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DISPLAYING AN ARIDITY INDEX AS A TOOL FOR MID-SEASON EVALUATION OF MIDWEST CORN YIELD

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1. INTRODUCTION

Because of the great economic importance of agriculture, it is favorable to recognize the degree of uncertainty regarding the season's harvest and to plan accordingly. The opportunity to benefit increases as lead-time of reliable information or prediction increases and the range of uncerainty narrows. Consequently, much work has been done to forecast crop yield. Walker (1989) reviewed the two main techniques of crop modeling, the simulation approach and the regression approach. Studies done with simulation models (e.g., Duchon 1986) require numerous details about crop management and environment. For yield estimation over a large area, the regression approach has been more widely used (Walker 1989). Because of the importance of moisture to crops and the harmfulness of limited moisture, it is natural to relate crop yield to the occurrence and severity of drought, which is usually expressed in terms of an index. Taylor (personal communication 2002) expains, "In order for index data to be a useful indicator for risk assessment, it must be simply derived and indicative of a result. The index concept is not intended to be rigorously predictive, but is expected to provide reliable assessment of risk and detection of risk change." Byun and Wilhite (1999) provide a summary of some drought indexes to preface their discussion of the advantages and disadvantages of the indexes:

> Most drought indexes are based on meteorological or hydrological variables. They include the Palmer Drought Severity Index (PDSI; Palmer 1965), Rainfall Anomaly Index (RAI; van Rooy 1965), deciles (Gibbs and Maher 1967), Crop Moisture Index (CMI; Palmer 1968), Bhalme and Mooly Drought Index (BMDI; Bhalme and Mooly 1980), Surface Water Supply Index (SWSI; Shafer and Dezman 1982), National Rainfall Index (RI; Gommes and Petrassi 1994), Standardized Precipitation Index (SPI; McKee et al. 1993, 1995), and Reclamation Drought Index (RDI; Weghorst 1996). The Soil Moisture Drought Index (SMDI; Hollinger et al. 1993) and Crop-Specific Drought Index (CSDI; Meyer et al. 1993; Meyer and Hubbard 1995) appeared after CMI. ... Of all the indexes, the PDSI is still the most widely used and recognized index on an operational basis (Byun and Wilhite 1999).

The popularity of the PDSI and CMI promotes uses, such as crop assessment, for which they were not intended (Meyer et al. 1993a), and in some situations prove to be quite unreliable (Meyer et al. 1991).

The following work provides the basis for applying the adapted aridity index described in this study to a sub-state level; namely climate/crop districts in several Midwest states. A monthly drought index computed by Walker (1989) is an example of an index perhaps better suited for regressions related to wheat yield. Walker (1989) observed a highly correlated relationship between the historical drought index and Canadian wheat yield, which he used to forecast 1987 Canadian wheat yield with the frequently updated drought index. As a step in separating the influence of weather from the influence of technology, Thompson (1986) presented a crop-weather model that related corn yield to preseason precipitation (September through June), June temperature, July precipitation, July temperature, August precipitation, and August temperature. Stephens et al. (1994) plotted a monthly weighted rain index against Australian district wheat yield. Because they were interested in wheat yield for all of Australia, they weighted each station's monthly rain according to the contribution percentage of the district to the total Australian wheat crop. Stephens et al. (1994) weighted the monthly rain according to its importance for the crop and made adjustments for soil moisture in drought or flooding situations. The index had a strong relationship to the average Australian wheat yield and Stephens et al. (1994) indicated that if the seasonal rainfall could be predicted accurately (such as with the Southern Oscillation), wheat yield assessment would be improved. Harouna and Carlson (1994) presented a monthly aridity index and evaluated Iowa corn and soybean trend adjusted yield against both July and August index values. Except for August, corn yields had the highest correlation to the aridity index when compared against July and August heat stress (Carlson 1990) and against July and August soil moisture levels (Shaw 1983). Harouna and Carlson (1994) suspected the correlation differences between the months were related to the crops' needs for varying amounts of water for each stage of development.

Harouna and Carlson's (1994) suspicions agree with Jensen (1968) and Nairizi and Rydzewski (1977) who showed that, for each crop growth stage, there are various yield responses to soil moisture stress. Indeed, this concept was reflected in Stephens' et al. (1994) weighting of monthly rain for Australian wheat and in Thompson's (1986) coefficients on the monthly precipitation terms in his model. Walker's (1989) area weighted drought index was also computed by summing

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the growth as a function of atmospheric demand and crop phenology.

Crop development, at some points in the life cycle, can advance to the next stage in just several days, so a monthly time scale can smooth the importance of the variable or split a growth stage into two pieces. A smaller time scale is likely to be better suited when dealing with crop growth and yield. Shaw (1983) applied weighting factors in 5-day groups on his daily stress index (SI). Shaw (1983) defined the stress index such that if corn transpired all the water it needed to maintain optimal growth, and if availability of moisture was sufficient, there was zero stress. The stress values become different from zero as the ratio of corn's actual evapotranspiration to the potential amount needed for maximizing production becomes different from 100 percent. When developing their crop-specific drought index (CSDI), Meyer et al. (1993a) recognized that crop development timing has to be considered when relating yield to drought or stress. The CSDI is also designated as a ratio of actual evapotranspiration to potential evapotranspiration, but crop development timing was incorporated by taking the evapotranspiration ratio to the power of a crop stage coefficient (Meyer et al. 1993a). Both authors reported satisfactory results with their respective indexes.

