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# Maize and soybean root front velocity and maximum depth in Iowa, USA

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ABSTRACT

Quantitative measurements of root traits can improve our understanding of how crops respond to soil and weather conditions, but such data are rare. Our objective was to quantify maximum root depth and root front velocity (RFV) for maize (*Zea mays*) and soybean (*Glycine max*) crops across a range of growing conditions in the Midwest USA. Two sets of root measurements were taken every 10–15 days: in the crop row (in-row) and between two crop rows (center-row) across six Iowa sites having different management practices such as planting dates and drainage systems, totaling 20 replicated experimental treatments. Temporal root data were best described by linear segmental functions. Maize RFV was 0.62 ± 0.2 cm $d^{-1}$ until the 5th leaf stage when it increased to 3.12 ± 0.03 cm $d^{-1}$ until maximum depth occurred at the 18th leaf stage (860 °Cd after planting). Similar to maize, soybean RFV was 1.19 ± 0.4 cm $d^{-1}$ until the 3rd node when it increased to 3.31 ± 0.5 cm $d^{-1}$ until maximum root depth occurred at the 13th node (813.6 °C d after planting). The maximum root depth was similar between crops ($P > 0.05$) and ranged from 120 to 157 cm across 18 experimental treatments, and 89–90 cm in two experimental treatments. Root depth did not exceed the average water table (two weeks prior to start grain filling) and there was a significant relationship between maximum root depth and water table depth ($R^2 = 0.61$; $P = 0.001$). Current models of root dynamics rely on temperature as the main control on root growth; our results provide strong support for this relationship ($R^2 > 0.76$; $P < 0.001$), but suggest that water table depth should also be considered, particularly in conditions such as the Midwest USA where excess water routinely limits crop production. These results can assist crop model calibration and improvements as well as agronomic assessments and plant breeding efforts in this region.

## 1. Introduction

Root systems affect plant growth, crop yields, and soil health, but studies on root characteristics are sparse. For example, plant breeding programs have focused on the selection of above ground plant traits for yield improvement (Tollenaar et al., 2004; Tollenaar and Lee, 2006) while giving little attention to the below-ground root morphology (Lynch, 2007). Among many root traits, root front velocity (RFV) and maximum depth are important because they determine the amount of water and nitrogen available for plant growth, as well as the amount of water and nitrogen vulnerable to leaching (Dunbabin et al., 2003). Indeed, deep, rapid-growth root systems may reduce losses of highly soluble nutrients such as nitrate (Lynch, 2013) because RFV closely matches the rate of nitrate leaching (York and Lynch, 2015).

Three-way interactions among crop genotype, management and environment determine maximum depth, RFV, and the ability of roots to extract water and nutrients. Relevant environmental factors include weather conditions (Watt et al., 2006), soil temperature and moisture (Weaver, 1926; Wang and Smith, 2004), ground water table (Stanley et al., 1980; Logsdon et al., 2009), soil-type and texture (Dwyer et al., 1996, Ball-Coelho et al., 1998), and nutrient availability (Lynch, 2007; Comas et al., 2013; Soylu et al., 2014). Management factors include the amount, type, placement and timing of fertilizer inputs (Dietzel et al., 2015; Lazicki et al., 2016), irrigation (Wang et al., 2014), tillage (Kaspar et al., 1991; Dweyer et al., 1996), row configuration (Whish et al., 2015) and others. Genotype factors include species identity (Borg and Grimes 1986) as well as variability between cultivars (Kaspar et al., 1984; Borg and Grimes, 1986; Yu et al., 2014). The mechanisms by

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which the above-mentioned factors affect root growth and final depth are complex, but soil conditions play a major role (Rich and Watt, 2013; Bao et al., 2014). For example, a compacted soil layer will reduce root growth, no matter if temperature or moisture are at optimum levels for root growth (Keating et al., 2003).

In a review study of 48 crops species, Borg and Grimes (1986) reported maximum root depths of 180–300 cm for maize, 150–200 cm for soybean, 150–300 cm for sorghum, 150–240 cm for rye, and 150–300 cm for wheat. The wide range reflects variable interactions among genotype, management and environment. The RFV exhibits similar variability: sorghum 2–4 cm $d^{-1}$ (Monteith, 1986; Robertson et al., 1993; Whish et al., 2005; Manschadi et al., 2008), maize 2.7–6 cm $d^{-1}$ (Taylor and Klepper, 1973; Dardanelli et al., 1997; Singh et al., 2010), soybean 3.5–4.5 cm $d^{-1}$ (Stone et al., 1976; Kaspar et al., 1984), 2–7 cm $d^{-1}$ for wheat and barley (Cohen and Tadmor, 1969) and chickpea 2.5–3.6 cm $d^{-1}$ (Kashiwagi et al., 2015). This variability indicates that use of generic values (i.e., averages) for root parameters across environments may result in misleading agronomic assessments of plant and cropping system performance.

In the Midwest USA, recent work has shown major changes in above ground plant growth between new and old era cultivars (Duvick and Cassman, 1999; Ciampitti and Vyn, 2012). Our literature review for Iowa, USA revealed that information on root parameters has not been updated since the mid 1980s when management practices and plant traits were different than those used presently (Mason et al., 1982; Kaspar et al., 1984; Borg and Grimes, 1986). Iowa is a high production region in the USA (75% of the landscape is occupied with maize and soybean, which contribute 12–15% to national grain production; USDA-NASS, 2015) and is also a region with water quality challenges. Shallow water tables exist in this region (Zhang and Schilling, 2006; Schilling, 2007; Logsdon et al., 2009) and subsurface drainage systems have been installed in many Iowa fields to increase crop yields by removing excess water (Helmers et al., 2012). Improved knowledge about maize and soybean RFV and maximum depth could greatly assist agronomists and crop modelers in analyzing and designing sustainable cropping systems. In this study, we analyzed maize and soybean RFV and maximum root depth data from 20 field experiments covering six sites in Iowa. We asked the following questions:

1) What is the RFV and maximum depth of maize and soybeans crops?
2) How much time does it take roots to occupy the space between rows and reach their maximum depth?
3) To what degree can we predict root depth over time and what is the best predictor among soil, crop and weather variables?
4) Does the water table level affect maximum root depth?

We hypothesized that RFV would be different between maize and soybean crops given their different structures; maize has a fibrous root system, whereas soybean has taproot system (Feldman, 1994; Lersten and Carlson, 2004). We also hypothesized that air temperature could be a good predictor of root growth given its use in simulation models (Keating et al., 2003; Yang et al., 2017). Finally, we also hypothesized that shallow water tables inhibit root growth because the lack of oxygen reduces roots' ability to take up water and nutrients (Dickin and Wright, 2008; Florio et al., 2014).

## 2. Materials and methods

### 2.1. Experimental sites

In 2016, field experiments with maize and soybean were established at six Iowa sites spanning a broad range of temperature, precipitation and soil type (Figs. 1 and 2). Basic soil information for the sites is provided in Fig. 1. Three sites, Central-Ames, Northwest, and Southeast had different planting dates as a sub-factor; one site, Southeast, had different drainage systems as a sub-factor (with and without subsurface drainage), and two sites, Central-Kelley and Northeast, had no sub-factors (Table 1). The combination of sites, crops, and management practices resulted in 20 experimental units (Table 1). Experimental plots were set in a maize after soybean rotation using local management practices and well adapted cultivars. Maize plots were fertilized before or at planting (about 168 kg N/ha) while soybean plots did not receive nitrogen fertilizer. Crops were growing without supplemental irrigation. Each treatment was replicated three times at each site except Southeast, which had two replications. The size of replicated plots varied among sites; range from 360 to 3600 $m^2$, with the largest plots being in Northeast experimental site. Weeds, pest and diseases were suppressed by spraying herbicides, insecticides and fungicides when necessary.

### 2.2. Root measurements

The distance between crop rows was 76 cm (the conventional spacing in Midwest maize and soybean plantings) in all treatments and sites except Northeast soybean, for which row spacing was 25.4 cm (Exp. 14; Table 1). Root depth measurements were taken in the crop row (in-row) and in the center of two rows (center-row) approximately every 10–15 days from planting until maximum root depth was observed. In Southwest, Central-Kelley and Central-Ames measurements were made weekly while in Southeast, Northwest and Northeast every other week. On each sampling date, four sub-replicate measurements in each replicate were manually sampled using conventional 1.8 × 41 cm steel soil probes. Extensions were attached to the probe to capture roots to 180 cm depth (Fig. S1, panel a). Root depth was recorded in the field as the maximum visible root tip depth (Fig. S1, panel b).

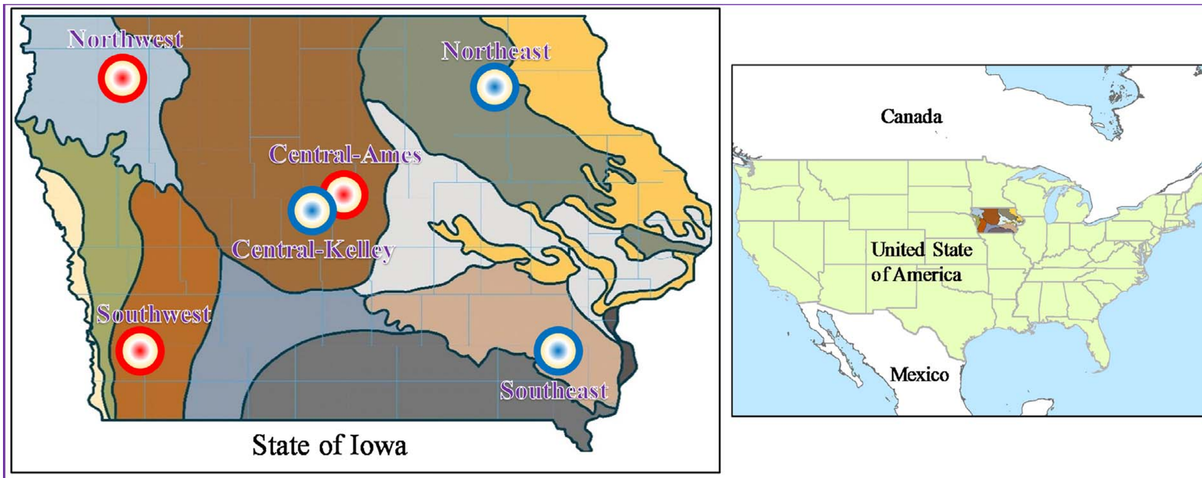
When the maximum root depth was achieved per treatment a 6.20 × 120 cm hydraulic soil core probe with extensions to sample to 200 cm depth (Giddings Machine Company, Windsor CO, USA; Fig. S1, panel c) was used to validate manual samples in 16 out of the 20 treatments. In the lab, root depth for each core was recorded as the maximum visible root tip depth. Sampling areas were selected to avoid weed contamination and plot edges.

### 2.3. Weather, crop, and soil measurements

Maximum temperature, global solar radiation, and precipitation were recorded from network stations positioned at the border of each of the six experimental sites (Iowa Environmental Mesonet, IEM). Long-term (35-year) historical weather data were also available for each site.

All the experimental sites (except Northeast) were instrumented with Decagon (Pullman, WA, USA) soil moisture, temperature, and groundwater table sensors recording data every 30 min. Moisture and temperature sensors were positioned at two depth (15 and 45 cm) in each replication. Wells with groundwater table sensors were positioned at the borders of the experiments and were not replicated per treatment. Soil nitrogen measurements were taken from all replicated plots every two weeks (0–30 cm) and monthly (30–60 cm). In each replication, 10 sub-samples were taken from in-row and center-row positions and homogenized. Field-moist soil samples were analyzed for $NO_3$-N and $NH_4$-N concentrations (Hood-Nowotny et al., 2010).

Destructive above-ground crop sampling per replication was conducted approximately every two weeks. The sampling area for maize was 1.5 $m^2$ and for soybean 1 $m^2$. Plants were counted and cut at the ground level and analyzed to derive the following parameters: growth stage, leaf area index, maize leaf number, soybean node and pod number, biomass accumulation per plant tissue (leaf, stem, and storage organ including husk, cobs and kernels for maize, and pod and grains for soybeans), as well as carbon and nitrogen concentrations per plant tissue. Crop and soil sampling took place on the same day as root sampling. Therefore, crop and soil data were used to explore correlations between root depth and crop, soil, and weather variables (see below).




| Site | Geographic coordinates | Texture | Drainage | SOM (g/100g) 0-30 cm | PAW (mm) 0-150 cm | Precipitation (May-Aug) (mm) |
|---|---|---|---|---|---|---|
| Northwest | 42°55'35.0"N 95°32'23.2"W | Silt clay loam | None | 3.7 | 307.0 | 348.3 |
| Northeast | 42°55'53.0"N 92°34'19.7"W | Loam | Subsurface | 3.1 | 267.0 | 656.4 |
| Central-Ames | 42°01'14.9"N 93°46'31.2"W | Loam | None | 3.9 | 285.0 | 451.0 |
| Central-Kelley | 41°55'16.0"N 93°45'02.2"W | Loam | Subsurface | 4.3 | 285.0 | 473.2 |
| Southwest | 41°18'46.5"N 95°10'21.8"W | Silt clay loam | None | 5.4 | 305.0 | 530.8 |
| Southeast | 41°11'38.3"N 91°28'56.0"W | Silt clay loam | Subsurface | 4.4 | 287.0 | 459.6 |

**Fig. 1.** Geographic distribution of the experimental sites across the state of Iowa. Blue symbols represent fields with subsurface drainage and red symbols represent fields without subsurface drainage. Background colors indicate different soil categories. Inset table shows coordinates, soil texture, soil organic carbon (SOM in g/100 g in the top 30 cm), drainage system, plant available water (PAW, in mm) across 150 cm soil profile, and the 2016 May to end of August precipitation. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

**Table 1**
Site location, treatment, planting date, cultivar maturity and planting to flowering average temperature and precipitation sum in each corn and soybean treatment. MG: maturity group; CV: coefficient of variation.

