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Optimization of Agricultural Field Workability Predictions for Improved Risk Management

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ABSTRACT

Improved prediction of the days available for field work, or field working days (FWDs), is an important consideration for adapting farming systems to increased weather variability. We developed modeling approaches to estimate robust soil moisture thresholds for FWDs. We used simulated soil moisture to train the model on the same type of data that would be used for FWD forecasting (prediction). These new models were tested against previously suggested thresholds for field workability. Model 1 used historical field work and weather records from three crop research centers in a logistic regression model. A soil moisture threshold of 1.10 times the plastic limit (1.10PL) was identified. Model 2 identified statewide soil moisture and temperature thresholds by optimizing the root mean square error of the predicted number of weekly statewide FWDs across a 52-yr data set. The resulting thresholds of either 0.88PL or 0.73FC (field capacity) and an average temperature requirement of at least 6°C yielded statistically smaller absolute errors for the state average FWDs and in eight of the nine crop reporting districts. The Model 2 thresholds also eliminated systematic overprediction present in previous thresholds. These results demonstrate that immutable theoretical thresholds for FWDs based on field-measured soil moisture can be suboptimal for prediction at a larger spatial scale due to consistent bias.

Weather variation is a key determinant of which days are suitable for field work in mechanized crop production systems (Apland, 1993; de Toro and Hansson, 2004; Rotz and Harrigan, 2005). Growing evidence of global climate change means the ability to predict field working days (FWDs) could become more important as a tool to guide agricultural adaptation to new and potentially more extreme weather conditions (Intergovernmental Panel on Climate Change, 2007). Spatial variability inherent to climate change complicates drawing conclusions even between locations separated by fewer than 100 km (Cooper et al., 1997; Kucharik et al., 2010). New methods must be robust enough to account for scales smaller than the current outputs of regional and global climate change models.

The core approach to FWD prediction has remained much the same since the introduction of soil moisture modeling to the topic in the 1970s (Link, 1968; Kish and Privette, 1973; Elliot et al., 1975). Soil moisture is assumed to be the primary influence on workability (Earl, 1997), whereby soil above a certain moisture threshold is considered unworkable. Common choices for the critical moisture threshold are either 90, 95, or 100% of the soil gravimetric moisture at field capacity (0.90, 0.95, and 1.00FC, respectively) or the point at which the soil transitions from a semisolid to a plastic consistency, also known as 100% of the plastic limit (1.00PL). These limits are related to the ability to either work the soil properly (such as in seedbed preparation) or avoid compaction, also known as trafficability (Rounsevell, 1993). Suitable thresholds are often site or soil specific (Rounsevell, 1993; deToro and Hansson, 2004), and no large spatial-scale validations of thresholds exist to our knowledge. Actual field records have proven difficult to use as a tool in model construction because the full range of workable conditions may not be represented by the particular days when work was required (Seeley, 1995). Current field workability models also assume that the soil moisture threshold for a given soil is the same for all types of field operations. De Toro and Hansson (2004) asserted that these oversimplifications in determining and simulating field workability probably understate the consequences of years with extreme weather. The ability to accommodate such extremes will become more important given significant changes in extreme weather noted by researchers both globally and within the United States (Groisman et al., 2001; Kunkel, 2003; Intergovernmental Panel on Climate Change, 2007).

The Intergovernmental Panel on Climate Change (2007) has concluded that the frequency of heavy precipitation events has probably increased in most areas of the planet. In the U.S. Midwest, annual precipitation has increased 5% since 1960, and the amount of precipitation associated with the top 1% of daily events has increased 31% (Karl et al., 2009). About one-third of this increase can be attributed to heavier

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Abbreviations: FC, field capacity; FWD, field working day; PL, plastic limit.

spring precipitation (Karl et al., 2009). Projections indicate that further increases in winter and spring precipitation are likely (Wuebbles and Hayhoe, 2004). Furthermore, increases in winter precipitation can profoundly influence spring soil moisture levels in mid-latitude regions where thawing soils can account for the highest moisture levels observed in a year (Robock et al., 2000).