The yield prediction method by Shaw (1983) works well for Iowa and is founded on solid physical principles. However, the actual and potential evapotranspiration used in the stress index are calculated with measurements of precipitation, pan evaporation, and estimation of crop stage. Therefore, a problem with the method arises because the pan evaporation network density, maintained by the National Climatic Data Center (NCDC) and disseminated through NOAA (National Oceanic and Atmospheric Administration) National Data Center Climate Data Online (NNDC-CDO) (http://cdo.ncdc.noaa.gov/) is not very great across the Midwest. For the existing locations, it is possible to assume the pan evaporation at a single station may be representative of its district. However, at least one district in each state for the 2000 and 2001 seasons did not encompass a pan evaporation station, and thus is not conducive for consistent yield predictions across the many Midwest districts. Indeed, there were 8 stations lost and only 2 gained from 2000 to 2001.

The yield prediction method by Meyer et al. (1993a) also works well over a range of climate conditions and geographical locations, but complete data acquisition here is also a potential problem. To compute the potential evapotranspiration for the CSDI, the following daily station data are needed, which were assumed to be representative of a crop reporting district (CRD), net radiation, wind, minimum temperature, maximum temperature, and 24-h averaged dew point (Meyer et al. 1993a). The actual evapotranspiration calculation in the CSDI needs daily precipitation from several stations and soil water data (Meyer et al. 1993a). Meyer et al. (1993a) used growing degree days to indicate when to use the next crop stage coefficient. It was thought that net radiation and soil water data would be troublesome to collect in near real-time and the CSDI would be slightly cumbersome to maintain. Because the evaluation of actual and potential evapotranspiration is not straightforward and is not easy to assess in near real-time, an alternate method is explored in the rest of this study.

With deference to Shaw's (1983) stress index, air temperature plays a large role in evaporation from plants, and precipitation is a major factor for the availability of moisture, so it was thought that they alone could also be used in determining the amount of yield a corn crop will produce. In a general sense, an average amount of precipitation during the growing season (assuming a sufficient initial soil water profile) will provide sufficient moisture for an average corn crop. However, drier and warmer than usual (i.e., arid) conditions will stress the corn crop, which according to Shaw's (1983) stress yield relationship will result in a lower yield. Carlson et al. (1996) used the aridity index from Harouna and Carlson (1994) to confirm that conditions were usually wet and cool, which is favorable for corn (Thompson 1988), when the smooth running average of the Southern Oscillation index was less than -0.8 (El Niño) during the summer. The aridity index by Harouna and Carlson (1994), which uses precipitation and maximum temperature data (that were readily available from a particular source on a nearly daily basis in 2001 and 2002), fits well with the concept of crop yield deviating from trend when the weather deviates from average. Its ability to predict corn yield was tested below.

The adaptation of the aridity index made use of some concepts from Shaw's (1983) corn yield prediction program which was based on soil moisture and crop moisture stress. As discussed above, stress does not have a constant influence on the yield during the crop life cycle. In order to resolve the corn phenology, Harouna and Carlson's (1994) aridity index was reduced to a weekly time scale.

2. METHODOLOGY AND DATA

2.1 Definition of the Aridity Index (AI)

Harouna and Carlson (1994) used monthly precipitation's normalized departure from average, a technique discussed by Barring and Hulme (1991), and subtracted it from the monthly maximum temperature's normalized departure from average, applied in the same manner, to calculate an aridity index. Such a definition corresponded to positive values for warmer and drier than average conditions, which tend to have a negative effect on corn yield. Although the term "aridity" becomes a misnomer, the index from Harouna and Carlson (1994) was modified (Equation 2.1) so it is the *weekly* maximum temperature's normalized departure from average (Equation 2.2) subtracted from the *weekly* precipitation's normalized departure from average (Equation 2.3).

The index of aridity for each climate week (i) and year (j) is given by (climate week 1 begins March 1 for any given year):

$$AI_{ij} = P'_{ij} - T'_{ij} \tag{2.1}$$

where

$$P'_{ij} = \frac{P_{ij} - \overline{P_i}}{S_{pi}} \quad (2.2) \qquad T'_{ij} = \frac{T_{ij} - \overline{T_i}}{S_{ti}} \quad (2.3)$$

T'_{ij} (P'_{ij}) is the standardized weekly average maximum temperature (total precipitation) for week i and year j.

$\overline{T_i}$ ($\overline{P_i}$) is the weekly average maximum temperature (total precipitation) over all years for week i.

T_{ij} (P_{ij}) is the weekly average maximum temperature (total precipitation) for week i and year j.

S_{ti} (S_{pi}) is the standard deviation of the average maximum temperature (total precipitation) over all years for week i.

The index equally weights the contribution of temperature and precipitation and generally gives negative (positive) values when the weather is warm and dry (cool and wet). This definition has the accumulation of weighted negative weekly AI values (discussed later) correspond to low yield. This results in a slope that generally appears positive when yield deviations (clarified later) are plotted against the weighted weekly AI seasonal sum, and allows users to associate AI less than zero with a decreased chance of good yield.

Shaw (1983) dealt with the yield's response to the timing of stress by implementing a weighting scheme. Since silking time for corn is the most sensitive to stress, Shaw (1983) accordingly weighted stress during silking the most heavily and reduced the weight as the time (in 5-day periods) before and after silking increased. Shaw's (1983) yield prediction method starts with an initial potential yield and subtracts from it as stress accumulates. Thus, yield loss can be assessed during the season by noting the sum of stress values at the particular time. At the end of the season, the summed stress values give a seasonal stress index. These concepts, weighting for phenology and summing the index throughout the season, were incorporated here with the weekly AI.

