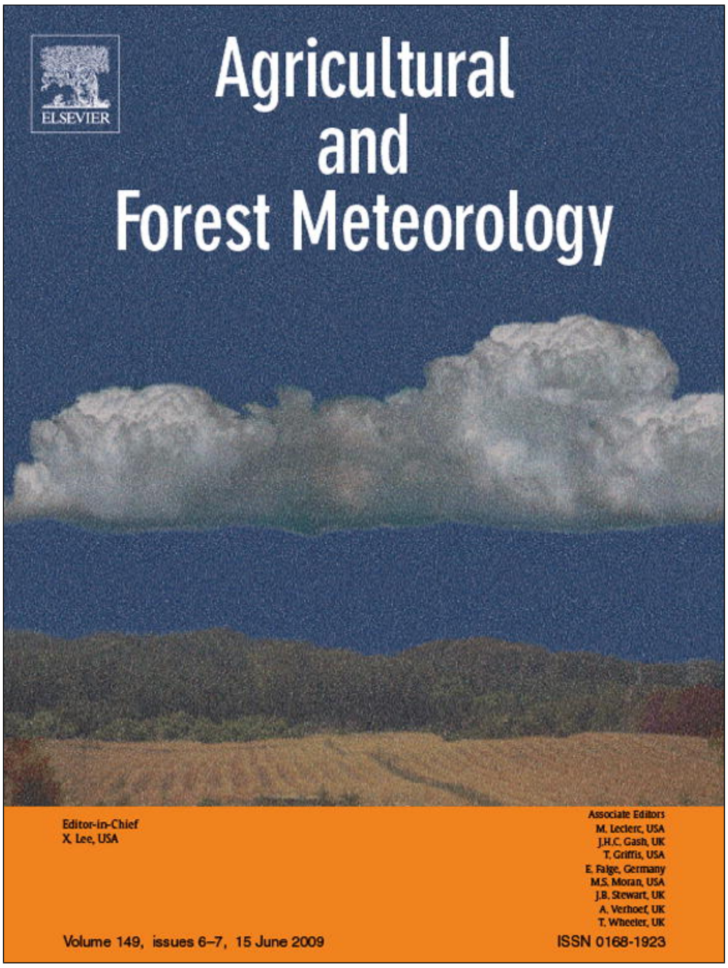
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Quasi-biennial corn yield cycles in Iowa

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ABSTRACT

Quasi-biennial cycles are often reported in climate studies. The interannual El Niño Southern Oscillation (ENSO) and North Atlantic Oscillation (NAO) are two phenomena containing quasi-periodicities of approximately 2.5 and 2.2 years. It is known that ENSO affects corn yield through weather patterns, NAO affects surface temperature and cloudiness, and surface temperature, rainfall, and radiation affect corn yield. However, a quasi-biennial pattern in corn yield and the combined effect of several climate signals on long-term U.S. corn yield are not known. Here we show statistically significant 2–3 year periods in long-term corn yield from one of the world's most important corn producing regions. High (low) yields are due in part to high (low) surface radiation and low (high) temperature early in the corn growing season coupled with sufficient (insufficient) rainfall later in the growing season. A statistical model we developed using three climate indices accounts for 54% of the interannual variation in Iowa corn yield. The most significant periodicities found in the model's spectrum are similar to the quasi-biennial periodicities in observed corn yield. We classify Iowa corn yield from several regional datasets (1960–2006) for 'low yield' and 'high yield' conditions as predicted by the model. The difference between observed corn yields for 'high' and 'low' yielding years was 19% ($p = 0.0001$). The results demonstrate a quasi-biennial pattern in long-term Iowa corn yield related to large-scale climate variability. This knowledge could lead to models that help guide springtime agricultural management decisions that improve profitability and reduce nitrate flux to groundwater, streams, rivers, and coastal oceans.

1. Introduction

The quasi-biennial oscillation (QBO) of the equatorial stratospheric winds is among the most well-known quasi-biennial climate patterns. This phenomenon consists of easterly and westerly wind regimes in the tropical stratosphere with a mean period of 28 months (2.3 years; Baldwin et al., 2001). Surface air temperatures also exhibit a quasi-biennial component, which may be associated with the North Atlantic Oscillation (NAO; approximately 2.2 year period; Mann and Park, 1994). Spectral analysis has helped detect quasi-biennial signals in precipitation (Rajagopalan and Lall, 1998), surface air temperature (Mann and Park, 1994), sea ice cover (Gloersen, 1995), tree rings (Rao and Hamed, 2003), and indices of ENSO (approximately 2.5 year period; Ghil et al., 2002). Despite the evidence for significant quasi-biennial variability in climate, previous studies have argued against a similar timescale crop signal in the U.S. (Black and Thompson, 1978).