Maize (*Zea mays L.*) planting dates in the U.S. Midwest average 2 wk earlier than three decades ago despite greater spring precipitation during the same period (Kucharik, 2006). Early planting has become a necessity due to the high thermal time requirements for newer, late-maturing maize hybrids (Sacks and Kucharik, 2011). This represents a risk to future farmers, as Midwest precipitation projections show increasing volatility for early spring (Easterling et al., 2000; Wuebbles and Hayhoe, 2004; Kucharik, 2008). Given that many farmers purchase seed of specific cultivars in advance based on the previous year's weather (Smit et al., 1997), an increase in spring weather extremes and variability could have a great economic impact on agricultural risk assessments through field workability.

Our goal of enhancing FWD prediction framed the central objective of this study: to develop and evaluate independent FWD estimation approaches based on statistical modeling of empirical management and environmental data. The methods differed in the spatial and temporal resolution of the data. We specifically set out to use simulated soil moisture, as opposed to field-measured soil moisture, to remove the disconnect between the soil moisture data used for model building and forecasting into the future. The first method developed was based on the statistical analysis of long daily time series of field records from Midwest crop research centers, whereas the second method was based on weekly USDA FWD reports.

MATERIALS AND METHODS

Field Working Day Data

Field records indicating on which days work was performed from three University of Illinois crop research centers were compiled as model training data. Daily information derived from field records included: date, type of field operation performed on that date, and the soil series worked that day. The three locations were the Northern Illinois Agronomy Research Center (NIARC) in Shabbona (41°51′ N, 88°51′ W); Crop Sciences Research and Education Center (CSREC) in Urbana (40°20′ N, 88°14′ W); and Dixon Springs Agricultural Research Center (DSAC) in Dixon Springs (37°26′ N, 88°40′ W) (Supplemental Fig. S1). Field records were available for NIARC from 1966 to 2009, for DSAC from 1976 to 2007, and for CSREC from 2000 to 2008. This amounted to 76 site-years of field records. The dominant soil series at each of the research farms were Flanagan silt loam (a fine, smectitic, mesic Aquic Argiudoll) at NIARC and CSRES and Grantsburg silt loam (a fine-silty, mixed, active, mesic Oxyaquic Fragiudalf) at DSAC (National Cooperative Soil Survey, 2012).

The weekly statewide average number of days reported available for field work was obtained from the National Agricultural Statistics Service (2011) Illinois crop progress and condition reports. These reports included the aggregated (i.e., which days were actually workable were not specified) weekly average number of days available for field work for the entire state of Illinois since 1959. Each of the state's nine crop reporting districts reported its own weekly average number of field working days starting in 1980. The statewide FWDs were calculated as the average of FWDs of each district. The overall scope of the data assembled is extensive in both time and space. State average FWDs for 695 wk are reported and 420 wk of reported FWDs for each of the nine crop reporting districts formed the validation data set.

Daily Weather Data

Daily temperature and precipitation time series corresponding to field record intervals were obtained directly from the crop research centers. For statewide soil moisture reconstruction (see below), necessary weather parameters were obtained from the National Climatic Data Center (2012). Several weather stations were selected for each reporting district, based on data completeness (Supplemental Fig. S1). Selected stations generally contained <5% days with missing temperatures out of the total and as many continuous years as possible between 1959 and 2010. Any missing values were imputed using the following criteria: persistence of minimum and maximum temperature from the previous day and no precipitation. As a result of these imputation criteria, estimates of modeled soil moisture may be conservative. A total of 50 weather stations were included in the statewide soil moisture reconstruction and provide extensive latitudinal and longitudinal coverage of Illinois (Supplemental Fig. S1).

Soil Information

Soil properties used for estimating the plastic limit (PL) and field capacity (FC), as well as the inputs necessary for calculating daily soil moisture, were obtained from the National Cooperative Soil Survey (2012). Parameters for each soil included textural content of clay (C) and sand (S) percentages and organic matter percentage (OM).The field capacity of each soil was estimated using 33kPa (Saxton and Rawls, 2006):

$$\begin{aligned}\mathrm{FC} &= X + \left(1.283X^2\right) - 0.374X - 0.015 \\ X &= -0.251S + 0.195C + 0.011\mathrm{OM} + \\ &\quad 0.006(S\times\mathrm{OM}) - 0.27(C\times\mathrm{OM}) \\ &\quad + 0.452(S\times C) + 0.299\end{aligned} \qquad [1]$$