A seasonal AI-yield relationship is different from a seasonal stress-yield relationship because, instead of starting with a potential yield and subtracting for stress, the AI method starts with a predicted yield extrapolated using trend line yield. The initial yield prediction deviates as the weekly AI sum deviates from zero. The weights applied to each week's AI were adopted from Shaw (1983) assuming the critical times for temperature and precipitation deviation from average are approximately the same as the critical times for stress. The seasonal progression of "weighted weekly AI" (AI_n) for weeks i = 11, 12, ..., 27 used for public information is computed by:

$$AI_n = \sum_{i=11}^{n} k_i AI_i \tag{2.4}$$

where k_i is the factor used to adjust for crop phenology at week i (Table 1). The value of AI_n can be zero if, for example, a cool and wet week followed a warm and dry week.

Climate Week (i)	**Begin Date**	**Weighting Factor (k_i)**
11	5/10	-0.5
12	5/17	-0.5
13	5/24	-0.5
14	5/31	0.5
15	6/7	0.5
16	6/14	0.5
17	6/21	1.0
18	6/28	1.0
19	7/5	1.0
20	7/12	1.0
21	7/19	2.2
22	7/26	1.6
23	8/2	1.3
24	8/9	1.3
25	8/16	1.3
26	8/23	1.0
27	8/30	0.75

Table 1 Climate week dates and corn phenology weighting factors.

2.2 Data

Daily precipitation and daily maximum temperature data were obtained from National Weather Service Cooperative Observer Program (COOP) stations disseminated by NCDC through NNDC-CDO (http://cdo.ncdc.noaa.gov/). For a given district, all available stations' daily data were sorted into the appropriate climate week and then averaged over the week and all stations. To standardize a given district's weekly precipitation and maximum temperature values with Equations 2.2 and 2.3, the 30-year (1971 to 2000) averages and standard deviations were used for the particular climate week. The standardized weekly precipitation and weekly maximum temperature were then used in Equation 2.1 to compute AI for all districts and for climate weeks 11, which begins May 10, through week 27, which begins August 30 (Table 1). After applying weighting, the index was summed over the season (hereafter seasonal AI or AI_{27}).

Corn yield data from the United States Department of Agriculture (USDA) National Agricultural Statistics Service (http://www.nass.usda.gov:81/ipedb/) were used to establish a relationship with AI_n. The USDA data consisted of district bushels acre^{-1} for the period 1980 through 2000. Though it is likely that irrigation costs would have a strong tie to AI, it was assumed irrigated corn yield would have a minimal tie to AI because irrigation overcomes the negative effect of warmer and drier than usual weather. Yields influenced by irrigation were avoided for districts in Kansas (KS), Nebraska (NE), South Dakota (SD), and North Dakota (ND) because non-irrigated yield data sets were available. Yields influenced by irrigation could not be avoided for districts in Iowa (IA), Illinois (IL), Indiana (IN), Missouri (MO), Minnesota (MN), and Wisconsin (WI) because the usually moister conditions in the eastern states means irrigation is used less and therefore a distinction was not made in the yield data. The states for which there was a distinction between irrigated and non-irrigated (KS, NE, SD, and ND; hereafter referred to as the western states) were analyzed separately from the states for which no irrigation distinction was made in the data (IA, IL, IN, MN, MO, and WI; hereafter referred to as the eastern states).

Corn yields have generally been increasing with time, so raw yields should not be compared to AI_n. For each district, linear regression was applied to the 1980 to 1999 yields. The residuals were then expressed as a percentage difference from the trend line. This percentage deviation of yield from the 1980 to 1999 linear trend will hereafter be referred to as YLD. Thus, the seasonal AI for each year, 1980 to 1999, had a corresponding YLD (except for SD from 1980 to 1983 and for ND from 1980 to 1981, for which relevant yield data were not available). Eastern states' YLD were less variable than the YLD for the western states, and could be modeled. Though western states' YLD was not modeled, both regions' AI_{27} and YLD were analyzed.

3. ANALYSIS

Figures 1a and 1b show YLD versus seasonal AI for the eastern states and the western states, respectively. Data plots for the extraordinary year of 1993 were included, but were not used for fitting models because, although the 1993 data plots fit with the other years' data plots, they were clearly more variable and would increase the uncertainty of predictions. Even though flooding in 1993 did not affect the entire 10-state area, all 1993 data were left out for simplicity. Average weather is less beneficial to a corn crop with increasing latitude (i.e., too cool), causing the relationship between seasonal AI and YLD to be less consistent. The data for northern districts in MN and WI did not fit well with the curve in Figure 1a, but were kept as part of the data set in the interest of broader application of the AI method. However, it was thought that this AI method should not be used for the 3rd district of MN because of the inconsistent relationship of this district's YLD to AI_{27}, so MN 3 was excluded.