Fig. 1 shows six counties in Iowa that cover nearly 9000 km^2 within the surface geologic region known as the Des Moines Lobe. This is an important corn producing region because it is among the highest corn producing and yielding regions in Iowa (Fig. 1), Iowa is generally the leading corn yielding and producing state in the U.S. (USDA-NASS, 2008), and the U.S. has produced approximately 40% of the world's corn since 2000 (FAOSTAT, 2008). Also, these six counties have the principal soil association of Clarion–Nicolette–Webster (ISU, 2004), which require artificial drainage for corn production. Artificial drainage coupled with a high corn yielding environment contribute to streams within the Des Moines Lobe to be among the greatest sources of nitrogen loading to the Mississippi River Basin (Goolsby et al., 2001), which has been implicated as a cause of hypoxia in the northern Gulf of Mexico. In general, anthropogenic perturbation of the global nitrogen cycle is of increasing concern (Gruber and Galloway, 2008), and food production is the major contributor (Galloway et al., 2003). Corn yield variability could affect nitrate flux because small changes in corn yield may have greater effects on N loss in artificially drained soil (Malone and Ma, 2009).

Long-term U.S. corn yield variability is often associated with weather variability such as temperature and rainfall (e.g., Lobell and Asner, 2003; Hu and Buyanovsky, 2003). Large-scale climate

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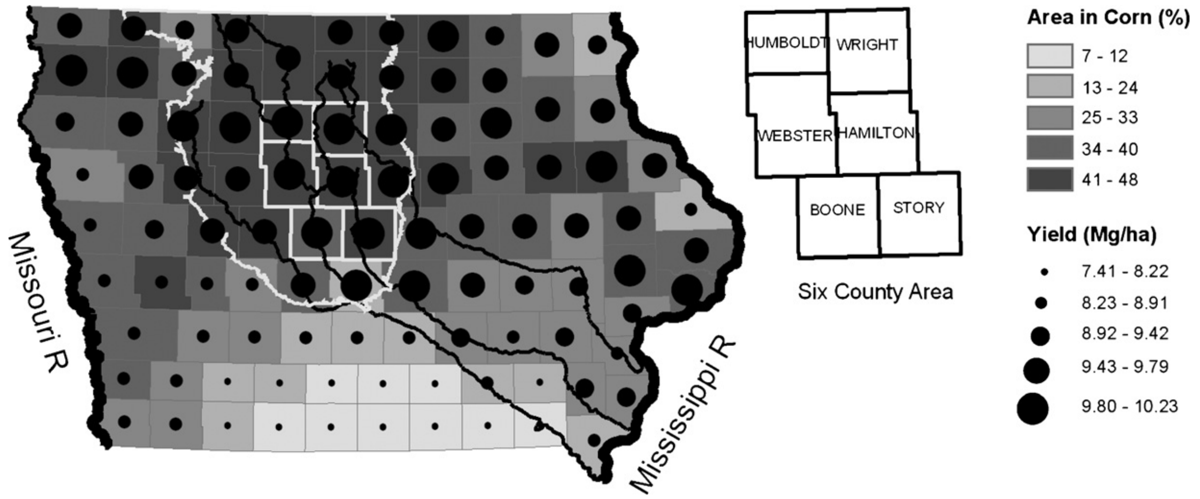

Fig. 1. Average corn yield and land area with harvested corn for each county in Iowa, 1995–2005. The large area outlined in north central Iowa represents the Des Moines Lobe surface geologic region. Six counties are outlined within the Des Moines Lobe. The major rivers draining the Des Moines Lobe area and flowing to the Mississippi River are also shown. Data from USDA-NASS (2008).

signals such as ENSO have been linked to corn yield variability in the U.S. corn-belt because of its association with growing season temperature and precipitation variability (e.g., Phillips et al., 1999; Carlson et al., 1996). Combinations of climate signals (ENSO and the NAO) have been found to affect agro-pastoral production in Africa (Stige et al., 2006). For example, in southern Africa strong associations were found between year-to-year variability of ENSO and corn yield. Also year-to-year NAO variability was associated with slaughter weights of goats in western Africa and rice yield in northern and central Africa. However, the combined effects of several climate indices on U.S. corn yield variability remain fairly unexplored. Also, the effects of annual variation in ground level solar radiation during the growing season on long-term corn yield in the U.S. remain fairly unexplored.