| Location | Exp. ID | Symbol (Figs. 4 and 6) | Treatment | Planting Date | Cultivar Maturity | Planting to flowering Avg. Temperature (°C) | Planting to flowering Precipitation sum (mm) |
|---|---|---|---|---|---|---|---|
| Corn experiments | | | | | | | |
| Central-Ames | 1 | (▲) | Early Planting | 26-Apr | 111-day | 19.6 | 224.5 |
| Central-Ames | 2 | (▲) | Late Planting | 16-May | 111-day | 22.0 | 237.6 |
| Central-Kelley | 3 | (★) | – | 18-May | 111-day | 22.5 | 239.5 |
| Northeast | 4 | (✳) | – | 23-Apr | 105-day | 18.5 | 483.6 |
| Northwest | 5 | (●) | Early Planting | 7-May | 105-day | 19.9 | 259.4 |
| Northwest | 6 | (●) | Late Planting | 1-Jun | 105-day | 22.4 | 174.6 |
| Southwest | 7 | (◆) | Early Planting | 26-Apr | 111-day | 19.4 | 390.6 |
| Southwest | 8 | (◆) | Late Planting | 15-May | 111-day | 21.8 | 321.7 |
| Southeast | 9 | (■) | Subsurface Drainage | 13-May | 111-day | 21.9 | 192.6 |
| Southeast | 10 | (■) | No subsurface drainage | 13-May | 111-day | 21.9 | 192.6 |
| | | | | | ***Average*** | ***21.0*** | ***271.7*** |
| | | | | | ***CV%*** | ***6.9*** | ***36.4*** |
| Soybean experiments | | | | | | | |
| Central-Ames | 11 | (△) | Early Planting | 6-May | 2.7 MG | 20.6 | 118.6 |
| Central-Ames | 12 | (△) | Late Planting | 3-Jun | 2.7 MG | 23.5 | 184.3 |
| Central-Kelley | 13 | (★) | – | 18-May | 2.7 MG | 22.4 | 100.5 |
| Northeast | 14 | (✳) | – | 26-Apr | 1.9 MG | 17.4 | 375.9 |
| Northwest | 15 | (○) | Early Planting | 7-May | 2.2 MG | 19.5 | 166.4 |
| Northwest | 16 | (○) | Late Planting | 1-Jun | 2.2 MG | 22.3 | 109.8 |
| Southwest | 17 | (◇) | Early Planting | 5-May | 3.1 MG | 20.3 | 231.7 |
| Southwest | 18 | (◇) | Late Planting | 20-May | 3.1 MG | 22.5 | 194.8 |
| Southeast | 19 | (□) | Subsurface Drainage | 22-May | 3.1 MG | 23.3 | 90.2 |
| Southeast | 20 | (□) | No subsurface drainage | 22-May | 3.1 MG | 23.3 | 90.2 |
| | | | | | ***Average*** | ***21.6*** | ***171.5*** |
| | | | | | ***CV%*** | ***9.7*** | ***53.8*** |

### 2.4. Data analysis

To detect differences between crops, management and site treatments (n = 20; Table 1) a randomized complete block analysis of variance (ANOVA) was performed. For the four sites that had different management practices (Table 1) a split-plot ANOVA was performed to detect differences between crops and management factors. Crops and management factors were the fixed effects and the site was the random effect. Within each crop, we performed a second statistical analysis and calculated the Tukey's test to determine statistical significant difference among mean values for all studied root attributes. The statistical analysis was implemented using *SAS 9.4* statistical package (SAS institute Inc., Cary, NC, US).

Linear and non-linear regression models were explored to fit root depth data over time and identify correlations between root depth and soil, crop, and weather variables (Archontoulis and Miguez, 2015). Linear, bi-linear and tri-linear segmental functions were selected to describe the progress of root elongation over time based on three criteria: determination coefficient ($R^2$), meaning of parameters, and ability to provide answers to specific objectives. The following bi-and tri-linear equations were used to calculate root parameters:

$$y = a + bx(x \le c) + bc\ (x > c) + d(x - c)(x > c) \quad (1)$$

$$y = a + bx(x \le c) + bc(x > c) + d(x - c)(x > c) + de(x - d)(x > e) + f(x \le e) \quad (2)$$

where $y$ is the root depth in cm, $x$ is the time in days, $b$ is the initial RFV in cm $d^{-1}$, $d$ is the second phase RFV in cm $d^{-1}$, and $c$ is the breakpoint between $b$ and $d$; $e$ the break point between $d$ and $f$, and finally $f$ is a plateau indicating the time when root elongation ceased. In a few cases, where the root elongation did not show a plateau (Exps. 5, 6, 15, 16; Table 2; due to limited measurements), linear regression was used:

$$y = a + bx(x \le c) \quad (3)$$

To identify variables that can predict root elongation we fitted non-linear models between root elongation and explanatory variables and then a combination of statistical indexes ($R^2$; Archontoulis and Miguez, 2015) to identify best predictors. The explanatory variables used in this analysis were: plant height, leaf number in maize, node number in soybean, leaf area index, plant biomass, thermal time (see below), cumulative rainfall and radiation since planting. Data analysis, model fitting and parameter estimation was done in GraphPad Prism 7.02 (GraphPad Software, Inc. San Diego, CA, USA). Thermal time was calculated as:

$$GDD = 0.5^* (Tmax + Tmin) - Tb \quad (4)$$

where GDD is the cumulative growing degree days since planting (°C d), Tmax and Tmin is the maximum and minimum daily air temperature (°C), and Tb is the base temperature. A base temperature of 8 °C was used for both crops (Ritchie and NeSmith, 1991; Wu et al., 2015).

## 3. Results

### 3.1. Weather and soil conditions

Compared to 35-year average weather conditions, the six experimental sites experienced a wide range of weather in 2016 (Fig. 1). Four sites had below average precipitation from June to mid-July, a period of rapid root growth (Fig. 2a). All sites were warmer than average until mid-July and cooler until the end of August, except for Northeast (Fig. 2b). Plant available soil moisture in the top 60 cm ranged from 120 to 240 mm across sites and temporal dynamics followed precipitation patterns (Fig. 2d). Soil temperature rapidly increased from May 1 (~10 °C) to middle of June (~23 °C) and fluctuated at that level until the end of August (Fig. 2e). Soil nitrate followed the same temporal patterns across sites, with high soil nitrate levels around the end of May and low nitrate levels in August (Fig. 2f).

**Table 2**

Main root system attributes in-row and center-row measurements (means ± standard error) for all field experiments. RFV: root front velocity phase I and phase II (cm $d^{-1}$), transition from phase I to phase II (days), maximum depth (cm), root ceased (days) and coefficient of determination $R^2$. CV: coefficient of variation.

| Location | Exp. ID | In-row measurements | | | | | | Center of two row measurements | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | RVF Phase I (cm $d^{-1}$) | RFV Phase II (cm $d^{-1}$) | Transition Phase I to II (days) | Max Depth (cm) | Root ceased (days) | $R^2$ | RFV Phase II (cm $d^{-1}$) | Max Depth (cm) | Root ceased (days) | $R^2$ |
| Corn Experiments | | | | | | | | | | | |
| Central-Ames | 1 | 0.61 ± 0.1 | 3.13 ± 0.1 | 39.9 ± 1.5 | 154 ± 4 | 79.6 ± 0.9 | 0.99 | 3.56 ± 0.2 | 146 ± 1 | 78.7 ± 1.4 | 0.95 |
| Central-Ames | 2 | 0.95 ± 0.6 | 2.98 ± 0.2 | 26.0 ± 3.1 | 142 ± 1 | 65.4 ± 1.6 | 0.97 | 3.58 ± 0.3 | 130 ± 1 | 61.2 ± 1.9 | 0.93 |
| Central-Kelley | 3 | 0.80 ± 0.3 | 3.47 ± 0.2 | 26.4 ± 2.1 | 148 ± 2 | 57.6 ± 1.3 | 0.97 | 3.47 ± 0.2 | 136 ± 2 | 62.1 ± 1.8 | 0.93 |
| Northeast | 4 | 0.32 ± 0.1 | 2.45 ± 0.1 | 47.8 ± 3.9 | 145 ± 2 | 87.5 ± 3.9 | 0.94 | 3.80 ± 0.5 | 141 ± 1 | 49.5 ± 2.7 | 0.88 |
| Northwest | 5 | 1.48 ± 0.2 | | – | 133 ± 2 | 65.3 ± 2.2 | 0.81 | 2.05 ± 0.2 | 145 ± 1 | – | 0.91 |
| Northwest | 6 | 1.47 ± 0.1 | | – | 89 ± 1 | 54.0 ± 0.0 | 0.95 | 1.46 ± 0.1 | 100 ± 1 | – | 0.99 |
| Southwest | 7 | 0.77 ± 0.1 | 3.37 ± 0.3 | 42.6 ± 2.6 | 157 ± 2 | 77.5 ± 1.5 | 0.97 | 3.87 ± 0.2 | 155 ± 5 | 79.6 ± 1.2 | 0.98 |
| Southwest | 8 | 0.47 ± 0.3 | 3.08 ± 0.4 | 33.5 ± 5.0 | 144 ± 1 | 71.8 ± 2.8 | 0.85 | 2.73 ± 0.2 | 148 ± 9 | 83.5 ± 2.4 | 0.94 |
| Southeast | 9 | 0.58 ± 0.2 | 3.44 ± 0.1 | 30.5 ± 4.1 | 142 ± 9 | 65.5 ± 4.4 | 0.95 | 3.94 ± 1.3 | 132 ± 8 | 63.8 ± 2.3 | 0.97 |
| Southeast | 10 | 0.47 ± 0.0 | 3.00 ± 0.3 | 27.1 ± 3.1 | 140 ± 5 | 67.0 ± 5.0 | 0.97 | 2.78 ± 0.3 | 129 ± 1 | 70.3 ± 2.8 | 0.91 |
| ***Average*** | | ***0.62 ± 0.2*** | ***3.12 ± 0.3*** | ***34.2 ± 8.3*** | ***139 ± 2*** | ***70.8 ± 9.2*** | | ***3.12 ± 0.8*** | ***137 ± 2*** | ***68.6 ± 11*** | |
| ***CV%*** | | ***33.6*** | ***10.7*** | ***24.2*** | ***13.6*** | ***13.0*** | | ***27.0*** | ***11.3*** | ***16.8*** | |
| ***P-value*** | | ***0.02*** | ***< 0.001*** | ***< 0.001*** | ***< 0.001*** | ***< 0.001*** | | ***< 0.001*** | ***< 0.001*** | ***< 0.001*** | |
| ***Tukey's test*** | | ***0.54*** | ***0.32*** | ***3.27*** | ***16.96*** | ***4.76*** | | ***1.02*** | ***9.25*** | ***1.69*** | |
| Soybean Experiments | | | | | | | | | | | |
| Central-Ames | 11 | 1.35 ± 0.1 | 3.88 ± 0.4 | 46.8 ± 2.1 | 146 ± 1 | 69.1 ± 1.2 | 0.98 | 4.58 ± 0.3 | 144 ± 2 | 71.0 ± 1.1 | 0.98 |
| Central-Ames | 12 | 1.50 ± 0.1 | 2.67 ± 0.0 | 9.7 ± 2.6 | 140 ± 7 | 56.9 ± 2.3 | 0.96 | 2.70 ± 0.1 | 137 ± 7 | 73.0 ± 0.0 | 0.92 |
| Central-Kelley | 13 | 1.25 ± 0.2 | 3.11 ± 0.2 | 28.9 ± 3.7 | 140 ± 2 | 60.1 ± 1.7 | 0.94 | 2.93 ± 0.2 | 143 ± 2 | 71.2 ± 2.2 | 0.92 |
| Northeast | 14 | 0.42 ± 0.2 | 3.90 ± 0.1 | 47.2 ± 2.1 | 154 ± 4 | 77.9 ± 1.1 | 0.92 | 2.38 ± 0.3 | 156 ± 7 | 86.0 ± 0.0 | 0.82 |
| Northwest | 15 | 1.20 ± 0.1 | | – | 120 ± 1 | 84.0 ± 0.0 | 0.96 | 1.79 ± 0.0 | 136 ± 2 | – | 0.91 |
| Northwest | 16 | 1.42 ± 0.1 | | – | 88 ± 1 | 54.0 ± 0.0 | 0.98 | 2.90 ± 0.4 | 81 ± 14 | – | 0.67 |
| Southwest | 17 | 1.66 ± 0.5 | 2.89 ± 0.3 | 30.2 ± 5.1 | 156 ± 6 | 61.3 ± 2.2 | 0.93 | 3.50 ± 0.3 | 156 ± 6 | 63.5 ± 2.0 | 0.93 |
| Southwest | 18 | 1.02 ± 0.7 | 3.17 ± 0.2 | 20.1 ± 4.8 | 142 ± 1 | 57.3 ± 1.8 | 0.93 | 3.06 ± 0.4 | 141 ± 9 | 60.7 ± 3.0 | 0.86 |
| Southeast | 19 | 1.32 ± 0.3 | 3.89 ± 0.0 | 21.8 ± 3.5 | 134 ± 4 | 58.0 ± 3.1 | 0.97 | 3.45 ± 0.3 | 127 ± 8 | 70.8 ± 2.8 | 0.94 |
| Southeast | 20 | 1.00 ± 0.2 | 2.99 ± 0.3 | 34.0 ± 4.9 | 135 ± 8 | 56.7 ± 7.2 | 0.98 | 3.20 ± 0.2 | 126 ± 4 | 75.5 ± 2.3 | 0.96 |
| ***Average*** | | ***1.19 ± 0.4*** | ***3.31 ± 0.5*** | ***33.3 ± 10*** | ***136 ± 2*** | ***62.1 ± 7.5*** | | ***3.25 ± 0.7*** | ***135 ± 2*** | ***71.5 ± 7.7*** | |
| ***CV%*** | | ***32.1*** | ***15.12*** | ***30.6*** | ***14.3*** | ***16.4*** | | ***24.3*** | ***16*** | ***10.7*** | |
| ***P-value*** | | ***0.01*** | ***< 0.001*** | ***< 0.001*** | ***< 0.001*** | ***< 0.001*** | | ***< 0.001*** | ***< 0.001*** | ***< 0.001*** | |
| ***Tukey's test*** | | ***0.66*** | ***0.51*** | ***6.98*** | ***5.45*** | ***4.23*** | | ***0.37*** | ***3.69*** | ***11.16*** | |

*Root data from the Northwest site were excluded from average and CV calculations.

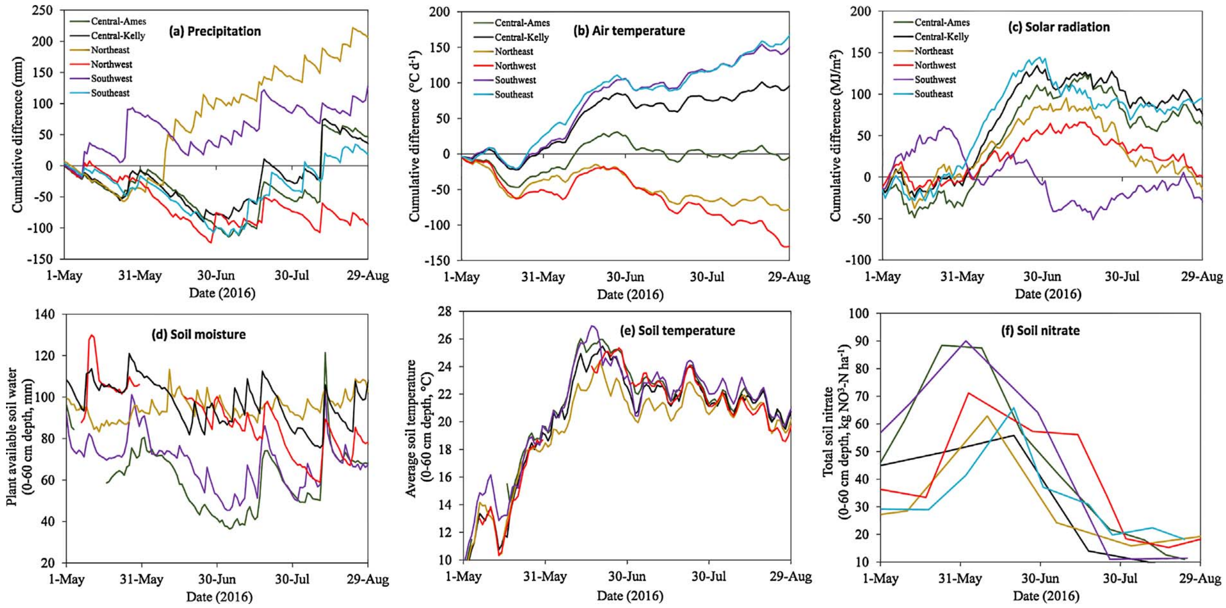


**Fig. 2.** Weather and soil conditions at the experimental sites: a) cumulative precipitation difference (2016 year minus 35 years average); b) cumulative temperature difference (2016 year minus 35 years average); c) cumulative radiation difference (2016 year minus 35 years average); d) average plant available soil water (0–60 cm depth); e) average soil temperature (0–60 cm depth); and f) total soil nitrate (0–60 cm depth). Note that maize plots were fertilized in May (about 168 kg N/ha) while soybean plots did not receive nitrogen fertilizer. Panel 2f illustrates the average soil nitrate from the two crops.