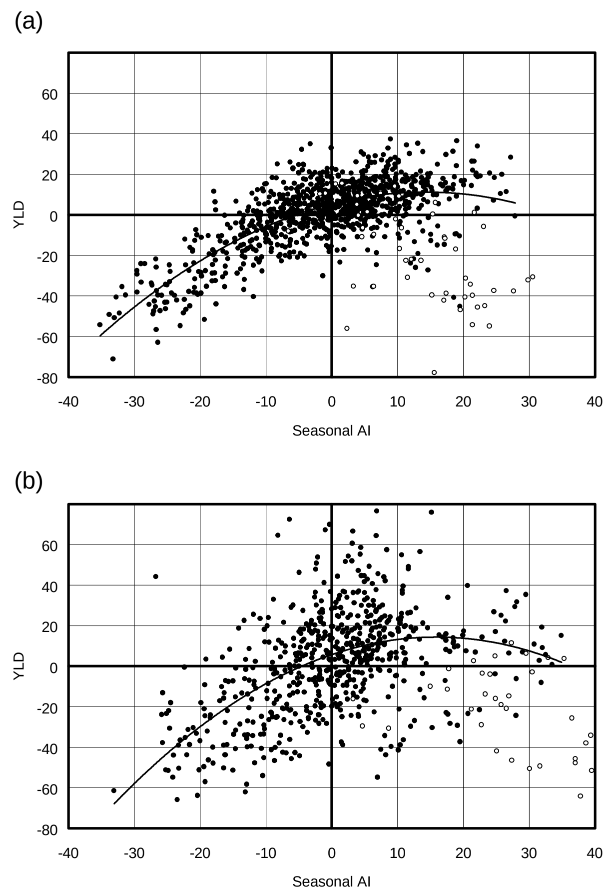

Figure 1 YLD versus seasonal AI from 1980 to 1999 for districts in the eastern states (a) and in the western states (b). Thin curved lines are the least squared fits of second order linear regression equations. 1993 was excluded from curve fitting, but plots are included as unfilled circles.

3.1 Late Season Relationship of YLD to AI and Application

It was clear from Figures 1a and 1b that highly negative seasonal AI is harmful to the corn crop because of the arid conditions. In other words, YLD values become increasingly negative as arid conditions persist (increasingly negative AI_n values). Theoretically and similarly, YLD values could become increasingly negative if very cool and wet conditions persist (increasingly positive AI_n values). Though the latter happens less frequently, the scatter on the positive AI_{27} side of the charts in Figures 1a and 1b support the idea. Average precipitation and average maximum temperatures (AI_n of approximately zero), more often than not, produced YLD above trend. These situations suggest a physically realistic quadratic relationship between YLD and AI_{27}.

Although better seasonal AI based yield models may exist, only a second order multiple regression model was explored in this study because of the physical basis for such a model. An alternate approach is discussed in Section 5. The general multiple linear regression model is given by Equation 3.1 (Ott 1993).

$$\hat{Y} = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_k x_k + \varepsilon \qquad (3.1)$$

To capture the quadratic relationship between YLD (the dependent variable) and AI_{27} (the independent variable), k = 2, x_1 was substituted with AI_{27}, and x_2 was substituted with $(AI_{27})^2$. Coefficients associated with the curves in Figures 1a and 1b are shown in Table 2 along with the estimated variance of the residuals [$\hat{\sigma}^2_\varepsilon$ where ε = YLD - ($\hat{Y}$ | $AI_{27} = ai_{27}$)].

Figure	$\hat{\beta}_0$	$\hat{\beta}_1$	$\hat{\beta}_2$	$\hat{\sigma}^2_\varepsilon$
1a (Eastern)	5.338	0.825	-0.029	123.0
1b (Western)	5.706	1.090	-0.034	506.2

Table 2 Coefficient estimates for models plotted in Figure 1 and the estimated variance of the residuals. Evidence was sufficient to suggest coefficients were not equal to zero.

The curve in Figure 1b is similar to the curve in Figure 1a. The relationship between YLD and seasonal AI was much less consistent for the western states (Figure 1b) than it was for the eastern states (Figure 1a). This is indicated by the large difference in $\hat{\sigma}^2_\varepsilon$ values in Table 2 and the difference in the patterns of residual scatter (not shown). For the eastern districts, residual scatter for a given setting of AI_{27} (ε_{AI}) was assumed to be normally distributed with mean equal to zero and variance equal to $\hat{\sigma}^2_\varepsilon$. The variance $\hat{\sigma}^2_\varepsilon$ was assumed to be constant for all AI_{27} settings and ε_{AI} were assumed to be independent (Ott 1993) though there might be some spatial dependence (Anderson personal communication 2002). This information can be used to estimate the probability that a particular eastern district YLD will be between arbitrary ranges given an AI_{27} value. The standard deviation for the western states' residuals was about twice that of the eastern states' residuals, and it was concluded that the uncertainty of $\hat{Y}$ for western districts was too high to be used with much confidence.

By assuming $\hat{\sigma}^2_\varepsilon$ is normally distributed, z-scores (Ott 1993) could be used to estimate the probability that a particular YLD would be within the arbitrarily chosen range of ±5 units (a "unit" here is 1 % of the trended yield) of the $\hat{Y}$ value for a given setting of AI_{27}. The z-score for 5 units was 0.4508 (or 5 units is an estimated 0.4508 standard deviations ($\hat{\sigma}_\varepsilon$ = 11.1) away from the mean). The corresponding probability for a z-score equal to ±0.4508 is 2*(0.177) or 0.354. This means there is about a 35% chance that actual YLD will be within ±5 units of the value calculated (assuming $\hat{Y}$ is the mean YLD for a given setting of AI_{27}) from the eastern states' model (assembled from the appropriate coefficients in Table 2). Compared to modeled YLD, approximately a third of actual YLD values will be over 5 units from the modeled YLD, approximately a third of actual YLD values will be under 5 units from the modeled YLD, and approximately a third of actual YLD values will be within 5 units of the modeled YLD.

The late season application becomes invalid if utilized too early. However, even if an evaluation could only be made at the end of week 27 (September 5), it would still be beneficial because the crop would stand about 2-4 weeks before harvest would begin, which is about September 22 (http://www.lgseeds.com/). If the modeled YLD is accurate enough, this lead-time could be enough to be quite serviceable. Fortunately, because of the importance of moisture during silking, it is quite possible to make valid computations a couple of months before season's end of modeled YLD based on the value of AI_n. Therefore, a weekly AI_n assessment has value even if the weather varies from average because an AI_n tending upward (downward) would indicate an above (below) trend YLD and/or continued gain (loss).