Here we analyze long-term corn yield from the Des Moines Lobe region of Iowa with daily temperature, rainfall, solar radiation, and monthly indices of NAO, SOI, and QBO. The Southern Oscillation Index (SOI) provides a quantitative measure of the ENSO cycle and the SOI correlates with future rainfall in some regions (Stone et al., 1996). This analysis should help answer several questions: does long-term corn yield variability in the U.S. contain a significant quasi-biennial component, what weather drives this phenomenon, is it related to large-scale climate variability, and what are the quantitative effects?

2. Materials and methods

2.1. Data

Table 1 summarizes the data used in this analysis, which includes county-level corn yield from Iowa, climate indices (SOI, QBO, and NAO), daily temperature, daily precipitation, and daily solar radiation. The QBO was briefly described above; the NAO and SOI consist of monthly records of fluctuation in north-south North Atlantic atmospheric pressure gradient (NAO) and the surface air pressure difference between Tahiti and Darwin, Australia (SOI). In Iowa, corn is generally planted in April or early May and harvested in October or November. Irrigation is not much of a factor in Iowa with less than 44,000 irrigated corn acres in 1998 (USDA-NASS, 1999) and more than 12 million planted corn acres (USDA-NASS, 2008). The timing of precipitation, temperature, and solar radiation with the most effect on corn yield variability should range from a few weeks before planting to a few weeks before harvest. Therefore, weather records were compiled that excluded winter and late fall periods.

We detrended the average annual corn yield from the six Iowa counties (Fig. 1) by first describing the linear trend through the "maximum" yield (Fig. 2a). The "maximum yield" is the 3-year maximum subject to the constraint that corn yield increases with time. This constraint is because technology, including seed genetics and fertilizer, increases corn yield with time after 1945 (Hu and Buyanovsky, 2003). Annual corn yield variation mainly due to changes in climate was obtained by subtracting the linear trend (maximum yield) and dividing by the trend (Fig. 2b). This represents the "yield fraction" ($yf = [yield/\{0.148 \times x - 285.23\}] - 1$), where x is the year. The linearly detrended corn yield can be thought of as the corn yield percent difference relative to the expected potential yield.

2.2. Spectral analysis

The spectral analysis focuses on the short-term variations in corn yield data, obtained by subtracting the polynomial component from yf (Fig. 2c). Polynomial and linearly detrended corn yield throughout this text (e.g., individual county corn yield) was detrended similar to this method. Linearly detrended data did not have the polynomial component subtracted.

Table 1
Data summary.

Data	Years	Data source and/or description
Annual county corn yield for Iowa	1950–2006	USDA-NASS (2008)
Monthly climate indices (NAO, SOI, QBO)	1950–2006	NOAA-ESRL (2008)
Daily rainfall (42.03°N, −93.80°W)	1960–2006	IEM (2008)
Daily temperature (42.03 N, −93.80 W)	1960–2006	IEM (2008)
Daily solar radiation (42.03 N, −93.80 W)	1960–1991	Meek (1997)
Daily solar radiation (41.96 N, −93.68 W)	1991–2006	Hatfield et al. (1999)

