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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