3.2 Early Season Relationship of YLD to AI and Application

At the beginning of the season, AI_n is set to zero. The start from zero, fractional weighting, and tendency for AI components to be near average usually keep the first weeks' AI_n values very small. As a result, the season end relationships seen in Figure 1 are not useful early in the season. Until weighting is heavier and AI_n has had a chance to accumulate, such that one can anticipate using the season-end relationship (a week or two before silking week, assumed to be week 21), Table 3 can be used to make AI_n-based evaluations of the crop's potential. Table 3 present the 1980 to 1999 eastern states' percentage of cases with above trend YLD for particular ranges of AI_n. Evidence to suggest the percentages on the tables are different than the unconditional chance of being above trend (62.5%) was determined with Equation 3.2, which is the normal approximation to the binomial test statistic (Ott 1993).

$$z = \frac{\hat{\pi} - \pi_0}{\sigma_{\hat{\pi}}} \qquad (3.2)$$

where $\hat{\pi}$ is a particular percentage from Table 3, π_0 is the unconditional percentage of being above trend (= 0.625), and $\sigma_{\hat{\pi}}$ = [$\pi_0(1-\pi_0)$n-1] 0.5 where n is the total cases associated with the particular percentage.

	% Cases above Trend ($\hat{\pi}$)			
AI	cw13	cw17	cw21	cw25
-32 to -30				AI < -12
-30 to -28				
-28 to -26				
-26 to -24				
-24 to -22				
-22 to -20				
-20 to -18				
-18 to -16				
-16 to -14				
-14 to -12				
-12 to -10				18.2†
-10 to -8			25.5†	49.2†
-8 to -6		66.7	38.8†	64.8
-6 to -4	55.0	35.0†	54.8	60.0
-4 to -2	63.1	48.6†	66.7	70.3
-2 to 0	58.3	64.5	65.4	68.1
0 to 2	69.0‡	73.1‡	71.1‡	67.9
2 to 4	51.5†	70.2	78.5‡	85.5‡
4 to 6		75.0	87.1‡	78.6‡
6 to 8		66.7	79.2‡	83.3‡
8 to 10			AI > 8	84.3‡
10 to 12				81.1‡
12 to 14				77.1
14 to 16				AI > 14
16 to 18				
18 to 20				
20 to 22				
22 to 24				

Table 3 For particular AI values, the percentage of eastern states' districts with positive YLD (1980 to 1999) at week 13 (2 months before silking), at week 17 (1 month before silking), at week 21 (about silking time), and at week 25 (about 1 month after silking). ‡ (†) indicates percentage is significantly (at the 0.05 probability level) higher (lower) than the unconditional percentage of cases above trend ($\pi_0 = 62.5\%$).

If $|z| > z_{\alpha/2}$ ($z_{\alpha/2} = 1.96$ for $\alpha = 0.05$), the hypothesis that a particular percentage is the same as the unconditional percentage ($\pi = \pi_0$) was rejected and the particular percentage was said to be higher than the unconditional percentage if z was greater than zero (‡) and lower than the unconditional percentage if z was less than zero (†).

After the third calculation of AI for the season for all years (week 13: about 2 months before silking), the range for AI13 was quite small (Table 3). However, some value can be derived from AI_{13}. If AI_{13} is between 0 and +2, there is a better than usual chance to be above trend (69.0%). If AI_{13} went above +2 and was too warm and dry (recall raw aridity was negatively weighted the first three weeks) early in the growing season, the associated probability of an above trend YLD (51.5%) was significantly lower than usual. At week 17 (about 1 month before silking), the range for AI_{17} was still somewhat narrow, but again certain AI values provide some meaning (Table 3). When AI_{17} was between 0 and 4, there was a strong likelihood (about 70%) of positive YLD and when AI_{17} was below -2 (except for a few cases with AI_{17} less than -6), there is a likelihood (roughly a 60% chance) of negative YLD.

Although the range for AI_{21} and AI_{25} is large enough for the season end YLD-AI_{27} relationship to be useful, early season methodology, as done with week 13 and week 17, can continue to be helpful. As AI_{21} and AI_{25} (Table 3) went below -8 and -10 respectively, more districts had below trend YLD than above trend YLD. Conversely, as AI_{21} and AI_{25} went above 0 and +2 respectively, a large percentage of districts achieved positive YLD.

4. TESTING LATE SEASON MODEL APPLICATION ON THE 2000 AND 2001 GROWING SEASONS

Based on the analysis and model equation for the eastern states, YLD were predicted for 2000 using the 2000 seasonal AI values. Figure 2 shows the 2000 seasonal AI, the modeled YLD for the eastern districts, and the actual YLD. The highly negative actual YLD in the western districts generally correspond to the white and light gray areas (where seasonal AI was less than zero) while most of the darker gray districts (where seasonal AI was greater than zero) had positive YLD. Good agreement between modeled and actual YLD occurred for the eastern two thirds of IA, central IN, and central IL. Modeled YLD for districts IA 1 and IA 4 were noticeably lower than the rest of the IA districts' estimates, but were still predicted to be above trend when actually the YLD were below trend. The northeast four districts of IA had reasonably consistent overestimation. Modeled YLD values for the southern tier of IA districts were about 10% above trend. For southwest IA, 10% above trend was a substantial overestimate, but modeled YLD for the other two districts of the southern tier had fair agreement with actual YLD. The model predicted YLD of greater than 7.5% above trend for all of WI. It was suspected that conditions were too cool and wet in WI for YLD to be substantially above trend, so predicted YLD were overestimates. Similar overestimates occurred in northeast IL and northern IN, again possibly from being too cool and wet. MN had both overestimates and underestimates because actual YLD increased from east to west, but AI_{27} decreased from east to west. Actual YLD for southern IL and southern IN were very large. Modeled YLD has a maximum because of the quadratic nature of the model. Seasonal AI for southern IL and southern IN were in a range where modeled YLD were near the maximum. Therefore, it wasn't possible for modeled YLD to be near the actual YLD. Out of 50 eastern districts, 21 had modeled YLD come within ±5 units of the actual YLD.