### *3.2. What is the rate of RFV and maximum depth?*

#### *3.2.1. Root front velocity*

In-row root elongation measurements showed a tri-linear pattern over time with an initial low rate (phase I) until 34 days after planting, followed by a fast rate (phase II) until 67 days after planting when the maximum depth was observed (Fig. 3; Table 2). The change in rate occurred at approximately 4.4 visible leaves for maize and 2.7 nodes for soybean. Root elongation rates for the center-row position followed a bi-linear increase, with a constant (fast) rate of increase followed by a plateau. Fig. 3 illustrates these temporal dynamics in two out of the 20 experimental units and Table 2 shows the parameters for all treatments.

During the initial phase, the in-row RFV ranged from 0.32 to 0.95 cm $d^{-1}$ for maize, and from 0.42 to 1.66 cm $d^{-1}$ for soybean across 16 treatments (Table 2, see values in cm °C $d^{-1}$ in Table S1). Treatment had a significant effect on the RFV during the initial phase ($P$ = 0.002) but not during the second phase ($P$ = 0.36). In the second phase RFV values ranged from 2.45 to 3.47 cm $d^{-1}$ for maize and from 2.67 to 3.90 cm $d^{-1}$ for soybeans (Table 2). On average, across all experiments, our results indicate that soybean roots grew 48% faster than maize during the first phase (Table 2). The center-row RFV ranged from 1.46 to 3.94 cm $d^{-1}$ for maize, and from 1.79 to 4.58 cm $d^{-1}$ for soybean, or from 0.13 to 0.24 °C $d^{-1}$ for maize and from 0.15 to 0.26 °C $d^{-1}$ for soybean across experiments (Table 2, and S1).

#### *3.2.2. Maximum root depth*

Across all treatments (n = 20), the maximum root depth ranged from 89 ± 11 to 157 ± 3 cm for maize and from 89 ± 12 to 156 ± 6 cm for soybean (Table 2). These variations were consistent in both sampling points, in-row and center-row. A statistical analysis considering all combinations of 20 treatments (site, crop and management) as independent treatments indicated significant differences

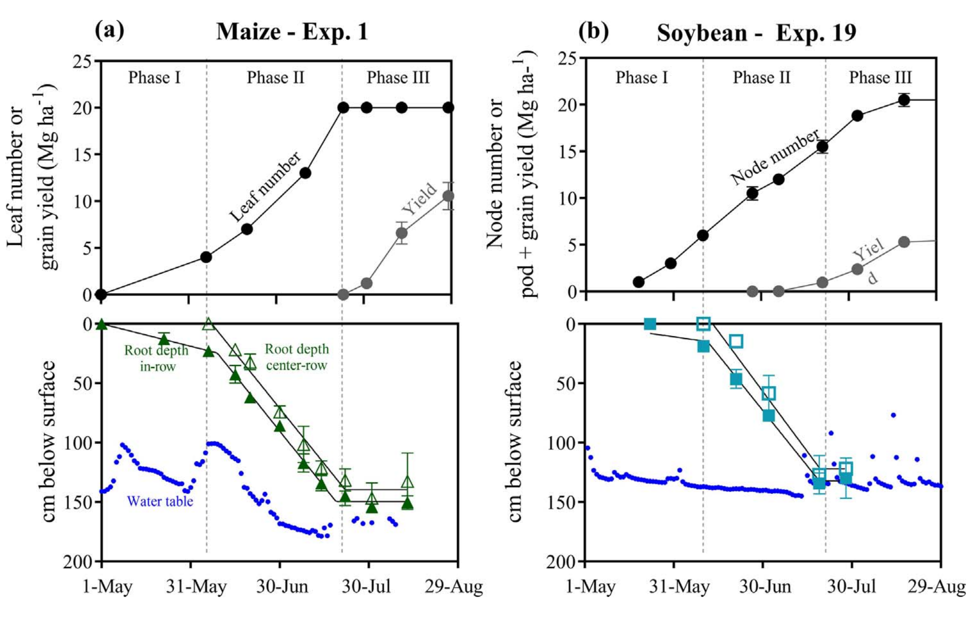



**Fig. 3.** Above- and below-ground plant characteristics and water table measurements in field experiment number 1 (maize) and 19 (soybean). Bottom panels: root depth measurements (triangles and squares), regression model fits to the root measurements (black lines) and water table dynamics (blue circles). Top panels: Leaf or node number (black symbols) and grain or fruit dry matter accumulation (grey symbols). Vertical broken lines illustrate the different phases observed in maize and soybean root growth. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

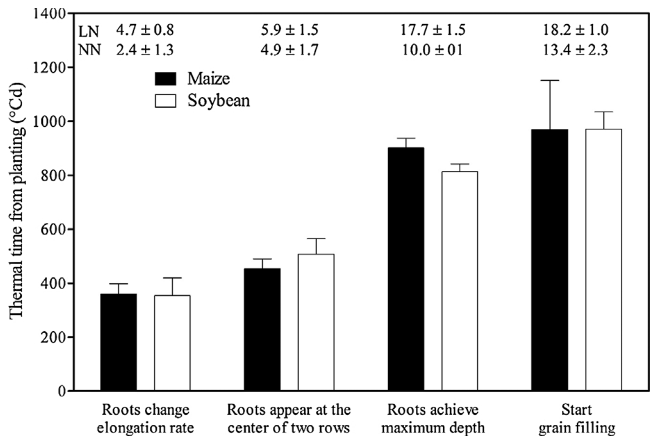



**Fig. 4.** Thermal time requirements for key root phenological events. Maize leaf number (LN) and soybean node number (NN) are shown. Data are average over 8 soybeans and 8 maize treatments (Northwest site treatments excluded). The error bars show the standard error of the mean values.

among them ($P$ = 0.001; Table S2). Within a site, statistical analysis indicated that there were significant differences in two of the three experiments in which different management treatments existed ($P$ = 0.05), but not between crops (Table S3). In the Northwest, Central-Ames and Southwest sites, where planting date was a factor in the analysis, we observed a 29%, 9% and 5% reduction in maximum root depth in both crops due to late planting (Table 2). At the Southeast site, where drainage systems were a factor in the analysis, we did not observe any substantial variation in root depth (Table 2; Fig. 3b). Interestingly, root depth did not exceed the depth of groundwater table (Fig. 3b).

### *3.3. How fast do roots occupy the center-row and when do they reach maximum depth?*

Roots reached the center-row at 42 ± 0.4 days after planting, equivalent to 480 ± 29 °C d (Fig. 4). The variation among crops and treatments was small (coefficient of variation 20.4%). In the only experiment where row-to-row spacing was 25.4 cm (Table 1; Exp. ID: 14) the time requirement to cover the space between two rows was 9 days. Maximum root depth was achieved about 70 days after planting for maize and 9 days earlier in soybean (Figs. 4 and S4; Table 2). In both crops root elongation ceased and maximum depth was observed about 10 days prior to start of grain filling (Fig. 4 and S4).

### *3.4. To what degree can we predict root depth and which is the best predictor among soil, crop and weather variables?*

Among six explanatory variables, thermal time was the best "easily measurable" estimator of root depth explaining 76–84% of the variation in both crops (Figs. 5 and S2, S3). Cumulative precipitation since planting was the worst estimator. Plant height explained 77–86% of the root depth variation, LAI explained 80–89% of the variation, leaf (maize) or node (soybean) number explained 84–90% of the variation, and above-ground biomass explained 84–90% of the variation. Following this exploratory analysis, root depth data were pooled by crop and measurement position (in-row versus center-row) to derive average predictive functions (Fig. 5). In this analysis, we fitted bi- and tri-linear models to derive biological meaningful parameters and the rates of increase per phase are provided in Fig. 5. Root elongation ceased at 886 °C d for maize and 816 °C d for soybean. The rate of root elongation in center-row measurements was lower and ceased later compared to the in-row measurements (Fig. 5).

### *3.5. Root depth and water table*

Depth to water table explained a large amount of variation in maximum root depth ($R^2$ = 0.61; $P$ = 0.0004: Fig. 6). The deeper the water table, the deeper maximum root depth. In this analysis, water table data was averaged for a period of two weeks prior to final root measurement date (beginning of grain filling period). That was necessary given the dynamic nature of water table in the soil. Across sites, the two-week average water table depth from the soil surface ranged from 79 to 214 cm (Fig. 6). The shallowest water table depth was observed in Southeast (plots without subsurface drainage) and the deepest was in Southwest site.

## 4. Discussion

Our destructive sampling approach to track roots captured interacting factors that the root system experiences under field conditions (Passioura, 2006; Paez-Garcia et al., 2015). By coupling root measurements with soil, crop and weather information, we were able to develop predictive functions (Fig. 5, S2 and S3) that could be used for root phenotyping in breeding programs where root growth has previously been largely ignored. Furthermore, results from this study that captured a range of environmental conditions using six sites and 20 treatments can inform crop model improvements, and assist agronomic and water quality assessments in the Midwest, USA.

### *4.1. Root front velocity*

Our frequent in-season root depth observations revealed two distinct phases in root elongation for corn and soybean (Fig. 5), which is in line with previous observations for sorghum (Robertson et al., 1993) and sunflower (Meinke et al., 1991). Corn and soybean crops had different RFV values early in the season but about the same during the mid-season (Tables 2 and S1), in contrast to our listed hypothesis. Previous studies reported a constant RFV (Kaspar et al., 1984) most likely due to a lack of high-resolution measurements to reveal the break point or due to position of measurement (in-row vs center of two rows; Figs. 3 and 5). In one of our six sites where less frequent measurements were taken (Northwest; Table 1) we were unable to calculate two rates (Table 2). This means that a strategic sampling is needed to capture key root parameters; our study provides guidance for future measurements (Fig. 4).

Compared to the limited experimental information available in the literature our soybean RFV values were higher compared to data from Nebraska (1.2–1.5 cm $d^{-1}$; Torrion et al., 2012), Kansas (1.5 cm $d^{-1}$; Mayaki et al., 1976) and Minnesota (1.7 cm $d^{-1}$; Allmaras et al., 1975), and lower compared to a glasshouse experiment (3.5–4.35 cm $d^{-1}$; Kaspar et al., 1983). This variation is likely related to different genotype, management, and environmental conditions among studies, as well as the methodology used to determine RFV (resolution of measurements and position; see coefficient of variation in Table 2). Our maize RFV values were comparable with previous reported values of 2.56–2.91 cm $d^{-1}$ (Singh et al., 2010); and lie in the middle of previous estimates: 3–6 cm $d^{-1}$ (Taylor and Kepler, 1973; Dardanelli et al., 1997), 1.3 cm $d^{-1}$ (Allmaras et al., 1975) and 1.1 cm $d^{-1}$ (Cahn et al., 1989).

In crop modeling use of a constant thermal time downward movement rate is common (Boote et al., 2008; Hammer et al., 2009; Yang et al., 2017). Theoretically this means that crop models over-predict root elongation in early growth stages (Fig. 4) and under-predict root elongation in later growth stages. These over- and under-predictions will affect water and nitrogen stress responses (e.g. Corre-Hellou et al., 2007). Process-based models such as DSSAT, APSIM, RZWQM, Hybrid-Maize, Adapt-N as well as commercial models are routinely used in this high production region to forecast crop yields (Morell et al., 2016), evaluate nitrogen rates to maize (Malone et al., 2010; Puntel et al.,

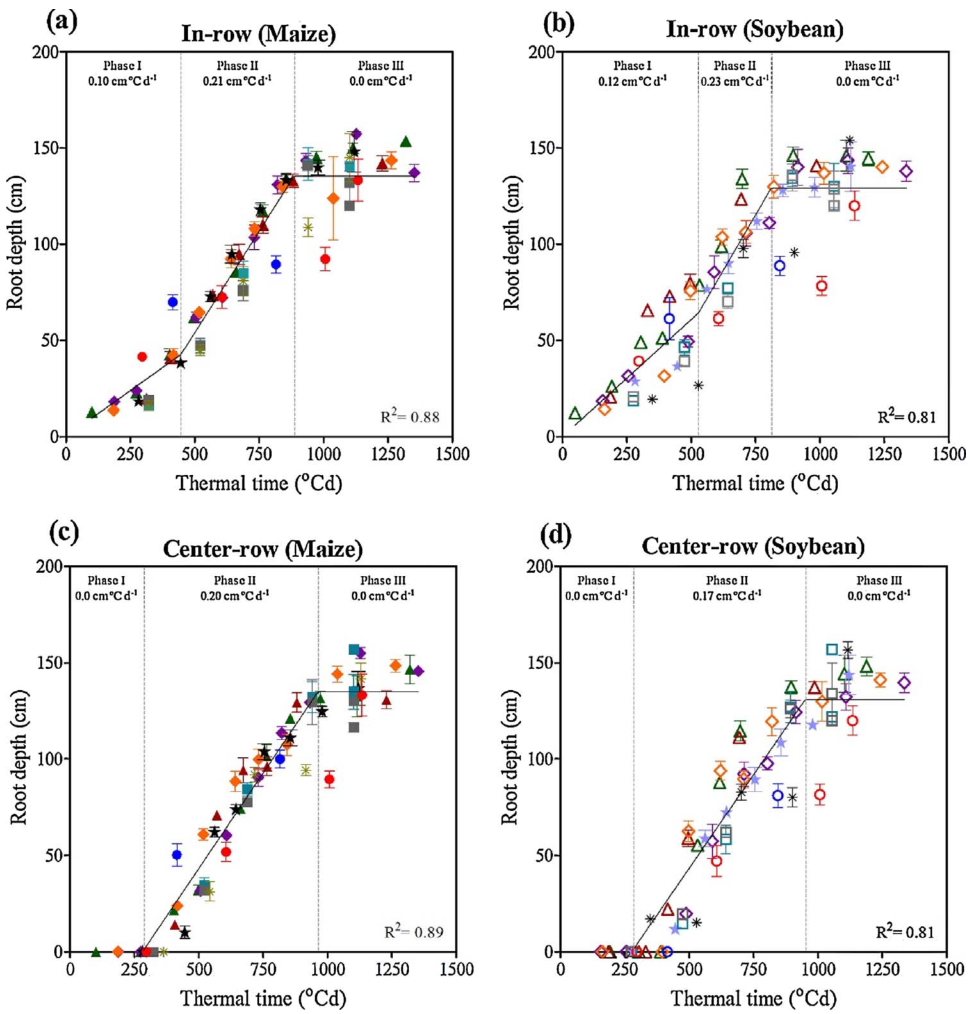



**Fig. 5.** Relationship between root depth and thermal time for maize and soybean crops in Iowa. Symbols explanations are provided in Table 1. Solid lines are bi- and tri-linear model fits (parameter values per treatment are provided in Table S1).

