ABSTRACT
Thermal heat sum indices are used to predict the duration of corn \((Zea mays L.)\) growth intervals. Surprisingly, there exists very few studies in agronomic literature that assess predictive accuracy of these indices. This paper contributes to this topic in several ways using USDA-NASS corn growth data for Iowa (IA) and Illinois (IL) which together cover about 30% of corn production in the United States. First, the dataset spans from 1996 to 2016 and covers all the districts in both Iowa and Illinois. Second, the data are used to evaluate the predictive accuracy of several types of thermal heat sum indices (bilinear and nonlinear) for granular growth intervals. Third, the evaluation is executed using out-of-sample contemporaneous forecasts. The results show that nonlinear thermal heat sum indices (HSIs) have superior predictive accuracy to bilinear indices, whereas linear HSIs turn out to be inferior. Overall, the predicted durations using nonlinear thermal HSIs for the Iowa and Illinois combined districts are reasonably accurate. There is little bias across most of the growth intervals despite including the 2009 and 2012 growing seasons with extreme weather conditions. The mean absolute percentage error (MAPE) of the predicted durations relative to actual is well within 10% for almost all growth intervals across combined districts in IA and IL with a low MAPE of 5% for the full growing season duration using the nonlinear thermal heat sum indices. In comparison with other growth intervals, the vegetative growth interval has the lowest MAPE for both IA and IL combined districts.

Core Ideas
This paper evaluates the predictive accuracy of thermal heat sum indices.

• The data used is extensive both spatially (district level data for Iowa and Illinois) and temporally (period 1996–2016).

• This data is used to evaluate the predictive accuracy of several types of thermal heat sum indices (e.g., bilinear and non-linear) for granular growth intervals.

• The evaluation is executed by a novel technique using out-of-sample contemporaneous forecasts.

Evaluating the Predictive Accuracy of Corn Phenological Durations in Iowa and Illinois
Faisal H. Zai,* Herbert Hamers, and Patrick E. McSharry

CORN is an important source of food and feed with a significant role in global food security (FAO, 2012). The United States is one of the largest producers of corn in the world with mainly rain-fed production spread over a wide region in the Midwest referred to as the Corn Belt. According to the USDA the United States accounted for 36% of the total global corn production in 2015–2016 with a yield of 10.57 t ha\(^{-1}\), which is more than double the global corn yield of 5.38 t ha\(^{-1}\) (USDA, 2017). This study focuses on corn grown in the Corn Belt states of IA and IL. The states of IA and IL together account for about a third of the corn produced in the United States (USDA-NASS 2016).

Temperature is the primary environmental factor affecting plant growth. Other factors such as precipitation, photoperiod (i.e., interval length during a calendar day when the plant is exposed to sunlight) and humidity have a second order impact on growth (Stewart et al., 1998; Streck et al., 2008). Moreover, these second order factors, particularly precipitation and photoperiod, have strong interactions with the main effect of temperature and it is difficult to separate this interaction effect (Major et al., 1983; Shaykewich, 1995; Olesen et al., 2012). Therefore, this study uses temperature as the primary factor to model phenological growth.

Ecologists relate the time required for a plant growth interval to the amount of heat accumulated during the growth interval. The accumulated heat is referred to as a thermal “heat sum” (HS). A plant requires a particular thermal HS to complete a growth interval as opposed to a particular number of calendar days (duration). The distinction becomes significant due to the temperature variation across growing seasons. For example, in a relatively warmer growing season the thermal HS required for a growth interval will accumulate faster in fewer calendar days. Therefore, in the warmer growing season the plant will complete the growth interval in a shorter duration. The concept of thermal HS is very common in agriculture and dates to the 1730s, when Reaumur

Published in Agron. J. 111:1–13 (2019)
doi:10.2134/agronj2018.04.0294
Supplemental material available online
Available freely online through the author-supported open access option
© 2019 The author(s).

Abbreviations: CHU, crop heat unit; CP, crop progress; CV, coefficient of variation; GTI, general thermal index; HS, heat sum; HSI, heat sum index; IA, Iowa; IL, Illinois; KDD, killing degree days; MAPE, mean absolute percentage error; NCDC, National Climate Data Centre; PRISM, parameter-elevation regressions on independent slopes model; RMSE, root mean square error.
(1735) suggested that these can be used to predict the duration of plant growth intervals (Wang, 1960; Shaykewich, 1995).

There are different models to calculate a thermal HSI and each model is referred to as a thermal heat sum index (HSI). The thermal HSI is an effective accumulation of daily thermal HS using a particular (non) linear regression model. This regression model attempts to capture the relationship between temperature and corn growth. A wide variety of regression models (and thermal HSIs) have been proposed in the agronomy literature, that attempt to model this relationship between temperature and corn growth (Plett, 1992; Yin et al., 1995; Kumudini et al., 2014).

This empirical agricultural study uses thermal HSIs described in the literature to predict the duration of corn growth intervals. These thermal HSIs are commonly referred to in the agronomy literature (Shaykewich, 1995; McMaster and Wilhelm, 1997; Tojo Soler et al., 2005; Kumudini et al., 2014). Furthermore, these thermal HSIs have been selected on the basis of how well they capture the observed relationship between temperature and corn phenological growth as well as acceptance by farmers. The selection of these HSIs is explained in more detail in the section on “Thermal Heat Sum Indices”.

Thermal HSIs are commonly used to predict corn growth because of their simplicity in operational environments since they only use temperature as an input to predict growth. Farmers use the contemporaneous (i.e., where thermal HSI value and growth interval duration are for the same growing season) thermal HSI to predict corn growth interval durations for the current growing season. These predictions are used to make various decisions at the start and during the growing season. These decisions include selecting appropriate corn hybrids (which mature before the onset of winter frost) at the start of the season, planning optimal planting and harvesting times and scheduling the optimal times for spraying herbicides and fertilizers (Shaykewich 1995). Farmers also use the predictions to arrange field scouting visits and for large farms this can save substantial time and expense. In terms of agricultural risk management, farmers also use the predicted corn growth stages to assess the impact of unpredictable extreme weather events such as heavy rains on the eventual corn yield and price. Agricultural insurance purchased by farmers to manage risk have indemnification payouts linked not to actual yield but instead to the weather indices which for example measure the precipitation at a nearby weather station. This results in a difference between actual loss and the insurance payout, that is, basis risk. Predicted (contemporaneous) growth interval durations can be used to reduce this basis risk and the insurance can provide better agricultural risk management to farmers (Dalhaus et al., 2018).