The PL of each soil was estimated based on (Keller and Dexter, 2012)

$$\begin{aligned}\mathrm{PL} &= 14.22(1.65) + 0.005\left(0.001\,C^2\right) + \\ &\quad 3.63\left(0.790\ \mathrm{OM}\right) - 0.048\left[0.017(C\times\mathrm{OM})\right]\end{aligned} \qquad [2]$$

Soil Moisture Estimation

A version of the Soil Temperature and Moisture model (STM^2), modified to automatically perform multiyear batch runs, was used to estimate the 10-cm-depth daily soil moisture at each location and for each soil type (Spokas and Forcella, 2009). This soil moisture model was chosen primarily due to the low input requirements for both soil properties and weather, which included daily precipitation, minimum and maximum temperature, soil textural qualities and organic matter content. The model has also proven reliable despite these low input requirements (Schutte et al., 2008; Spokas and Forcella, 2009; Perreault et al., 2013). Location, elevation, a general climate classification, and estimated average wind speeds were also specified.

Statewide Soil Moisture Reconstruction

To recover the daily field workability information contained in the National Agricultural Statistics Service crop progress reports, daily soil moisture conditions at point locations across the state were reconstructed in two steps. First, the Laboratory Pedon Data Map available through the National Cooperative Soil Survey (2012) was used to identify measured soils representative of agricultural fields within a few kilometers of each weather station (see above). Between one and three soils were associated with each of the weather stations based on the availability of soil samples measuring the parameters needed for soil moisture estimation (see above), for a total of 97 soil–weather combinations. Second, the daily weather time series and the corresponding soil properties were input to STM^2 to reconstruct statewide daily soil moisture conditions at each weather station location from 1959 to 2010, a total of 5499 different yearlong soil moisture time series. This collection of time series gives a simplified and approximate overview of statewide soil moisture conditions at particular points that span the state.

Model 1: Logistic Regression Field Workability Threshold

Logistic regression (Agresti, 2007) implemented in R (R Core Team, 2014) was used to analyze field records from the three crop research centers for the binary response *work* (whether or not field work was observed on each day between Day of Year 90 and 180, April–June). Other information collected or derived included estimated daily soil moisture, estimated PL, day of week, year, day of year, number of previous workdays observed in the same season, growing degree days, and type of field operation performed (tillage, planting, spraying, or fertilizing).

Using maximum likelihood methods (Burnham and Anderson, 2002), logistic regression models were fit individually to each research center's record to avoid the confounding effects of management differences across sites. The approach assumed that additional predictors in the model captured the signal produced by management decisions (necessity to perform field work), leaving the field workability signal in the data to be captured by soil moisture. A binary representation of soil moisture (above or below a threshold value) was chosen over a continuous soil moisture variable due to better model performance. Soil moisture thresholds used to create the binary soil moisture variable at each site were determined by iterating through different threshold values and choosing the threshold from the model that had the lowest Akaike information criterion value (Burnham and Anderson, 2002). A final threshold was calculated as an average of the site-specific thresholds, weighted by the observed number of FWDs.

Model 2: Best Statewide Workability Threshold

Field workability thresholds were determined at the statewide scale, using the statewide soil moisture reconstruction (see above) from 1959 to 2010 and the associated statewide weekly reported FWDs. While the data used were specific to Illinois, the model could be performed at other spatial scales and locations with similar data. For example, the data used are freely available in crop progress and condition reports for most of the United States on the statewide and state crop reporting district levels (National Agricultural Statistics Service, 2011). To find the best thresholds (standardized by either PL or FC), an iterative optimization procedure was implemented in R (R Core Team, 2014) to maximize the RMSE of predictions based on

$$\varphi(t)=\begin{cases}1, & \text{if}\left[\theta(t)<\text{moisture threshold}\right] \\ & \text{and}\left[\lambda(t)\geq\text{temperature threshold}\right] \\ 0, & \text{otherwise}\end{cases} \quad [3]$$

where $\varphi(t)$ is the indicator of whether Day t is workable, $\theta(t)$ is the soil moisture on Day t, and $\lambda(t)$ is the air temperature on Day t.