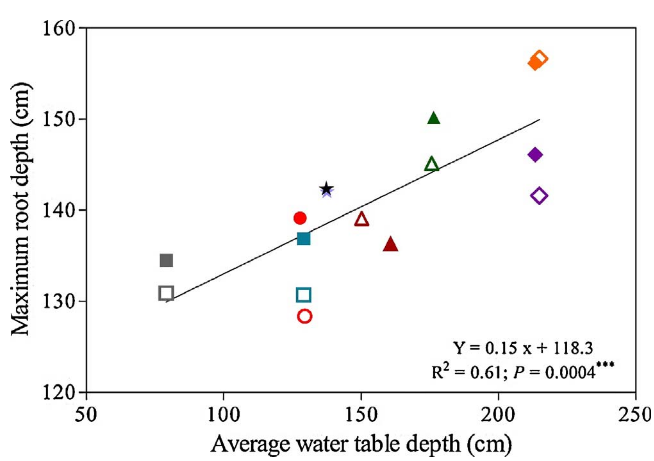



**Fig. 6.** Relationship between water table and the average of maximum root depth for maize and soybean across 16 field experiments. Water table data averaged two weeks prior to the final root measurements. Closed symbols represent maize and open symbols represent soybean. Symbols explanation is provided in Table 1.

2016; Sela et al., 2017), and benchmark management practices (Thorp et al., 2008; Wang et al., 2016) and climate change impacts (Wang et al., 2015; Paustian et al., 2016; Jin et al., 2017; Schauberger et al., 2017). To our knowledge, the validity of the root parameters used in the above modeling studies have not been evaluated. Our results can assist both calibration of model parameters as well as development of improved functions towards more accurate model simulations in this region. For instance linking RFV parameters to leaf number in corn and node number in soybean (Fig. 4) may improve the simulation of root depth and plant available water/nitrogen. Importantly our measurements revealed that the position of root measurement can greatly affect results and RFV parameters (Table 2).

### 4.2. Time to cover the center-row and cease root growth

Another important result from this study is the determination of the time needed for the root system to cover the space between 76 cm crop rows (6th leaf stage for maize; 40 days after planting; 450 °Cd; Figs. 4 and S4). This information can support improved modeling of the root system and inform in-season nitrogen placement to maize. Rapid root growth into the center-row may explain the general lack of fertilizer banding effect on crop yield in the US Midwestern cropping areas (Randall and Hoeft, 1988; Mallarino et al., 1999).

The timing when root transition occurs from slow to fast rate of increase was related to leaf number (Figs. 3 and 4 and S3 and 4). The time when maize reached maximum depth was approximately at silking or 10 days before the start of grain filling, which is in agreement with previous reports (Dwyer et al., 1988; Liedgens et al., 2000; Fageria and Moreira, 2011). On average, soybean root elongation ceased before or at the onset of pod and grain accumulation (Figs. 4 and S4) with few exceptions (Fig. 3). We expected soybean roots to keep growing during grain filling and cease root elongation later than maize due to indeterminate growth pattern (Kaspar et al., 1978; Torrion et al., 2012).

This might be explained by the short maturity cultivars used in Iowa (Table 1) and due to water table depth that might constrained further root growth (Fig. 6).

### 4.3. Maximum root depth

Our maximum depth observations for maize and soybean agree with earlier observations made in Iowa (Mitchell and Russell, 1971; Taylor and Keppler, 1973; Stone et al., 1976; Mason et al., 1982; Kaspar et al., 1984). This suggests that root traits have not changed over time (in contrast to plant traits; Duvick and Cassman, 1999; Ciampitti et al., 2012) given the 30 years difference between our study and previous measurements in Iowa. Compared to other environments our maximum depth measurements for both crops were different from other studies (range: 68–240 cm; Allmaras et al., 1975; Garay and Wilhelm, 1983; Canadell et al., 1996; Dardanelli et al., 1997; Araki et al., 2000; Qi et al., 2012; Gao et al., 2014). We believe the variation is due to interaction between genotypes, management and environment, and in particular due to two factors: cultivar length cycle and shallow water tables, and also soil temperature and moisture content (Reyes et al., 2015; van Oosterom et al., 2016). The fact that maize and soybean maximum root depth measurements were similar in this study (Table 2) might be attributed to the fact that roots cannot grow under saturated water conditions due to the lack of oxygen (Weaver, 1926; Stanley et al., 1980; Armstrong and Drew, 2002; van Oosterom et al., 2016) and therefore differences between crops could not be easily observed.

Many crop growth modelers work with the assumption that roots grow in a conical shape. For example, Yang et al. (2017) recently improved the Hybrid-Maize model from having a conical root shape to a uniform distribution until 30 cm followed by a conical root distribution to the bottom of the profile. In contrast, we found that roots occupy the full soil profile relatively quickly and there was no difference in maximum depths between these two sampling positions (Table 2). Our results suggest that maize and soybean roots is possible to take up water and nutrients from the entire profile in the study sites (Table 2). However, the root system shape and ability to extract water depends on the agronomic practices used (e.g. row configuration; Whish et al., 2005).

### 4.4. Predictability of root growth and water table effects

The strong correlation between root depth and easily measurable plant variables ($R^2 > 0.77$) could be considered as useful information for root phenotyping in breeding programs (Fig. 5, Figs. S2 and S3) where root growth has been largely ignored. Thermal time was the best "easily measured" estimator for root elongation in line with our hypothesis (Fig. 5). However, in all correlations we found an increased variability in root elongation estimations at the deepest depths (see phase III in Fig. 5). About 61% of this variability was explained by water table depth in our study (Fig. 6), which confirms our initial hypothesis. This is a very important finding because it indicates that in addition to temperature, water table depth during the growing season should be considered for maximum root depth estimation in this environment, which is also common in many cropping areas at the Corn Belt regions in US. Most of the crop models applied in this region (see references above) estimate root depth as a function of temperature, in agreement with our results, but do not simulate water table depth and its impact on root and plant growth, which is another area for model improvement.

Literature studies have shown a 7–27% maize yield increase with decreasing water table depth from 0.5 m to 1.5 m in Iowa (Ahmad and Kanwar, 1991; Kalita and Kanwar, 1992; Helmers et al., 2012) and an optimum water table depth for maximizing maize production in other environments (Florio et al., 2014). In our study we did not find a significant correlation between water table depth and yield (*$P > 0.30$; Fig. S5*), but observed root depth variation in response to water table depth (Fig. 6). Crop yield response to water table is simply expression of root functioning in response to moisture conditions. More studies are needed to fully understand the mechanisms by which root water and nitrogen uptake as well as root senescence are affected by shallow water tables (e.g. Stanley et al., 1980; Dickin and Wright, 2008). This becomes even more important considering the increasing climate variability in this region (Dai et al., 2015) and the fact that in-season precipitation (35-year average: 498 ± 20 mm) is above the optimum amount found (320–430 mm) to maximize production and environmental performance of maize and soybean systems in Iowa (Dietzel et al., 2016).

## 5. Conclusion

This study provided new data on RFV and maximum depth for maize and soybean crops across six sites and 20 experimental treatments in Iowa, USA. Our results demonstrated that maize and soybean root systems had different RFV values early in the season but similar RFV values during the mid-season and reached about the same maximum depth in the study sites. For RFV we found two different rates of increase (early and late) during crop growth. Root system attributes such as time to reach maximum depth, time to reach the center of two rows, and time when RFV change rate from early to late phase were quantified and could be useful in process-based models to provide answers to practical management questions. The correlations between below-ground and above-ground plant traits could be useful to assist phenotyping in breeding programs. A particularly important result from this study was the significant correlation between maximum root depth and water table depth. Our results suggests that besides temperature that drives RFV, water table levels should also be taken into account for maximum root depth determinations in this environment, which is also common in many cropping areas at the Corn Belt region of the US.

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## Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.fcr.2017.09.003.

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# How does inclusion of weather forecasting impact in-season crop model predictions?

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A B S T R A C T

Accurately forecasting crop yield in advance of harvest could greatly benefit decision makers when making management decisions. However, few evaluations have been conducted to determine the impact of including weather forecasts, as opposed to using historical weather data (commonly used) in crop models. We tested a combination of short-term weather forecasts from the Weather Research and Forecasting Model (WRF) to predict in season weather variables, such as, maximum and minimum temperature, precipitation, and radiation at four different forecast lengths (14 days, 7 days, 3 days, and 0 days). This forecasted weather data along with the current and historic (previous 35 years) data were combined to drive Agricultural Production Systems sIMulator (APSIM) in-season corn [*Zea mays L*] and soybean [*Glycine max*] grain yield and phenology forecasts for 16 field trials in Iowa, USA. The overall goal was to determine how the inclusion of weather forecasting impacts in-season crop model predictions. We had two objectives 1) determine the impact of weather forecast length on WRF accuracy, and 2) quantify the impact of weather forecasts accuracy on APSIM prediction accuracy. We found that the most accurate weather forecast length varied greatly among the 16 treatments (2 years × 2 sites × 2 crops × 2 management practices), but that the 0 day and 3 day forecasts were, on average, the most accurate when compared to the other forecast lengths. Overall, the accuracy of the in-season crop yield forecast was inversely proportional to forecast length ($p = 0.026$), but there was variation among treatments. The accuracy of the in-season flowering and maturity forecasts were not significantly affected by inclusion of weather forecast length ($p = 0.065$). The 14 day forecast provided enough lead time to improve flowering prediction in 8 out of the 16 treatments. The fact that maximum temperature was the most accurate predicted variable by WRF was the reason for improvements in flowering predictions. Our results suggest that a weather forecast from WRF was not better than historical weather for yield prediction.

## 1. Introduction

Forecasting crop production in-season is becoming increasingly important for agricultural producers to make informed crop management and financial decisions (Hansen et al., 2004; Hansen and Indeje, 2004; IPCC, 2013; Newlands et al., 2014). Access to near real-time agronomic information could potentially lead to increased profitability by adapting nitrogen management, chemical applications, planting and harvest dates (Horie et al., 1992; Lawless and Semenov, 2005; Howden et al., 2007). Furthermore, improved methods of forecasting crop production can also be beneficial in making marketing decisions that could increase farm profitability (Anderson, 1973; Jones et al., 2000; Brandes et al., 2016; Johnson et al., 2016).

There are several approaches currently being used or developed to produce in-season crop forecasts, which cover a broad range of largely empirical/statistical techniques to more physically based approaches (Basso et al., 2013). Different approaches have tradeoffs between increasing inference and explanatory power as well as customization at the scale and resolution needed for individual decision makers and land managers. For example, there are yield forecasting approaches that rely on crop models, which are driven by a combination of current and historical weather data (Cantelaube and Terres, 2005; Chipanshi et al., 2015; Ferrise et al., 2015), remote sensing and satellite image analysis (Myers, 1983; Basso et al., 2013; Bolton and Friedl, 2013), and in-season farmer-based surveys (NASS, 2015).

Crop modeling offers explanatory power in addition to forecasting power but this comes at the cost of extensive amounts of input data and parameters (Basso et al., 2012; Puntel et al., 2016). Locally adapted and tested crop simulation models allow one to quickly explore the production outcomes of a range of management alternatives under a range

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of forecast climatic conditions (Hammer et al., 1996; Meinke et al., 1996; Carberry et al., 2000; Jones et al., 2000; Royce et al., 2001). Remote sensing techniques are mostly descriptive and well suited for regional scale forecasting (Atzberger, 2013). Farmer-based surveys are helpful to obtain information directly from the field, but rely on voluntary participation and do not have strong predictive insight.

Crop phenology and final yields are highly dictated by weather variables such as radiation, precipitation, and temperature (Barnett and Thompson, 1982; Tollenaar et al., 2017). Thus, the accuracy of predicting weather inputs is critical for crop simulation based yield forecast and the addition of a weather forecast could potentially add value. However, there are obstacles due to the lack of accurately forecasted weather data that is available in near real-time and compatible with crop model weather input requirements (Hansen et al., 2004).

The majority of current crop model forecasting approaches rely on the combination of current and historical weather data to calculate yield probabilities in regions ranging from Australia (Carberry et al., 2009), to Canada (Chipanshi et al., 2015), and Europe (Williams and Falloon, 2015) as well as, USA (Archontoulis et al., 2016a; Morell et al., 2016). A difference among the above listed crop model forecasting approaches is the number of historical weather years used, the structure of the crop models, the temporal resolution of weather data (hourly vs daily) and the number of weather variables (e.g. solar radiation, temperature, precipitation, humidity and wind speed) needed by different crop models.

Among the aforementioned weather variables, temperature and precipitation forecasts can be easily found and they have been tested in crop models (Gowing and Ejieji, 2001; Basso et al., 2013; Asseng et al., 2016). These studies, suggest that multi-day weather forecasts may be accurate enough for yield and phenology predictions but did not test the impacts of forecasted solar radiation or weather forecasts of different lengths. This is most likely due to the difficulty in obtaining readily available daily radiation output from weather forecasts. To our knowledge, there are a few weather forecasting models that provide nearly complete forecasted weather data (including solar radiation), that is easy to obtain for use in crop models. These include National Digital Forecast Database (NDFD; 4-day forecast), the Climate Forecast System (CFS; 6-months forecast), and the Weather Research and Forecasting model (WRF) that can be run for different forecast lengths of one's choosing.

Including a weather forecast that produces a consistent set of all key weather variables and is run explicitly for an area where crop yields and phenology are to be predicted could have advantages. For example, we could see if the forecasted weather is greatly different from normal or historical weather (commonly used in yield forecasting). A crop model capable of reflecting the impact of anomalous weather on key agronomic variables (e.g. yield and phenology) could give lead time to adjust strategic in-season management decisions. This predictability offers the potential to adjust agricultural management decisions to expected climatic variations to reduce adverse impacts or take advantage of favorable conditions (IPCC, 2013; Newlands et al., 2014). Greater lead time would give users more time to plan operations, but may come at the cost of decreased forecast accuracy.

