, 2002). The increasing food demands have to be matched by a corresponding increase of food supply. An unbalanced supply-demand relation can lead to tight food markets and rising food prices. To release the pressure in food supply, increased exploitation of arable land, crop productivity growth and increases in cropping intensity are often employed (Rosegrant *et al.*, 2012). Productivity growth is the most critical component of agricultural supply increases. However, there are many factors that can affect crop yields negatively. Annual crop yields are strongly controlled by specific hybrids and specific growing conditions, including weather and nutrient availability. Further, at different growth stages, the magnitude of influence could be different for each factor.

Among all of the factors, soil moisture could have the most complicated relationship with crop development. We can subcategorize the impact of this factor into two parts. One is water deficiency, and the other is excess water stress. Both of them will negatively affect plant growth and threaten crop yields. Limited soil moisture results in a decrease of plant water uptake. Drought will also cause plant tissue dehydration and in turn reduce shoot and root growth, membrane integrity and decrease crop production. Drought-induced crop yield reduction is well documented by many researchers. In the 1930s in the southern Great Plains of the US, drought caused as much as a 50% reduction in corn and wheat yields (Warrick, 1984). The 1988 Midwest US drought led to a 30% reduction in US corn production and cost three billion dollars in direct relief payments to farmers (Rosenzweig and Hillel, 1988). The recent 2012 drought affected at least 60% of farms in the US, and caused the lowest national yield value since 1995, 123.4 bu/acre (Crutchfield, 2012)

Limited water supply (drought) is not the only factor affecting crop growth. If soil water is oversupplied, oxygen transport rates in the soil are reduced, adversely affecting root metabolism and retarding root development. In such cases, a paradoxical phenomenon may occur where the plant wilts not due to lack of water but due to a lack of oxygen. The relative proportion of water to air plays an important role in plant health. The optimum moisture content for healthy growth recommended by Kirkham and Powers (1972) is 25% of total soil pore space for both water and air content. Boyer (1982) found that 41% of crop losses in the United States are caused by drought, while excess water causes crop losses of 16% on average. In the United States, 25% of the soils are threatened by drought, and 16% are too wet, both resulting in a limit to crop production (Boyer, 1982).

Historically, much of the Midwestern U.S. has been faced with excess water. Due to previous glacial activities, dense till restricts water infiltration, which means much of this area maintains a high water table and is very poorly drained (Thompson and Bell, 1998; Muenich, 2011). Under such conditions, organic matter is easily accumulated, resulting in some of the most fertile lands in the world (Blann *et al.*, 2009), but also requiring drainage to make the region workable. Without drainage improvements, this region is subject to delayed planting, denitrification, manganese deficiency, poor root development, depressed nodule activity in legumes, and serious root diseases (Ohio Agronomy Guide, 14th Edition). These soils can be the most or least productive ones, depending on how they are managed. Therefore, in the Midwestern U.S., croplands in poorly drained condition are likely to be drained using subsurface tile lines to release excess water problems and guarantee the healthy growth of crops (Naz *et al.*, 2009).

Understanding the role of soil moisture in crop yield variation will bring great benefits to a range of users in the Midwestern U.S., including farmers and crop marketing agencies. Many studies have investigated the close relationship between soil moisture or moisture related bioclimatic indices and plant yields (Torell *et al.*, 2011; Singh *et al.*, 1998). Bioclimatic or agro-meteorological indices are preferred

over meteorological metrics by land managers, because of their clearer association with crop phenology and management practices (Matthews *et al.*, 2008). Bioclimatic indices used in previous research to explore drought effects include annual maximum soil moisture deficit (Brown, 2013), Soil Moisture Percentile (SMP) (Mishra and Cherkauer, 2010), and the Evapotranspiration Deficit Index (ETDI) (Narasimham and Srinivasan, 2005). When soil water is oversupplied, the soil aeration capacity (SAC) (Viesser, 1977) and the Least Limiting Water Range (LLWR) (Benjamin *et al.*, 2003) metrics are often employed to evaluate crop yield response. All of these indices have been found to be good indicators of crop yield under dry or wet conditions, respectively.

To explore the response of crop growth to climate variability and estimate crop yield under various climate conditions, crop growth modeling is often employed. A good model should be able to capture soil moisture dynamics under various climate conditions. The response of crops to both oversupplied and limited moisture conditions must also be clearly reflected. Thus the close relationship between crop production and moisture related bioclimatic variables (Physical-Physiological index) should be addressed by the model for serious analysis of future climate impacts. Although there are many crop modeling studies and most of the models used have water balance modules, only a few of them evaluate model performance for both soil moisture and yield prediction (Saseendran *et al.*, 2004; Mkhabela and Bullock, 2012). Furthermore, not all models consider crop response under excess water conditions. For example, Hybrid-Maize (Yang *et al.*, 2004), AquaCrop (Steduto *et al.*, 2009) and Cropsyst (Stockle, *et al.*, 1994) only consider yield reduction under drought stress, which limits use in areas that suffer from excess water problems, such as fields with limited drainage in the Midwest U.S.

The main objective of this paper is to study the role of climate variability on crop yield at four sites across the Midwestern U.S. with extended data sets of climate observation and crop yield. The Soil and Water Assessment Tool (SWAT) is used in this study because of its robustness in water quantity simulation and the availability of modules to represent plant response in both dry and wet soil conditions.

SWAT's ability to capture daily soil moisture was first tested at four Natural Resources Conservation Service (NRCS) - Soil Climate Analysis Network (SCAN) sites. The model's ability to represent historical corn production using observed climate (1991-2010) was then evaluated at the same sites. The response of simulated crop yields to the timing and duration of different bio-climate extremes (related to drought and aeration stress) was explored. Finally, yield reduction due to individual stresses for a longer historical period (1941-2010) was investigated through frequency analysis.

2. METHODS

2.1. SWAT model overview and modification

The Soil and Water Assessment Tool (SWAT) was developed by USDA-ARS and is widely used to assess the impact of climate variability on hydrologic process and crop production. The Hydrologic Response Unit (HRU) is the basic spatial unit required for simulation. It is a lumped land area, possessing unique combinations of land use, soil and slope within a subbasin. The hydrologic cycle is simulated based on a water balance equation of soil water content, including evapotranspiration, surface runoff, infiltration, percolation, shallow and deep aquifer flow (Arnold et al., 1998). A detailed description of SWAT hydrological simulation can be found in Neithsch *et al.*, (2009).