This optimization could be performed at the crop district scale for improved performance, but we demonstrate it here at the statewide level for more easily interpretable results. In addition, our record for statewide FWDs begins 21 yr (from 1959–1979) before reports at the crop district scale. An initial threshold was assumed so that each soil moisture time series in the soil moisture reconstruction was expressed as a series of 0 or 1 values corresponding to no workability being predicted or a workable day predicted, respectively. Statewide FWDs were predicted as the average of the weekly number of FWDs predicted among all crop reporting districts, emulating the calculations in the National Agricultural Statistics Service reports. The average number of FWDs for each district was calculated as the average predicted number of FWDs among weather stations. The FWDs associated with each weather station were calculated as the average number of FWDs predicted among all the soils corresponding to that station. This ensured that no single weather time series had greater influence than any other within a district, regardless of the number of soil measurements available for that station. The root mean squared error (RMSE) of the predicted number of weekly FWDs compared with the reported FWDs was calculated at each step. The procedure was repeated, incrementing the threshold in terms of FC or PL by 0.01 in each step (Fig. 1a). After achieving a minimum RMSE based on soil moisture threshold, the same iterative procedure was used to further optimize RMSE by finding a temperature threshold with the soil moisture threshold held fixed (Fig. 1b).

Model Verification

Six threshold models were compared using the statewide soil moisture reconstruction. These included: 0.90FC, 1.00FC, and 1.00PL (representing thresholds previously used in application studies), 1.10PL obtained by Model 1, and two optimal statewide thresholds derived from Model 2 with soil moisture

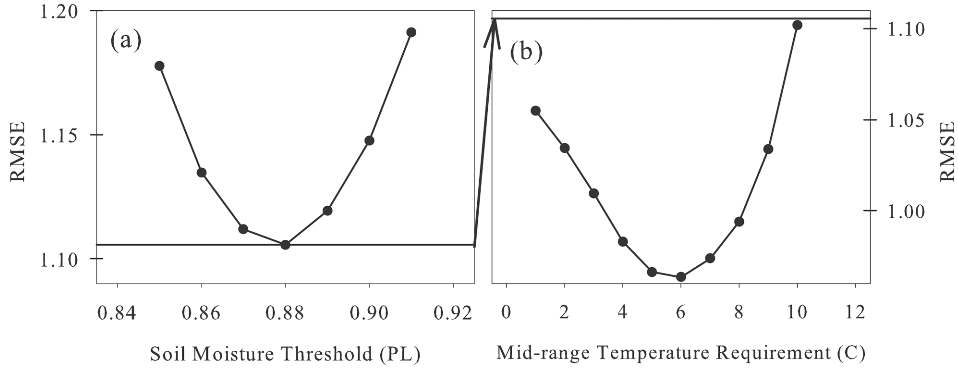

Fig. 1. Iterative optimization of root mean squared error (RMSE) of statewide field workability predictions over soil moisture thresholds scaled by soil plastic limit (PL) and daily temperature requirement (°C).

standardized by either FC or PL. The National Agricultural Statistics Service reports allow predictions to be verified for each of the nine crop reporting districts in the state in addition to the statewide average. The predictive performance of each threshold was measured using the same statewide soil moisture reconstruction across the entire period of the records. Differences in FWD prediction are introduced only by the different soil moisture thresholds for workability and the introduction of a temperature threshold for the two Model 2 models. The two metrics for verifying FWD predictions from each threshold were RMSE and the bias (average deviation of prediction) from the National Agricultural Statistics Service reported weekly number of FWDs. The RMSE is a measure of the overall goodness of fit, while the average deviation is an indicator of systematic bias in the predictions.