To determine the tradeoff between accuracy and lead time of weather forecasts into crop model predictions we incorporated four different weather forecast lengths from the Weather Research and Forecasting Model (WRF) into the Agricultural Production Systems sIMulator (APSIM) crop model, which were used to predict crop yields and phenology. The overall goal was to determine the dependence of the weather forecast accuracy and length on the performance of APSIM yield and phenology predictions. We hypothesized that:

1) the accuracy and variability of crop yield predictions will be inversely proportional to the weather forecast length and
2) the inclusion of an explicit weather forecast will reduce crop yield prediction uncertainty and produce a reliable estimate with more lead time relative to using historical variation alone.

To test these hypotheses, we utilized a well-calibrated crop model with a set of 16 treatments (2 years × 2 sites × 2 crops × 2 management practices) and calculated metrics to assess accuracy and variability for four forecasts lengths (0 day, 3 day, 7 day, and 14 day). We also conducted a weather variable sensitivity analysis on APSIM simulations of yield to quantify the impacts of error in each weather variable. We selected crop yield and phenology as variables to test the impact of WRF inclusion because both are of great interest to stakeholders and also because these variables are affected differently by weather, e.g. phenology is mostly driven by temperature while yield is affected by all variables. Our approach is the first to combine a complete set of forecasted data for all four weather variables needed in the APSIM model for in-season forecasts.

## 2. Methods

### 2.1. Field experiments

Our coupled weather and crop forecast experiment was evaluated at two Iowa sites, the Agricultural Engineering and Agronomy Research Farm in Ames, IA, (42°01′20.37″N, 93°46′36.05″W) and the Northwest Research Farm in Sutherland, IA (42°55′28.78″N, 95°32′20.39″W). At each location, corn and soybean crops were grown over two years (2015–2016) in a corn-soybean rotation. Two planting dates (early and late planting) were included in the experimental design; approximately 3–4 weeks apart. The combination of sites, years, crops, and management resulted in 16 treatments which were used to test WRF and APSIM model predictions. The 16 treatments were, Ames corn early (ACE), Ames corn late (ACL), Ames soybean early (ASE), Ames soybean late (ASL), Sutherland corn early (SCE), Sutherland corn late (SCL), Sutherland soybean early (SSE), and Sutherland soybean late (SSL) over two years. Management details per experiment are provided in supplementary Table S1.

### 2.2. Crop and weather observations

In each site several soil, crop, and weather variables were measured during the growing season. Weather data were recorded hourly by a weather station located at the borders of each experiment (Iowa Environmental Mesonet; IEM; https://mesonet.agron.iastate.edu/). Crop variables such as phenology, morphology (leaf or node number, leaf area index), biomass accumulation and partitioning to different plant tissues, and carbon and nitrogen concentration were measured destructively 8–10 times over the growing season (data not shown). Grain yield at physiological maturity was harvested and expressed with 0% moisture in this paper. Soil moisture and groundwater measurements at different soils depths were obtained every 30 min using Decagon sensors (data not shown). Soil nitrate was measured bi-weekly from April to November every year at the forecast sites (data not shown). The soil and crop data were used to calibrate the APSIM soil and crop models used in this study, which is part of a larger forecast project (Archontoulis et al., 2015; 2016a,b).

### 2.3. The WRF model description and configuration

The Weather Research and Forecasting Model (WRF V3.6.1; Skamarock et al., 2008) was used to forecast weather variables required for input into the crop model with varying forecast lengths (14 days, 7 days, 3 days, and 0 days). WRF was chosen for the ability to obtain radiation data from the forecasts. The 0 day forecast was a combination of current and historical weather, with no forecast from WRF. WRF was run with two domains, the outer domain had a grid spacing of 51 km, while the inner domain was centered over the Central U.S. with a grid spacing of 17 km (Harding et al., 2016 and Sines, 2016). There are two external data sources needed to run the Weather Research and Forecasting Model, the first is static geographical data and the second is gridded meteorological data. For static geographical data, information from the U.S. Geological Survey (USGS) and the Moderate Resolution Imaging Spectroradiometer (MODIS) were used and for gridded meteorological data, 3-hourly data from the Global Forecast System (GFS) were used. This gridded data was chosen for its ability to forecast up to 14 days in advance, which is the longest forecast being used in this study. More information of the WRF model configuration can be found in supplementary Table S2.

WRF model outputs were analyzed for each forecast site using Matrix Laboratory and Statistics Toolbox (MATLAB, Release 2015b, The MathWorks, Inc., Natick, Massachusetts, United States). WRF provided hourly output that was averaged into daily output, which is the time step APSIM uses. Daily maximum and minimum temperature (°C), total daily precipitation (mm) and daily radiation (MJ day$^{-1}$) were obtained from the forecast data per location. These forecasts were initialized on the 1st and 16th of every month from May through October. From the WRF output we used shortwave surface total of solar irradiance, including direct and diffuse to calculate daily radiation (referred to as radiation hereafter; Skamarock et al., 2008).

Weather files were then made for APSIM by using the current year's observed weather, from the IEM, up to the forecast date, then the WRF weather forecast was included for the forecast time period, and lastly, 35-years of historical weather data were added to the file (Fig. 1). For example, if June 1st was the forecast date, the observed weather for 2015 from January 1st to May 31st would be the first piece of weather information in the file. Then, the WRF forecast would be inserted for the number of days being forecasted, if the forecast was a 3 day weather forecast the dates June 1st to June 3rd would be added to the file. Lastly, 35 years of historical weather data would be added for the remainder of the year, from June 4th to December 31st, to capture the range of historical variations. This process was done for four different WRF forecast lengths and at both locations each time the crop model was run, creating eight different weather scenarios for each forecast date.

### 2.4. The APSIM model description and configuration

The Agricultural Production Systems sIMulator (APSIM; Keating et al., 2003; Holzwort et al., 2014) is an advanced simulator of agricultural systems. The APSIM software combines several process-based models in a modular design and is open source. The model operates at field scale that runs on a daily time step. The APSIM version 7.8 was used in this study.

Briefly, the corn and soybean crop models in APSIM simulate daily biomass accumulation using a combined light and water use efficiency approach (Keating et al., 2003). Water and nitrogen stresses on crop growth, leaf elongation and senescence, phenology and grain accumulation are included in the crop models. Daily biomass gain is distributed to various plant organs using phenological driven algorithms. Crop phenology is calculated using a 3-h approach and crop specific cardinal temperatures (Wilson et al., 1995; Robertson et al., 2002). Grain yield is the product of many processes within the model. In terms of soil modeling, the following APSIM models were used in this study: the SWIM model (Huth et al., 2012) for simulation of soil water and fluctuating water tables which uses the Richards equation, the SoilN and Surface Organic matter models (Probert et al., 1998; Thorburn et al., 2001) for the simulation of carbon and nitrogen cycling per soil layer and residue decomposition which affects soil carbon, nitrogen, water, and temperature. For more information on the APSIM models we refer to the on-line documentation: (www.apsim.info).

Over the past years the APSIM model has been successfully applied in Iowa regions to simulate production (Hammer et al., 2009; Archontoulis et al., 2014a,b; Dietzel et al., 2016; Puntel et al., 2016; Jin et al., 2017) and environmental aspects of US Midwestern corn and soybean cropping systems (Malone et al., 2007; Archontoulis et al., 2016a,b; Basche et al., 2016; Martinez-Feria et al., 2016).

### 2.5. APSIM simulation set-up, calibration, and sensitivity analyses

The simulation of soil and crop variables started January 1st each year. Profile soil water, nitrate, and ammonium values were initialized by running the model for historical years (corn-soybean rotation with known management) and were adjusted after January 1st (if needed) to match pre/in-season soil water and nitrogen field measurements (Archontoulis et al., 2015; 2016a,b). Total soil carbon and nitrogen were measured to a 1 m depth at each site. Hydrological parameters were taken from Web Soil Survey (Soil Survey Staff, 2006) and calibrated to match soil water and groundwater measurements (Table S3). Local crop cultivars were used in the simulation (Archontoulis et al., 2014a,b). In the corn model we made the following changes: the radiation use efficiency parameter increased to 1.8 from 1.6 g MJ$^{-1}$, the critical N concentrations for stem and grain were modified (decreased) to match observations. In the soybean model we decreased the grain N critical concentration to better match experimental data (from 6.5 to 5.8%). Changes to crop model parameters were based on 2015 data and were maintained in 2016 simulations. Higher RUE values and lower grain N concentrations for modern hybrids compared to default APSIM parameters are also supported by literature data (Duvick and Cassman, 1999; Lindquist et al., 2005; Ciampitti and Vyn, 2012).

To explore the relative impact of weather variables into APSIM crop model predictions of yield and phenology we performed a sensitivity analysis by changing one weather variable at a time (e.g. radiation) by +30%, +15%, −15% and −30%. This analysis was performed across all 16 treatments. To quantify the probability that changing weather variables by 15% and 30% were in the context of historical variability we performed a second analysis using 35 historical years. For this analysis the average of all 35 years of historical data were calculated for maximum temperature, minimum temperature, precipitation, and radiation. This average value was then increased and decreased by positive and negative 15% and 30% to obtain a range of values. Each

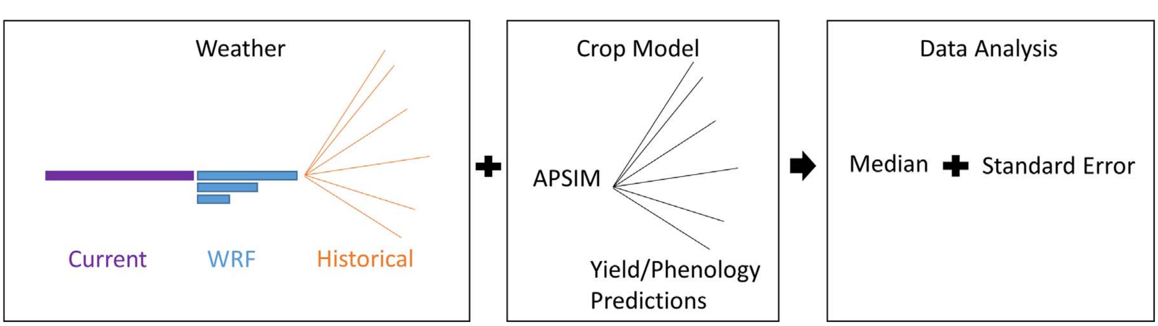


**Fig. 1.** Visual representation of combining weather with the crop model to obtain yield and phenology predictions. Weather is broken down into 3 categories, current, WRF forecasts (3, 7, and 14 day), and 35 years of historical weather.

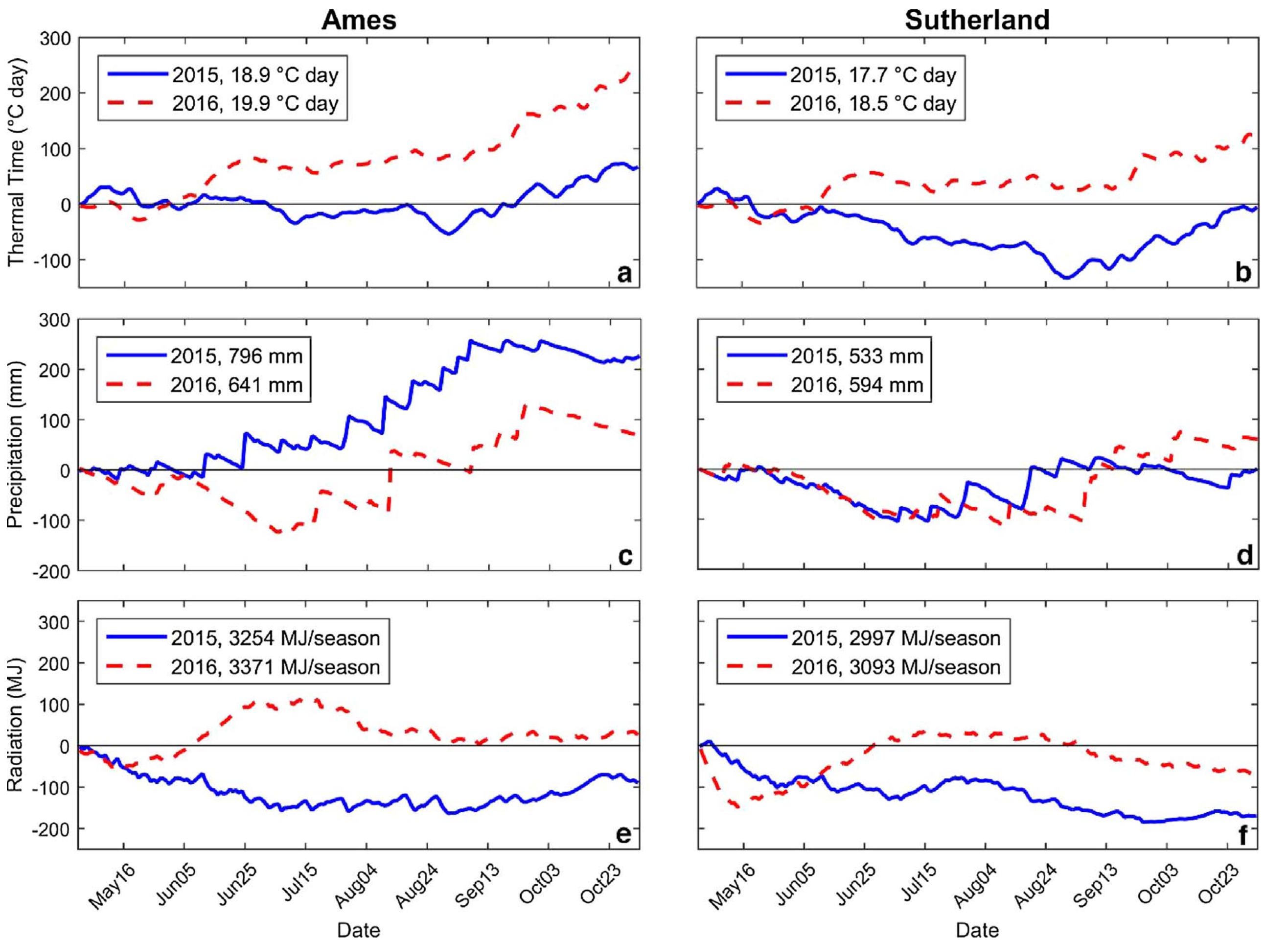


**Fig. 2.** Cumulative difference in thermal time (a, b; base temperature zero), cumulative difference in precipitation (c, d), and cumulative difference in radiation (e, f) between 2015 and 2016 minus 35 historical years (climatology; 1980–2014) for Ames (a, c, e) and Sutherland (b, d, f) Iowa, USA.

individual year was then compared to the increased and decreased values to determine if that change in weather variable occurred and how often in the last 35 years. Yearly values were placed into categories, category 1 (−30% to −15%), category 2 (−15% to 0%), category 3 (0% to 15%), category 4 (15% to 30%) and category 5 (30% and up) and percentages were calculated based on how many years of the 35 were in that category.