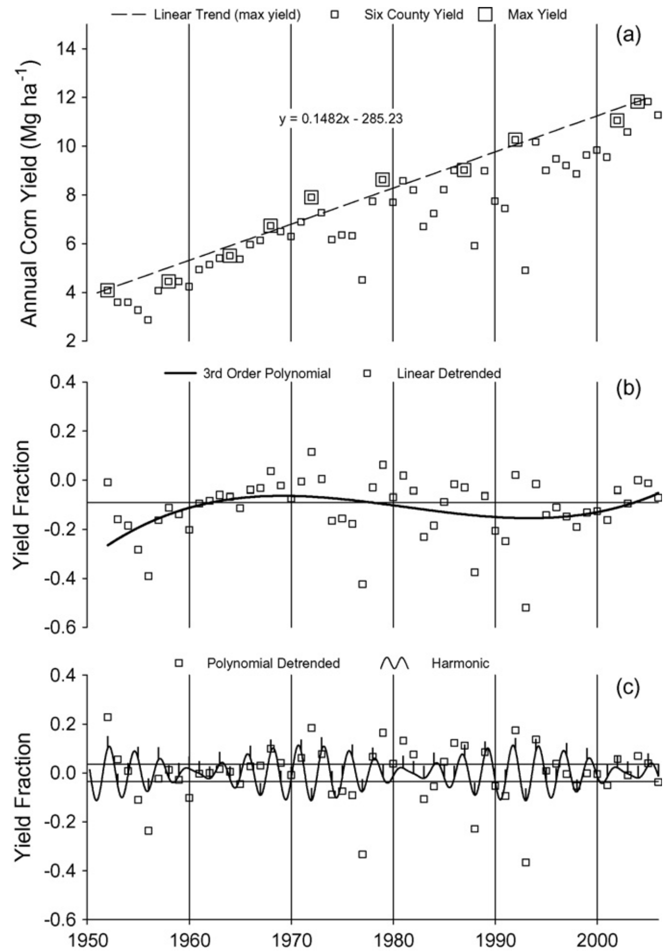

Fig. 2. Annual corn yield for the "six county" area. (a) The small squares show the average annual corn yield from six Iowa counties described in Fig. 1. The large squares show the 3-year maximum yield with the constraint that corn yield increases with time. A linear trend is fitted to the maximum yield. (b) As (a), with the linear trend removed and the third order polynomial fitted to the data superimposed. The median of "neutral" yield was inserted at −0.09 (see text for description). (c) As (b), with the polynomial and the mean subtracted (squares), and the harmonic pattern with two periods (2.3 and 2.6 year) fitted to the data superimposed. The black lines slightly above and below zero are at ±0.035, which were selected as the bounds for "neutral" (see text for description). The small black vertical dashes represent the cyclic pattern at harvest (same time as the polynomial detrended corn yield fraction, black squares).

The multitaper method of spectral analysis was used to detect periodicities in polynomial detrended long-term corn yield. In cases where the signal-to-noise ratio is low (such as climate data), the multitaper method provides a better trade off between spectral resolution and statistical variance than single taper methods (Mann and Lees, 1996). This method also allows for detection of purely harmonic (periodic) signals and broader-band (quasi-periodic) signals, and is relatively easy to test the spectral components for statistical significance. ASUM (2003) was used for the multitaper spectrum with four data tapers ($n = 4$) and a bandwidth of $2.5/N$, where N is equal to 55 years (1952–2006). The sapa package from R was used for coherence spectrum (http://cran.us.r-project.org/). Further details of the multitaper method are described elsewhere (e.g., Rao and Hamed, 2003; Lees and Park, 1995).

Rao and Hamed (2003) included significance levels of $p < 0.1$ for studying regional hydrologic and climatic data using multitaper analysis where several different datasets point to a regional periodicity. We are testing for periodicity within the Des Moines Lobe region of Iowa. Therefore, we use the Fisher method of combining tests of significance (Fisher, 1948) to determine the optimal statistical significance of the periodicities for the "six county" area without considering spatial correlation effects. The Fisher method can be summarized as $X^2_{2k} = 2\sum \ln(1/P)$, where X^2_{2k} is chi-square with $2k$ degrees of freedom, k is the number of combined tests (six in our case for the six different Iowa counties, Fig. 1), and P is the p-value for independent tests.

2.3. Regression analysis

Multivariate regression was performed using weather variables (temperature, rainfall, solar radiation) as predictors and transformed corn yield fraction (yf_t) from 1960 to 2006 as the dependent variable. The linearly detrended corn yield fraction of Story county, which was transformed to approximate normality [$\text{yf\_t} = (\text{yf} + 3)^8/8$], was used for this part of the regression analysis because ground level long-term global solar radiation (wavelength of 285–2800 nm) records are available in Story county Iowa beginning in 1960 (Meek, 1997). The regression analysis included linear, quadratic, and interactive weather predictors (e.g., temperature × precipitation, temperature^2, precipitation^2). A second order polynomial regression was used because weather variables such as temperature and precipitation can have a non-monotonic effect on yield (e.g., Lobell et al., 2007). The interaction terms were included because variables such as precipitation may affect corn yield differently at high and low temperature. We used a combination of selection procedures to develop the final equation such as stepwise, cross-validation, and manual selection of variables. Manual selection of variables was based on statistical relationships, simplicity, and knowledge of corn growth processes and is comparable to Lobell et al. (2007), where manual variable selection was based on statistical relationships and knowledge of crop phenology. The final set of variables is mechanistically plausible and tested using cross-validation.