Plant growth is also simulated at the HRU level. The growth cycle of each plant is regulated by specific attributes in the SWAT plant database, as well as the timing of operations in the management files. Growing Degree Days are often used to define crop growth period and schedule management operations, but SWAT makes use of a variant, the heat unit or PHU . Crop planting date is decided by the fraction (fr_{PHU0}) of annual total PHU_0 (heat unit accumulation above 0 °C). The plant begins to accumulate PHU (heat unit accumulation above the plant specific base temperature T_{base}) after planting until it reaches PHU_{mat} (heat unit accumulation to maturity), which is also defined by crop type and cultivar. The value of fr_{PHU} is the ratio of current PHU to PHU_{mat} and is used to decide the timing of other

management operations, such as fertilizer/pesticide application (< 1.00), and harvest (>1.00). The crop has reached maturity when $fr_{PHU}=1.00$.

Under optimal conditions (no growth stress), daily biomass accumulation (Δbio ; kg/ha) is regulated by leaf area index (LAI) development, light interception (k_l), photosynthetically active radiation (H_{day} ; MJ m⁻²), and radiation-use efficiency (RUE ; 10⁻¹ g/MJ).

$$\Delta bio = 0.5 H_{day} \bullet (1 - \exp(-k_l \bullet LAI)) \bullet RUE \quad (1)$$

For annual crops, LAI accumulates each day following an optimal leaf area development curve, with similar shape, but different parameters for different plants. LAI increases from the planting date until it reaches the maximum LAI value and is then stable until the senescence point ($DLAI$) is attained. LAI drops from this point until the crop reaches maturity.

Actual daily growth varies from the optimal growth rate due to an accumulation of stresses, which include water deficit or excess, nutrient limitation, extreme temperature, pests, and diseases. The total actual biomass accumulation over the growing season is calculated as:

$$bio = \sum_{i=1}^d \Delta bio_i \bullet [1 - \max(wstrs, astrs, tstrs, nstrs, pstrs)] \quad (2)$$

Where bio is the total plant biomass on a given day (kg ha⁻¹), and Δbio_i is the increase in total plant biomass on day i (kg/ha). The terms $wstrs$, $astrs$, $tstrs$, $nstrs$ and $pstrs$ represent drought, aeration, temperature, nitrogen and phosphorus stress, respectively and are the five growth constraints considered by SWAT. d is the number of days from planting to the simulation day. In our case, auto fertilization is applied to avoid any nutrient limitation. Therefore, stress from nutrient limitation is not considered in this research.

SWAT considers daily water stresses either under oversupplied or limited conditions (aeration and drought stress). Aeration stress (*astrs*) is related to a function (*satco*) of porosity, field capacity and soil water content in the soil profile.

$$satco = \frac{\theta - \theta_{fc}}{\eta - \theta_{fc}} \quad (3)$$

Where θ is the soil water content in the soil profile (mm water), θ_{fc} is field capacity for the entire soil profile (mm water), and η is the soil water content at saturation (mm water). The variable *satco* is the fraction of saturation over field capacity in the soil profile and is used to define aeration (excess water) stress based on a function from the APEX model (Steglich and Williams, 2008):

$$astrs = \frac{satco}{satco + \exp(b1 - b2 * satco)} \quad (4)$$

Plotting *astrs* versus *satco*, an S-shaped curve can be attained. The S-shaped curve is used to describe the behavior of many processes (aeration stress, potential harvest index, P plant use-soil P concentration) in the APEX model. The variables *b1* and *b2* control the shape of the S-curve and therefore the degree to which the plant experiences stress due to an increasing excess of soil water.

The original SWAT aeration algorithm calculates *astrs* based on the water content for the entire soil profile. This could be suitable if the plants' root system is in or close to maturity status, but will not reflect conditions leading to aeration stress earlier in the growing season when plant roots are shallow. We modified the original aeration stress calculation algorithm so that it considers root depth. The modified algorithm only considers aeration stress in the root related soil layers instead of the whole soil profile (Fig.1).

Drought stress is defined as a comparison between actual and potential plant transpiration:

$$wstrs = 1 - \frac{w_{actualup}}{E_t} = 1 - strsw \quad (5)$$

Where $wstrs$ is the drought stress for a given day, E_t is the maximum plant transpiration on a given day (mm water), $w_{actualup}$ is the actual amount of transpiration on a given day or total plant water uptake for the day (mm water), $strsw$ is the ratio of actual to maximum transpiration.

Compared with eq. (3), $strsw$ has a similar pattern with $satco$, which are both physical parameters, showing the ratio of an actual to a potential condition. Aeration and drought stresses are physiological parameters, which are transformed from physical parameters, like $satco$ and $strsw$. The transformation method is quite subjective and mostly based on expertise and experience (Kozak et al., 2006). Therefore, like aeration stress, a new equation to calculate drought stress is introduced, which is shown in eq. (6). The S-curve method is used to adjust yield which is over/under sensitive in some places to the original drought stress.

$$wstrs' = 1 - \frac{strsw}{strsw + \exp(c1 - c2 * strsw)} \quad (6)$$

Daily biomass is controlled by stresses and keeps accumulating until the accumulated heat units reach PHU_{mat} , then biomass keeps constant until harvest. Annual yield is then separated from total above-ground biomass (bio_{ag}) via multiplying the harvest index (HI). HI is a function of the optimal harvest index (HI_{opt}) and fr_{PHU} . If heat units do not accumulate to PHU_{mat} , HI is less than HI_{opt} . Therefore, early harvesting results in less yield from accumulated aboveground biomass. Otherwise, HI is close to HI_{opt} , which means that above ground biomass transfers to crop yield at an optimal rate. Water deficiency also affects the value of HI during the active growing season ($0.5 < fr_{PHU} < DLAI$), with the actual harvest index for each crop, HI_{act} , calculated as

$$HI_{act} = (HI - HI_{min}) \bullet \frac{\gamma_{wu}}{\gamma_{wu} + \exp[6.13 - 0.883 \times \gamma_{wu}]} + HI_{min} \quad (7)$$

where HI_{min} is the harvest index for the plant in drought condition and represents the minimum harvest index allowed for the plant, and γ_{wu} is the ratio of actual to potential evapotranspiration for the active growing season.

In sum, the complicated process of crop growth is mathematically simplified by SWAT considering potential accumulation (heat unit based) of biomass and growth stresses. Annual crop yield is then calculated from the total biomass and harvest index.

2.2. Study Area and Data

Four soil moisture monitoring sites established by the NRCS-SCAN across the Midwest USA (Fig. 2) were used in this study: Boone, IA (42°1'N, 93°44'W), Woodbury, IA (42°26'N, 95°46'W), Madison, OH (39°57'N, 83°26'W) and Mason, IL (40°19'N, 89°54'W). All provide 5-6 years of continuous daily soil moisture data at multiple depths. This offers a valuable chance to evaluate model performance in soil moisture prediction. Current land use/cover information is based on site pictures on the NRCS website, which resulted in all sites being classified as range grass using default SWAT parameters. Soil, crop and weather data used in this study are summarized in Table 1.