The same methodology that was used to test 2000 was applied to the 2001 season. Figure 3 again shows the seasonal AI, the modeled YLD for the eastern districts, and the actual YLD, but for 2001. According to seasonal AI, 2001 was generally warmer and drier than 2000. Again, the highly negative actual YLD generally correspond to the white and light gray areas (where seasonal AI was less than zero) while most of the darker gray districts (where seasonal AI was greater than zero) had positive YLD. There were several districts for which agreement was good between the modeled YLD and the actual YLD. Of these, many were grouped. One group included much of WI and extended into southeast MN and north central IA. Another group was northern IN and northeast IL. A pair of good estimates was hindcast for districts IA 7 and IA 8 with the model.

Three regions were areas of substantial underestimation. The first covered northwest WI and extended into central and northwest MN. The second area was composed of districts in eastern IA, northwest IL, and the southeast WI district (WI 9). Lastly, many of the southern IL and southern IN districts had underestimated YLD and were similar to the pattern seen for southern IL and southern IN for the 2000 application The large 2001 model error for the districts in southern IL and southern IN is not explained by the modeled YLD maximum because most of the seasonal AI values for these districts were not really in that range where the peak modeled YLD occurs. These districts just did really well under conditions slightly less cool and wet than the 2000 growing season. Out of 50 eastern districts, 24 had modeled YLD come within ±5 units of the actual YLD.

A plausible rule of thumb for the AI-YLD relationship is a one-to-one proportion, even for the western states. Sign agreement between seasonal AI and YLD was much more common than seasonal AI and YLD having opposite signs. In Figure 1a (1b), for sign agreement, there are 385 (236) plots in the upper right quadrant and 267 (186) in the lower left quadrant while the opposite sign quadrants, the upper left and the lower right, had only 207 (103) and 88 (84) plots respectively. Thus, mapping the latest AI_n for all districts would be useful because AI_n less than zero would signify which areas and their extent have the greatest chance of being below trend.

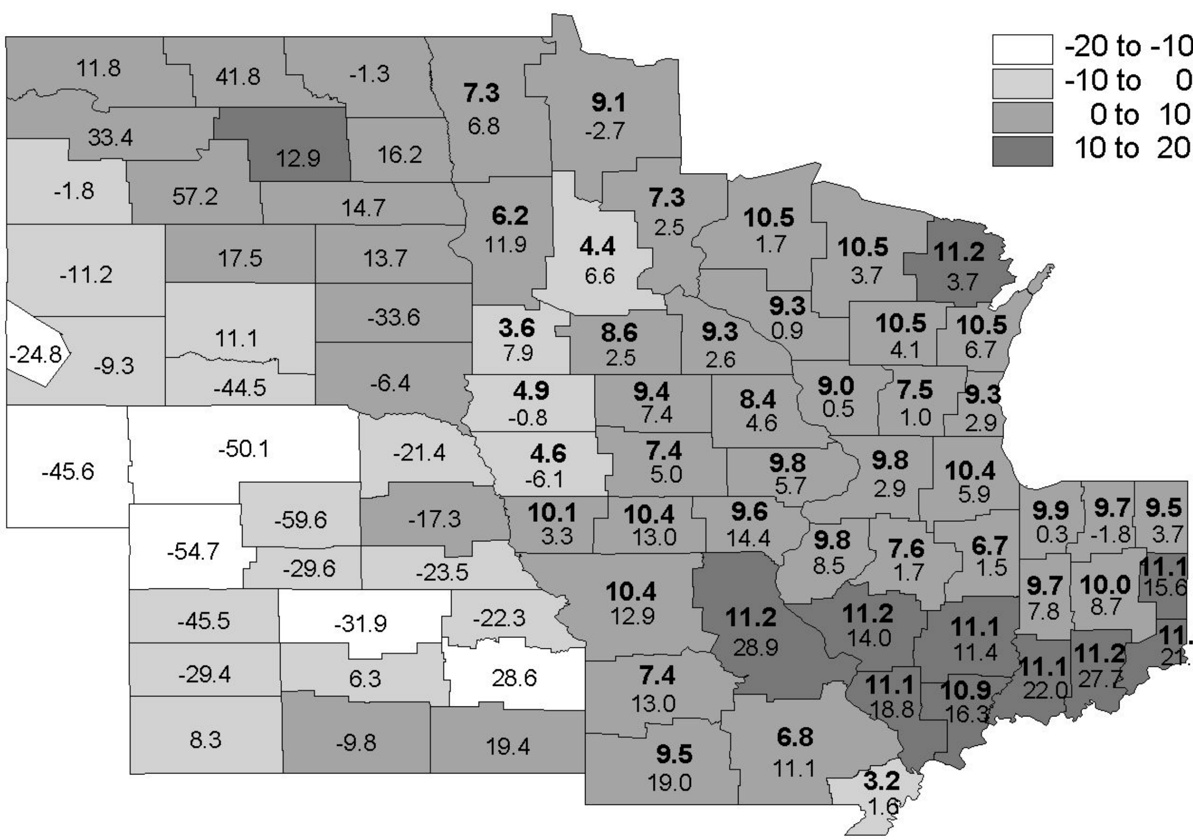

Figure 2 District seasonal AI (shaded at intervals of 10 units), actual YLD (small text), and modeled YLD (large bold text) for 2000.