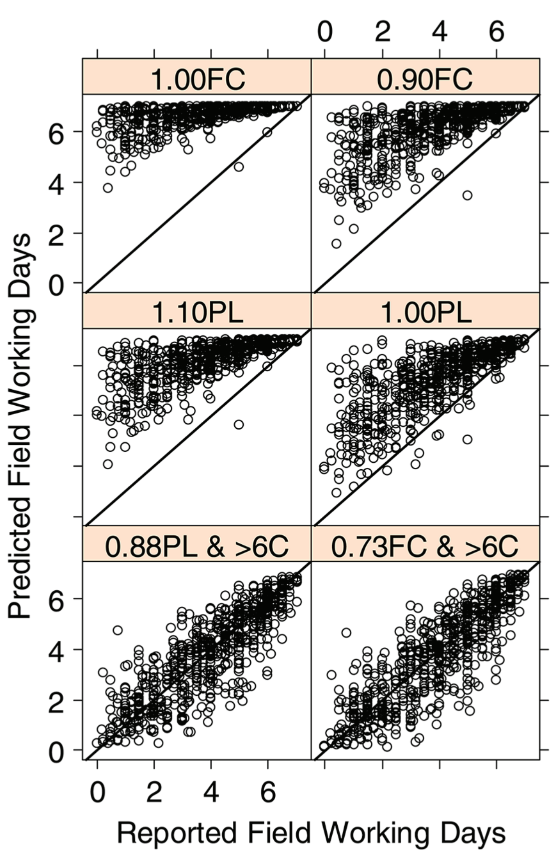

Fig. 2. Relationship between reported and predicted weekly statewide field working days in Illinois (1959–2010) for six different threshold models defined as coefficients multiplied by soil field capacity (FC) or plastic limit (PL). The bottom two models are identified by an optimization procedure and require average daily temperature to be at least 6°C.

RESULTS

A strong bias in weekly statewide FWD prediction was observed when using the 0.90FC, 1.00FC, 1.10PL (Model 1), and 1.00PL thresholds (Fig. 2). Furthermore, biases occurred in the same sign across all crop reporting districts, indicating that they are systematic. The positive bias for the 0.90FC, 1.00FC, 1.10PL, and 1.00PL thresholds indicated overestimation of available field working days week by week. Model 1 does a poor job of identifying an accurate threshold for FWD availability when applied at the statewide or crop district scale.

The Model 2 thresholds of 0.88PL or 0.73FC and an average temperature of at least 6°C eliminated prediction biases at the statewide level (Fig. 2). At the crop reporting district level, predictions based on Model 2 thresholds had some biases, but the biases were generally low in magnitude across all districts and varied in sign. Some spatial patterns in prediction biases were observed, with a tendency toward slight overprediction in the southeast (East-Southeast and Southeast districts) portion of the state and a tendency for underprediction in the north (Northwest and Northeast districts) (Supplemental Table S1).

Statistical comparisons of thresholds were limited to the 1.00PL and Model 2 thresholds due to their clear superiority over other thresholds (Table 1). While RMSE and bias are appropriate measures to summarize the overall predictive performance of each threshold, they do not allow for statistical testing. To attach statistical significance to the improvement in prediction, absolute prediction errors were compared using pairwise *t*-tests. Both optimized thresholds achieved statistically smaller absolute errors (corresponding to improved prediction) in eight of the nine crop reporting districts when compared with 1.00PL predictions (Table 1). Improvement in statewide prediction performance was >0.75 FWDs per week, which can be attributed to the elimination of systematic prediction biases. The 1.00PL threshold did perform as well as the optimized thresholds in the Southeast Crop Reporting District, but this appears to be the exception and not the rule. The improvement of optimized thresholds over the 0.90FC, 1.00FC, and Model 1 thresholds was even greater. For instance,

Table 1. Comparison of pairwise absolute weekly prediction errors between the three best-performing field workability models for Central (C), Northeast (NE), Southeast (SE), Northwest (NW), West-Southwest (WSW), East-Southeast (ESE), and West (W) Illinois crop reporting districts and statewide from 1959 to 2010. A positive number indicates that the first threshold performed more poorly.

	Mean difference in pairwise error									
Threshold† contrast	C	NE	SE	SE	NW	WSW	ESE	E	W	State
1.00PL vs. 0.88PL	0.80***	0.78***	–0.14 ns	0.36***	0.82***	0.67***	0.42***	0.89***	0.73***	0.81***
1.00PL vs. 0.73FC	0.74***	0.76***	0.07 ns	0.35***	0.80***	0.59***	0.24**	0.52***	0.71***	0.79***
0.88PL vs. 0.73FC	–0.06***	–0.03ns	0.21***	–0.01 ns	–0.02 ns	–0.08***	–0.18***	–0.37***	–0.03 ns	–0.02***

** Significant at $P < 0.01$; ns, not significant at $P < 0.05$.

*** Significant at $P < 0.001$.

† Thresholds consist of a coefficient multiplied by either field capacity (FC) or plastic limit (PL) of the soil, where exceeding the threshold indicates no field work can take place. The 1.00PL threshold is a theoretical threshold for field workability, while the 0.73FC and 0.88PL thresholds were determined from optimization on statewide reported data and include a minimum average temperature requirement of 6°C.

the RMSE in prediction was reduced by >1.5 FWDs per week using the optimized thresholds (Supplemental Table S1).