2.3. Model implementation

2.3.1 Crop yield calibration steps

Simulation of crop yield is dependent on both biophysical processes and the simulated soil moisture via the stress functions (bioclimatic variables). Model implementation therefore followed a multistep procedure as illustrated in Fig. 3. The statistical metrics mentioned in Fig. 3 will be addressed in section 2.3.3.

2.3.2 Simulated crop yield upscaling

Due to the spatial scale difference of observed (detrended county level yield from the National Agriculture Statistic Service (NASS)) and simulated yields (SWAT single HRU scale), these two datasets cannot be compared directly. The scale discrepancy will affect inter-annual variations, because data averaged to coarse scales are less variable than data for small plots, which introduces a bias in the yield calibration (Maltais-Landry and Lobell, 2012). Therefore, in this study, an approach to upscale simulated yield from HRU to county was developed, considering the effect of arable soil varieties on yield across the county.

First, arable soils from the NRCS SSURGO (Soil Survey Geographic Database) in each county were classified into different groups based on the two properties (NRCS curve number and saturated hydraulic conductivity) that most influence SWAT simulated hydrology (Fig. 4). Secondly, the model was run for various soil groups without calibration to provide yield values based on the default parameter set. Then, the model was run at the SCAN site in each county using the default and calibrated parameter sets. The yield difference between the SCAN site simulations with the two parameter sets was treated as bias. This bias was employed to adjust the simulated yield values for the other arable soil groups based on the assumption that calibration would have similar influence on all soil groups. The proportion of each arable soil (Fig. 4) in each county is also considered when upscaling the crop yield simulated for the individual HRUs representing SCAN sites to the whole county, as follows:

$$Y_{county}^{cali} = \sum_{n=1}^N (Y_{plot}^{cali} - Y_{plot}^{def} + Y_n^{def}) \times \frac{A_n}{A_{arable}} \quad (8)$$

Where Y_{county}^{cali} is the county level crop yield after upscaling; N is the number of arable soil groups simulated in the county; Y_n^{def} is the annual simulated crop yield for soil n , using the default parameter set; Y_{plot}^{cali} is the simulated yield at plot scale using calibrated parameters; Y_{plot}^{def} is the simulated yield at plot

scale using default parameters; A_n is area of soil n in each county; and A_{arable} is the total area of arable soil in each county.

2.3.3 Model performance evaluation

To evaluate the deviation of the soil moisture content and crop yield simulations, statistics of mean bias error (MBE), Willmott's index of agreement (d), and the normalized root mean square error (N-RMSE) were calculated. MBE measures the average tendency of the simulated data to differ from their observed counterparts (Gupta *et al.*, 1999). The d -statistic (Willmott, 1982) reflects the degree to which the simulated variation estimates the measured variation (Han, *et al.*, 2010), which has a value between 0 and 1, where higher values of d indicate better model performance. Since it overcomes the insensitivity to additive and proportional differences between observed and simulated data, the d -statistic is more appropriate to evaluate soil water content when compared with the correlation coefficient (Legates, and McCage, 1999). As recommended by Legates and McCage (1999), a complete assessment of model performance should also include at least one error index for diagnostic purposes. Therefore, N-RMSE (Loague and Green, 1991) is employed in this study, which is the root mean square error (RMSE) divided by the average observed soil moisture or crop yield. RMSE indicates error in the units of the constituent of interest, while N-RMSE includes a normalization factor, making the resulting statistic comparable across constituents. A value of N-RMSE smaller than 10% indicates that the model is an excellent predictor, between 10 and 20% is a good predictor and between 20 and 30% is a fair predictor (Bannayan and Hoogenboom, 2009). These three metrics were used to evaluate model performance both in soil moisture and annual crop yield.

2.3.4 Soil moisture content calibration

Observed soil water content during the winter period (Nov to Feb) is often missing from SCAN datasets, presumably due to soil freezing. Moisture data in the winter period is less related to crop yield in the Midwestern US, since crops have either been harvested or have not been planted. Therefore, our soil

moisture calibration is just based on observed data from March 1st to Oct. 31th for each year. This captures soil moisture prior to planting, which is more important to crop growth than variations in soil moisture through the winter.

Measured soil moisture contents were compared with daily simulated values for different layers. A 10 year spin up period was used to minimize the impact of uncertain initial moisture conditions. Site specific soil physical properties used to parameterize moisture are summarized in Table 2. Hydrologic parameters that were manually adjusted to calibrate soil moisture are listed in Table 3.

2.3.5 Management timing parameterization

SWAT calculates heat unit accumulation at a daily scale, and uses those values to control when important management decisions are made. Frequently, an exact date for planting and harvest is assigned in SWAT, but heat unit accumulation can also be used to vary planting time from year to year. This method is more consistent with actual practice and was used for these simulations. The accumulation of heat units also helps to define different phenology stages, or at least the approximate timing of their occurrence. We used this relationship to compare simulated plant growth stages to those provided in the USDA-NASS database, and to calibrate the crop growth model within SWAT to improve the simulation of corn yields. Default and calibrated parameters are shown in Table 4, while the calibration process is described below.

2.3.5.1 Planting

Planting time determines when the simulated crop begins to accumulate biomass. Incorrect planting time will directly affect the timing of other management stages, and finally cause incorrect simulation of annual total biomass and yield. For the two sites in Iowa, Boone and Woodbury, the default crop model settings resulted in planting dates consistently later than the mean planting date from 20 years of NASS data (Fig. 5). This was adjusted by changing the value of fr_{PHU0} to start crop growth more in line with observations. The simulations reflect corn planting time very well after proper parameterization for

all 20 years. For Mason and Madison, the default settings are good enough, so there is no change of fr_{PHU0} in these two counties.

2.3.5.2 Maturity

In SWAT, maturity date is controlled by total heat unit accumulation from the date of planting. Compared with the NASS data, the default maturity date was too early (Fig. 5(2a-2d)). Therefore, PHU_{mat} was adjusted. In the Midwestern U.S., the average mid-season commercial corn hybrid requires 130 days or 2700 growing degree days (GDD) from planting to maturity (Neild and Newman, 1990). GDD is another daily heat unit calculation method similar to PHU, and conversion between them is straightforward. To do this, GDD and PHU were accumulated from the observed planting date for each year, and the PHU for the day that GDD reaches 2700 is obtained. Fig. 5(2a-2d) reflects the simulated maturity date before and after parameterization, indicating that 2700 GDD (around 1652 to 1712 PHU in all sites) accumulation from the planting date results in a simulated maturity time that compares well to observed data.