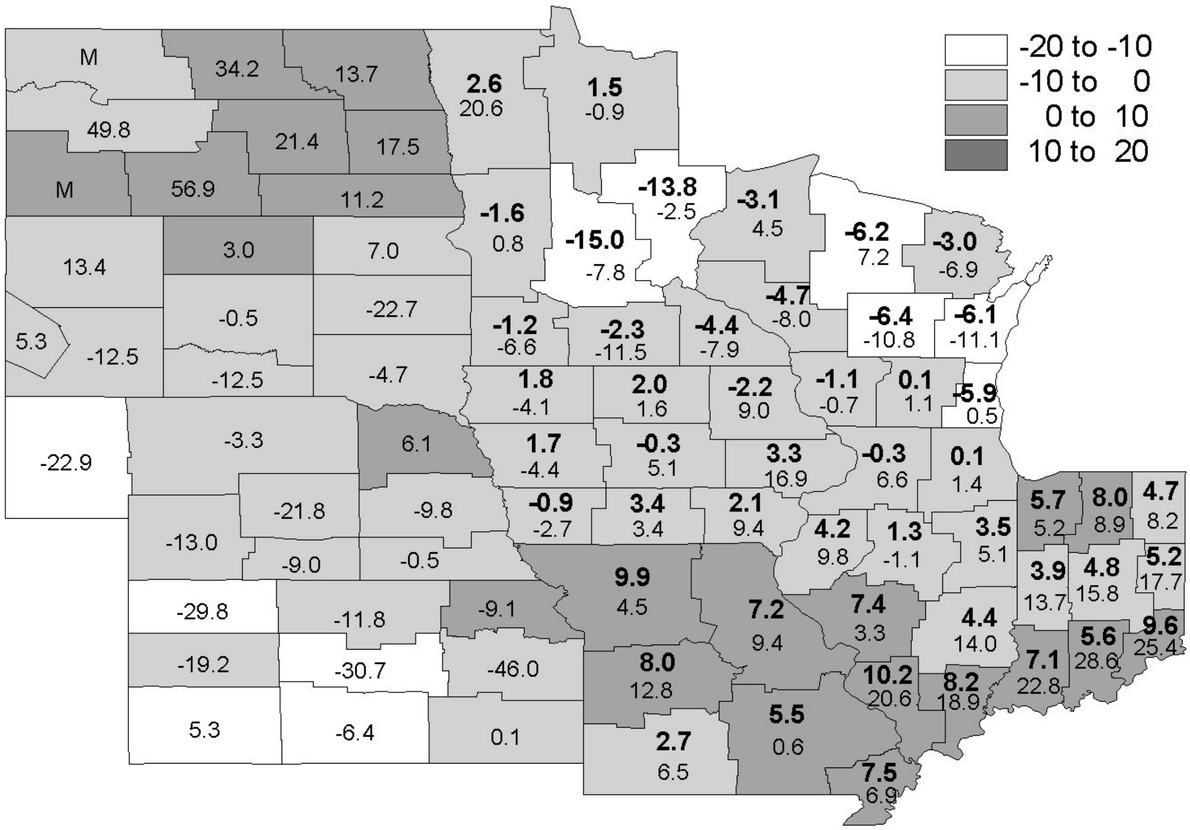

Figure 3 District seasonal AI (shaded at intervals of 10 units), actual YLD (small text), and modeled YLD (large bold text) for 2001.

5 DISCUSSION

5.1 Considering the Definition of AI

At this developmental stage of the AI method, the definition of AI was kept simple. The definition of AI used here was a special case of an expanded definition (Equation 5.1) that accounts for different contributions to "aridity" from precipitation and temperature at different times during the season.

$$AI_n = \sum_{i=11}^{n} k_i \left(a_i P'_i - b_i T'_i\right) \qquad (5.1)$$

On a monthly scale, precipitation in July is a bigger factor than temperature for YLD, but contributes less to YLD than temperature in August (Thompson 1986). Differing contributions to AI from precipitation and temperature on a weekly scale were beyond the scope of this study. When it was stated that precipitation and temperature were equal contributors to the weekly AI, it was assumed $a_i = b_i = 1$ for all weeks (i).

The corn phenology weighting factor (k_i) was also rigid. All weighting was applied with respect to having main silking occurring during climate week 21 and all weighting was applied to all districts equally. In IA, there is a good chance that silking will occur in or near week 21, but silking may happen at different times in other locations. To adjust weighting with each weekly processing of AI as conditions warrant, either timely observations of silking dates would need to be obtained or crop stage would need to be estimated with growing degree days. To improve the AI method, it is recommended that further work be done to find optimal corn phenology weighting and to incorporate it with the optimal contribution factors of precipitation and temperature.

Aside from weighting factors, there are other fundamental issues with the AI definition. One issue is the possibility of certain combinations of extreme weather weeks causing AI_n to be near neutral at any particular time. The extreme weather could quite likely result in a fairly large below trend YLD, but if opposite weather occurred for enough weeks, the resulting AI_n value would not indicate the drastic negative YLD. For example, if July was arid, and August was proportionally cool and wet, then AI_n would be near zero, but the crop would have performed poorly because of the July conditions. The method, as it stands now, allows AI_n to move back toward zero even though irreversible yield loss may have occurred. In other words, the crop's ability to recover from aridity or flood is quite limited, but the AI method does not account for this limitation.