However, despite their widespread use there are very few studies in the agronomic literature that evaluate the predictive accuracy of the different type of thermal HSIs (Kumudini et al., 2014; Roberts et al., 2012; Rivington and Koo, 2010). The objective of this study is to evaluate the predictive accuracy of the thermal HSIs selected.

The results show that nonlinear thermal HSIs have higher predictive accuracy than the linear and bilinear thermal HSIs for the combined districts in IA and IL for all growth intervals. This is in accordance with findings in the existing literature (Plett, 1992; Kumudini et al., 2014). The evidence shows that this study makes the following methodological contributions to the existing literature:

(i) Employing a more rigorous statistical framework to evaluate the predictive accuracy of thermal HSIs using an out-of-sample cross-validation procedure to evaluate the predictive accuracy of the 1-yr ahead forecasts. Existing literature uses the in-sample coefficient of variation (CV) to evaluate thermal time model precision. Out-of-sample cross-validation procedure has a clear advantage over the in-sample CV method when evaluating model predictive accuracy. This is because in-sample methods measure precision in terms of how well the models fit to the data (and may cause over-fitting) without measuring predictive accuracy which is what out-of-sample cross-validation methods are specifically designed to evaluate.

(ii) More extensive temporal data: this is to our knowledge the first time that district level data for all districts in IA and IL from 1996 to 2016 has been used for predicting corn growth. Kumudini et al. (2014), which is the most extensive study of precision of thermal time models (HSIs) for corn growth in the literature uses field trial data from various undisclosed locations in the North American Corn Belt from 2007 to 2011 and four field locations in Indiana and Ohio during 1991 to 1994. Importantly, Kumudini et al. (2014) measure the precision but not the predictive accuracy of thermal HSIs.

(iii) Using more granular growth interval data: this study uses granular interval data for seven corn phenological growth intervals. Relative to this study, Kumudini et al. (2014) with less granular temporal data or growth interval information, therefore lacks statistical rigor especially on the evaluation of predictive accuracy.

**MATERIALS AND METHODS**

The predictive accuracy is evaluated for different growth intervals in each district in IA and IL. Corn growth data reported by the USDA-NASS for the growing seasons from 1996 to 2016 and daily temperature data from the parameter-elevation regressions on independent slopes model (PRISM) daily dataset has been used. The relationship between contemporaneous thermal HSI and growth interval duration is modeled using a linear regression equation with the thermal HSI as the independent variable and the interval duration as the dependent variable. For each thermal HSI for each growing season from 2006 and 2016 the previous growing seasons from 1996 are used to fit the linear regression equation parameters and then generate a contemporaneous out-of-sample duration forecast. For example the data from 1996 to 2005 (sample) are used to fit a linear regression equation which is then used to calculate a contemporaneous 2006 forecast (out-of-sample). The out-of-sample forecast is then compared with actual reported duration to evaluate the predictive accuracy of the different thermal HSIs. This is one of the most widely used methods for estimating the predictive accuracy of the linear regression equations (James et al., 2000).

**DATA DESCRIPTION**

Corn Growth Interval Data from 1996 to 2016

Genetically modified (GM) corn hybrids were widely adopted in the United States after they became commercially available in 1996 (Fernandez-Cornejo and Caswell, 2006; Shen and Liu, 2015; Fuglie et al. 2007). It is important to allow for the adoption of GM corn hybrids in the United States when predicting
the duration of corn growth intervals. Therefore, this study uses historical corn growth data from 1996 to 2016.

USDA-NASS produces a weekly national Crop Progress (CP) report during the growing season (April–November) for selected crops including corn. The CP report produced at 1600 h eastern time on each Monday (or first business day of the week) shows the progress and condition for the preceding Sunday. Hence the CP reports show the weekly progress and condition with just a day’s reporting lag.

Crop corn growth progress and condition estimates in the CP report are based on survey data collected each week during the growing season. The non-probability crop progress and condition surveys include input from approximately 3600 respondents who rely on visual observations to provide subjective estimates of crop corn growth and evaluations of crop conditions (Crop Progress, 2017). The survey data are collected using surveys at the county level, which are then aggregated for the district and state levels. The two chosen study states, IA and IL, are two of the seven states that have both state-level and district-level corn growth, which together accounted for about half the U.S. corn production in 2016 (USDA-NASS, 2016). For the other corn producing states only state level aggregated corn growth stage is reported.

According to the USDA-NASS definition, “districts” represent a group of counties in a state on the basis of “geography, climate and cropping practices.” (USDA-NASS FAQ, 2018). Hence it has been assumed here that districts are a homogenous group of counties with respect to corn growth conditions. The U.S. states, on the other hand are large agricultural units and cannot be assumed to be sufficiently homogenous with respect to corn growth. Ideally, county level corn growth data should be used, however this is not currently available and the district level is the lowest level of corn growth data available to us from USDA-NASS.

The spatial focus of this study is the districts in IA and IL. Iowa lies to the Northwest of IL and there are nine districts each in IA and IL (Supplemental Fig. S1). The average corn planted area (in hectares) from 1996 to 2016 (courtesy USDA-NASS) is higher in the combined district in IA at 0.46 million ha compared with 0.45 million ha in the IL combined districts.

It is not reasonable to assume that all the corn in a district will grow concurrently as it is unlikely that all the corn in a district will be planted on the same day. Following the difference in planting day, the corn in a district is likely to be at different stages of corn growth at any one reporting date. It is assumed that corn in a particular district attains a particular stage of corn growth when 50% of the crop in the district is reported to have attained that corn growth stage. The CP reports do not report the date when 50% of the crops attain a particular corn growth stage but instead report the percentage of the total district corn crop at various corn growth stages on the reporting day. The calendar date that corresponds to 50% growth for each corn growth stage is estimated by interpolating between the reported calendar dates bracketing the 50% attained phenological growth. The interpolation is performed using the logistic function which is a well-known plant growth function (Yin et al., 2002). This interpolation process gives us estimated calendar date when 50% of the corn crop in a district attains a particular corn growth stage during each growing season from 1996 to 2016.

Once the calendar dates for all the corn growth stages are available the duration required for each corn growth interval is simply the number of calendar days between the growth interval start and end dates (both inclusive).