2.3.5.3 Harvest

Similar to planting date, PHU fraction is adjusted for harvest (fr_{PHUhar}) to better reflect observed harvest date. For some cold years, heat units do not accumulate to the required harvest amount and the crop is terminated on the 352nd day of the year. Harvest date before and after parameterization is also shown in Fig. 5(3a-3d).

2.3.5.4 Senescence

Senescence is not a management timing, however, like other management practices it relates to crop biomass accumulation. When corn reaches some fraction of PHU_{mat} , LAI begins to decrease. This fraction is used as an adjustable parameter (DLAI) to control the beginning of senescence. Usually, senescence happens at around the end of the grain filling period (Nielsen, 1998), but no clear criteria for the timing of natural senescence is defined. Current literature provides the timing of senescence in some

specific years. For example, Dohleman *et al.* (2009) recorded the corn planting, senescence and maturity timing (Day of year) in Champaign, IL (40.033N, 88.233W). With this information and the recorded daily temperature data from the nearest NOAA station, the heat unit between planting and senescence were calculated. The senescence point relative to the PHU for maturity was 0.786 and 0.759 in 2007 and 2008, respectively. Similarly, Yang *et al.*, (2003) recorded the planting, emergence and maturity date of corn in Manchester, IA (42.47N, 91.45W). They found that LAI decreases 85-90 days after emergence. Thus, DLAI in this area was calculated as 0.751 for 2002. Since our study plots are close to these sites, DLAI was set to 0.75 (around the end of denting stage for a 2700 GDD corn).

2.3.6 Annual yield amount/variation calibration

For crop yield calibration, HI_{opt} , HI_{min} , RUE , $b1$, $b2$, $c1$ and $c2$ were chosen to adjust the annual yield. RUE , HI_{opt} and HI_{min} are often considered the most sensitive parameters affecting mean annual crop yield in SWAT crop growth studies (Anderson *et al.*, 2009; Nair *et al.*, 2011; Sun and Ren, 2012). The S-curve transformation parameters for aeration stress ($b1$, $b2$), and drought stress ($c1$, $c2$) were used to modify the yield sensitivity to environmental stresses in this study. Thus, variation of yield is regulated by four S-curve transformation parameters. The parameters $b1$ and $c1$ control the position of the curve, with smaller $b1$ or $c1$ values increasing the initial slope of the S-curve which in turn increases the sensitivity of crops to small levels of aeration or drought stress. Large values of $b1$ or $c1$ decrease the initial slope so that yields are not substantially affected until higher levels of aeration or drought stress. The difference ($b1-b2$) or ($c1-c2$) controls how closely the S-curve passes through the 1-1 point on both relationships. For use of the equation, we calculate $b2$ or $c2$ from the value of $b1$ or $c1$ to keep the tail of the curve within 0-3% of a final value of aeration or drought stress of 1.

For aeration stress, S-curves used by three previous models (Steglich and Williams, 2008; Neitsch *et al.*, 2009; Du *et al.*, 2005) are shown in Fig. 6, which are all above the 1:1 line, indicating that aeration stress grows rapidly for relatively low fraction of saturation, but stays stable in a high stress

status, when relative saturation (*satco*) keeps increasing. For drought stress, a 1:1 line is shown as the SWAT default setting, which means no s-curve transformation; drought stress equals $1-AET/PET$, and stress responds to AET/PET linearly. Suggested calibration ranges for the aeration and drought stress scaling functions are displayed as gray shaded zones. Any curve in the shaded zone could be chosen by end users as a possible one to transform the physical parameter (*satco* or $1-AET/PET$) to physiological parameter (aeration or drought stress).

The calibration range was selected based on the area under any possible s-curve. Actually, this area also reflects the mean stress value, supposing *satco* or $1-AET/PET$ is evenly distributed between 0 and 1. Take drought stress for example, the area under the 1:1 line is 0.5, indicating that the mean stress value is 0.5. The suggested calibration range constrains the mean stress between 0.35 and 0.65 (15% deviation from the 1:1 line). Similar to drought stress, considering the response of aeration stress to different percent saturation, any curve with mean aeration stress between 0.5 and 0.85 is suggested for calibration, which covers all three previous models and stays above the 1:1 line.

A 20-year period (1991-2010) is used for crop yield calibration and validation. Crop yield calibration is executed in years (6-7 years) which have observed soil moisture data at the SCAN sites and moisture calibration is described in Section 2.3.4. The remaining years (13-14 years) in this period are used for crop yield validation. Parameters employed for crop yield calibration are summarized in Table 5.

All sites were assumed to be undrained when calibrating crop yield with the exception of Boone, IA. Fig.7 shows that the bottom layers (below 46 cm) of the edge-of-field SCAN site in Boone, IA are almost saturated, indicating a very serious continuous aeration stress for crops. Tile drainage is widely applied in Midwest when soil is poorly drained (Singh *et al.*, 2006; Schilling and Helmers, 2008). Therefore, when modeling crop yield in Boone, IA, it was assumed that all fields are tile drained.

2.3.7 Weekly biomass accumulation validation

Reasonable annual yield can also be achieved by adjusting harvest index even if the biomass accumulation is incorrect (equifinality in crop yield calibration). Under such situations, the model either consistently over or underestimates daily biomass accumulation, or incorrectly reflects crop responses under oversupplied/limited water conditions. Therefore, to overcome the potential for equifinality, the final biomass at maturity and the seasonal biomass curve are evaluated to ensure an appropriate model representation in daily biomass as well. However, due to the scarcity of field collected biomass data, it is difficult to calibrate daily biomass accumulation curves in the study plots. Singer *et al.* (2011) evaluated radiation use efficiency near Ames, Boone County, IA, which provides a total of 16 consecutive weekly biomass samples in maize for year 2005. Since SWAT simulates biomass at a daily scale, it is reasonable to compare our simulation results with their observed data.

2.3.8 The relationship between crop yield and climate variability.

When the model is not only able to capture the annual yield amount and variation, but also a reasonable daily biomass accumulation rate, it can be considered as a valuable tool to explore how climate variability affects annual crop yield. We extend model application to a longer period (1941-2010) to investigate climate stress to crop yield.

