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Full Length Research Paper

Application of a satellite-based climate-variability impact index for crop yield forecasting in drought-stricken regions

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A quantitative index is applied to monitor crop growth and predict agricultural yield in drought-stricken regions. This Climate-Variability Impact Index (CVII), defined as the monthly contribution to overall anomalies in growth during a given year, is derived from 1 km MODIS Leaf Area Index. The CVII integrated over the growing season represents the percentage of the climatological production either gained or lost due to climatic variability during a given year and is positively correlated with crop yields. In two test cases presented here, a statistical model is trained using the historical CVII and yield records and is then applied to predict crop yields for Illinois in 2005 as well as North and South Dakota in 2006. The model predictions are consistent with USDA's estimates obtained after harvesting. Since the CVII are available in near real-time, the model predictions can also be obtained monthly before the end of the growing season. The in-season CVII model shows predictability comparable to the concurrent NASS estimates. In addition, these model forecasts improve as more CVII series are added in the late season. Finally, this research highlights the need for explicit monitoring of vegetation growth when estimating yield as drought-monitoring indices such as the Standardized Precipitation Index can both overestimate and underestimate implied changes in vegetation in drought-stricken regions.

Key words: Remote sensing, leaf area index, crop monitoring, early yield forecast, drought index, climate impacts.

INTRODUCTION

The interannual variations of crop yields are strongly affected by the environment and its variability. To get the pre-harvest information on crop yields, numerous crop growth simulation models are generated using crop state and climate variables at the crop/soil/water/atmosphere interfaces (Monteith, 1977). Most of these models require complex and detailed inputs to address the plant physiology process (Allen et al., 1998), soil water balance (Sepaskha et al., 2006), as well as the interactions between soil and root systems (Zand-Parsa et al., 2006).

In addition, plot-scale field experiments with specific soil types, water stress, nitrogen contents and management processes are required for validation of the models (Boling et al., 2007). More importantly, these crop growth simulation models are crop-dependent, which makes it difficult to use a single model to produce yield forecasts for different crops. Even for the same crop, it is not easy to make comparisons among different simulation models, each of which may be suited for specific locations. For example, many rice simulation models have been developed since 1980s, which include the RICEMOD designed for potential production in rainfed environments (McMennamy and O'Toole, 1983), SIMRIW for yield forecasting in Japan (Horie et al., 1995), RLRice in north-east Thailand (Fukai et al., 1995), and ORYZA series for tropical lowland rice (Ten Berge and Kropff, 1995, Bouman and Laar, 2006). In general, the results of these models are complex and depend on the type of the stress, the intensity of stress, the duration of the stress, and the state of the crop development when stress is imposed (Vyn and Hooker, 2002). As a result, these crop

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growth models are limited to specific regions/periods /species due to significant spatial-temporal variations of the stress variables and their characteristics.

A second type of yield forecast is based on data collected from farm operations and field observations, which require numerous time and labor in order to get a full sample size. In addition, these field studies have to be repeated frequently throughout the growing-season. The National Agricultural Statistics Service (NASS) monitors the crop conditions and yields via monthly-conducted Objective Yield Surveys in thousands of fields. In the early season, plant population per acre and, later in the season, crop's stage of development and the number of immature and mature fruits are recorded by the NASS enumerators. Based on counts, measurements, and weights obtained from plots in random samples, NASS can make forecasts and estimates of crop yields at state-level by applying different models depending upon crop type (NASS2, http://www.nass.usda.gov/Data_and_Statistics/pub1554.pdf).

Finally, since the early 1980s, vegetation indices derived from satellite data have been applied for crop monitoring and forecasting purposes. These indices include the ratio of the reflectance at near infrared to red and the normalized difference vegetation index (NDVI) from Landsat (Rudorff and Batista, 1990), as well as NDVI (Hochheim et al., 1998) and Vegetation Condition Index (VCI) (Kogan, 1990 and 1995) from the Advanced Very High Resolution Radiometer (AVHRR) . In general, these remotely-sensed metrics of vegetation activity have the following advantages: a unique vantage point, synoptic view, cost effectiveness, and a regular, repetitive view of nearly the entire earth's surface (Johnson et al., 1993), thereby making them potentially better suited for crop monitoring and yield estimation at large scales. As an example, the NDVI-based VCI from AVHRR is widely used for crop prediction, environmental monitoring, and drought monitoring/assessment (Kogan, 1990 and 1995; White et al., 1997).

Another vegetation index, the Climate-Variability Impact Index (CVII), is derived from Moderate resolution Imaging Spectroradiometer (MODIS) Leaf Area Index (LAI). The MODIS data have improved calibration, geometric registration, atmospheric correction, and cloud screening (Goward et al., 1991; Sellers et al., 1994), which provide a significantly improved basis for vegetation monitoring and yield predictions (Justice et al., 1998; Running et al., 1994; Zhang et al., 2003). In addition, LAI, which is a key parameter in most ecosystem productivity models (Sellers et al., 1997), is an improved metric over the Normalized Difference Vegetation Index (NDVI), which saturates during high-growth periods (Carlson and Schmugge, 1990; Carlson and Ripley, 1997; Paltridge and Barber, 1988). Previous studies have shown that integrated LAI over the growing season is highly correlated with crop yield because both the magnitude and duration of photosynthetic activity is considered (Tucker et al., 1980; Hatfield, 1983).

We have previously demonstrated that the LAI-based CVII can quantify the percentage of the climatological annual production either gained or lost due to climatic variability and that it has a potential application in crop monitoring and yield estimation (Zhang et al., 2004, 2005, 2006). As a continuation of this effort, in this paper we will analyze the relationships between the CVII and crop yield using two case studies for a drought year in Illinois (2005) and a drought year in North and South Dakota (2006). A description of the data used in this study is provided with the methodology used in developing the CVII model. Detailed discussions on the results of the two case studies followed by some discussions of the in-season predictability of the CVII models are also provided. Operational product development and dissemination are discussed.

DATA

MODIS IGBP land-cover Map

The MODIS land-cover classification product identifies 17 classes of land cover in the International Geosphere-Biosphere Programme (IGBP) global vegetation classification scheme (Friedl et al., 2002). This scheme includes 11 classes of natural vegetation, 3 classes of developed land, permanent snow or ice, barren or sparsely vegetated land, and water. The latest version of the IGBP land-cover map is used to distinguish croplands from the other biomes in this research.