### 2.6. In-season forecast of crop yields and phenology

In-season forecasts of crop yields and phenology were driven by a combination of actual, historical, and WRF-simulated weather data (Fig. 1). The in-season forecast started at crop planting and was updated every 14 days until the end of the growing season. Each time we used actual weather data up to the date of forecast, followed by 14, 7, 3, or 0 days WRF forecasted data and finally by 35 historical weather years (1980–2014). For each forecast (except the last one where the full weather was known) the model provided 35 predictions for crop yields and phenology for 2015 and 2016. From these data we calculated the median prediction and the standard error. The combination of 16 crop treatments, 11 in-season forecasts, four lengths of WRF forecasted data and 35 years of historical weather resulted in 24,640 simulations.

### 2.7. Model evaluation and data analysis

Different metrics were used to evaluate WRF and APSIM prediction accuracy. We computed the root mean square error (RMSE) and the normalized root mean square error (NRMSE) to estimate the actual and relative error associated with weather, crop yield, and phenology predictions (Archontoulis and Miguez, 2015). To compare the forecast accuracy of the WRF model all of the 14 day WRF forecasts for each weather variable were concatenated to form a full forecasted weather data set from May through October each year. We also calculated the number of days that WRF weather variables had an absolute error of 20% or below compared to observed values using the following equation:

$$\%Error = 100^{*}\left(\frac{F - O}{O}\right) \tag{1}$$

where $F$ is the forecasted value and $O$ is the observed daily weather value. For maximum temperature, minimum temperature, and radiation the error percentage was calculated daily for each forecast, while precipitation forecasts were summed over the forecast period and then compared to the sum of the observed days. Once the percent error was calculated the number of days (per month) that had an error below 20% were summed together for each forecast length and then normalized to get a value between 0 and 1. This 20% benchmark was set based on the results of the weather sensitivity analysis (shown later).

To detect periods within the season when the forecasted weather had notable errors, we calculated cumulative differences between forecasted and observed data for all weather variables. To evaluate the accuracy of the combined APSIM-WRF models yield and phenology forecasts across 16 field trials, we calculated a cumulative index per trial that accounts for all 14 in-season forecasts by using the following equation:

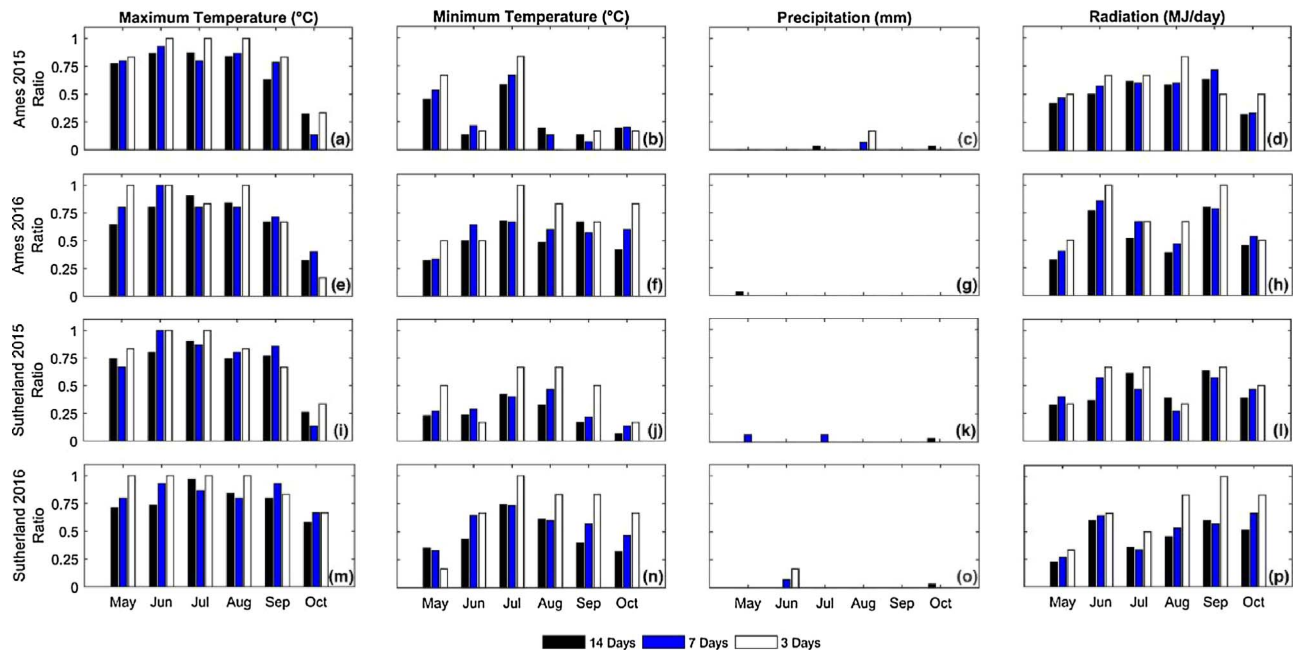


**Fig. 3.** Normalized values of the 20% error (calculated using eq. 1) for each forecast length. A value of 1 means that all individual forecast days had an error below 20%, while a value of zero means that all individual forecasted days had an error above 20%. Maximum temperature (a, e, i, m), minimum temperature (b, f, j, n), precipitation (c, g, k, o), and radiation (d, h, l, p), throughout the growing season for Ames 2015 (a–d), 2016 (e–h), and Sutherland 2015 (i–l) and 2016 (m–p).

$$\textit{Cumulative Accuracy} = \frac{1}{\sum \left| \frac{y_{ti} - y_{final}}{y_{final}} \right|} \tag{2}$$

Where $y_{ti}$ is the simulated yield at time $t_i$ (approximately every 14 days after planting until the end of the season), and $y_{final}$ is the final simulated yield using observed weather data. The absolute accuracy value of each yield forecasting date was taken and then summed cumulatively over the entire growing season to get the total amount of accuracy for each forecast length. The absolute value was taken to avoid compensation of over-predictions with under-predictions. The higher the number the more accurate the forecast was. A linear regression was performed to determine if yield and phenology prediction accuracy was inversely proportional to forecast length. A $p$-value $< 0.05$ was considered significant.

## 3. Results

### 3.1. Observed weather conditions versus 35-year average

Temperature, rainfall and radiation followed different patterns throughout the 2015 and 2016 years as compared to the 35-year average (Fig. 2). Across the growing seasons, Ames was both warmer and wetter than the 35-year average in both years. Weather in Sutherland was similar to the 35-year average in 2015 and warmer and wetter in 2016. Cumulative thermal time in Ames and Sutherland was larger in 2016 than in 2015 (Fig. 2a and b). Total precipitation in Ames was above climatology for both years, while Sutherland had precipitation closer to average (Fig. 2c and d). Cumulative radiation in Ames was close to historical average in 2016 and a bit less in 2015, while Sutherland had both years less than historical average (Fig. 2e and f).

### 3.2. WRF model performance

Daily maximum temperature was forecasted the most accurately with an average RMSE and NRMSE of 4.9 °C and 20.3%, respectively, across years and sites. In terms of the accuracy of other weather variables, there were inconsistencies between the two study years. In 2015 daily radiation was second most accurately forecasted (RMSE = 8.3 MJ $m^{-2}$ $season^{-1}$; NRMSE = 45%) across sites, followed by daily minimum temperature (RMSE = 5.4 °C; NRMSE = 49%), and finally, daily precipitation (RMSE = 10.6 mm; NRMSE = 327.0%). In 2016 daily minimum temperature was forecasted the second most accurately (RMSE = 4.4 °C; NRMSE = 34%), after maximum temperature, followed by daily radiation (RMSE = 8.6 MJ $m^{-2}$ $season^{-1}$; NRMSE = 44%), and daily precipitation (RMSE = 12.7 mm; NRMSE = 438.5%), across sites.

The 14 day forecast, overall had the most error during the growing season and the 3 day forecast had the least amount of error (Fig. S1). Maximum temperature was the weather variable with the smallest error (Fig. S1a, e, i, m). Minimum temperature in 2015 had more error than in 2016, especially in Sutherland 2016 where error in minimum temperature was low (Fig. S1b, f, j, n).

To determine if WRF over or under prediction comes from a few individual days or is consistent across days we counted the number of days per month where WRF predictions exceeded 20% error (Fig. 3). Maximum temperatures were forecasted the most accurately for each day across sites and years with ~90% of the forecasted days having error below 20% (Fig. 3a, e, i, m). Radiation was forecasted the next most accurately with > 60% of the forecasted days having below 20% error (Fig. 3d, h, l, p). Minimum temperature forecasted within 20% error in approximately 50% of the days per month (Fig. 3b, f, j, n), while daily precipitation accuracy was very low (Fig. 3c, g, k, o). Also, our results indicated that WRF simulations were more accurate across all variables for the months June, July, and August compared with May, September, and October forecasts (Fig. 3).

### 3.3. APSIM model performance and sensitivity analyses

The APSIM model simulated flowering date and maturity date with a RMSE of 2.8 days and 8.3 days respectively across all 16 treatments (Fig. 4a). The simulation of biomass production of soybean had a RMSE of 756 kg $ha^{-1}$ and corn a RMSE of 1932 kg $ha^{-1}$ (Fig. 4b and c). Corn yield had a RMSE of 975 kg $ha^{-1}$ and soybean yield had a RMSE of 608 kg $ha^{-1}$ (data not shown).

The APSIM crop simulations were most sensitive to changes in

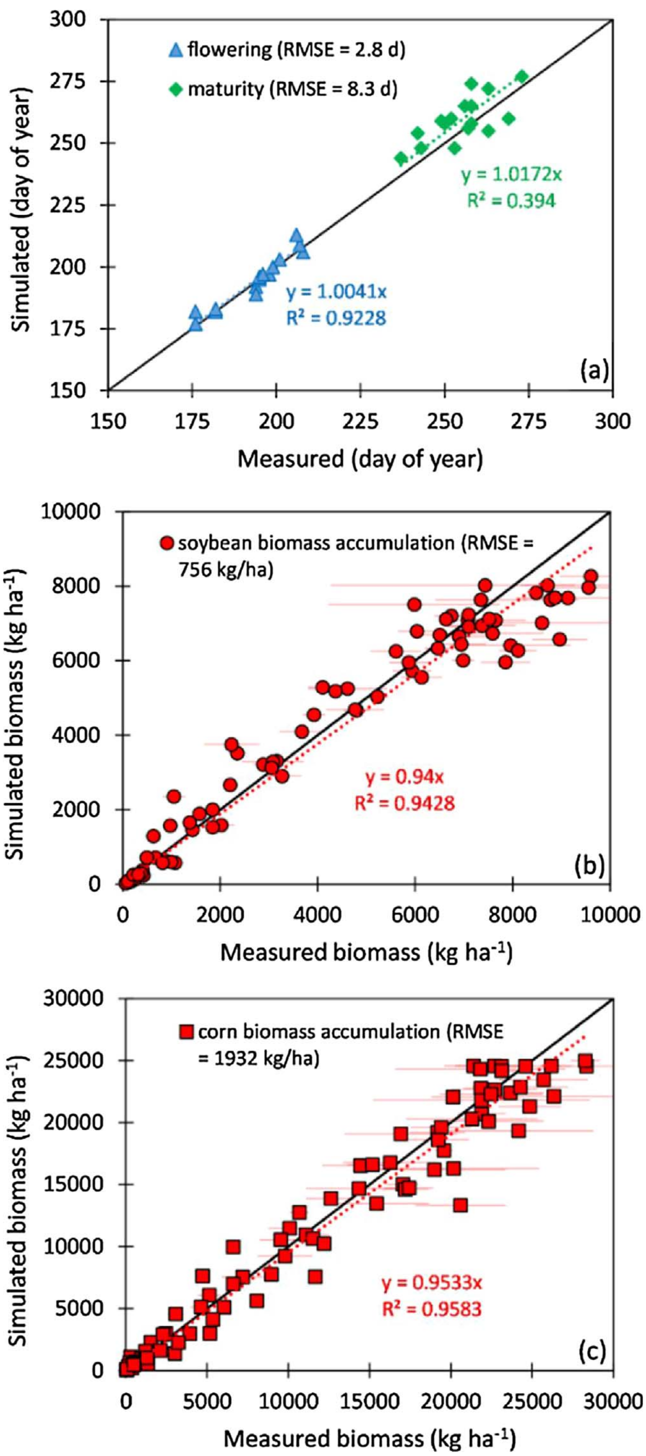


**Fig. 4.** Measured versus APSIM model simulated flowering date, maturity date (panel a) and biomass accumulation per crop (panels b and c). Horizontal red lines indicate standard error of the mean (n = 3 replications). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

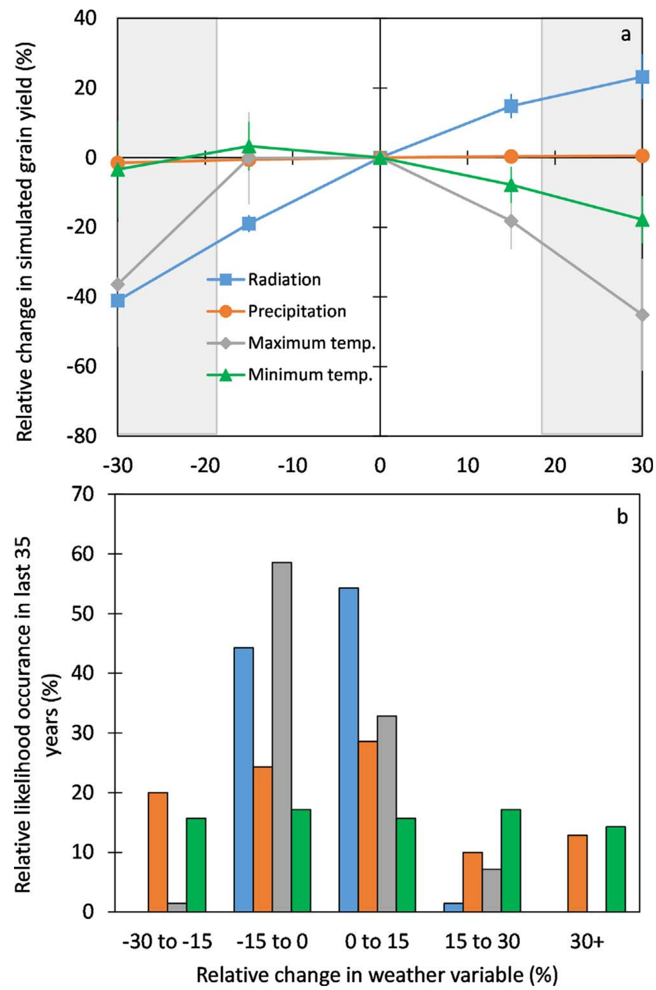


**Fig. 5.** Weather sensitivity analysis figure, showing the impact of weather variable changes of negative and positive 15% and 30% and how those impact yield in panel a. Panel b is showing the percent likelihood of a change in weather variable happening over the last 35 years. The white empty space in panel a represents the 20% error that was chosen for weather variables.

radiation and temperature but not to precipitation across 16 field trials (Fig. 5a). Historically precipitation and minimum temperature varied the most, while radiation varied the least in the weather sensitivity analysis (Fig. 5b). Of the 35 historical years of weather variables, precipitation varied among all 5 categories (Fig. 5b). Yield was positively impacted by increased radiation and the effect was higher in the soybean simulations. Maximum temperature was the most influential weather variable and deviations, either positive or negative, resulted in yield reductions (Fig. 5a). In the 35 historical years change in radiation and maximum temperature mostly happened in the range of −15% to 15% (Fig. 5b). Decreasing minimum temperature by 15% caused the yield to go up but increasing minimum temperature caused the yields to decline (Fig. 5a). Minimum temperature over the last 35 historical years was evenly split among the different categories of change in weather variable.