**Daily Temperature Data from 1996 to 2016**

Daily temperature data (minimum, maximum, and mean) are required to calculate the daily HS required for corn growth intervals. Daily minimum and maximum temperature from 1996 to 2016 for each U.S. county included in this study were downloaded from the PRISM daily dataset. It is generally accepted that PRISM is a good interpolation procedure (Schlenker and Roberts, 2009). The PRISM dataset has good spatial resolution (Johnston and Matlock, 2011) and also has good temporal resolution because it reports daily data from 1981. The National Climate Data Centre (NCDC) is commonly used as a weather data source in the agronomic literature, however the PRISM data are preferred here because the NCDC has data gaps for outlying (rural) areas (Johnston and Matlock, 2011).

The district level temperature is derived as the weighted average of the county temperatures. The averaging weights for the counties are set equal to the county average corn planted area from 1996 to 2016.

**Thermal Heat Sum Indices**

The thermal HSIs used in this study have been selected on the basis of the type of mathematical function relating temperature and corn growth. Six thermal HSIs (Table 1) have been selected, two each for the following regression types: linear, bilinear, and nonlinear. It is important to note that the thermal HSI parameters for each of the six thermal HSIs are assumed to be fixed and also assumed to be spatially invariant across the IA and IL districts. In an ideal scenario, these parameters should be calibrated for each district, however this will require detailed field trial data under controlled environmental conditions, which is not available.

An explanation of the choice of these six thermal HSIs is as follows. Growing degree days 1030 (GDD1030) HS index is one of the earliest and most commonly used thermal HSIs in the United States. It was developed by Gilmore and Rogers (1958) and uses daily minimum and maximum temperatures as inputs. This thermal HSI effectively uses a base temperature of 10°C with linear growth between the base (10°C) and upper (30°C) thresholds with no marginal growth outside these thresholds. Hence any heat above the 30°C threshold is not considered beneficial for plant growth. To test the threshold (10, 30) sensitivity, a variation of the GDD1030, the growing degree days 834 (GDD834) HSI is included. The GDD834 HSI has a base of 8°C and upper threshold of 34°C with no marginal growth outside these thresholds. The (8, 34) thresholds are based on the thermal HSI developed by Jones and Kiniry (1986) who used intra-day (3 hourly) temperature as opposed to the daily minimum/maximum temperature inputs used in GDD1030 HSI. Only daily temperature data but no intra-day temperature data has been used in this study.

There have been many studies investigating the relationship between temperature and growth, with one of the earliest ones conducted by Lehenbauer (1914). Lehenbauer (1914) and many others since then have shown that the relationship between temperature and corn growth is nonlinear such that growth increases from low temperatures (just above freezing) to optimum temperatures (close to 30°C) and then declines at high
Table 1. Description of the thermal HSIs used in this study.†

<table>
<thead>
<tr>
<th>Thermal HSI</th>
<th>HS type</th>
<th>Regression model to calculate the daily HS using temperature</th>
<th>Daily temperature inputs</th>
<th>Daily temperature input conditions</th>
</tr>
</thead>
<tbody>
<tr>
<td>GDD1030</td>
<td>Linear</td>
<td>[T_a = \frac{T_{\text{max}} - T_{\text{min}} - 10}{2}]</td>
<td>[T_{\text{min}} \text{ and } T_{\text{max}} \text{ are daily temperature minimum and maximum values respectively. All temperatures are measured in °C.}]</td>
<td>[T_e = T_{\text{min}} \text{ if } T_{\text{min}} &lt; 10 \text{, then } T_e = 10 \text{, and } T_{\text{max}} = T_{\text{max}} \text{ if } T_{\text{max}} &lt; 30 \text{, then } T_{\text{max}} = 30 \text{.}] Gilmore and Rogers (1958)</td>
</tr>
<tr>
<td>GDD834</td>
<td>Linear</td>
<td>[T_a = \frac{T_{\text{max}} - T_{\text{min}} - 8}{2}]</td>
<td>[T_{\text{min}} \text{ and } T_{\text{max}} \text{ are daily temperature minimum and maximum values respectively. All temperatures are measured in °C.}]</td>
<td>[T_e = T_{\text{min}} \text{ if } T_{\text{min}} &lt; 8 \text{, then } T_e = 8 \text{, and } T_{\text{max}} = T_{\text{max}} \text{ if } T_{\text{max}} &lt; 34 \text{, then } T_{\text{max}} = 34 \text{.}] Jones and Kiniry (1986)</td>
</tr>
<tr>
<td>KDD1030</td>
<td>Bilinear</td>
<td>[T_a = \frac{T_{\text{max}} - T_{\text{min}} - 10 - \text{KDD}}{2}]</td>
<td>[T_{\text{min}} \text{ and } T_{\text{max}} \text{ are daily temperature minimum and maximum values respectively. All temperatures are measured in °C.}]</td>
<td>[T_e = T_{\text{min}} \text{ if } T_{\text{min}} &lt; 10 \text{, then } T_e = 10 \text{, and } T_{\text{max}} = T_{\text{max}} \text{ if } T_{\text{max}} &lt; 30 \text{, then } T_{\text{max}} = 30 \text{.}] Gilmore and Rogers (1958)</td>
</tr>
<tr>
<td>KDD834</td>
<td>Bilinear</td>
<td>[T_a = \frac{T_{\text{max}} - T_{\text{min}} - 8 - \text{KDD}}{2}]</td>
<td>[T_{\text{min}} \text{ and } T_{\text{max}} \text{ are daily temperature minimum and maximum values respectively. All temperatures are measured in °C.}]</td>
<td>[T_e = T_{\text{min}} \text{ if } T_{\text{min}} &lt; 8 \text{, then } T_e = 8 \text{, and } T_{\text{max}} = T_{\text{max}} \text{ if } T_{\text{max}} &lt; 34 \text{, then } T_{\text{max}} = 34 \text{.}] Jones and Kiniry (1986)</td>
</tr>
<tr>
<td>CHU</td>
<td>Nonlinear</td>
<td>[\text{CHU}<em>{\text{min}} = 1.8(T</em>{\text{mean}}^2 - 4.4)] [\text{CHU}<em>{\text{max}} = 3.33(T</em>{\text{mean}} - 10) - 1.184(T_{\text{mean}} - 10)^2] [\text{CHU} = \frac{\text{CHU}<em>{\text{min}} - \text{CHU}</em>{\text{max}}}{2}]</td>
<td>[T_{\text{mean}} \text{ is the daily mean temperature. All temperatures are measured in °C.}]</td>
<td>[T_e = T_{\text{min}} \text{ if } T_{\text{min}} &lt; 4.4 \text{, then } T_e = 4.4 \text{, and } T_{\text{max}} = T_{\text{max}} \text{ if } T_{\text{max}} &lt; 10 \text{, then } T_{\text{max}} = 10 \text{.}]</td>
</tr>
<tr>
<td>GTI</td>
<td>Nonlinear</td>
<td>[\text{GTI}<em>{\text{veg}} = 0.043177(T</em>{\text{mean}}^2) - 0.000894(T_{\text{mean}})^3] [\text{GTI}<em>{\text{rep}} = 5.3581 + 0.01178(T</em>{\text{mean}})^2]</td>
<td>[T_{\text{mean}} \text{ is the daily mean temperature. All temperatures are measured in °C.}]</td>
<td>[T_e = T_{\text{min}} \text{ if } T_{\text{min}} &lt; 4.4 \text{, then } T_e = 4.4 \text{, and } T_{\text{max}} = T_{\text{max}} \text{ if } T_{\text{max}} &lt; 10 \text{, then } T_{\text{max}} = 10 \text{.}]</td>
</tr>
</tbody>
</table>