Another consideration in regard to the defining equation of AI is the possibility of AI being near zero when a week's weather is wet and warm or cool and dry. It was assumed that these conditions would have approximately the same effects as average conditions. "Warm" would indicate higher transpiration, but "wet" would mean precipitation would be sufficient to sustain the higher water usage. Similarly, "cool" would indicate lower transpiration, so "no rain" would not be harmful. Finally, normalizing a precipitation distribution that is not normal does not promote symmetry between the possible positive and negative values of the P′ term. For example, a positive P′ value can be very high, but a negative P′ value can only go so low because a district's average weekly precipitation cannot go below zero. Instead of normalizing precipitation to calculate P′, perhaps the P′ term would be more consistent with some sort of percentile scheme.

5.2 A Possible Alternate Model

Flooding had a large influence on the shape of the parabolic model. Too much water is harmful to the crop, so YLD could be largely negative when AI_n was largely positive. If a distinction were made between flooding and no flooding when AI_n was high, such that the model excluded flooding situations, it would have a smaller tendency to underestimate YLD. Although underestimation is inherent near the peak of the parabolic model, excluding flood situations would shift the peak such that the model would better represent crops that were not flooded. From a physical point of view, excluding flood situations would nullify the quadratic relationship of YLD to seasonal AI. If many of the plots from the lower right quadrant in Figure 1a were justifiably eliminated, the relationship of YLD to AI_{27} would look quite linear. A logical next step then is to account for flooding and use a linear regression model or combinations of linear regression models. A single order linear model would not have the problem of underestimating YLD because of having some possible maximum value, as did the quadratic model used in this study. Using a linear model for the 2000 and 2001 seasons would likely bring more of the plots on the right side of the chart inside the ±5 unit interval.

5.3 Other Error Sources

There are other possible sources of error. For high aridity, irrigated corn may do well and keep the total yield relatively higher even though AI_n is quite low. Thus, the total yield in the eastern states may have contributions from irrigated corn, which may have influenced the yield deviation used here for the eastern states. Other issues besides irrigation may be factors. Meyer et al. (1993a) acknowledge soil quality, hybrid type, and damaging elements, such as insects, disease, hail, and wind, impact yield and may be sources of error. Thompson (1986) studied the effects of climate change on the upward trend in corn yield, and thus had to separate the influence of weather from the influence of greater fertilization, improved genetics, improved pest control, and improved management.

6. CONCLUSIONS

6.1 Summary

For a growing season, a method to judge whether a week's average maximum temperature and average precipitation were helpful or harmful to the season-end corn yield was presented. Hindcasting was done on the 2000 and 2001 corn growing seasons with mixed results. Of the modeled YLD for 2000 and 2001, about 45% of the predictions for the districts came within ±5 units of the actual YLD. For most weeks, the chance of an eastern states' district having positive YLD diminished as AI_n went below certain values and was significantly better than the unconditional chance when AI_n went above certain values. Operationally, a model that predicts yield to ±10 % is considered acceptable and to ±5 % is excellent. On this basis, this model is of value because it is reasonably accurate and is simple to implement on a week-by-week basis. When this (AI) model shows cause for concern, a user may desire to invest effort in a more detailed assessment.

During the 2-year evaluation (2000-2001), the model accuracy for the period improved as the season progressed. On June 6, the model correctly classified 47 percent of the crop-reporting districts in the Corn Belt. On July 4, 60 percent were correctly classified. After August 1, the accuracy of classification was 75 percent. Because both years had yields very near the long-term trend, this is considered a very good result. The AI model also performed well under worst-case considerations. That is, it did not predict a substantial number of above-trend yields that proved to be under the trend.

6.2 Discussion of Making the AI System Operational

For upcoming growing seasons, two main items should allow for meaningful dissemination of AI information (primarily via the World Wide Web). Maps of district AI_n will display the spatial extent of warmer and drier or cooler and wetter than average weather. The other important item will be a sequential sample for each district. Because there are 85 districts in the Midwest, it would be awkward to produce 85 time series charts each week. An alternative would be to set up the map so each district has a link to an automatically generated chart.

Examples from the end of the 2000 and 2001 season are available along with an operational 2002 product (see URL associated with this paper). As in these examples, the AI product for upcoming seasons could include appropriate charts and tables, which would allow users to make decisions based on their own assessment of the historical relationship.

6.3 Future Work

The AI method has potential for improvement. First, the raw weekly AI could be refined by dealing with the P′ term differently and by considering how much each term is contributing at what points in the growing season. The next adjustment would be a more realistic crop phenology weighting scheme. After these steps, the seasonal AI should again be plotted against YLD, but perhaps without YLD influenced by flooding, such that a linear model might be appropriate. Even if the relationship does not prove to be more consistent after the changes, AI results should still be compared to results from previous studies such as the ones authored by Shaw (1983), Thompson (1986), Harouna and Carlson (1994), and Meyer et al. (1993), which were discussed in Section 1. Such comparisons would help better determine the value of the AI methodology.

The AI methodology could include an incorporation of operational long-range weather forecasts to project the summer's possible AI tendencies. A shorter term AI forecast, especially the precipitation component, might be made based on the trend of the low-level flow from the Gulf of Mexico. If the AI method proves to be successful, it would be natural to extend it to soybeans and other crops. It could also be extended beyond the Midwest. Eventually extrapolation from the 1980 to 1999 yield trend would need to be reevaluated because the upward trend of yield due to technology will likely level off. Averages used to normalize temperature may also have to be reevaluated to match the current climate with the appropriate past climate.

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