To better explore the role of climate variability (limited/excess water) on annual crop yield, the whole crop growing season is divided into six stages based on corn phenology (Table 6). Each period includes 2-3 phenological stages, which are controlled by GDD. The beginning and ending GDD values are defined by Neild and Newman (1990). For all six stages, the total amount and intensity of aeration stress (*astrs*) and drought stress (*wstrs*) were calculated from the SWAT simulation as indices to represent climate variability. Stress intensity is calculated from total stress amount divided by days with stress (days with non-zero stress). Stress indices were also calculated for the entire vegetative stage (first three phenological periods), entire reproductive stage (last three phenological periods) and entire crop growing

period (all six phenological periods). Both Pearson and Kendaul-Tau correlation coefficients were used to quantify the relationship between detrended observed crop yields and simulated climate variability for all nine periods in four counties.

To explore yield reduction due to individual stresses, the model was first run without any stress, from 1941 to 2010. The source code has been modified to remove all stresses, so biomass accumulated in each day as reflected in eq (2) is always the potential biomass. Simulated yield in this run is considered to be potential yield. Then only one stress (either drought or aeration stress) at a time is considered in the model simulation. This method allows us to compare yield reduction by the individual stresses to potential yield. All simulated crop yields are upscaled to county level based on the methods described in section 2.3.2. Then, simulated relative yield reduction is calculated as:

$$\text{Relative yield reduction} = (\text{Potential yield} - \text{Yield by only one stress}) / \text{Potential yield} \quad (9)$$

Similarly, relative yield reduction for county level observed data is also generated. First, a linear regression was applied to 70 years of NASS observed yield (Fig. 8). Then the regression line is shifted upward until it intersects with the highest observed yield. The shifted line is considered the observed potential yield. Relative yield reduction for the observed data is calculated through the observed potential yield and NASS observed data.

For all 70 years, the non-exceedance probabilities are calculated using the Weibull formulation. Both simulated and observed yield reduction associated with the respective non-exceedance probabilities are then plotted in Fig. 13. Similar to flood frequency analysis, the non-exceedance probabilities can be converted to a return period by inverting the values.

3. RESULTS

3.1 Model performance in soil moisture prediction

Model performance at Boone, IA is shown in Fig. 7 as a representative of the soil moisture calibration process for all SCAN sites. In order to better illustrate the overall model performance, only annual average daily values for the 5-6 year period are shown. Statistics for model performance for all four sites are summarized in Table 7. The model captures the interannual soil moisture variation and annual average amount very well in most years for most soil layers. At the Boone, Woodbury and Madison sites, simulation results are good for soil moisture, with d-statistics greater than 0.8 and MBE values less than 10%. A larger mean bias was found in Mason, IL when compared with the other three sites. The model also underestimates soil moisture in summer and fall in Mason. The relatively poor performance in this site is due to sandy soils and missing site precipitation. A high sand content at this site results in poor soil capacity to hold water. Therefore, the absolute value of soil moisture is much lower than the other three. Although the absolute difference is small, a large relative difference may occur. The SCAN site at Mason, IL only has one year's site recorded precipitation, so the inverse distance method is used to generate site precipitation from another station. Unfortunately the closet NOAA weather station is still 14.3 km away (Havana, IL), so the precipitation records are not as accurate as those from other sites resulting in the poorest performance for this site.

The soil in Boone, IA is poorly drained and there is no subsurface drainage at the field edge where the site is located, so the bottom layers are saturated. The model is able to reflect this after proper calibration. Poor d-statistic values in the bottom two soil layers at Boone are caused by variation of simulated and observed moisture around the saturated value. Under saturated conditions, the model generates relatively constant moisture, while the observed data fluctuates around this constant value due to instrument noise. The effect of noise could be covered if observed data itself varies. Therefore, the variance of simulated soil moisture is lower than observed data measured by soil sensors.

3.2 Model performance in crop yield/biomass prediction

The model captured annual average yield well. Mean bias error is less than 10% (Figure 9 and Table 8). Normalized root mean square error (N-RMSE) is less than 15%, indicating a good fit and accuracy in predicting yield (Tubiello *et al.*, 2002; Maltais-Landry and Lobell, 2012). In addition, the model is able to capture the interannual variation of crop yield in Woodbury, Madison and Mason. For example, in Woodbury, IA, the d-statistic for both calibration and validation periods are higher than 0.8, and the simulation predicts both higher (years 1999, 2008, 2009) and lower yields (1993, 2000, 2006) correctly.

Although for some specific years and plots, the model has trouble, SWAT still does a good job at predicting the annual yield amount and variation in the study area. Compared to previous yield modeling studies (Heng *et al.*, 2009; Mkhabela and Bullock, 2012; Sun and Ren, 2013), the model overall performance is satisfactory. We also compare model performances with and without moisture calibration in Fig. 9. We found that model performance in corn yield estimation is poor for all four sites if soil moisture evaluation is skipped. For Woodbury and Mason, the model has trouble capturing the interannual variability in crop yield, while for Boone and Madison, the model either underestimates or overestimates crop yield. This indicates the importance of evaluating soil moisture in crop yield predictions.

To check the performance of simulated daily biomass accumulation, model output from Boone, IA was compared with Singer's observed data (Fig. 10). They match very well, indicating a good model performance in simulating daily biomass accumulation at Boone, IA in 2005. Since daily biomass accumulation data is very limited, there is not enough available data to evaluate daily biomass simulation in other sites at other years.

3.3 Role of climate variability on crop yield

The relationship between the climate variability indices and annual crop yield are summarized in Tables 9 and 10. Yield versus drought/aeration stress for specific growth stages are plotted in Fig. 11 and 12. Statistically significant correlations between yield and drought stress intensity were found in early reproductive (silking to blister) and middle reproductive (dough, denting) periods. Person's r is -0.38, -0.54 and -0.41 for silking and blister stage at Woodbury, IA, Mason, IL and Madison, OH, respectively. For Madison, OH, significant correlation ($r=-0.48$, -0.43) between drought stress intensity and corn yield was also observed in the V12-V16 and dough -denting periods. Corn yield in both Woodbury and Madison is substantially correlated with drought stress intensity during the reproductive period ($r=-0.37$ and -0.55, respectively). Results indicate that crops are more sensitive to drought stress from V12 to denting stage than during other phenology stages, especially compared to the early vegetative period. Drought stress intensity in those stages could serve as a good indicator for crop yield. Reproductive organs are formed in the late vegetative period (V12 – V16). Any drought stress in this period will negatively affect ear formation and tassel emergence. Pollination and fertilization happen in the early reproductive period (silking and blister). Success during this stage of development is critical to the final harvest in fall. In contrast, environmental stress occurring in this period can easily abort kernels and in turn reduce crop yield. Kernel abortion in dough and denting stage is not as common as at blister stage, but stress can still continue to reduce kernel weight and finally results in yield reduction (Nielsen, 2008). Therefore, our representation of drought stress is consistent with real conditions.