Similar to the regression analysis using weather variables, multivariate regression was performed using climate variables (NAO, QBO, SOI) as predictors and transformed "six county" corn yield fraction (yf_t) from 1960 to 2006 as the dependent variable. This analysis was conducted because weather variables such as precipitation and temperature that contribute to corn yield variability could be related to larger scale climate variability such as ENSO. In addition, the quasi-biennial component of the NAO may be associated with patterns of surface air temperature (Mann and Park, 1994) and cloudiness (Warren et al., 2007). Higher cloud cover during the daytime is associated with lower incoming ground level radiation, including lower photosynthetically active radiation (PAR). We did not find research that reports correlations between QBO and PAR variability, however, the QBO affects ground level UV-B radiation (Zerefos et al., 1998) and ozone to latitudes of 15–60°N with the maximum effect at approximately 30–40°N (Baldwin et al., 2001). Increased surface UV-B radiation is generally reported to reduce corn yield, but may improve drought tolerance for some plants (Sullivan et al., 2003).

2.4. Cross-validation

We used "k-fold" rather than "leave one out" cross-validation to test the regression equations because climate indices can be serial correlated (e.g., Sabbattelli and Mann, 2007). The data were split into 7 blocks of 39 or 40 observations for model calibration and 6 or 7 omitted values for model validation. The data used were 1960–2006 from Story county or "six county" yf_t and the predictands for the regression equations (see predictand definition below). The two equations with the final set of included variables produced the lowest predictand residual sum of squares (CV PRESS statistic) and lowest mean square error (MSE) for all the steps in the regression procedure. Predictand is the predicted value for the observations omitted from the calibration blocks. The seven validation blocks were 1960–1966, 1967–1973, 1974–1980, 1981–1987, 1988–1994, 1995–2000, or 2001–2006. Note that leave one out cross-validation shows a lower residual sum of squares than *k*-fold suggesting *k*-fold is a more conservative cross-validation technique for our analysis (results of leave one out cross-validation not presented).

2.5. Categorization of data

After the regression analysis with climate indices, we categorized the observed yf according to "high", "neutral", and "low" yield years as determined from the regression equation. Carlson et al. (1996) categorized Midwestern corn yield according to extremes of the Southern Oscillation Index (SOI). Our intents included: maximizing the number of years categorized as "high" or "low", maximizing the difference between "high" and "low" yielding years, and avoiding a classification system unrepresentative of the mean or median yield difference from the "high–low" split. Although somewhat arbitrary, we identified 50% of years as "neutral", which was a reasonable compromise for our objectives as discussed in more detail below (Section 3.3). We also categorized the observed yf as "high", "neutral", and "low" as determined by the spectral analysis, which was used to help quantify the quasi-biennial effect.

3. Results and discussion

3.1. Spectral analysis of detrended observed corn yield

Fig. 2c shows the average annual corn yield fraction from 1952 to 2006 of the six Iowa counties (Fig. 1) with the long-term linear and polynomial trends removed (Fig. 2a and b). Fig. 3a shows the spectrum of Fig. 2c using the multitaper method. The largest spectral magnitude is centered on a frequency of about 0.4 cycles per year (2.5 years). The *F*-statistic in proximity to this frequency suggests two significant periods of 2.3 and 2.6 years (frequencies of 0.43 and 0.38 cycles per year; $p < 0.1$). Using the Fisher (1948) method of combining tests of significance for the six different counties (see Table 2) results in both periods (2.3 and 2.6 years) having an optimum statistical significance at $p < 0.01$ without considering spatial correlation effects.