† HSI, heat sum index; GDD, growing degree days; KDD, killer degree days; CHU, crop heat units; GTI, general thermal index; HS, heat sum.

Temperatures beyond the optimum temperature (Tollenaar et al., 1979; Yin et al., 1995). The GDD1030 and GDD834 HSIs, simply assume no marginal growth (but no decline in growth) for high temperatures beyond the upper thresholds. To allow for the detrimental effects of high temperature on corn growth bilinear and nonlinear thermal HSIs have been included in this study. Despite the nonlinear impact of temperature on plant growth, linear HSIs such as the GDD1030 and GDD834 are very commonly used in the United States because of their simplicity. Hence, they are included in the analysis.

Killing degree days (KDD) is a measure of the detrimental (killing) impact of high temperatures on corn growth beyond a maximum (temperature) threshold. The KDD daily maximum temperature threshold in set at 30°C in this study, which is similar to the threshold used in previous studies (Cross and Zuber, 1972; Schlenker and Roberts, 2009; Butler and Huybers, 2015). The KDD1030 HSI is a bilinear HSI, which modifies the GDD1030 HSI by applying a linear penalty for daily maximum temperature above the KDD threshold of 30°C effectively reducing the value of the GDD1030 HSI. Similarly, KDD834 is a bilinear thermal HSI with a linear penalty for the GDD834 accumulation for the daily maximum temperature above the KDD threshold of 30°C.

To capture the nonlinear impact of temperature on plant growth nonlinear thermal HSIs have been considered in this study. The general thermal index (GTI) and crop heat units (CHU) HSIs represent nonlinear thermal HSIs in this study. Nonlinear thermal HSIs, in particular, the CHU have been in common use in Canada since the 1960s (Shaykewich, 1995; Kumudini et al., 2014). Research has further shown that the relationship between growth and temperature is not uniform across different corn growth intervals (Butler and Huybers, 2015). The GTI HSI attempts to capture this by allowing for different temperature-growth functions for vegetative (planting to silking) and reproductive (silking to maturity) stages. The choice of nonlinear indices is restricted to two indices which is equivalent to the number of linear and bi-linear indices in this study. The CHU and GTI HSIs have been selected specifically because previous assessments of precision of thermal HSIs in the literature such as Kumudini et al. (2014) show that these two nonlinear HSIs have better precision than other nonlinear HSIs.

**Evaluation of Thermal Heat Sum Index Predictive Accuracy**

In this study, the selected thermal HSIs (Table 1) are used to forecast the contemporaneous duration of growth intervals. The horizon of the forecast duration is 1 yr. The duration forecasts are next compared with actual reported durations to evaluate the predictive accuracy of the different thermal HSIs. The objective of this study is to evaluate the predictive accuracy of thermal HSIs. The predictive accuracy of the HSIs is evaluated using out-of-sample cross-validation. The most accurate thermal HSI found using this process is referred to as the “best index” for the growth interval in the district. $H_{i,j,k}^{(l)}$ is defined as the value of the thermal HSI $j$ for growth interval $k$ and district $l$, in the growing season $i$. $D_{i,j,k}^{(l)}$ is defined as the (observed) duration of growth interval $k$ for district $l$ in growing season $i$. Note that the observed values for are not dependent on the thermal HSI used, that is, they do not vary for different values of is calculated using the observed daily temperature and growth interval duration data. A linear regression model is used to define the relationship between the growth interval duration, $D_{i,j,k}^{(l)}$ and $H_{i,j,k}^{(l)}$:

\[
D_{i,j,k}^{(l)} = a_{i,j,k} + b_{i,j,k} \times H_{i,j,k}^{(l)} + \varepsilon_{i,j,k}
\]

where $a_{i,j,k}$ and $b_{i,j,k}$ are the regression intercept and slope respectively and $\varepsilon_{i,j,k}$ is the model error. The linear regression model is selected to improve the accuracy of the contemporaneous forecasts by debasing and rescaling the output of the thermal
**RESULTS AND DISCUSSION**

**Preliminary Data Analysis**

Seven corn growth intervals (Supplemental Fig. S2) are investigated in this study. The duration of the full growing season interval for the IA districts ranges between 160 and 180 days and is higher than the duration for the full growing season interval in the IL districts which ranges between 150 and 170 days (Supplemental Fig. S3, USDA-NASS). The full growing season interval durations are higher for the IL northern districts in comparison with the southern IL districts. This suggests that there is a North South divide with higher full growing season durations in the north of IL. The North South divide for the IL districts is also visible in the vegetative, reproductive, and R-1 intervals. The full growing season interval durations are shorter in the southern IL districts probably because the southern IL districts are warmer than the northern districts and the HS required for growth accumulates over a shorter duration. Noticeably this North South divide is less apparent for the IA districts. Evidently the North South divide is less apparent for some growth intervals such as the R-2 interval (Supplemental Fig. S4) than others and this highlights the heterogeneity within the growth intervals. Generally, the growth interval durations between IA and IL districts are different implying spatial heterogeneity.