MODIS LAI

The retrieval technique of the MODIS LAI algorithm is as follows. For each land pixel, given red and near-infrared reflectance values, along with the sun and sensor-view angles and a biome class, the algorithm uses model-generated look-up tables to identify likely LAI values corresponding to the input parameters. This radiative transfer based look-up is done for a suite of canopy structures and soil patterns that represent a range of expected natural conditions for the given biome type (Knyazikhin et al., 1998). The mean value of the LAI values found within this uncertainty range is taken as the final LAI retrieval value. In certain situations, if the algorithm fails to localize a solution either because of biome misclassification/mixtures, high uncertainties in input reflectance data or algorithm limitations, a backup algorithm is utilized to produce LAI values based upon the empirical relationship between NDVI and LAI (Myneni et al., 1997).

The latest version of MODIS global LAI from February 2000 through August 2006 was taken to characterize the crop activity in this study. The 8 day LAI products are distributed to the public from the Earth Observing System (EOS) Data Gateway Distributed Active Archive Center. The 8 day products also provide quality control variables for each LAI value that indicate its reliability. The monthly global product was composited across the 8 day products using only the LAI values with reliable quality. In this paper, monthly LAI at 1-km resolution are used to generate our Climate-Variability Impact Index (CVII). As these will be compared with estimates of crop production reported at county/state levels, the vegetation-based CVII fields are aggregated over the corresponding counties/states using the county boundaries 2001 map from the National Atlas of the United States (nationalatlas.gov).

Crop production

The county- and state-level production data in drought-stricken regions are from the National Agricultural Statistics Service (NASS) at the United States Department of Agriculture (USDA) (http://www.nass.usda.gov/Data_and_Statistics/Quick_Stats/). USDA provides two independent sets of county crop data: one is a census of agriculture, which is released every five years; the other one is annual county crop data, which is based on reports from samples after harvesting. We used the annual crop estimates in this study.

In addition to the actual production observations obtained after harvesting, NASS also provides monthly expected corn yield forecasts based on corn objective yield surveys. These are released each month from August through November. The yield forecasts are based on two important variables: the number of ears and average ear weight. The sample ear count can be observed early in the season or projected from models based on plant population if the crop is late developing. The average ear weight is projected from kernel row length models before the corn matures or is substituted by the historical average weights when ears are not present. During the growing season, the enumerators from NASS revisit the sample plots monthly to obtain measurement of stalks, ears, kernel row length, and ear diameter according to the development stage (NASS2, http://www.nass.usda.gov/Data_and_Statistics/pub1554.pdf). Based on these fine scale measurements, corn yield is projected at that state level. In this sense, the yield forecasts from NASS might fluctuate but will become more accurate over the course of the growing season.

In this research, both the end-of-season crop estimates for corn and spring wheat, as well as the in-season monthly expected corn yields from NASS, are used as a comparison with the end-of -season and early-yield forecast obtained from the CVII model. For comparison purposes, the survey-based crop production estimates throughout the paper are normalized by the 2000 – 2004 mean.

$$Y' = 100\times \frac{Y}{\bar{Y}} \tag{1}$$

Standardized precipitation index

The standardized precipitation index (SPI) was developed to identify drought or wet events at a given temporal scale for any station that has historic rainfall data (Mckee et al., 1993). The long-term rainfall distribution fits a gamma distribution well, and can be used to calculate the probability of monthly or seasonal variations. The probabilities are then normalized by the inverse normal function to make them comparable between stations. By changing the temporal scale, the SPI can identify short-term and long-term droughts. In this research, the 3 months SPI values through July of each year, provided by National Drought Mitigation Center (http://www.drought.unl.edu/monitor/spi.htm), are used to identify water deficit conditions during the growing season.

METHODOLOGY

We previously developed a quantitative index to study the relationship between MODIS leaf area index (LAI) and crop production. This Climate-Variability Impact Index (CVII), defined as the monthly contribution to anomalies in annual growth, quantifies the percentage of the climatological production either gained or lost due to climatic variability during a given month. For a given pixel p, let L(p,m,y) be the LAI in month *m* and year *y*, $L'(p,m)$ ($L'(p,m) = \frac{1}{N_y}\sum_{y} L(p,m,y)$) be the climatological LAI in month m and $L'(p)$ ($L'(p) = \sum_{m} L'(p,m)$) be the climatological annual LAI. The index CVII (*p, m, y*) in month *m* and year *y* is then calculated as:

$$CVII(p,m,y) = 100 \times \frac{L(p,m,y) - L'(p,m)}{\Sigma L'(p)} \tag{2}$$

In this research, we used the 1 km resolution MODIS LAI data, from 2000 to 2006, to generate the Climate-Variability Impact Index. The MODIS land cover map at 1-km resolution was used to select broadleaf and cereal crop pixels. Crop production estimates are given at county- and state-levels by the U.S. Department of Agriculture. Accordingly, we aggregated LAI over the same regions by overlapping the LAI map with the county map and then calculated the Climate-Variability Impact Index for each county.

By examining the integrated CVII over the growing season, this LAI-based index can provide both fine- scale and aggregated information about vegetation productivity for various crop types.

Previous work has shown the CVII can capture crop loss during historical droughts (Zhang et al., 2004) and is well-correlated with agricultural yield at various spatial scales (Zhang et al., 2005). In this research, the LAI-based CVII is summed over the growing season, which is from April to August, using the following equation:

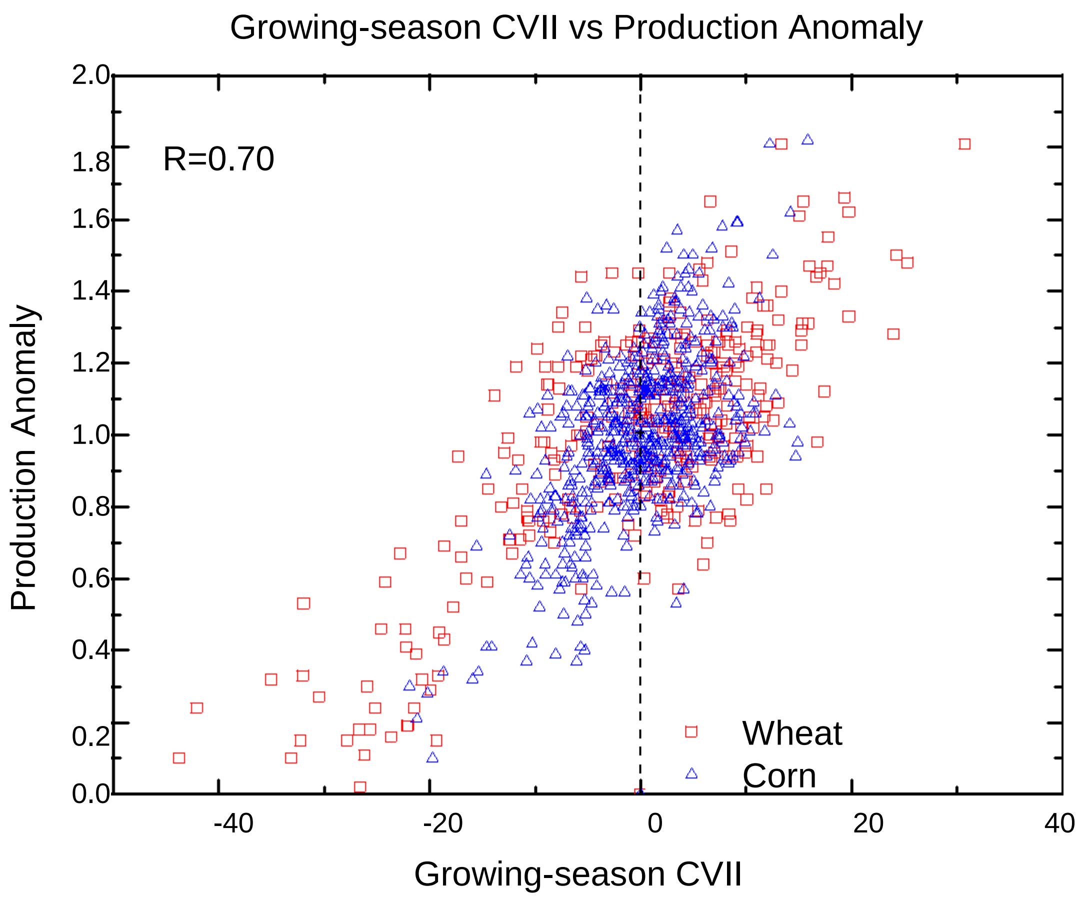

Figure 1. Relationship between growing-season (Apr -Aug) CVII and crop production over the study regions of Illinois, South Dakota and North Dakota. MODIS landcover maps are used to select the cereal crops (wheat) and broadleaf crops (corn). The growing-season CVII is calculated for each county using equation 3 in section 3. The production anomaly is normalized by the 2000 - 2004 average using NASS's estimates for each county. Red squares represent the counties where corn is the majority crop and blue triangles represent the counties where wheat is the majority crop.

$$CVII(p,y) = 100 \times \sum_{m} \frac{[L(p,m,y) - L'(p,m)]}{L'(p,m)} \qquad (3)$$

In this manuscript, this LAI-based CVII is used to model yield forecast in two drought- stricken regions. One is for the extreme drought that occurred in 2005 over Illinois. The second is for the drought of 2006 which affected large parts of the continental US. During this year North and South Dakota were two of the most drought-stricken areas.

In order to get production information in the study regions from the integrated CVII, linear models are trained using the historical data from 2000 to 2004. Actual yield observations from USDA for each county are the dependent variable, and the integrated CVII from April to August is the predictor. Then the model is applied to produce crop yield forecasts for 2005 and 2006 for the given study regions. Our previous results suggest that the CVII-based empirical model provides significant predictability for both the sign and magnitude of production variations over the training regions (Zhang et al., 2005).

Figure 1 demonstrates this strong positive correlation between the crop production and the CVII for counties in both Illinois and North and South Dakota. While the CVII increases from negative 40% to positive 40%, the production anomaly increases from less than 10% to nearly 200% of the climatological mean. In general, fifty percent of the variance in crop production can be explained by the CVII, which agrees with previous studies at local scales (Zhang et al., 2005).

Our previous results also show that the CVII/production relationship (as given by the regression coefficient between the two) may be crop-independent for certain crops (Zhang et al., 2005). To test whether the regression coefficients are strongly dependent on crop types in the different study regions and for the two different crop types, we fitted three linear models for the 2000-2004 CVII and production anomalies. The first model uses all the corn sample counties from the study regions. The second model uses all the wheat sample counties. The third model uses both corn and wheat sample counties. From Table 1, we note that the three models are similar and the coefficients are significantly different than zero ($p < 0.0001$). The 95% confidence intervals of the coefficients of the three models overlap, which indicates that these three linear models are not significantly different from each other. Our results demonstrate that the CVII-production relationship appears to be crop-independent for the study regions at county-level. This agrees with our previous study in which corn in Illinois and spring wheat in North Dakota have similar CVII-production relationship at crop-reporting district scales. More importantly, the

Table 1. Linear model between Crop production (dependent) and Climate-Variability impact index (independent) at county Level. The first model is generated from corn counties. The second model is generated from wheat counties. The third model is generated both corn counties and wheat counties.

Model	Unstandardized coefficients		t	Sig.	95% Confidence interval	
	B	Std. error			Lower	Upper
1 Constant	1.00	0.007	137.85	<.0001	0.985	1.014
CVII	0.024	0.001	17.94	<.0001	0.021	0.026
2 Constant	1.009	0.012	86.85	<.0001	0.986	1.032
CVII	0.021	0.001	21.57	<.0001	0.019	0.023
3 Constant	1.003	0.006	161.81	<.0001	0.991	1.015
CVII	0.022	0.001	28.94	<.0001	0.020	0.023

full sample model for the study regions has almost identical regression coefficients as previous results (Zhang et al., 2005). In the following, we will use the full sample model to predict the 2005 corn yield for Illinois and the 2006 crop production (corn and wheat) for North and South Dakota.

It should be noted that because the model predictions are based upon the regression coefficient, they tend to have smaller variance than the actual observations. To alleviate this difference, we scaled the predictions by the ratio of the interannual standard deviation of the state-average observed and modeled estimates using the following equation:

$$P_i' = (P_i - 1) \times \frac{\sigma_o}{\sigma_m} + 1 \qquad (4)$$

Where Pi is the original model prediction for county i, Pi' is the scaled model prediction for county i, and are the interannual standard deviation of the state-average observed and modeled estimates respectively. The climatological mean, one, is subtracted so that only the anomalies are scaled.

RESULTS

2005 Corn yield forecast at Illinois

Illinois contains 102 counties and the principal crop in Illinois is corn, which is approximately 50% of all crops by area. The corn production in Illinois comprises more than 17% of the United States total, based on the records from 2000 to 2004. Figure 2 demonstrates the fluctuations of the corn yield and production in Illinois from 2000 to 2005. In general, the corn yield and production have similar variations for the previous six years. During this period, 2004 had a maximum yield of 180 bushel and 2002 had a minimum yield of 135 bushel.