Compared to drought stress, no clear relationship was detected between aeration stress and yield. The significant relationship ($r=-0.72$) in the reproductive period at Boone, IA is caused by one outlier (Fig. 12a). Although yield reduction due to increasing of aeration stress is expected, the county-level statistics do not show this. The impact of aeration stress on yield may be more easily found at plot scale, but is masked by other fields when yield information is at the county level. More detailed explanation on aeration stress impacts on yield are addressed in the discussion section.

3.4 Long term crop yield reduction due to climate stress

Fig. 13 reflects the relative crop yield reduction due to individual stresses (either drought or aeration stress) based on 70 years data. The relative yield reduction based on observed data is also shown in the same figure, which is higher than the simulated yield reduction by either individual stress. Under natural conditions yield reduction is caused by the interaction of many factors including water availability but also nutrient deficiency, temperature, disease, pest infestation and weed problems, so it is not surprising that the relative yield reduction based on observed data is the highest among the three.

In all four sites, yield reduction caused by drought stress is much higher than aeration stress, especially for long return periods. For a 100 year return period, the relative yield reduction caused by drought stress ranges from 30% to 50%, however the biggest yield reduction caused by aeration stress is still less than 30%. Compared to the relative yield reduction due to drought stress, aeration stress causes relatively stable yield reductions, ranging from 0 to 20% in all return periods. The yield reduction in Boone, IA caused by aeration stress is always close to zero, due to the simulation of subsurface drainage conditions at this site. Under natural conditions, the yield reduction is most likely higher than zero for long return periods. Generally speaking, compared to aeration stress, drought stress is still the dominant factor impairing crop yield in the historical period.

4. DISCUSSION

Although overall the model successfully reflects the annual yield amount and interannual variability in crop yield, there are still some sites and years for which the model did not capture yield very well. For instance, in Madison, OH, the model underestimates corn yield by around 2 t/ha in 1993, 1994 and 2005, but for the year 2010, higher yields are predicted by the model (Fig. 9-4b). A similar situation happens in Boone, IA where SWAT estimates of yield are higher in 2010 than 2004, while detrended NASS observed data indicates the reverse.

Madison, OH experienced a severe drought in 2005. In addition to the drought stress parameters $c1$ and $c2$, HI_{min} is also used to adjust yield. Therefore, yield reduction by drought is considered by the model twice, which may lead to underestimation of corn yield. For 1993 and 1994 in Mason, IL, even when all stresses are turned off, the model potential yield is 6.3 and 8.3 t/ha, which is still below the detrended NASS yield. Therefore, yield underestimation in these two years is not caused by inappropriate stress functions. Though adjusting growth parameters may increase yields in 1993 and 1994, this would lead to bias in the simulated mean yield amount.

Warm daily minimum temperatures between silking and denting in 2010 might be responsible for the low yield observed in Boone, IA (Elmore, 2010). Since heat stress in SWAT is a function of daily mean temperature, such an impact cannot be clearly reflected in the simulation, which overestimates yield.

Besides those specific reasons mentioned above, yield inconsistency can be attributed to two other aspects: 1) missing site precipitation data and 2) upscaling from field to county level for yield comparisons. The most extreme over/underestimation years occurred during the yield validation period, when site recorded meteorological data was not available. Since crop yield is first modelled at the plot scale, any site missing direct local climate observations has increased uncertainty in the final simulation result. The nearest NOAA weather station is 14.3 km and 8.7 km away from the SCAN plots in Mason, IL and Madison, OH respectively. For Mason, IL, even in the calibration period, only one year's site climate record is available, which also explains why model performance in this site is relatively poorer than Woodbury and Madison. For yield comparison purposes, plot simulated yield was upscaled to county level considering soil varieties across the county. In the upscaling method, the same calibration offset ($Y_{plot}^{cali} - Y_{plot}^{def}$) was added for different soils across the county. However, due to the differences in soil properties, the calibration influence for different soils may diverge from each other. Due to the lack of data, it is hard to refute or prove this assumption.

Model performance at Boone, IA is the poorest among all four sites (Table 8). First, the model has trouble capturing the yield trend in the calibration period. Secondly, it overestimates yield in the validation period, by as much as 3 t/ha in 1993 (Fig.9). There are a couple of possible explanations for this difference. 1) SWAT is unable to handle extreme flooding situations well. Flooding is different from aeration stress because it may kill plants instead of reducing biomass. Other effects caused by flooding, such as leafy tassel (crazy top), ear rot and premature kernel sprouting are not considered in SWAT. The year 1993 is recorded as having experienced extreme flooding in Boone, IA (Iowa flood recovery coordination team, 1994). In addition, SWAT cannot represent the effects of flooding caused by neighboring streams (Srinivasan *et al.*, 2010).

In addition, the model may poorly represent the soil moisture of the drained field. The soil used in plot simulation is not arable without the installation of subsurface drainage due to the saturation of the deeper monitored soil layers. Although tile drainage was introduced into the simulation to more accurately reflect soil conditions experienced by crops, no observational data was available to evaluate the simulated condition. Inappropriate tile drainage parameters will affect the sensitivity of the crop to aeration. For this application we used typical values for subsurface drainage (D_{drain}=1200 mm, T_{drain}=52 hr, G_{drain}=25 hr) as recommended by Du *et al.*, (2005). Additionally, tile drainage can affect soil properties, though not significantly (Jia *et al.*, 2008), introducing additional uncertainty into our simulations for the site.

Compared to drought stress intensity, no significant relationships were found between simulated aeration stress and observed crop yield at any evaluated phenology stage. Since aeration stress is more localized within the field rather than at the county scale, when investigating the relationship between aeration stress and yield, it is more likely to be identified when tested against field collected yield data, which was not available for this analysis. Additionally, if the soil is too wet for planting in the spring, farmers may delay planting, replant, change to faster maturing hybrids, or switch fields from corn to

soybeans that need fewer days to mature. For example, Dohlemn and Long (2009) found that in 2008, the corn planting date was delayed until June 18th compared to May 11th, 2007 in Urbana, IL due to very wet soil, and farmers changed hybrid from PI CV 34H35 to Dekalb 61-69. No significant difference was found in final corn biomass production (18.4 vs. 19.2 t/ha). Such hybrid change is not considered in the model simulations. In the simulations presented here, planting date is assigned by heat unit, so simulated planting date only considers temperature but not soil moisture. Therefore, the model may underestimate simulated yield under wet conditions and the aeration stress function alone may be insufficient to capture the impact of wet conditions on corn production.