The 2009 corn growing season was an abnormally cool and wet (due to high precipitation) both in IA and IL (State of the Climate [NOAA] 2009). On the other hand, the weather in the 2012 growing season was extremely hot and dry for both IA and IL (State of the Climate [NOAA] 2012) because of a severe drought in the United States. In fact, the 2012 agricultural drought in the United States is considered the most severe since 1988 and eventually the 2012 average corn yields were the lowest since 1995. The years 2009 and 2012 are distinct outliers for the full growing season intervals in most of the IA districts with an unusually longer than average duration in 2009 and shorter than average in 2012 (Supplemental Fig. S3). The surprising finding is that these years were not that unusual for the full growing season interval in the IL districts. This suggests that the impact of the abnormal weather in 2009 and 2012 was not uniform across IA districts and IL districts again stressing the differences between IA and IL. Noticeably the growing seasons in 2009 and 2012 do not appear to be outliers for the other growth intervals in IA and IL. This shows that the response of growth interval durations is quite different to abnormal weather conditions. Moreover, the impact of extreme weather differs across districts even within the same state. This is probably...
because the intensity of abnormal weather conditions varies both spatially and temporally in its incidence.

**DEPENDENCY ANALYSIS**

The analysis starts with a simple exploration of the dependency between the thermal HSI and growth interval duration. The dependency between a thermal HSI and growth interval duration is measured by calculating the Pearson correlation between the contemporaneous thermal HSI and growth interval duration for the growing season for all the combined districts. This gives us yearly correlations for each growing season from 1996 to 2016 for each thermal HSI and growth interval for all the combined districts in IA and IL. The yearly correlations are very noisy, and it is not possible to differentiate between the different thermal HSIs using this yearly correlation data. Therefore, the average correlation is analyzed over the period 1996 to 2016 to smoothen the random noise in yearly data for the IA and IL combined districts (Supplemental Table S1; Supplemental Table S2). For the IA combined districts, the correlation for the nonlinear HSIs is higher than the linear HSIs. The GTI HSI has the highest average correlation for the full growing season, reproductive and R-4 intervals, whereas the CHU index has the highest average correlation for the vegetative and R-1 growth intervals. Noticeably, the correlation is negative (with the 95% upper confidence limit less than zero) for the full growing season interval for the linear thermal models. Significantly for the full growing season and reproductive intervals in the IL combined districts the correlation is more negative (with 95% upper confidence limit less than zero) for linear thermal HSIs in comparison with the IA combined districts. A negative correlation between the thermal HSI and interval duration is counterintuitive because it is not possible to accumulate less HS over a longer duration in a growing season.

It is not clear why some thermal HSIs have a negative average correlation over the period 1996 to 2016. As a result the yearly correlations are analyzed to see if the average is negative due to relatively unusual growing seasons. Given the noise in the yearly correlation data, the moving 10-yr windows (starting from 2005 [window 1996–2005] to 2016 [window 2007–2016] for each thermal HS index) is used to smoothen the yearly correlations. The moving correlations for the different growth intervals in the IA combined districts follow a similar pattern and therefore, only the moving averages for the full growing season interval (Supplemental Fig. S5) are considered. A significant feature in the moving correlations for the full growing season interval is the steep decline in the moving correlation in 2009. Noticeably, the moving correlations generally move up following the 2009 decline. The moving correlation results for the full growing season interval in the combined IL districts (Supplemental Fig. S6) are by and large similar to the combined districts in IA.

Conspicuously in both the IA and IL combined districts (Supplemental Fig. S5; Supplemental Fig. S6) the moving correlations for the linear GDD1030 and GDD834 thermal HSIs switch from positive to persistently strong negative after 2009 for the full growing season interval. The nonlinear thermal HSIs do not exhibit this move from positive to consistent negative moving correlation. The bilinear thermal HSIs exhibit temporary weakness when the moving correlations turn temporarily negative. The persistently negative moving correlation implies an inverse relation between the thermal HSI and growth interval duration, which is counterintuitive. This inverse correlation highlights a weakness of the linear thermal HSIs relative to nonlinear and bi-linear thermal HSIs and compels us to exclude these HSIs (GDD1030, GDD834) from this study. It is surprising that there is no corresponding visible strong impact of the 2012 U.S. drought in the combined districts in IA and IL.

The impact of 2009 and 2012 is further analyzed by calculating the correlations over 1996 to 2016 by removing the 2009 and 2012 growing season data (Supplemental Table S3). The correlations increase after removing the 2009 growing season across all growth intervals and thermal HSIs. In fact, the negative correlation in the case of the linear thermal HSIs for the full growing season interval is no longer significantly negative with the 95% confidence interval (–0.17, 0.12) encompassing zero. Removing the 2012 growing season however appears to have relatively limited impact on the correlations for the IA combined districts. The impact of removing 2009 growing season is relatively muted for the IL combined districts (Supplemental Table S4) in comparison with the IA combined districts. This highlights the relative difference in the impact of the 2009 extreme for IA and IL combined districts with the impact being more severe in the IA combined districts. In fact, the correlation for the full growing season (and reproductive) interval remains negative (with the 95% upper confidence limits still below zero) even after removing the 2009 growing season. Removing the 2012 growing season has relatively limited impact on the correlations for the IL combined districts. This shows that the correlations are more susceptible to years with relatively high precipitation (as in 2009) and less to years with relatively low precipitation and drought-like conditions (as in 2012) in the IA combined districts (and to a lesser extent in the IL combined districts). This is an important distinction between abnormal weather conditions and seems reasonable because thermal HSIs by definition do not measure the impact of precipitation directly. They do so only indirectly through the interaction between precipitation and temperature but this interaction is unlikely to capture the impact of unusually high precipitation such as in 2009. Noticeably the impact of removing 2009 on the correlations is different for the IA and IL combined districts.

The analysis highlights the differences between the IA combined districts and IL combined districts in terms of the dependency between contemporaneous thermal HSIs and growth interval durations. The individual district level data within IA and IL are analyzed next. This is referred to as “stratification”. The stratification across districts was done to understand if there are any principal geographical differences in the dependency between thermal time HSIs and growth interval durations between the districts within IA and IL. The results showed that the districts within IA and IL, respectively, are relatively spatially homogeneous.

Overall, there is no compelling evidence for spatial heterogeneity between the districts within IA and IL, respectively, in terms of the dependency between thermal HSIs and growth interval durations. As a result, the districts in each state are combined. The effect of combining the district data is expected to not only reduce the impact of randomness in the results but also make the analysis more practical in an operating environment.
EVALUATION OF THERMAL HEAT SUM INDEX PREDICTIVE ACCURACY

Equipped with a better understanding of the relative weakness of the linear thermal HSIs to the extreme weather in the 2009 growing season, the study moves on to the main objective of evaluating the predictive accuracy of the remaining four thermal HSIs for the combined districts in IA and combined districts in IL. The preceding dependency analysis shows the counterintuitive persistent negative correlation between contemporaneous thermal HSI and growth interval duration for linear thermal HSIs. This is compelling evidence to exclude these indices from this study. Henceforth only the bilinear and nonlinear thermal HSIs are considered when evaluating the thermal model predictive accuracy in this study. Moreover, given the differences between the IA combined districts and IL combined districts these are analyzed separately.