In the 2005 growing season, Illinois suffered an extreme drought condition with the April – September rainfall ranked 10th lowest in the past 113 years (NCDC: http://www.ncdc.noaa.gov/oa/climate/research/monitoring.html#state). By the end of August 2005, counties throughout Illinois were declared agricultural disaster areas and corn yields were predicted to be 30% less than the record year of 2004 by NASS (Figure 2) . However, after most of the corn had been harvested by the end of October, the Illinois Agricultural Statistics Service indicated the overall corn yield is 145 bushels per acre, or 7% below the previous 5-year average (NASS1: http://www.agstats.state.il.us/releases/crop.pdf; USDA1: http://usda.mannlib.cornell.edu/reports/nassr/field/pcp-bb/2005/crop1005.pdf)

In the following, we compare the meteorological conditions represented by the 3-month SPI for May-July and the vegetative production represented by the integrated CVII map over the continental US in 2005 and 2002 (we show maps for 2002 because it had comparable crop losses to those expected in 2005 according to NASS). In general, on a continental scale the Apr.-Aug. integrated CVII agrees with the 3-month SPI maps (Figure 3). For instance, the severe drought conditions present over the western US in 2002 led to a significant decrease in vegetative production. In contrast, in the same region the excess vegetation production in 2005 agrees with the moderately wet conditions represented by the SPI. However, focusing on Illinois, the 3-month SPI through the end of July indicates Illinois suffered a severe drought during the 2005 growing season, while conditions were slightly-above normal during 2002. US Drought Monitor maps produced by USDA/NOAA (US Drought Monitor 1, http://drought.unl.edu/dm/archive.html) indicate similar conditions during 2005 ("extreme drought" in Illinois) and 2002 ("dry" in Illinois). Hence, it is not surprising that the 2005 harvest in Illinois was expected to be substantially worse than in 2002. However, the April-August integrated CVII maps for Illinois suggest a decrease in vegetation growth of only about 10% in 2005 compared with a 10 – 20% decrease in 2002 (right panels of Figure 3), which qualitatively matches the NASS yield estimates for these two years. As mentioned the CVII maps do not measure yield directly, however we can apply the empirical statistical model to predict corn yield information in 2005. The model predictions and NASS estimates of corn yield in Illinois are plotted in Figure 4, in which 2000 to 2004 are in-sample years and 2005 is the out-of-sample year.

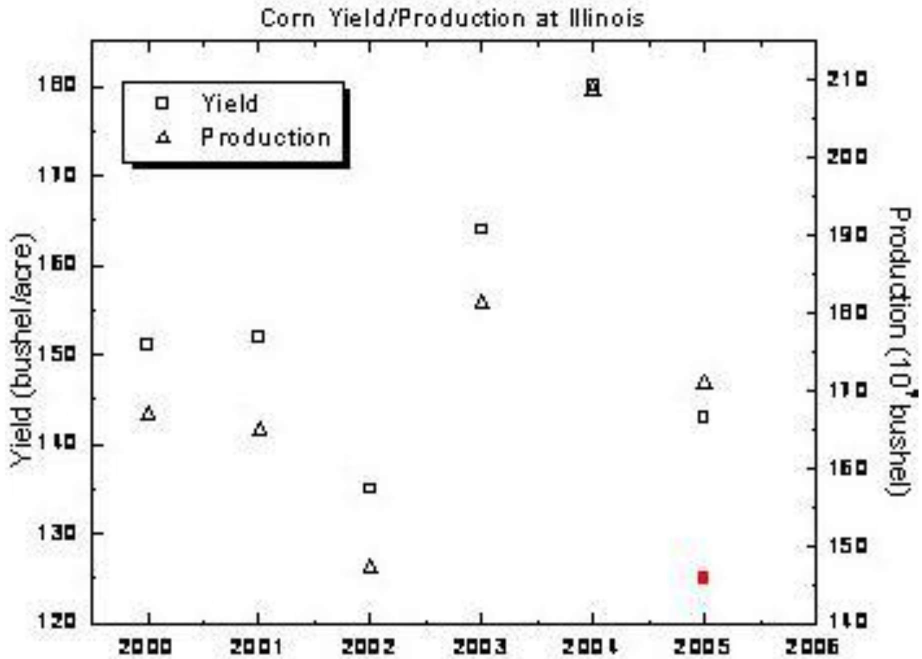

Figure 2. Corn yield/production at Illinois from 2000 to 2005. Black open squares show the variation of corn yield (bushel/acre) released in December of the given year; blue open triangles show the variation of production (bushel) released in December of the given year. The red filled square shows the 2005 yield prediction from the National Agricultural Statistics Service (NASS) released in August 2005.