Finally, although it has been established that the sensitivity of yield to stress is different for different growth stages, the same drought/aeration stress transformation algorithm is used. In other words, instead of using the same stress transformation function for all stages, it is better to use a steeper s-curve in critical/susceptible periods to intensify stress, while using a mild transformation in other stages. In this study, yield calibration does not consider susceptibility. Furthermore, “crop death” is not considered in the simulation process. “Crop death” never happens, even under extreme stress (flooding year 1993 in Boone, IA). Plants can always recover until the date of harvest.

5. SUMMARY AND CONCLUSIONS

In this study, the SWAT model was used to explore the relationship between climate variability and crop yield at four sites in the Midwestern USA. Soil moisture was first calibrated at plot scale. The calibrated model was used to extend the observational records between 1991 and 2010 to better capture the effect of climate variability on crop yields. The relative yield reduction in a longer period (1941-2010) due to individual stresses was also explored.

After appropriate parameter calibration, SWAT is capable of reproducing observed soil water content at different depths in all study sites, even when the site is faced with a serious excess water problem (Boone, IA). Mason, IL has the poorest model performance, which is due to the missing of site precipitation. Overall, absolute values of mass balance error (MBE) are less than 10%, d-statistics are greater than 0.6, N-RMSE<25%, for most soil layers at most sites, indicating a decent model performance in soil moisture estimation.

Before calibrating crop yield in the study area, the fraction of heat units was adjusted to ensure that the timing of important management practices (planting and harvest) and maturity dates are consistent with NASS crop progress data. After this management timing parameterization, the crop growth period is more reasonable, especially for maturity date, which was too early before adjustment for all four sites. This step is also the prerequisite to clearly define important phenology stages in the study area. Drought and aeration stress parameters (b1, b2, c1, c2) accompanied with other traditional biophysical parameters (HI_{opt} , RUE , HI_{min}) were used to adjust site crop yield, which was then upscaled to county level. The model did a good job capturing the average crop yield for all study areas. Annual yield variation is also successfully reflected in Woodbury, IA, Mason, IL, and Madison, OH. The difference in simulated yield before and after soil moisture calibration highlights the importance of considering both hydrological parameters and crop growth parameters in the yield calibration process.

Based on this work, we can conclude the following:

1. Annual yield is inversely correlated with drought stress intensity in the early and middle reproductive stage in most sites (Woodbury, Mason and Madison), indicating that early and middle reproductive periods are more critical than other stages. Reproductive organs are formed in the late vegetative stage, while pollination and fertilization happen in the reproductive period, making the crop more susceptible in those stages.

2. There is no significant relationship between crop yield and aeration stress at any of the four sites. This might be due to the different impact of aeration stress with respect to spatial scales, as well as the low frequency of events in the historical record. The impact of aeration stress on crop yield reduction may be more easily found at plot scale, and may be mitigated by delayed planting or replacement of hybrid.

3. Observed yield reductions vary between about 20% for 2 year return periods to 50-80% for 100 year return periods. The relative yield reduction of observed data is caused by the interaction of nutrient deficiency, moisture and temperature conditions, diseases, pest and weed problems, which should be higher than any individual stress. Analysis of long term simulated yield reduction indicates that drought stress is the dominant factor affecting yield in the historical period when compared with aeration stress both at short and long return periods (high/low probability of exceedance). For a 70 year return period, total yield reduction due to drought stress is 8.1%, 17.5%, 15.2% and 9.7%, respectively, for Boone, Woodbury, Madison and Mason.

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Fig. 1 Aeration stress algorithm modifications

Fig. 2 Geographic location of the four NRCS-SCAN plots across the Midwest USA

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Fig. 3 Crop yield calibration strategy

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Fig. 4 Typical arable soil types and their weight factors in the four study counties

Fig.5 Management timing for the four study counties. The gray shaded zone reflects the date range for each management practice recorded by NASS State Crop Progress Data, with top and bottom defined by the begin and end dates. Blue squares indicate the 50% date of NASS data. Black circles indicate the default management date from SWAT. Red circles indicate the calibrated date. 1a) to 1d) reflect the corn planting date for four counties; 2a) to 2d) reflect maturity date; 3a) to 3d) reflect harvest date.

Fig. 6 Suggested calibration range for aeration/drought stress scaling function

Fig.7 Calibrated vs. observed volumetric soil moisture content (average daily value for 6 years) in Boone, IA. (a) 0-20cm, (b) 46-58cm, (c) 94-119 cm

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Fig. 8 Observed potential yield calculation

Fig. 9 Model performance in yield a) calibration and b) validation for: 1) Boone, IA, 2) Woodbury, IA, 3) Mason, IL 4) Madison, OH. Solid line indicates the simulated yield after following the crop yield calibration strategy (Fig. 3). Dash line indicates simulated corn yields, if moisture calibration was skipped (hydrologic parameter adjustment in Fig. 3).

Fig. 10 Model performance in daily biomass accumulation in 2005 at Boone, IA.

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833 **Fig.11 Relationship of corn yields with drought stress intensity in silking-blister period at a)Boone,**
834 **IA; b) Woodbury, IA; c) Madison, OH; d) Mason, IL.**

Fig.12 Relationship of corn yields with aeration stress intensity in reproductive period at a) Boone, IA; b) Woodbury, IA; c) Madison, OH; d) Mason, IL.

Fig.13. Relative crop yield reduction due to drought stress or aeration stress. Relative yield reduction is calculated by eq. (9), which is shown on the y-axis. Recurrence probability which is represented as “return period” associated with the amount of yield reduction is shown in the x-axis. Red and blue dots represent the relative yield reduction caused by drought and aeration stress. Black triangles are relative yield reduction of observed data.