The predictive accuracy of the bilinear and nonlinear thermal is evaluated using box plots of cross-validation r² values for the combined districts in IA (Fig. 1 and 2). On average across all the growth intervals the nonlinear thermal HSIs CHU and GTI have higher cross-validation r² values (i.e., higher predictive accuracy) than the bilinear thermal HSIs. This is consistent with the other related agronomy work that suggests that the nonlinear thermal HSIs have better precision (Kumudini et al., 2014). This is also consistent with the findings in the preceding dependency analysis. Furthermore, the GTI HSI has the highest average (across districts) cross-validation r² for five growth intervals full growing season, reproductive, R-2, R-3, and R-4 intervals. Meanwhile the CHU HSI has the highest average (across districts) cross-validation r² for the vegetative and R-1 intervals in the combined IA districts. This split between the GTI and CHU preference in the growth intervals is consistent with the finding in the preceding dependency analysis. Noticeable is the...
relatively low GTI average (across districts) cross-validation $r^2$ for the R-1 interval in comparison with the other thermal HSIs. This is again similar to the finding in the dependency analysis in the preceding section. This relative inaccuracy of the GTI HSI for the R-1 interval is probably driven by the difference in the relationship between temperature and growth for this growth interval relative to other growth intervals. Distinctively, the CHU HSI (averaged across districts) does much better at capturing this relationship for the R-1 interval.

Next the predictive accuracy of the bilinear and nonlinear thermal HSIs is evaluated using box plots of cross-validation $r^2$ values for the IL combined districts (Fig. 3 and 4). Unlike the IA combined districts, the difference in the average (across districts) cross-validation $r^2$ values is smaller between the different
thermal HSIs for the IL combined districts. This is probably due to the higher noise in the IL district level growth data. This again emphasizes the difference between the IA and IL combined districts. The GTI HSI has the highest average (across districts) cross-validation $r^2$ value for the full growing season, R-3 and R-4 growth intervals while the CHU HSI has the highest average (across districts) cross-validation $r^2$ value for the R-2 and R-1 intervals in the combined IL districts. For the vegetative and reproductive intervals in the IL combined districts the average (across districts) cross-validation $r^2$ value for the GTI HSI is only slightly higher than the CHU HSI value. The relative average (across districts) cross-validation $r^2$ value for the GTI HSI is again surprisingly low for the R-1 interval in the IL combined districts. Since this is a consistent finding across the IA and IL combined districts, it is most likely because the GTI HSI does not explain the relationship between temperature and growth in this interval as well as for other intervals.

The best thermal HSI for each growth interval is the index with the highest average cross-validation $r^2$ value across all the districts within the state (Table 2). The GTI HSI is the best for the full growing season, reproductive, R-3 and R-4 intervals across the IA and IL combined districts. Meanwhile, the CHU HSI is the best for the R-1 interval across the IA and IL combined districts. For the vegetative and R-2 intervals the selection of the best HSI differs across the IA and IL combined districts. Overall our findings across the IA and IL combined districts suggest that the nonlinear thermal HSIs have higher predictive accuracy than the bilinear models for all growth intervals across all the combined districts in IA and IL. This is consistent with the findings in the existing literature. However the existing literature is generally limited in terms of the spatial and/or temporal coverage and certainly does not consider the granularity of growth intervals as in our study (Plett, 1992; Kumudini et al., 2014). The results in this study are more robust as they show higher predictive accuracy of nonlinear thermal HSIs across a much larger spatial and temporal dataset with more granular growth intervals.

The results also show that the GTI HSI has better predictive accuracy than the CHU HSI overall which is where the findings here differ in previous agronomy work (Kumudini et al., 2014) which suggests that the CHU HSI has overall better precision than the GTI HSI. Note that the best thermal HSI has been selected on the basis of the average cross-validation $r^2$ across the IA combined districts and IL combined districts. The average cross-validation $r^2$ values for the combined districts have been used because the study does not find any evidence for spatial heterogeneity within the districts in the states in the dependency analysis. A separate stratified analysis showed that the best thermal HSI for each individual district by using the cross-validation $r^2$ values for each district and growth interval. The findings for the individual districts were similar to those for the combined districts and hence have not been reported here. Using combined districts to derive the best thermal HSI is the more practical approach in an operating environment and averaging across data also mitigates the noise in the district level data and is thus the preferred approach here.

Table 2. The best thermal heat sum index (HSI) for the growth intervals in the combined districts in Iowa (IA) and Illinois (IL). The best thermal HSI is defined as having the highest average cross-validation $r^2$ value across the combined districts in IA and the combined districts in IL.

<table>
<thead>
<tr>
<th>Growth interval</th>
<th>IA combined districts</th>
<th>IL combined districts</th>
</tr>
</thead>
<tbody>
<tr>
<td>Full growing season</td>
<td>GTI†</td>
<td>GTI</td>
</tr>
<tr>
<td>Vegetative</td>
<td>CHU</td>
<td>GTI</td>
</tr>
<tr>
<td>Reproductive</td>
<td>GTI</td>
<td>GTI</td>
</tr>
<tr>
<td>R-1</td>
<td>CHU</td>
<td>CHU</td>
</tr>
<tr>
<td>R-2</td>
<td>GTI</td>
<td>CHU</td>
</tr>
<tr>
<td>R-3</td>
<td>GTI</td>
<td>GTI</td>
</tr>
<tr>
<td>R-4</td>
<td>GTI</td>
<td>GTI</td>
</tr>
</tbody>
</table>

† GTI, general thermal index; CHU, crop heat unit.

This section validates the best thermal HSI by comparing the predicted growth interval durations with the observed interval durations published by USDA-NASS for the years 2006 to 2016 separately for IA combined districts and IL combined districts. The predictions are compared with the observed durations by fitting a validation linear regression and report the validation regression slope and regression $R^2$ (validation $R^2$). Good correspondence between the actual and predicted values is reflected by:

i. The validation $R^2$ value being close to one.

ii. The slope in the validation regression equation being close to one.