Fig. 2c shows the optimized cyclic, harmonic pattern of the polynomial detrended data obtained using non-linear regression with two periods of 2.3 and 2.6 years, where it accounts for 24% of the variance. This pattern was categorized as high, low, and neutral, with approximately 50% of corn yield falling into neutral (0.035 to -0.035) and 50% falling into either high (>0.035) or low (<-0.035). The observed annual corn yield fraction for the "six county" area without polynomial detrending (Fig. 2b) was then grouped according to this classification, resulting in low, neutral and high median observed yield fractions of -0.19, -0.09, and -0.03. The difference between the high and low median yield fraction for this area is then 0.16 ($p < 0.05$ using the one-sided median test). Three out of 11 "low" observations were higher than "neutral" (1967, 1969, 1972; Fig. 2b and c) and 5 out of 16 "high" observations were lower than "neutral" (1955, 1957, 1976, 1997, 1999; Fig. 2b and c). The most obvious outlier compared to the optimized harmonic pattern is 1972 (Fig. 2c); the observed data deviate from a harmonic pattern partly because truly harmonic signals are rarely detected in climatic and geophysical time series (e.g., Ghil et al., 2002).

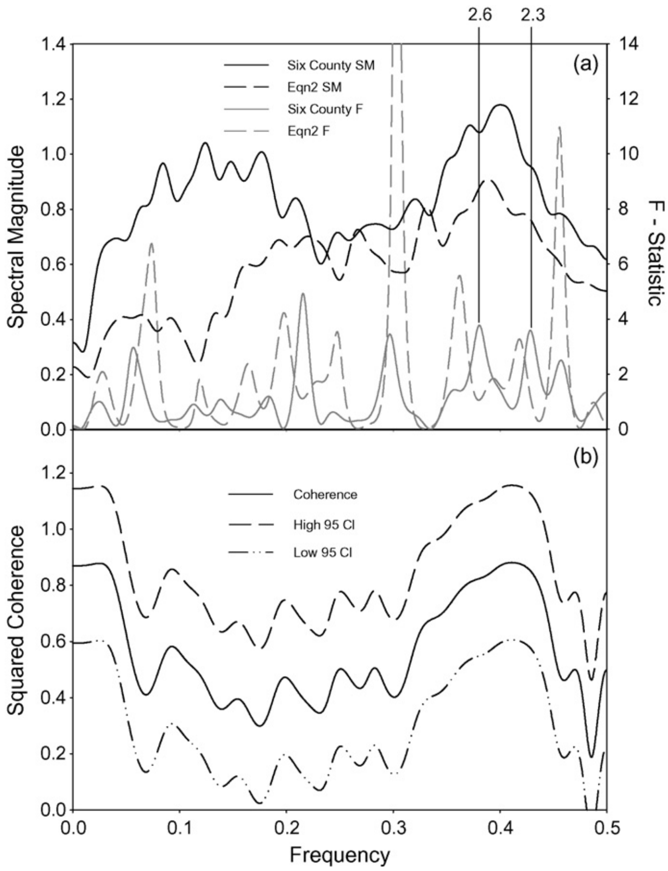

Fig. 3. Spectral analysis of "six county" and climate indices predicted corn yield fraction (Eq. (2)). (a) The multitaper spectrum of six county polynomial detrended yf (Fig. 2c) and Eq. (2) predicted yf that was polynomial detrended, with the *F*-statistic periodicity. (b) The coherency between time series, with 95% confidence bands.

Table 2
Periodicities in polynomial detrended corn yield fraction for different areas within Iowa*.

Area	Frequency (cycles/year)		Period (year/cycle)		*F*-statistic		*p*-value[a]	
	1	2	1	2	1	2	1	2
"six county"	0.38	0.43	2.62	2.34	3.78	3.58	0.09	0.10
Story	0.38	0.43	2.63	2.33	3.83	3.30	0.09	0.11
Boone	0.38	0.43	2.62	2.33	2.61	4.18	0.15	0.07
Hamilton	0.38	0.43	2.64	2.34	4.15	2.88	0.07	0.13
Webster	0.38	0.43	2.64	2.34	3.19	2.22	0.11	0.19
Humbolt	0.38	0.43	2.62	2.33	4.62	5.64	0.06	0.04
Wright	0.39	0.42	2.57	2.36	3.96	3.13	0.08	0.12

* The two periods reported for each county are the nearest significant periods to the "six county" area of 2.62 and 2.34.
[a] *p*-value with 2 and 6 degrees of freedom ($2n - 2$), where n is equal to four data tapers.