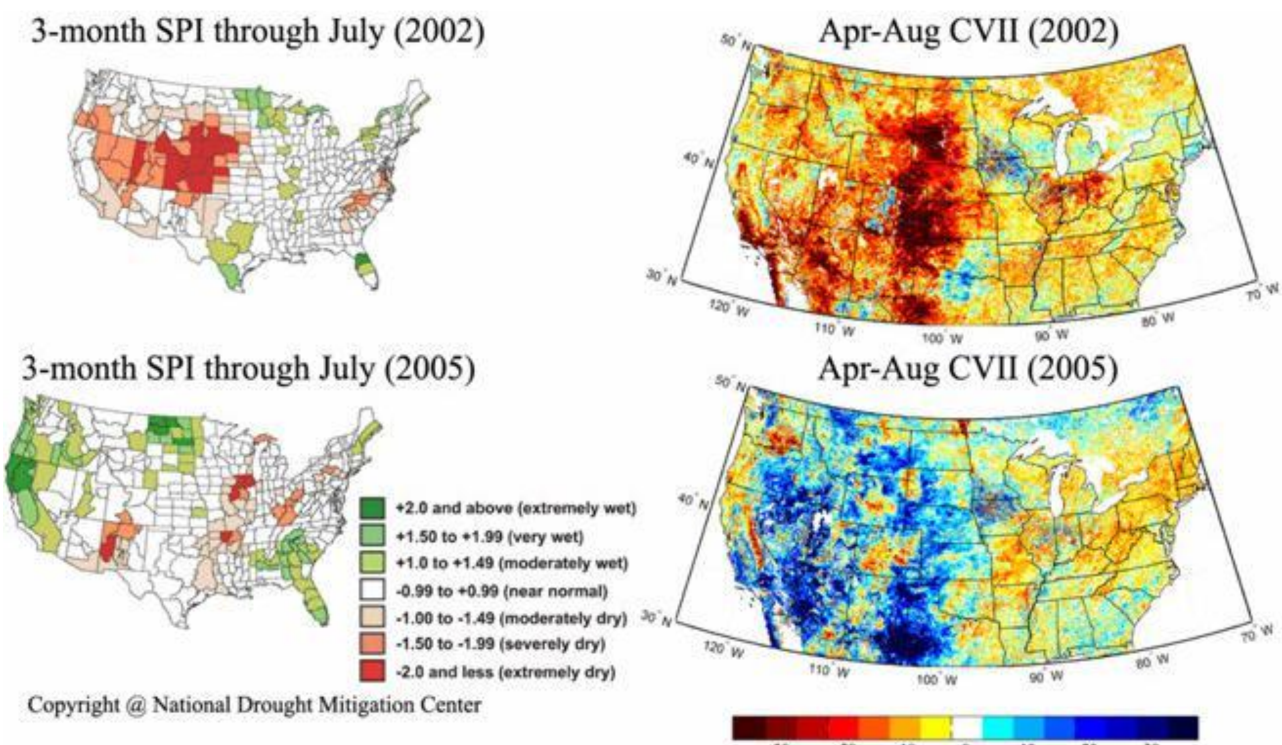

Figure 3. 3-month Standardized Precipitation Index (SPI) vs. the growing-season Climate-Variability Impact Index (CVII) in 2002 and 2005. 3-month SPI maps are produced by National Drought Mitigation Center (http://www.drought.unl.edu/monitor/spi.htm). CVII values represent fractional loss (red) or gain (blue) of vegetation growth during the growing season (April-August), compared with the 2000 - 2004 mean.

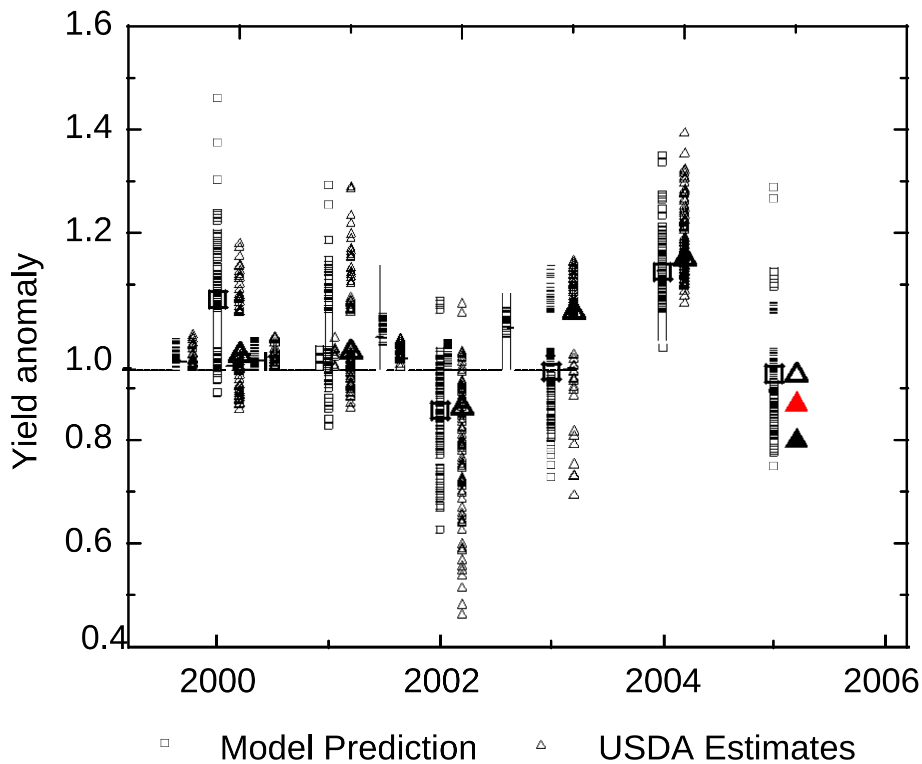

Figure 4. Model predictions (squares) vs. USDA estimates (triangles) of normalized yield in Illinois counties - see text for details. Yields of '1' represent average conditions from year 2000 to 2004. Bold symbols represent the state-wide average; light symbols represent individual counties. At the time of the work, the latest USDA estimate for 2005, released in October, only includes a preliminary state-wide value. The bold triangle represents the state-wide estimate made by USDA released in August (dark color) and September (red color) 2005. For comparison, the CVII-based estimates are available by mid-September.

(It should be noted that the predictions calculated from the model are the anomaly from the mean, not the absolute value. The climatological mean is needed to obtain the actual yield.) Significant decreases in crop yield during 2002 are successfully captured by the model, as are the record yields in 2004 (NASS1), which is expected. More importantly, the model predicts a 7% decrease compared to the previous 5 year average, or 145 bushel/acre overall,in 2005 corn yield in Illinois which is almost identical to the actual state-wide corn yield from NASS released after the harvesting (8% decrease, or 143 bushel/acre). It should be noted that the model works best at regional scales when the variation of the yield is large enough. At local (county-wide and smaller) scales, individual fluctua-tions in the remotely-sensed data may introduce excessive noise into the aggregate field and weaken the linear relationship (Zhang et al., 2005).

Figure 4 also plots the NASS forecasts made in August, September and October for comparison. In general, the NASS forecasts become more accurate over the course of the growing season. As the sample fields are revisited later in the season, updated observations improve the quality of the forecasts. In this study, NASS released the first forecast in August, which suggested a 20% decrease compared to the climatological mean, or 125 bushel/acre overall. This estimate represented a 10 bushel/acre decrease compared with the record loss of 2002 (135 bushel/acre). After the crop variables were measured in September at the sample plots, NASS updated its forecasts to a 13% decrease, or 136 bushel/acre. After most of the farms had been harvested, the October and November release from NASS indicated a corn yield of 145 bushel/acre in Illinois, which is the same as our model predictions made using the April-August integrated CVII (and released in mid-September).