### 3.4. Accuracy of in-season forecast and forecast length

The accuracy of in-season crop yield forecasts varied by treatment when compared to simulated final yield (Fig. S2, Fig. 6a and Table 1). Yield and maturity date had a similar pattern of an inverse relationship between forecast length and accuracy, while flowering date had the opposite pattern with the 14 day forecast being the most accurate.

For example corn yield for both years in Ames was most accurately forecasted by the 0 day forecast. In both 2015 and 2016 the 3 day forecast was most accurate for ASE treatment and in 2015 the 14 day was the most accurate for SSL treatment. Overall, the 0 day forecast was most accurate 37.5% of the time, the 3 day forecast 25% of the time, the 7 day forecast 25% of the time and the 14 day forecast 12.5% of the time (Table 1) for simulations of yield across all 16 treatments. The simulated yields were similar to the median value for all of the forecast lengths and the measured yield from the field was also similar in the majority of treatments (Fig. 7). For example, in 2015 forecasted yield

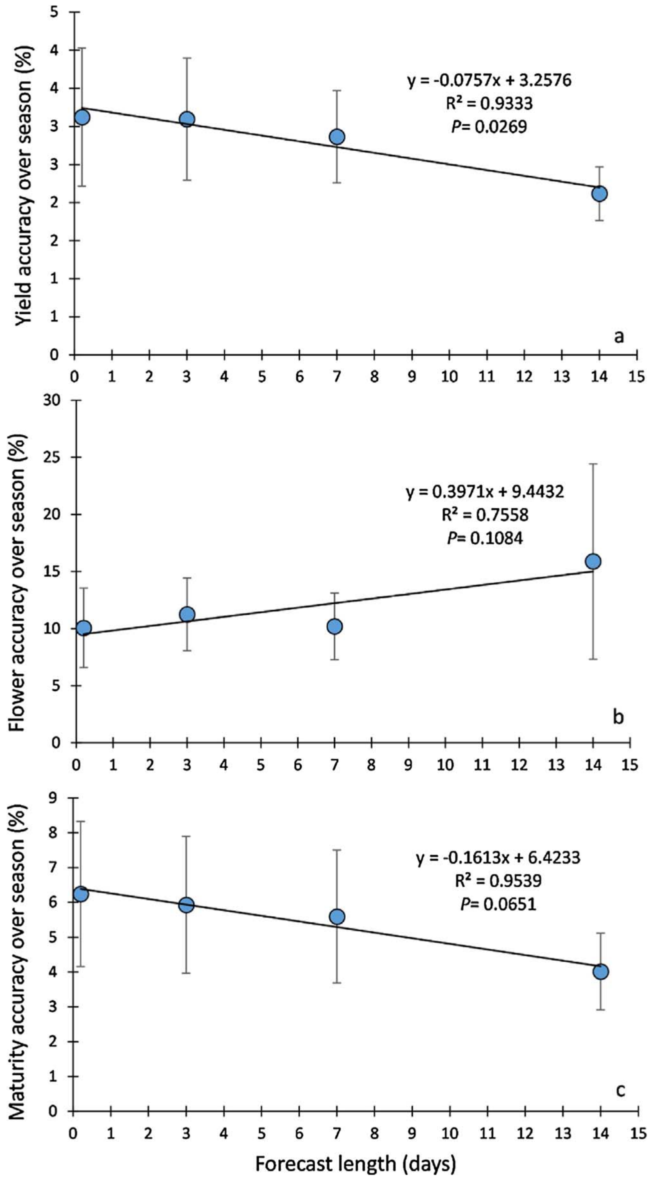


**Fig. 6.** Percentage of inaccuracy over the entire growing season by forecast length for yield (a), flowering date (b), and maturity date (c).

medians were similar to observed and simulated yields for ASE and ACE (Fig. 7a and c). In 2016, SLC was the only boxplot that had a median value for observed yield that was not similar to the forecast lengths or simulated yield (Fig. 7p).

Unlike yield, flowering date had very uniform results for each treatment in 2015 and then inconsistent results in 2016 (Fig. S3 and Table 2). Flowering date was not inversely proportional to forecast length ($p = 0.1$; Fig. 6b). In 2015, the 14 day forecast was the most accurate for flowering date for almost every treatment except ACE and ASE. Overall, the 0 day forecast was most accurate 22.7% of the times, the 3 day forecast 27.3%, the 7 day forecast 13.6%, and the 14 day forecast 36.4% (Table 2) for simulations of flowering. Variability in flowering date prediction (reflected by the box-plot) was very small between forecast lengths (Fig. S4).

Similar to yield, maturity date in 2016 had consistent results with the 0 day forecast being the most accurate for every treatment except for SSE where the 3 day forecast was the most accurate (Fig. S5; Table S4). In 2015, the results varied greatly by treatment. Across treatments maturity date was inversely proportional to yield, but it was not statistically significant ($p = 0.065$; Fig. 6c). Across 16 treatments, the 0 day forecast was most accurate 52.9% of the times, the 3 day forecast 23.5%, the 7 day forecast 17.7% and the 14 day forecast 5.9% for simulations of maturity. Like flowering date, variability for maturity date did not vary widely between forecast lengths (Fig. 8). For all of the treatments the median values of the boxplots were very consistent and did not vary between forecast lengths (Fig. 8).

### 3.5. Yield prediction uncertainty over growing season

The uncertainty in crop yield prediction (reflected by the standard error across 35 simulations) decreased over the entire growing season, as more of the crop forecasts were forced by observed weather, as opposed to historical weather (Fig. 9). Around flowering date for corn, the variability in yield prediction decreased by 50% (Fig. 9a). In contrast the uncertainty reduced less by soybean flowering date (Fig. 9b). Both corn and soybean standard error decreases to 50% around 800 GDD after planting.

It is interesting to note that 11 of the 16 yield forecasts at planting time matched end-of season final yields within 10% error, irrespectively of weather forecast length (Fig. S2). Similarly flowering and maturity forecasts at planting time match final observations within 10% error in 15 out of 16 treatments (Figs. S3 and S5).

## 4. Discussion

Inclusion of in-season weather into crop model prediction of crop yields and phenology has been proposed as a means to increase the accuracy of crop model predictions (Lawless and Semenov, 2005). We tested this in a high agricultural production region, Iowa, USA, which represents 15% and 12% of the total USA corn and soybean production respectively (NASS, 2015). To our knowledge this is the first work to evaluate weather forecast impacts on crop model prediction that covers maximum and minimum temperature, precipitation, and radiation needed for crop models and a range of crop, sites, year, management treatments.

### 4.1. Impact of WRF inclusion into APSIM forecast

Our first hypothesis that the accuracy and variability of crop yield predictions will be inversely proportional to the weather forecast length was partially supported by our results (Fig. 6). Our results showed that the shorter (0 day and 3 day) forecasts were the most accurate for yield and maturity date prediction, while the 14 day forecast was the most accurate for forecasting flowering date in 8 of the 16 study cases (Tables 1 and 2, and S4; Fig. 6). Flowering date occurs in the middle of the season and is mainly driven by temperature, the accuracy in flowering date with the 14 day forecast was better than for maturity date and yield. That the 0 day yield forecast was most accurate meant that a weather forecast from WRF was not better than historical weather, however in these cases the difference between the accuracy of the 0 day yield forecast and the other yield forecast lengths was not enough to rule out using short-term weather forecasts (Fig. S2).

Maximum temperature and radiation were the two variables in the weather sensitivity analysis that had the largest impact on yield (Fig. 5a). However, in the historical 35 years both maximum temperature and radiation had zero years in category 1 and category 5, so the likelihood of either variable having the large impacts on yield is small (Fig. 5b).This lead us to set a 20% error (Eq. 1) as a benchmark point to evaluate WRF predictability of weather variables against observation (Fig. 5a). Interestingly, APSIM can encounter an error of 20% in precipitation and still have acceptable yield predictions (Fig. 5a). There are two possible explanations for this lack of sensitivity. First, the soils in the study sites have a high plant available water holding capacity (> 250 mm; WebSoilSurvey), on average 641 mm of precipitation during the season (Fig. 2), plus shallow water tables (varies from 1 to 1.7 m below surface during the growing season; Archontoulis et al.,

**Table 1**
Cumulative absolute value of accuracy for yield calculated by Eq. (2) among the different forecast lengths. The bold numbers had the best accuracy over the entire growing season. The higher the number is, the better the accuracy.

| Cropping System | Acronym | Panels in Fig. S2 | Weather Forecast Length | | | |
|---|---|---|---|---|---|---|
| | | | 14 day | 7 day | 3 day | 0 day |
| Ames Soybean Early 2015 | ASE-15 | a | 1.97 | 2.21 | **3.06** | 2.52 |
| Ames Soybean Late 2015 | ASL-15 | b | **3.25** | 3.16 | 2.53 | 2.33 |
| Ames Corn Early 2015 | ACE-15 | c | 2.65 | 4.14 | 4.63 | **4.77** |
| Ames Corn Late 2015 | ACL-15 | d | 3.07 | 5.52 | 7.35 | **8.22** |
| Ames Soybean Early 2016 | ASE-16 | e | 1.15 | 1.43 | **1.87** | 1.82 |
| Ames Soybean Late 2016 | ASL-16 | f | 1.72 | 2.16 | 2.34 | **2.77** |
| Ames Corn Early 2016 | ACE-16 | g | 1.10 | 1.22 | 1.28 | **1.32** |
| Ames Corn Late 2016 | ACL-16 | h | 2.48 | 2.87 | 2.77 | **3.01** |
| Sutherland Soybean Early 2015 | SSE-15 | i | 1.54 | **4.36** | 2.67 | 2.24 |
| Sutherland Soybean Late 2015 | SSL-15 | j | 3.03 | **3.88** | 2.69 | 2.78 |
| Sutherland Corn Early 2015 | SCE-15 | k | 1.35 | 1.75 | **2.08** | 1.98 |
| Sutherland Corn Late 2015 | SCL-15 | l | 2.31 | 3.90 | **5.09** | 4.87 |
| Sutherland Soybean Early 2016 | SSE-16 | m | 2.25 | **2.53** | 2.44 | 2.39 |
| Sutherland Soybean Late 2016 | SSL-16 | n | **2.76** | 2.30 | 2.27 | 1.95 |
| Sutherland Corn Early 2016 | SCE-16 | o | 1.76 | 2.80 | 4.91 | **5.38** |
| Sutherland Corn Late 2016 | SCL-16 | p | 1.52 | **1.61** | 1.54 | 1.58 |
| # of times (fraction) most accurate of 16 most accurate | | | 2(12.5%) | 4(25%) | 4(25%) | 6(37.5%) |

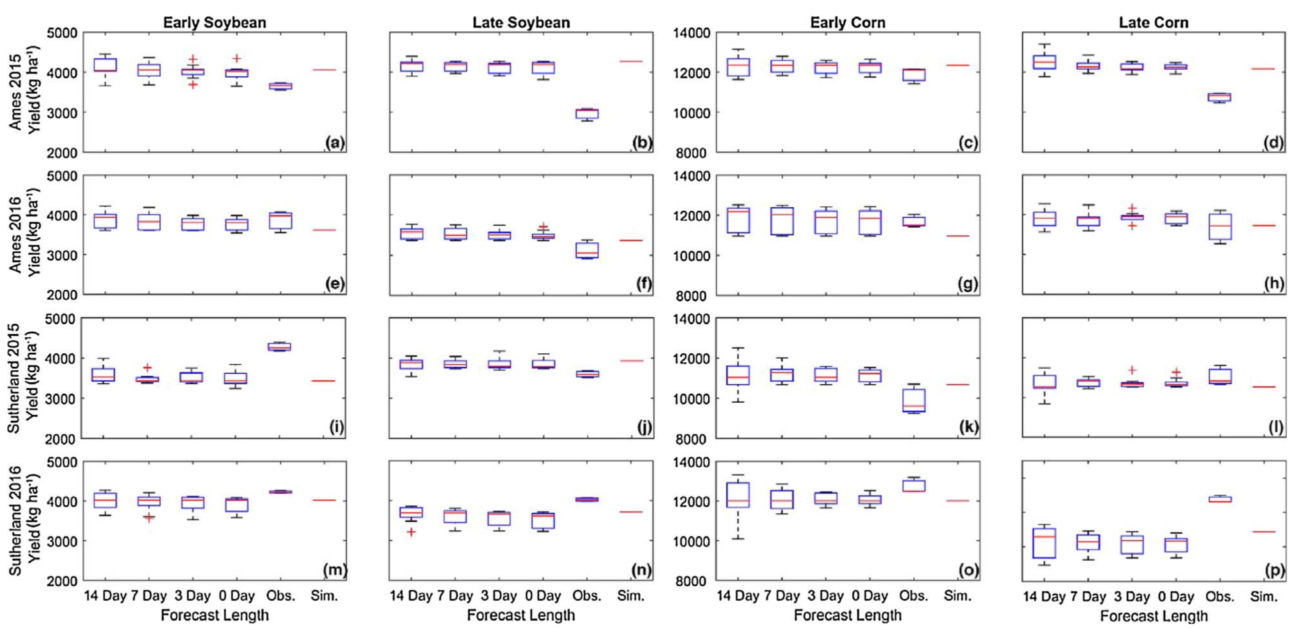


**Fig. 7.** Boxplots showing variability in yield prediction for each forecast length averaged across the season (~10 forecasts) for Ames and Sutherland. Variability in the observed yields (Obs.) and APSIM model simulations using actual weather data (sim) are also showed.

unpublished) that cumulative effect could buffer water stress, and make APSIM crop yield prediction insensitive to precipitation. Second, there were many days when precipitation was zero, a value which remained the same when multiplied by 15% or 30% during the APSIM weather variable sensitivity analysis.