The predictions are less accurate for the full growing season interval in the 2009 and 2012 extreme years relative to other years with 2009 and 2012 clear outliers for the full growing season interval in the IA combined districts (Fig. 5). The full growing season interval durations are overestimated for 2012 and underestimated for 2009 in the IA districts. The impact of removing the 2009 and 2012 growing seasons on the validation $R^2$ is assessed later in this section. Noticeably, for the vegetative interval the drought in 2012 is not an outlier for the combined districts in IA even though it is for the full growing season interval. This emphasizes the differences between growth intervals for the IA combined districts with respect to the extreme 2012 weather impact.

The predictions in 2012 are more accurate for both the full growing season and vegetative intervals in IL combined districts (Fig. 6) suggesting that the 2012 drought was perhaps less extreme in IL districts in comparison with the IA districts. This is a surprising finding probably because the 2012 U.S. drought was not uniformly destructive across the IA and IL districts. The finding also highlights the importance of allowing for spatial heterogeneity when modeling the impact of extreme weather. This lower sensitivity to 2012 and also to 2009 to a lesser extent explains why the results for the full growing season and vegetative intervals for the combined districts in IL are generally more accurate (higher cross-validation $R^2$) than for the IA combined districts.

Overall the prediction using the best thermal HSI for the IA and IL combined districts is reasonably accurate (validation $R^2 > 0.5$) with little bias (validation slope close to 1) across all growth intervals even including the extreme years of 2009 and 2012 (Supplemental Table S5). Note, however, that in the case of the IA combined districts the validation $R^2$ is low ($R^2 < 0.5$) for the full growing season ($R^2 = 0.19$), vegetative ($R^2 = 0.48$) and reproductive ($R^2 = 0.28$) intervals. In the case of the IA combined districts the slopes are significantly different from one for only two intervals, that is, the vegetative and R-1 intervals for which the 95% confidence intervals are less than one. As a

VALIDATION OF THE BEST THERMAL HEAT SUM INDEX

The predictions are less accurate for the full growing season interval in the 2009 and 2012 extreme years relative to other years with 2009 and 2012 clear outliers for the full growing season interval in the IA combined districts (Fig. 5). The full growing season interval durations are overestimated for 2012 and underestimated for 2009 in the IA districts. The impact of removing the 2009 and 2012 growing seasons on the validation $R^2$ is assessed later in this section. Noticeably, for the vegetative interval the drought in 2012 is not an outlier for the combined districts in IA even though it is for the full growing season interval. This emphasizes the differences between growth intervals for the IA combined districts with respect to the extreme 2012 weather impact.

The predictions in 2012 are more accurate for both the full growing season and vegetative intervals in IL combined districts (Fig. 6) suggesting that the 2012 drought was perhaps less extreme in IL districts in comparison with the IA districts. This is a surprising finding probably because the 2012 U.S. drought was not uniformly destructive across the IA and IL districts. The finding also highlights the importance of allowing for spatial heterogeneity when modeling the impact of extreme weather. This lower sensitivity to 2012 and also to 2009 to a lesser extent explains why the results for the full growing season and vegetative intervals for the combined districts in IL are generally more accurate (higher cross-validation $R^2$) than for the IA combined districts.

Overall the prediction using the best thermal HSI for the IA and IL combined districts is reasonably accurate (validation $R^2 > 0.5$) with little bias (validation slope close to 1) across all growth intervals even including the extreme years of 2009 and 2012 (Supplemental Table S5). Note, however, that in the case of the IA combined districts the validation $R^2$ is low ($R^2 < 0.5$) for the full growing season ($R^2 = 0.19$), vegetative ($R^2 = 0.48$) and reproductive ($R^2 = 0.28$) intervals. In the case of the IA combined districts the slopes are significantly different from one for only two intervals, that is, the vegetative and R-1 intervals for which the 95% confidence intervals are less than one. As a
Fig. 5. Shows the relationship between the actual and predicted interval durations for the best thermal heat sum index (HSI) for the Iowa (IA) combined districts for the full growing season and vegetative intervals. Each data point in the graphs represents a district in a particular growing season. The blue data points represent the districts in year 2012, while the green data points represent the districts in 2009. The years 2009 (abnormally cold and wet) and 2012 (abnormally hot and dry) represent opposite weather extremes. Validation $R^2$ is a measure of how well actual (observed) durations are forecasted with a value of one indicating a perfect forecast.

Fig. 6. Shows the relationship between the actual and predicted interval durations for the best thermal heat sum index (HSI) for the Illinois (IL) combined districts for the full growing season and vegetative intervals. Each data point in the graphs represents a district in a particular growing season. The blue data points represent the districts in year 2012, while the green data points represent the districts in 2009. The years 2009 (abnormally cold and wet) and 2012 (abnormally hot and dry) represent opposite weather extremes. Validation $R^2$ is a measure of how well actual (observed) durations are forecasted with a value of one indicating a perfect forecast.
Table 3. Mean absolute percentage error (MAPE) relative to actual duration for the Iowa (IA) combined districts and Illinois (IL) combined districts with (and without the 2009 and 2012 yr) for the seven growth intervals and four thermal heat sum indices (HSIs) for the IA combined districts and IL combined districts.

<table>
<thead>
<tr>
<th>Growth interval</th>
<th>MAPE†</th>
<th>MAPE (after removing 2009 and 2012)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>KDD1030</td>
<td>KDD834</td>
</tr>
<tr>
<td>Full growing season</td>
<td>5.6%</td>
<td>5.5%</td>
</tr>
<tr>
<td>Vegetative</td>
<td>6.8%</td>
<td>6.4%</td>
</tr>
<tr>
<td>Reproductive</td>
<td>8.5%</td>
<td>8.3%</td>
</tr>
<tr>
<td>R-1</td>
<td>12.9%</td>
<td>12.0%</td>
</tr>
<tr>
<td>R-2</td>
<td>11.6%</td>
<td>11.1%</td>
</tr>
<tr>
<td>R-3</td>
<td>17.2%</td>
<td>17.0%</td>
</tr>
<tr>
<td>Full growing season</td>
<td>5.2%</td>
<td>5.1%</td>
</tr>
<tr>
<td>Vegetative</td>
<td>8.1%</td>
<td>6.6%</td>
</tr>
<tr>
<td>Reproductive</td>
<td>8.7%</td>
<td>8.9%</td>
</tr>
<tr>
<td>R-1</td>
<td>7.0%</td>
<td>6.8%</td>
</tr>
<tr>
<td>R-2</td>
<td>9.1%</td>
<td>7.9%</td>
</tr>
<tr>
<td>R-3</td>
<td>12.4%</td>
<td>12.0%</td>
</tr>
<tr>
<td>R-4</td>
<td>21.0%</td>
<td>21.3%</td>
</tr>
</tbody>
</table>

† KDD, killing degree days; CHU, crop heat unit; GTI, general thermal index.