2006 yield forecast at North and South Dakota

The previous section detailed a case study of the application of our LAI-based CVII in corn yield forecast at Illinois in 2005, which was predicted to be a particularly bad year based upon meteorological conditions but which was found to have suffered only mild crop losses despite the drought conditions. This section examines how the relationship between crop production and CVII can provide information to generate predictions of crop production for North and South Dakotas in 2006, again

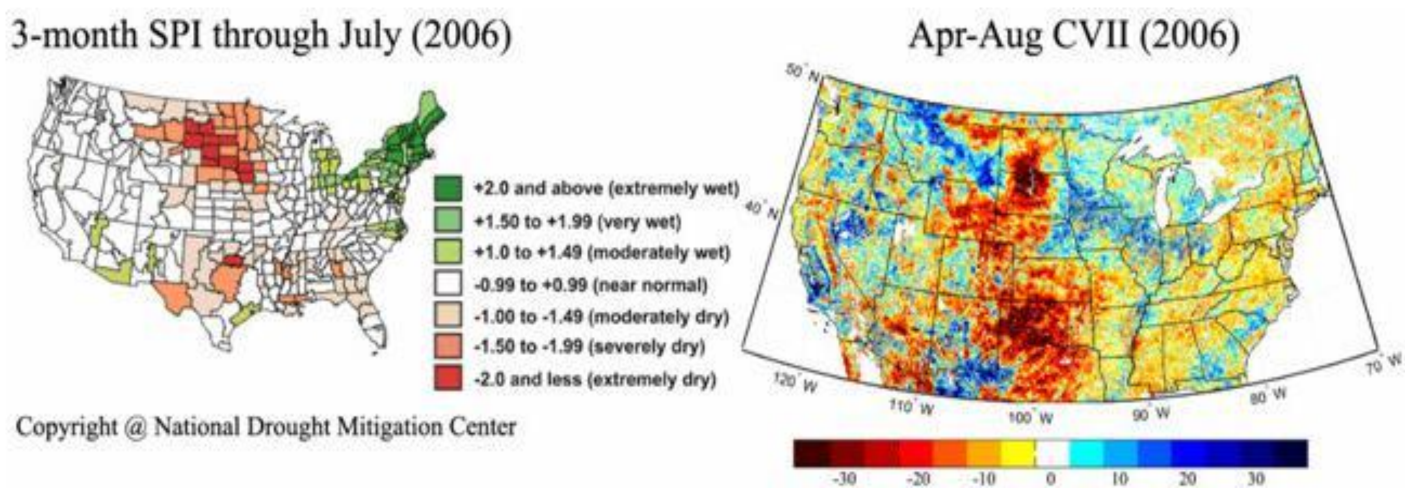

Figure 5. 3-month standardized precipitation index (SPI) vs. the growing-season climate-variability impact index (CVII) in 2006. 3-month SPI maps are produced by national drought mitigation center (http://www.drought.unl.edu/monitor/spi.htm). CVII values represent fractional loss (red) or gain (blue) of vegetation growth during the growing season (April-August), compared with the 2000 - 2005 mean.

another year with severe drought conditions.

In 2006, the persistence of anomalous warmth made the summer the second warmest June-August period in the continental US in the past 110 years. Combined with the below-average precipitation, large parts of the country were under drought conditions (NOAA News Online, http://www.noaanews.noaa.gov/stories2006/s2700.htm). Although late summer precipitation improved drought conditions in some regions, an area stretching from south central North Dakota to central South Dakota is identified as drought-stricken, with the potential for significant crop loss according to the US drought monitor map released in August 2006 (US Drought Monitor Map: http://drought.unl.edu/dm/archive/2006/drmon0725.htm). For example, by the end of August 2006, 60% of the topsoil and 70% of the sub-soil in North Dakota, and 65% of the topsoil and 75% of the sub-soil in South Dakota was in unfavorable soil water conditions (USDA, http://usda.mannlib.cornell.edu/usda/nass/WWStateStories//2000s/2006/WWStateStories-08-29-2006.pdf).

The reduced soil water content would suggest a decrease in vegetative production.

Both the 3 months SPI through the end of July and the April-August integrated CVII map identify two drought-stricken centers in 2006: North and South Dakota, as well as Texas and Mississippi (Figure 5). The CVII map indicates up to 40% of the climatological vegetation growth in the center of the two drought-stricken regions is lost during the growing season of 2006. Hot spots are also found in Arizona and the border along Arkansas and Mississippi. In addition, about average or slightly above-average vegetation growth is found along the corn-belt regions centered in Illinois and Iowa, which agrees with the estimates from NASS (not shown).

Based on the full model trained on historical CVII/yield relationships, the 2006 corn and wheat production are predicted at county- and state-level in North and South Dakota (Figure 6). In general, the model predictions agree with the USDA estimates at state-wide scale in 2002, 2003 and 2005. Our model overestimated the crop production in 2001 and underestimated the crop production in 2004. Importantly, for 2006 (the out-of-sample year) the model predicts a 23% decrease compared to the climatological mean in wheat and 4% decrease in corn, compared with the latest state- wide NASS estimates of 15% decrease in wheat and 1% increase in corn (released in November). While not as accurate as the 2005 predictions for Illinois, they actually represent a better prediction than the NASS September forecasts released concurrently with the CVII-based estimates (Figure 7).

Possibility of early yield forecast using CVII

The two case studies indicate that drought-monitoring indices based upon meteorology data alone may miss important variability in vegetative production (Zhang et al., 2004). In the case of corn yield in Illinois, drought-monitoring indices such as SPI can both overestimate (2005) and underestimate (2002) changes in vegetation. This highlights the need for explicit monitoring of vegetation growth when estimating yield. While the satellite-based estimates of yield are not necessarily a substitute for those provided by ground-based methods (as done by agricultural services for instance), satellites can provide a secondary, independent estimate that can pinpoint regions where agricultural failure is greatest.

In addition, because the satellite data used to derive the CVII are available in near real-time (with a typical lag of approximately 2 weeks between when the image is taken and the product is available), satellite-based data can