DISCUSSION

The evaluation of model performance in this study cautions against using established FWD thresholds without proper validation. Several factors complicate the reliability of these thresholds, including management decisions that affect soil moisture (i.e., tillage), the model used to simulate soil moisture, and the depth where soil moisture is measured. It is important to account for these differences for reliable risk assessments, which can depend on location and scale. This is especially true when projecting into the future, where a changed climate would invalidate retrospective studies of empirical FWD probabilities. As a solution to these complications, we investigated two new methods for obtaining a field workability threshold using empirical data sources that made few assumptions.

Model 1 used logistic regression on field records from three crop research centers located in Illinois for a combined 76 site-years. The soil moisture threshold resulting from Model 1 had poor predictive performance at larger spatial scales and serves to highlight the difficulty of using observational field records to build field workability models. There are several reasons to expect inaccuracies from workability thresholds derived from field records. Seeley (1995) pointed out that the precise timing required for some research projects result in "forced workdays," i.e., a day when soil is worked when it would usually be considered too wet. Second, days on which soils could be worked but were not because no work was required can account for a significant portion of the data. A final complication to prediction arises from precipitation events occurring on the boundaries between days (Rounsevell, 1993). The net result is a day that may be classified as unworkable based on a soil moisture threshold despite work being performed before rain occurred. These three phenomena are major sources of noise and complicate the identification of a threshold using field records.

Model 2 eliminates or controls for errors introduced by forced workdays and unworked workable days by training on data that report FWDs regardless of whether or not they were used. In addition, Model 2 uses a larger amount of data making it more robust to the influence of errors from precipitation events on the boundaries between days. The training data for Model 2 are specific to Illinois, but the model methodology of threshold identification through optimization should be applicable for different spatial scales and locations with similar data. For Illinois statewide FWDs using the STM^2 soil moisture model at the 10-cm depth, Model 2 identified workability thresholds of 0.88PL and 0.73FC, with an additional requirement of the average daily temperature being at least 6°C. These thresholds are quite close to the optimal soil moisture for tillage (0.90PL) identified by Mueller et al. (2003). This strengthens the conclusions reached by Model 2 and the validity of the method. It also demonstrates that the National Agricultural Statistics Service classified workable days close to the optimal workability for tillage at the statewide scale. The recognition of temperature as a limiting factor in field workability in addition to soil moisture was particularly important in improving the total number of April FWDs predicted in a season. Errors were reduced by including the temperature consideration in the Model 2 threshold by as many as 9 d in some seasons (Supplemental Fig. S2). While including a temperature threshold clearly improved Model 2 prediction (Fig. 1b), it would also have improved the predictions of all the other thresholds if it had been included (Supplemental Fig. S3). This improved performance from including temperature, regardless of the soil moisture threshold used, highlights the importance of incorporating temperature into FWD models.

With or without the inclusion of a temperature threshold, previously used thresholds of 0.90 to 1.00FC led to excessive overprediction of FWDs at multiple spatial scales. Similarly, a 1.00PL threshold also tended to overpredict the availability of FWDs. The errors resulting from overprediction were especially prominent in April and May (Fig. 3a). This is especially important because this is the temporal window when many important maize and soybean [*Glycine max* (L.) Merr.] management practices typically occur in the state. In other words, this overprediction occurs at the time when FWDs are likely to have the greatest economic value. Figure 3b shows that Model 2 still has this slight trend in error but also indicates that this optimized threshold is more reasonable for other operations because bias is reduced. Small biases also appeared spatially related in Model 2, with underprediction in the Northeast and Northwest districts and overprediction in the Southeast and East-Southeast districts. Errors in weather, soil, or both could account for these spatial patterns of bias given that we expect these inputs to have spatial structure. Nevertheless, these Model 2 prediction biases are quite small in comparison to biases introduced through other thresholds.