The validation results are better for the IL combined districts with only one low validation $R^2$ ($R^2 = 0.25$) for the reproductive interval and the 95% slope confidence intervals encompassing the value of one for all the growth intervals. Noticeably, the validation $R^2$ is consistently low for the reproductive interval for both IA and IL combined districts. The major difference between the IA and IL districts is the higher regression $R^2$ values for the full growing season ($R^2 = 0.53$) and vegetative ($R^2 = 0.69$) intervals in the IL combined districts. In particular, there is no suggestion of a bias in the predictions for the vegetative interval in the IL combined districts unlike the IA combined districts. There is a suggestion of a small bias for the R-1 interval in the IL combined districts (95% confidence interval (0.84, 1) and the IA combined districts (95% confidence interval (0.73, 0.97). The consistency of this bias in the R-1 interval for both the IA and IL combined districts suggests that environmental factors other than the temperature might have an impact on corn growth during the R-1 interval.

The impact of removing the 2009 and 2012 growing seasons on the validation $R^2$ and slope (Supplemental Table S6) is considered in this study. The validation $R^2$ moves up (from $R^2 = 0.19$ to $R^2 = 0.31$) for the full growing season interval in the IA combined districts for the best thermal HSI. Similarly, the validation $R^2$ moves up in most cases across the IA and IL combined districts after removing the 2009 and 2012 growing seasons. The confidence intervals for the slopes become smaller across most growth intervals in the IA and IL combined districts after removing the 2009 and 2012 growing seasons. However, removing the 2009 and 2012 growing seasons does not remove the bias for the vegetative and R-1 intervals in the IA combined districts. Importantly, removing the 2009 and 2012 growing seasons does not alter the choice of the best thermal HSI as the validation $R^2$ and slope for the best thermal HSI remains high relative to the other thermal HSIs.

The MAPE relative to actual durations is less than 5% for the full growing season intervals in both the IA and IL combined districts (Table 3). However, the MAPE for the IA and IL combined districts is different for the other growth intervals but almost always within 10%. Generally, removing the 2009 and 2012 growing season decreases the MAPE for the IA combined districts and IL combined districts. The decrease in MAPE is relatively higher for the IA combined districts in comparison with the IL combined districts. This is because the impact of the extreme weather is 2009 and 2012 was relatively more extreme in the IA combined districts.

Table 4. Best thermal heat sum index (HSI) and mean absolute percentage error (MAPE) of the predicted durations relative to actual durations for each growth interval in Iowa (IA) and Illinois (IL) combined districts.

<table>
<thead>
<tr>
<th>Combined districts</th>
<th>MAPE†</th>
<th>MAPE (after removing 2009 and 2012)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>KDD1030</td>
<td>KDD834</td>
</tr>
<tr>
<td>Full growing season</td>
<td>4.7%</td>
<td>5.4%</td>
</tr>
<tr>
<td>Vegetative</td>
<td>4.7%</td>
<td>4.8%</td>
</tr>
</tbody>
</table>

† GTI, general thermal index; CHU, crop heat unit.
CONCLUSIONS

In conclusion, it is found that the nonlinear thermal HSIs have higher predictive accuracy than the bilinear (and linear) HSIs for both the IA and IL combined districts in terms of predicting contemporaneous corn growth interval durations (Table 4). The GTI HSI has higher predictive accuracy than the CHU HSI across most growth intervals in the combined districts in IA and IL. However, the relative ranking of the GTI HSI is unusually low for the R-1 interval in both the IA and IL combined districts. This highlights the relative heterogeneity of the growth intervals with respect to environmental factors in particular the R-1 interval. Overall, the predicted growth interval durations are reasonably accurate (within 5–10% of the actual durations), with low bias for most growth intervals in the combined districts in IA and IL despite the fact that the 2009 and 2012 extreme weather growing seasons are included.

It was expected that the nonlinear thermal HSIs would have better predictive accuracy. This was tested and the results show that this is true using a large spatial and temporal dataset with more granular growth intervals. However, only two nonlinear thermal HSIs are covered in this study. The current study needs to be extended to include more nonlinear thermal HSIs.

The study predicts the contemporaneous growth interval durations for granular U.S. corn phenological growth stages for the districts in Corn Belt states of IA and IL. This is important because many important farming operations such as corn hybrid selection, planning optimal planting and harvest times, application of fertilizers and herbicides and arranging field scouting visits depend on accurately predicting contemporaneous growth interval durations during the growing season. In terms of agricultural risk management, the predicted growth interval durations can also be used by farmers to assess the agricultural risk exposure to extreme weather in terms of the impact on corn yield and price. Agricultural insurance available to farmers carries a basis risk because the insurance indemnification is often linked to local weather indices instead of the actual yield. Predicted (contemporaneous) growth interval durations along with weather indices can be used to reduce this basis risk resulting in more efficient agricultural insurance available to farmers.

The main focus of this study is using thermal HSIs to predict corn growth interval durations for the districts in IA and IL. These two states account for about a third of the U.S. corn production. The current study, however, needs to be extended to include other states in the Corn Belt so that these results can be used to derive broader forecasts of corn growth at the U.S. national level. In addition to including more U.S. states, more nonlinear thermal HSIs should be included in the extended study. A further improvement can also be made by assessing the sensitivity of the predictions to the thermal HSI parameters which are assumed to be spatially invariant in the current study.

Finally, this work focused only on the corn grown in the United States and is predicated on detailed corn growth data with a wide spatial and temporal coverage. The work should be extended to include corn growing areas outside the United States. However, the detailed historical growth data available in the United States is not likely to be available for most settings outside the United States. A solution might be to use satellite data where available. Regardless of whether the growth data are available it is not clear if the results here can be extended to other crop growing areas. However, given the clear preference for nonlinear thermal HSIs to predict corn growth in IA and IL it is believed that these thermal HSIs will perform well in other similar rainfed corn growing environments.

SUPPLEMENTAL MATERIAL

An appendix containing supplemental tables and figures related to this study is available online.

REFERENCES