Table 1 Data used in this study

Data	Source	Unit	Description	Data Process
Soil moisture content	NRCS-SCAN	Percentage	Layer specific daily data (5, 10, 20, 50, 100 cm)	Bias-correction to avoid observed data over porosity
Site specific soil physical properties	NRCS-SCAN, pedon report.	g/cm ³ , percentage	Number of layers, bulk density, field capacity, permanent wilting point, porosity	NA
County level crop yield	NASS quick stats 2.0	Bu/acre	Annual corn yield	Best-fit least square regression method to remove trend
State level crop progress	NASS quick stats 2.0	weeks	Weekly update of farmer activities and crop phenological stages, like emergence, silking, dough, dented, and physiologic maturation at state level	NA
Weather	NRCS-SCAN, NOAA	mm, °C	Daily precipitation and temperature	NOAA stations within 30km used to generate precipitation when SCAN has missing data using inverse distance weighting method

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Table 2 Soil water content parameterization

Parameters	Physical Meaning	Boone, IA	Woodbury, IA	Madison, OH	Mason, IL
Por_i	Porosity of soil layer i**	0.365-0.529	0.453-0.478	0.284-0.479	0.310-0.374
FC_i	Field capacity of soil layer i**	0.290-0.470	0.320-0.350	0.220-0.380	0.090-0.310
PWP_i	Permanent wilting point of soil layer i**	0.130-0.270	0.150-0.210	0.100-0.200	0.040-0.170
DEPIMP_BSN (mm)	Depth to impervious layer for modeling perched water table	1200	NA	NA	NA
sol_zmx (m)	Maximum rooting depth	0.46	2	2	2

856 **i indicates different soil layers. For Boone, IA, i=1, 2...6; For Woodbury, IA, i=1, 2...5; For
857 Madison, OH, i=1, 2...7; For Mason, IL, i=1, 2...6.

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Table 3 Hydrologic parameter calibration

Parameters	Physical Meaning	Boone, IA	Woodbury, IA	Madison, OH	Mason, IL
ESCO:	Soil evaporation compensation coefficient	0.979	0.97	0.5	0.966
EPCO	Plant transpiration compensation coefficient	0.02	0.2	0.6	0.99
CN2	Runoff curve number	59	59	81	58
Ksat_i(mm/hr)	Saturated hydraulic conductivity of soil layer i**	0.09-0.19	0.10-0.19	0.01-0.20	0.11-4.64
GW_REVAP	Groundwater re-evaporation coefficient	0.02	0.2	0.02	0.02
β_w	Water use distribution parameter	10	10	9	10

860 **i indicates different soil layers. For Boone, IA, i=1, 2...6; For Woodbury, IA, i=1, 2...5; For
861 Madison, OH, i=1, 2...7; For Mason, IL, i=1, 2...6.

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Table 4 Parameters adjusted for management time and potential growth curve

Original Values					Adjusted Values			
	fr _{PHU0}	PHU _{mat}	fr _{PHUhar}	DLAI	fr _{PHU0}	PHU _{mat}	fr _{PHUhar}	DLAI
Iowa	0.15	1451	1.2	0.7	0.11	1652	1.1	0.75
Ohio	0.15	1512	1.2	0.7	0.15	1712	1.1	0.75
Illinois	0.15	1536	1.2	0.7	0.15	1700	1.15	0.75

Table 5 Parameters used for yield calibration for the four sites

	HI _{opt}	RUE	HI _{min}	b1	b1-b2	c1	c1-c2
Boone, IA	0.504	36.18	0.262	0.485	-9.098	0.8858	-3.6977
Woodbury, IA	0.493	33.07	0.3276	3.916	-3.326	-1.879	-4.201
Mason, IL	0.473	34.91	0.171	3.093	-3.402	-0.024	-8.925
Madision , OH	0.508	33.94	0.306	-1.365	-7.416	-2.188	-8.626

Table 6 Growing degree day requirements for different phenological stages of 2700 GDD corn

Phase	Stage			GDD (F)
Vegetative	Planting	V2	V4	0-345
	V6	V8	V10	345-740
	V12	V14	V16	740-1135
Reproductive	Silking	Blister		1135-1660
	Dough	Denting		1660-2190
	Dented	Physiological maturity		2190-2700

Table 7 Model performance in predicting soil moisture content at the four SCAN sites

	Mass Balance Error (%)	d statistic	N-RMSE (%)
Boone, IA	2002-2008	2002-2008	2002-2008
Layer1	-0.53	0.92	12.11
Layer3	1.24	0.27	1.40
Layer6	2.11	0.47	2.82
Woodbury, IA	2004-2009	2004-2009	2004-2009
Layer1	-4.74	0.82	21.49
Layer2	-2.25	0.87	14.16
Layer3	-0.29	0.79	14.60
Layer5	3.43	0.89	7.64
Madison, OH	1998-2003	1998-2003	1998-2003
Layer1	-8.83	0.84	19.94
Layer3	-3.85	0.82	10.40
Layer6	0.25	0.88	6.42
Mason, IL	1998-2002	1998-2002	1998-2002
Layer1	-14.42	0.77	24.52
Layer2	-4.77	0.64	14.33
Layer5	0.93	0.50	7.85

Table 8 Model performance in predicting corn yield in the four SCAN counties

	Calibration Period			Validation Period		
	N-RMSE(%)	MBE(%)	d	N-RMSE(%)	MBE(%)	d
Boone, IA	11.99	-3.81	0.09	12.07	-1.21	0.66
Woodbury, IA	8.74	-5.82	0.92	7.64	-2.04	0.84
Madison, OH	12.40	7.14	0.77	9.86	-4.41	0.76
Mason, IL	6.26	-1.61	0.78	13.94	-4.80	0.75

Table 9 Correlation coefficient (Pearson's r) between corn yield and drought stress intensity for different growth stages

	Boone, IA	Woodbury, IA	Mason, IL	Madison, OH
Planting , V4	0.25	0.33	-0.06	-0.11
V6, V8, V10	0.32	-0.29	-0.03	-0.28
V12, V14, V16	0.15	-0.28	-0.26	-0.48**
Silking, Blister	0.11	-0.38**	-0.54**	-0.41**
Dough, Denting	-0.03	-0.28	-0.19	-0.43**
Dented, Maturity	0.18	-0.02	0.01	-0.19
Vegetative stage	0.19	0.07	0.06	-0.32
Reproductive stage	0.22	-0.37**	-0.22	-0.55**
Whole growing period	0.20	-0.23	-0.15	-0.35

**** means significant correlation with $p < 0.05$**

895 **Table 10 Correlation coefficient (Pearson's r) between corn yield and aeration stress**
896 **intensity for different growth stages**

	Boone, IA	Woodbury, IA	Mason, IL	Madison, OH
Planting , V4	0.04	0.13	-0.29	0.19
V6, V8, V10	0.22	0.21	0.38	0.30
V12, V14, V16	0.08	0.17	0.39	-0.25
Silking, Blister	0.15	-0.06	-0.09	0.03
Dough, Denting	0.23	-0.03	-0.35	0.31
Dented, Maturity	-0.71**	0.18	0.02	-0.07
Vegetative stage	0.23	0.38	0.27	0.26
Reproductive stage	-0.72**	0.02	-0.22	0.21
Whole growing period	-0.72**	0.27	-0.02	0.34

897 **** means significant correlation with $p < 0.05$**

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