The second part of our hypothesis that the inclusion of an explicit weather forecast will reduce crop yield prediction uncertainty and produce a reliable estimate with more lead time relative to using historical variation alone was also partially supported. WRF weather forecasts provided APSIM the ability to give decision makers lead time when deciding management changes due to the addition of forecasted weather data. Having enough lead time to make decisions can be benefited by using forecast lengths with the least variability (Hansen and Indeje, 2004). When comparing the standard error of yield of all of the forecast lengths, the 14 day forecast always had the smallest standard error (Fig. 9c and d). This can be due to the increased amount of consistent weather data being included into the APSIM weather file, because there is less variability in the weather forecasts that would have an impact on APSIM. This brings us to believe that including a 14 day forecast into APSIM can provide decision makers enough lead time to make field decisions when compared to a 0 day forecast that has no lead time. The 14 day forecast could provide decision makers enough time to get the equipment or chemicals they need to make changes to the management practices during the growing season, given also that the phenology prediction was good (Fig. 9c and d). This agrees also with findings from Asseng et al. (2016) and Gowing and Ejieji (2001) that a 14 day forecast may be sufficient to allow for decision making and management practices to be altered to have an effect on final yield. However, the 14 day forecast may not be reliable enough for end-of season yield predictions. The 14 day forecast can provide the lead time while the 3 day forecast can be used to make the final decision on what day to spray chemicals, apply side dress, or even harvest.

In general, over the entire growing season there is a decrease in normalized standard error (a measure of uncertainty) of the median yield predictions as the season progresses (Fig. 9). Reliable crop forecasts have the potential to greatly aid decision making in identifying

**Table 2**
Cumulative absolute value of accuracy for flowering calculated by Eq. (2) among the different forecast lengths. The bold numbers had the best accuracy over the entire growing season. The higher the number is, the better the accuracy.

| Cropping System | Acronym | Panels in Fig. S3 | Weather Forecast Length | | | |
|---|---|---|---|---|---|---|
| | | | 14 day | 7 day | 3 day | 0 day |
| Ames Soybean Early 2015 | ASE-15 | a | 8.57 | 20.00 | 20.00 | **30.03** |
| Ames Soybean Late 2015 | ASL-15 | b | **22.52** | 9.00 | 9.00 | 7.50 |
| Ames Corn Early 2015 | ACE-15 | c | 16.81 | 16.81 | **21.01** | **21.01** |
| Ames Corn Late 2015 | ACL-15 | d | **65.79** | 21.98 | 16.50 | 9.43 |
| Ames Soybean Early 2016 | ASE-16 | e | 2.84 | 2.84 | **3.00** | **3.00** |
| Ames Soybean Late 2016 | ASL-16 | f | 4.56 | **5.86** | 5.13 | **5.86** |
| Ames Corn Early 2016 | ACE-16 | g | 5.18 | 5.00 | 5.18 | **5.39** |
| Ames Corn Late 2016 | ACL-16 | h | **19.16** | 16.75 | 16.75 | 13.40 |
| Sutherland Soybean Early 2015 | SSE-15 | i | **13.61** | 11.34 | **13.61** | 8.50 |
| Sutherland Soybean Late 2015 | SSL-15 | j | **46.95** | 6.72 | 9.40 | 7.83 |
| Sutherland Corn Early 2015 | SCE-15 | k | **5.73** | 4.10 | 4.78 | 4.30 |
| Sutherland Corn Late 2015 | SCL-15 | l | **9.00** | 5.14 | 8.00 | 6.54 |
| Sutherland Soybean Early 2016 | SSE-16 | m | **8.57** | **8.57** | **8.57** | 7.50 |
| Sutherland Soybean Late 2016 | SSL-16 | n | 11.49 | 11.49 | **22.99** | 15.34 |
| Sutherland Corn Early 2016 | SCE-16 | o | 7.20 | 7.20 | **8.47** | 8.00 |
| Sutherland Corn Late 2016 | SCL-16 | p | 6.00 | **10.50** | 7.41 | 7.41 |
| # of times (fraction) most accurate of 22 most accurate | | | 8(36.4%) | 3(13.6%) | 6(27.3%) | 5(22.7%) |

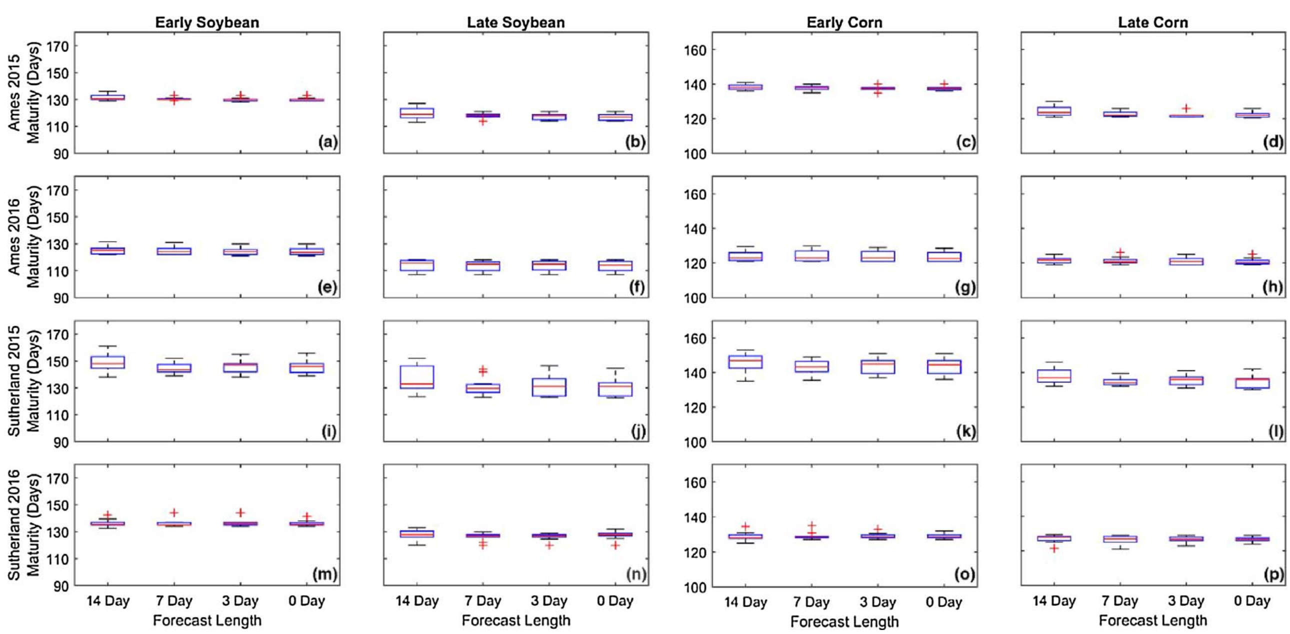


**Fig. 8.** Boxplots showing variability in maturity date (measured in days) for each forecast length for Ames 2015 (a–d), 2016 (e–h), and Sutherland 2015 (i–l) and 2016 (m–p). Early planted soybean (a, e, i, m), late planted soybean (b, f, j, n), early planted corn (c, g, k, o), and late planted corn (d, h, l, p) are displayed.

potential risks and benefits. However, it is important to ask when during the growing season a near-final forecast can be made. This question requires further investigation, but our work indicates that uncertainty substantially decreases from 100% (at planting) to 50% about 800 °C-days after planting (Fig. 9a and b).

The first forecast of yield from APSIM was close to the final simulated yields at the end of the season in many of the treatments and earlier than published studies (Quiring and Legates, 2008; Fig. S2). We believe this is a very important finding and provides opportunities to assist N-rate recommendations in the Midwest, given that nitrogen is applied at planting or early in the season (Puntel et al., 2016). In particular, process-based models have shown to be capable to assist N management decisions (Hammer et al., 1996; Shaffer, 2002; Kersebaum et al., 2005; Rahn et al., 2010; Nendel et al., 2013; Puntel et al., 2016), but so far the majority of models have being applied ex-post, which limits in season decision making. Forecast of growing season characteristics in time to adjust strategic pre-planting or in-season N management decision, offers the potential to account for climatic variations and to reduce adverse impacts or take advantage of favorable conditions.

The fact that APSIM median predictions (median predication from 35 years of APSIM run on that date) at planting time matched end-of season yields is most likely due to: a) accurate characterization of initial soil water and nitrogen, surface organic matter, cultivar characteristics, and model structure; and b) because 2015 and 2016 weather conditions were not outside of the 35 year climatology. Results from this work can inform other modeling platforms and research groups working on forecasting crop yields and environmental aspects of cropping systems: DSSAT (Jones et al., 2003; Hoogenboom et al., 2015), SALUS (Basso et al., 2010, 2012), Hybrid-maize (Yang et al., 2004).

### *4.2. Reasons for over/under predictions of crop yields during the season*

Through the mechanistic approach that APSIM simulates yields we were able to isolate the instances where yield predictions were inaccurate and identify the reasons. In many cases an inaccurate weather

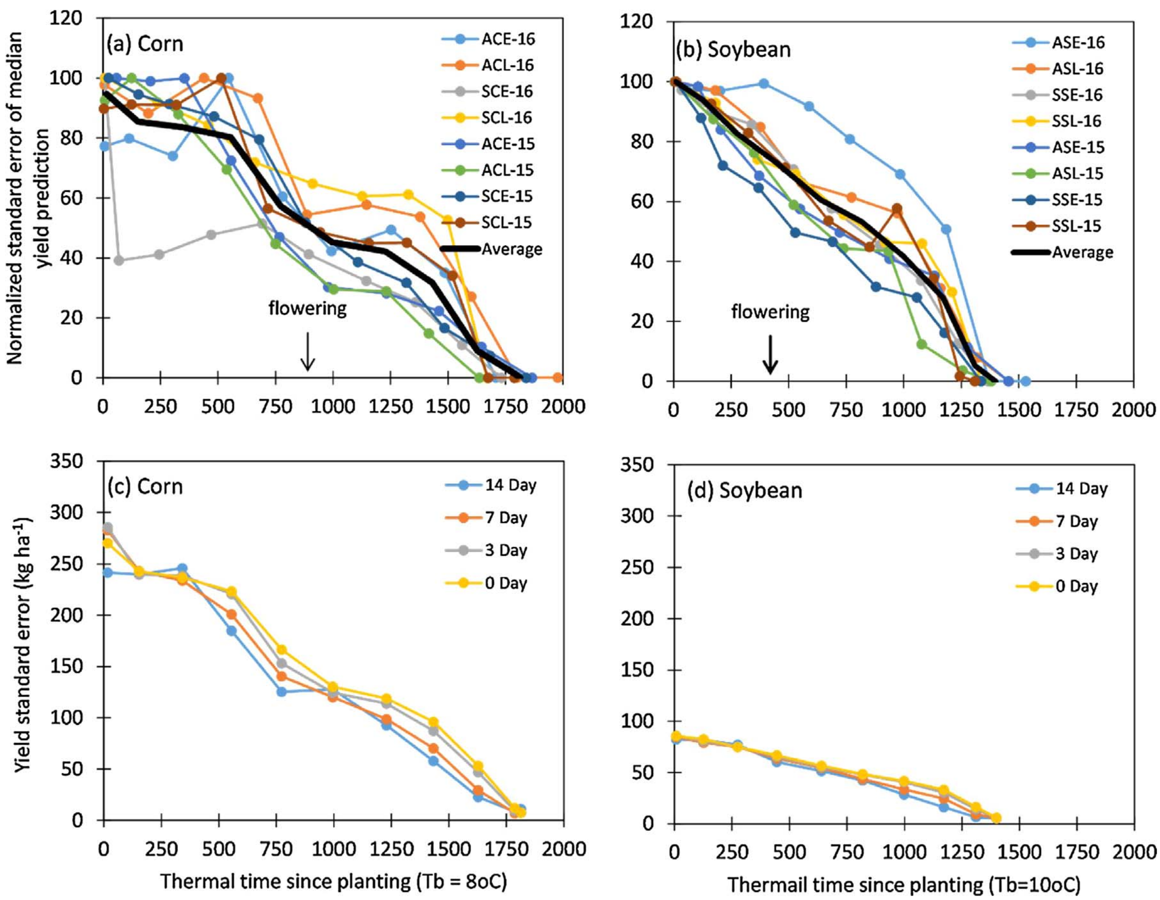


**Fig. 9.** Normalized standard error of median yield prediction for all corn (a) and soybean (b) treatments over the 2015 (15) and 2016 (16) growing season. Yield standard error for corn (c) and soybean (d) by forecast length.

forecast was the cause of the inaccuracies in the APSIM forecast predictions during the season. For example in 2015, early planted corn in Sutherland had two instances where the APSIM model predictions deviated substantially from the measured end-of-season yields. The underestimation (negative peak around July 1st; Fig. S2k) was influenced by minimum temperature in the 2nd week of the 14 day forecast. The forecast was too cold by 6.6 °C on average for the 2nd week of forecast, which explains why the 7 day forecast did not experience as much of a shift as the 14 day forecast. The over-prediction (positive peak around August 1st; Fig. S2k) was due to an increase in daily radiation in the WRF forecast compared to the actual observed weather by about 41%. In 2016 there was a similar peak (over-estimation) around August 15th that appeared in all 16 treatments, mostly in the 14 day forecast length. This was due to an increase in temperature in the WRF forecast relative to the observed weather by 4 °C a day during the 2nd week of the 14 day forecast (Fig. S2g, h, o, p). These examples suggests that APSIM is affected by the quality of the weather forecasts input into the model, at least during certain times during the growing season (Kouadio et al., 2015).

### *4.3. In-season forecast efforts and challenges*

Our approach is the first to combine a complete set of forecasted data for all four weather variables needed in the APSIM model for in-season forecast. Previous efforts integrating WRF predictions into APSIM focused on future climate impacts (until 2050; Jin et al., 2017). The analysis presented here is in-line with the findings of Asseng et al. (2016) but adds additional insight into each of the meteorological forcing variables and their relative contribution to uncertainty. Overall, the weather forecast used in our study was less accurate than that of Asseng et al. (2016) in terms of precipitation, but more realistic since it was an actual weather forecast and not an always correct forecast and included all weather variables. With a better weather forecast it seems that the APSIM predictions would only become more accurate, providing an even better yield forecasting tool. Gowing and Ejieji's, (2001) study was the most similar to ours in the sense that they used a real weather forecast implemented into their crop model. They used a 7 day weather forecast and their meteorological conditions that were unavailable (radiation) were estimated (sun-hours) for the forecasted period. In our study, radiation was explicitly predicted by WRF without the need to use sun-hours.

While our study focused on using different forecast lengths, another way that weather forecasting could be incorporated would be to use ensemble weather forecasting (Gneiting and Raftery, 2005). Ensembles would provide many results for each forecast, instead of just one set of results, but the computation efforts substantially increases. Other gridded meteorological conditions besides the GFS could also have been used, however since we wanted 14 days as the longest forecast we used the GFS. For simplicity, the current study uses the raw output from WRF. Future adjustments to the approach could include common weather forecasting procedures such as statistical corrections using post-processing methods (i.e. MOS; Mendoza et al., 2015).

### *4.4. Conclusions*

Forecasting crop production in-season is becoming increasingly important for agricultural producers to make informed crop management and financial decisions. Our approach contributed both methodologically and with results to further improve how in-season crop production forecasting can be done. The most important results are: 1) inclusion of weather forecasting into crop model added little value to end-of season yield predictions; 2) phenology predictions, which are largely used to schedule management operations, were benefited by the weather forecast; and 3) the accuracy of weather forecast was inversely related to the forecast length (0, 3, 7 and 14 days).

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## Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.fcr.2017.09.008.

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