3.2. Weather variables and corn yield fraction

We then investigated the timing and sensitivity of weather variables affecting annual corn yield and thus the quasi-biennial pattern. This resulted in the following cross-validated equation (Supplementary Table 3), which accounts for 89% of the variation in Story county annual corn yield fraction (yf; Fig. 4a):

$$\begin{aligned} \text{yf} = \{&[-25748 - (356.7 \times \text{Ltemp}) + (6.357 \times \text{Ltemp}^2) + (7.288 \times \text{Eprecip}) - (5.240E-\\ &3 \times \text{Eprecip}^2) + (2321 \times \text{Etemp}) - (43.82 \times \text{Etemp}^2) - (5.920E-3 \times \text{Eprecip} \times \text{Lprecip}) +\\ &(0.11095 \times \text{Erad} \times \text{Lprecip}) - (0.1267 \times \text{Eprecip} \times \text{Ltemp})] \times 8\}^{(1/8)} - 3 \end{aligned} \tag{1}$$

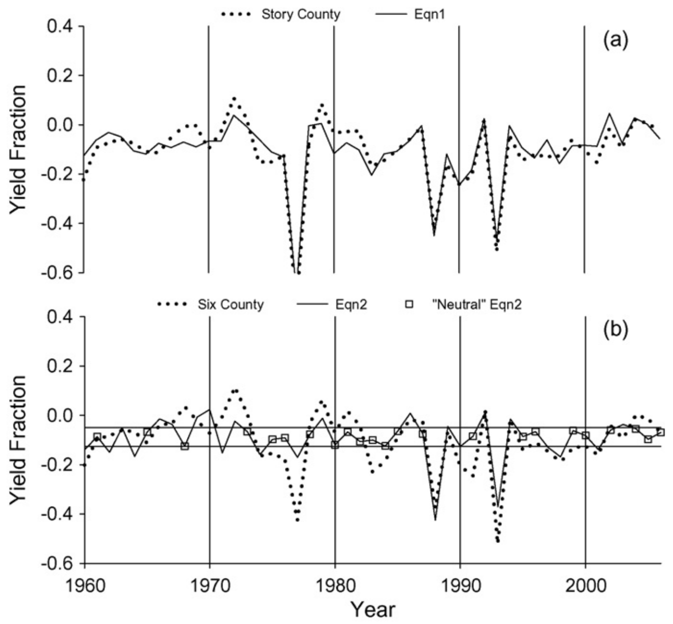

Fig. 4. Annual corn yield fraction (yf). (a) The Eq. (1) predicted annual corn yield fraction with the observed Story county corn yield fraction. (b) The Eq. (2) predicted annual corn yield fraction with the observed "six county" corn yield fraction. The small squares show "neutral" Eq. (2) predicted corn yield (see text). The horizontal black lines at −0.126 and −0.05 were selected as the bounds for "neutral" (see text). Corn yield fraction values before 1960 were not included in the regression analysis (Eqs. (1) and (2)) because radiation data before 1960 are not readily available.

where Etemp and Ltemp are early and late season average daily maximum temperature (°C) for May 10–July 23 and July 24–August 17, Eprecip and Lprecip are early and late season total precipitation (mm) for April 25–July 3 and July 4–September 1, and Erad is early season average daily radiation (MJ/m^2/day) for May 15–June 13. Late season radiation was not a significant term in Eq. (2) ($p > 0.2$).

The equation was developed by systematically adjusting the pentads (5-day) included in weather variable calculation, which minimized the variance between annual observed yf and Eq. (1) predicted yf. This "pentad adjustment" was necessary because within-season weather variations are needed to explain long-term weather effects on corn yield (Hu and Buyanovsky, 2003).