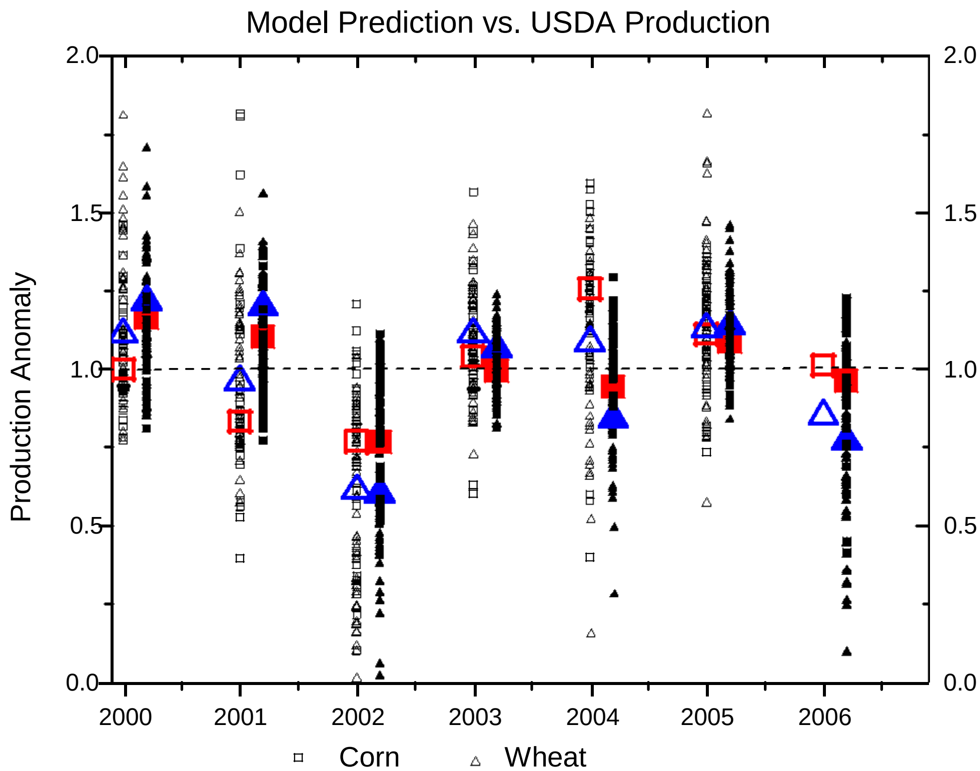

Figure 6. Model predictions (filled symbols) vs. USDA estimates (open symbols) of normalized crop production at North and South Dakota. Yields of '1' represent average conditions. Bold symbols represent the state-wide average; light symbols represent individual counties. Red squares represent corn production and blue triangles represent wheat production. At the time of the work, the latest USDA estimate for 2006 only includes a preliminary state-wide value.

provide yield estimates before the end of the growing season. For instance, the forecast of 145 bushel/acre (7% decrease compared to the climatological mean) at Illinois was produced in mid-September, compared with the USDA's forecast of 136 bushel/acre at the same time (Figure 3), and the USDA's forecast of 145 bushel/acre released in October and November (Figure 3). As such, acceptable model forecasts of corn yield could be obtained at least one month prior to the end of the growing season due to the advantages of the satellite data. In the following, we examine the possibility of early forecast using our model.

Figure 7 shows the relationship between actual corn yield, NASS's forecasts released in August, September and October, and our model predictions made during July, August, and September using CVII for South Dakota from 2000 to 2006. As mentioned, the model predictions based on integrated CVII have a typical lag of approximately 2 weeks. As such, the April - July/August/ September integrated CVII predictions are concurrent with the NASS estimates released in August/September/ October respectively. The actual corn yield of South Dakota is estimated by NASS after harvesting in each year and is used as the actual yield for the given year. During this period, 2004 has a maximum yield of 130 bushel/acre and 2002 has a minimum yield of 95 bushel/acre. Generally both the NASS forecasts and CVII predictions show similarities: both capture the corn failure in 2002, significantly underestimate the corn yield in 2004, and significantly overestimate the corn yield in 2001. Other times, however the two estimates differ. As discussed above, in mid-August 2006 the CVII model predicted a corn yield of 108 bushel/acre for South Dakota, which is almost identical to the actual yield of 107 bushel/acre. In comparison, the NASS estimate released in August predicted a yield of 100 bushel/acre and in October predicted a 105 bushel/acre.

Figure 8 shows the averaged absolute percentage difference of the model predictions and NASS estimates compared to the actual yield over the course of the growing season. In general, the predictability of both NASS and CVII improves over the course of the growing season. For example, the CVII predictions by the end of July have a 7% deviation from the actual yield, while the CVII predictions by September have only a 4% deviation. Overall, the CVII model can provide significant predictability (less than 10% error) at the state-average level by the middle of the growing season and at least 1 - 2 months earlier than the start of the harvesting. In addition, averaged over the period from 2000 to 2006, the

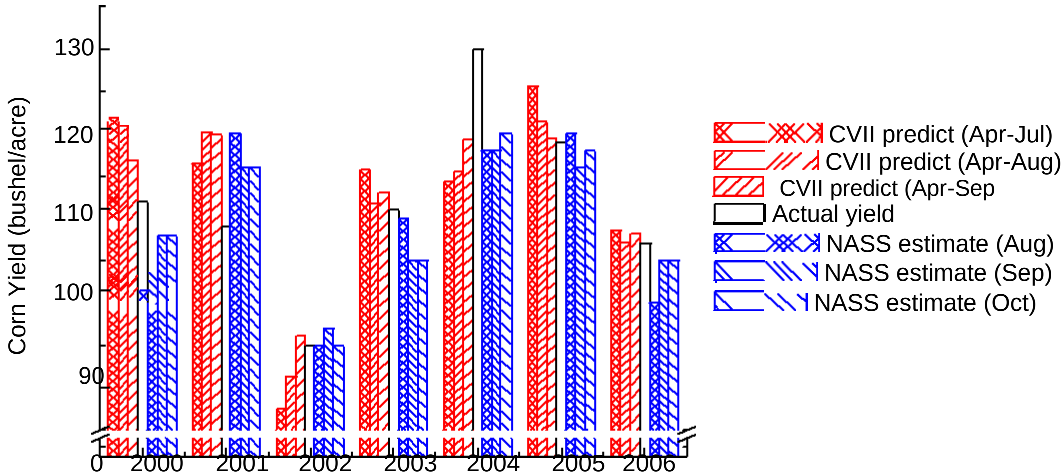

Figure 7. The actual corn yield and the estimated yield in South Dakota made by NASS and CVII model over the course of the growing season. The NASS estimates (blue bars) are released in August, September and October for each year. The CVII model predictions (red bars) are based upon the CVII values at the end of July, August, and September. The model predictions based on integrated CVII have a typical lag of approximately 2 week so that the April-July/August/September integrated CVII predictions are concurrent with the NASS estimates released in August/September/October respectively. The actual yield is observed by NASS after harvesting.