The primary utility of FWD prediction models is in risk assessment models. These models examine the relationship between management timing and factors such as changing climate (Cooper et al., 1997), machinery selection (Apland, 1993), or simply year-to-year weather variability (Rounsevell,

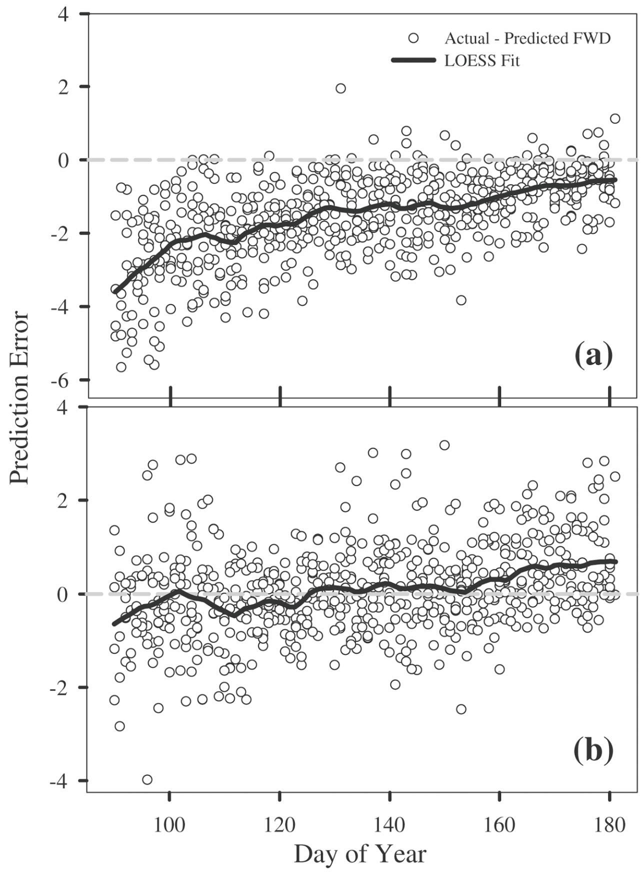

Fig. 3. Weekly Illinois statewide field working day (FWD) prediction error over day of year resulting from using (a) the plastic limit (1.00PL) soil moisture threshold for workability and (b) the optimized soil moisture threshold of 0.88PL with required average temperature of at least 6°C from 1959 to 2010. The solid LOESS lines indicate a local smoothing of the data points by the *loess* function.

1993). An unbiased model is required to appropriately quantify these risks. Accurate estimation of FWDs in April and May is especially important because FWDs during this time are associated with planting operations. Planting date is an important yield-influencing factor for both soybean and maize, where losses are incurred when planting outside optimal time windows (Lauer, 2009). In particular, the optimal maize planting date for much of Illinois occurs in the middle of April (around 11–20 April). Based on field studies conducted in Illinois, planting completed 2 wk later (around 1 May) than the optimal window resulted in an approximately 5% decrease in yield, with an additional 0.06 Mg/ha (~1 bu/acre) decrease per additional day of delayed planting past 1 May (Nafziger, 2008). Furthermore, the yield loss per day accelerates as planting is further delayed (Lauer, 2009). While overprediction of FWDs in most years would not affect the modeled planting date with respect to this window, it could for more extreme years. At the statewide level, for weeks when >30% of the maize area was reportedly planted, there was an average of 7.7% of the area planted per workable days observed. As a result, even though the reduction in prediction bias achieved by Model 2 may appear small, it could account for a considerable percentage of the area planted in extremely wet years.

CONCLUSIONS

Reducing bias in FWD predictions can contribute to risk management in field crop production. In wet or cold seasons, erroneously predicted FWDs could appreciably affect modeled impacts by pushing planting operations outside of the optimal yield window. In such cases, bias in FWD estimation would understate economic risks. To provide a more accurate and unbiased assessment of the implications of climate change on crop production, researchers need to carefully consider the threshold for field workability. Validation using multisite and long-term data sources will be a required step for accurate future assessments of climate change impacts on field workability. If possible, thresholds should be determined with a robust data set using the same soil moisture model, locations, and spatial scale as the future projections. Temperature should also be considered to improve prediction accuracy. Choosing these thresholds using optimization based on observed FWDs represents a way of obtaining robust and accurate thresholds that eliminate systematic prediction bias.

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