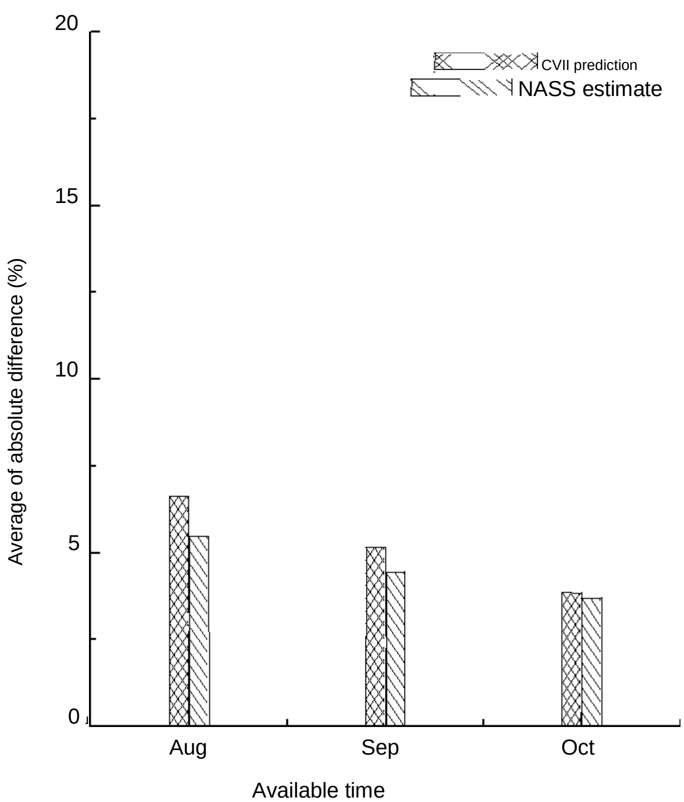

Figure 8. The average (absolute) percentage difference of CVII model predictions and NASS estimates to the actual corn yield in South Dakota over the 2000 - 2006 period. The model predictions based on integrated CVII have a typical lag of approximately 2 week so that the April- July/August/September integrated CVII predictions are concurrent with the NASS estimates released in August/September/October respectively.

CVII predictions have comparable skill to the concurrent NASS forecasts at state-averaged scales in the middle of the growing season. At the same time, the high-resolution CVII values allow us to identify specific regions that are affected by crop loss with greater precision than the coarse-scale state-wide estimates can (Figures 3 and 5).

While only seven years could be used in this study due to limited availability of MODIS data and the USDA estimates, our results suggest that the LAI-based CVII is a good predictor for the crop production. At the same time, some of the data limitations will be eliminated once more when satellite data become available in the future; at that point more robust tests of the predictive capabilities of the CVII will be possible. In addition, the future application of 8 day or 16 day MODIS LAI will also help improve the temporal resolution of the model predictions and may provide yield forecasts earlier and with comparable predictability.

OPERATIONAL PRODUCT DEVELOPMENT AND DISSEMINATION

As mentioned, the MODIS LAI products are available with a lag of approximately 1 - 2 weeks between when the image is taken and the product is available. As such, the CVII maps, both for the globe and for interesting regions, can be generated and put on the web for near real-time monitoring. Based on these two case studies and previous results (Zhang et al., 2004, 2005, 2006), an Experimental Center for Remote Observations of Production (ECROP) site has been constructed to provide real-time CVII maps, production estimation, and validation for the continental US and Europe in the Department of Geography at Boston University (http://www.bu.edu/dev/ecrop/home.html). Starting in 2007, crop yield forecasts will be performed during the course of the growing season. In addition, with future validation efforts, fine temporal CVII maps at 8 day or 16 day scales can be produced for detailed crop development monitoring and earlier yield forecasts. In turn, these operational products can provide detailed information on food availability to policy makers and market managers.

Conclusion

In this paper, a quantitative index is applied to monitor crop growth and predict agricultural yield in drought-stricken regions. Derived from 1 km MODIS Leaf Area Index, the Climate-Variability Impact Index (CVII) quantifies the percentage of the climatological production either gained or lost due to climatic variability during a given month. In addition, the CVII integrated over the growing season represents the fractional loss or gain of vegetation growth for each vegetated pixel over the globe during a given year and is positively correlated to crop yields. For instance, about 50% of the variance in crop production of the study regions in this paper could be explained by variations in the CVII.

In this paper, a statistical model is trained using the historical CVII and yield records and is then applied to predict crop yields for Illinois in 2005 as well as North and South Dakota in 2006, two regions that suffered extreme droughts during the respective years. Research indicates the models trained from corn and wheat counties have similar regression coefficients at the 95% significance level, hence a single model is used for both regions and both crop types (that is corn yield in Illinois and corn and spring wheat yields in the Dakotas). The model predictions are consistent with USDA's estimates obtained after har-vesting. For instance, the model predicts a 7% decrease in 2005 corn yield in Illinois (compared to the previous 5 year average or 145 bushel/acre overall), which is almost identical to the actual state-wide corn yield from NASS released after the harvesting (8% decrease, or 143 bushel/acre). For the Dakotas, the CVII predictions indicated a 23% decrease in wheat and a 4% decrease in corn, compared with the state-wide post-harvesting NASS estimates of a 15% decrease and 1% increase respectively.

Additional findings are also provided by these two case studies. For instance, although on a continental scale the CVII maps integrated over the growing season agree with the growing season water deficit conditions represented by 3 months SPI through July, our results highlight the need for explicit monitoring of vegetation growth when estimating yield. The case study in Illinois in particular demonstrates that drought-monitoring indices based upon meteorological data alone, such as SPI, may miss important variability in vegetative production (Zhang et al., 2004, 2006) because they can both overestimate and underestimate impacts upon vegetation in drought-stricken regions.

In addition, because the satellite data used to derive these indices are available in near real-time (with a typical lag of approximately 1 - 2 weeks between when the image is taken and the product is available), the CVII model may be able to provide yield estimates before the end of the growing season. Here we show that the CVII model can provide significant predictability (less than 10% error) at the state-average level at least 1 - 2 months prior to the start of the harvest. Averaged over the period from 2000 to 2006, the in-season CVII predictions have comparable skill to the concurrent NASS forecasts at state- averaged scales. In addition, the model forecasts improve as more CVII series are added in the late season. For instance, the CVII predictions for corn production in South Dakota based upon the April - July data, have a 7% deviation from the actual yield, while the CVII predictions based upon the April - September data, have only a 4% deviation.

While the satellite-based estimates of yield are not necessarily a substitute for those provided by ground-based methods (as done by agricultural services for instance), satellites can provide a secondary, independent estimate that can pinpoint regions where agricultural failure is greatest. These operational CVII maps and yield forecasts can be produced in a timely manner and disseminated to the public through an Experimental Center for Remote Observations of Production (ECROP) at the department of Geography in Boston University. Overall, the high temporal and spatial resolution as well as the availability of the timely access to the needed MODIS products makes CVII a useful tool for near real-time crop monitoring and yield forecasts before harvesting. More importantly, the cost effective-ness and repetitive, near-global view of earth's surface suggest this LAI-based CVII may significantly improve crop monitoring and yield estimation at regional scales. Furthermore, with inclusion of fine temporal resolution MODIS data, future applications of the 8 day and 16 day CVII maps may provide detailed crop monitoring at different growth stages and provide earlier warning signals.

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