Fig. 5 illustrates the complex relationship among weather variables and corn yield estimated using Eq. (1). For example, two of the most sensitive variables are Erad × Lprecip and Etemp, and high Etemp will cancel any positive benefits of high Erad (Fig. 5). This agrees with Muchow et al. (1990), where worldwide locations with lower temperature and higher solar radiation had maximum corn yield. Also, corn yield depended positively on Lprecip and an interaction between Lprecip and Erad: radiation affected yield positively at high Lprecip, but less so at low Lprecip (Fig. 5), which is supported by the smaller slope of the linear trend through the predicted data (Fig. 6a). Corn yield was relatively unaffected by Lprecip under the conditions of low Erad and high Eprecip (Figs. 5 and 6c). Corn yield was negatively affected by increasing Ltemp but more so under high Eprecip (Figs. 5 and 6d), suggesting that central Iowa corn yield may be more sensitive to higher temperature under high Eprecip but further research is needed to confirm this. Although further research is needed, Hu and Buyanovsky (2003) discussed that dry conditions in the planting and early growing season could stimulate growth of a larger and deeper root system favouring high corn yields because more moisture could be obtained from deeper layers during later growth. If the root system is shallower under high Eprecip, corn may also have a higher likelihood of nitrogen stress because of reduced access to soil nitrate leached below the root zone under high Eprecip. Increasing Eprecip and Etemp tend to improve corn yield until approximately 300 mm and 27 °C then yield decreases with increasing Eprecip and Etemp (Figs. 5 and 6b). High temperature early in the growing season (high Etemp) may reduce the duration of growth during this period. Muchow et al. (1990) explained that the primary influence of temperature is on growth duration. Lower temperature increases the length of time that the crop can intercept radiation, including during the vegetative period. Under favourable growing conditions, biomass accumulation is directly proportional to the amount of radiation intercepted, and grain yield is directly proportional to biomass at a given harvest index (ratio of grain mass/biomass).

Therefore, Eq. (1) produces results that are plausible from our mechanistic understanding of corn growth under variable temperature, precipitation, and radiation. Additionally, observations of higher corn yield with higher Lprecip and lower Ltemp (Figs. 5 and 6c and d) are in agreement with other research. Although corn yield can increase with above average July and August temperatures when rainfall is sufficient (Runge, 1968), below average July and August temperatures and above average July and August rainfall are generally associated with higher corn yield (Malone et al., 2007; Hu and Buyanovsky, 2003; Wilhelm and Wortmann, 2004; Thompson, 1986, 1969).

This regression analysis links long-term corn yield with late May through early June radiation (Erad). Even the earliest mechanistic plant growth models included solar radiation as a sensitive variable (Curry, 1971). However, research is sparse that links solar radiation variability to long term observed crop yield variability. One exception reported lower solar radiation and lower winter Florida vegetable yields during El Niño winters (Hansen et al., 1999). Another study included average solar radiation values for the growing season in the analysis of long-term climate effects on corn yield (e.g., Lobell and Asner, 2003). The difficulty obtaining quality long-term radiation records may help explain why many of the long-term corn yield studies focus on rainfall and/or temperature variations without including radiation in the analysis (e.g., Phillips et al., 1999; Sun et al., 2007; Carlson et al., 1996; Hu and Buyanovsky, 2003).

3.3. Climate indices and corn yield fraction

To investigate the relationship between corn yield and larger-scale climate variability, we constructed a statistical model that predicts annual corn yield as a function of three climate indices. The following cross-validated equation (Supplementary Table 3) describes the resulting model, which accounts for 54% of the variation in the "six county" corn yield fraction (yf; 1960–2006; Fig. 4b):

$$\mathrm{yf} = \{[-196.68 + (130.08 \times \mathrm{nao}) + (33.496 \times \mathrm{qbo_d}) - (0.733 \times \mathrm{qbo_d^2}) - (2.073 \times \mathrm{soi^2})] \times 8\}^{(1/8)} - 3 \quad (2)$$

where 'nao' is the average monthly North Atlantic Oscillation (NAO) for May–July for the planting year; '$\mathrm{qbo_d}$' is the average August–October minus May–July quasi-biennial oscillation (QBO) difference before planting; and 'soi' is the average monthly Southern Oscillation Index (SOI) for October–December before planting. A constant was added to the climate indices in the regression analysis, which increased the values for all years to greater than 1.0 (5, 25, and 9 was added to nao, $\mathrm{qbo_d}$, and soi, respectively). For the most part interpreting Eq. (2) is straight forward with increasing corn yield with increasing nao and decreasing soi. The variable $\mathrm{qbo_d}$ had little effect on corn yield below about 30 but corn yield decreased rapidly with $\mathrm{qbo_d}$ greater than 30.

The variable nao correlated positively with Erad (r = +0.43; p = 0.002); soi^2 correlates negatively with Lprecip (r = −0.32;

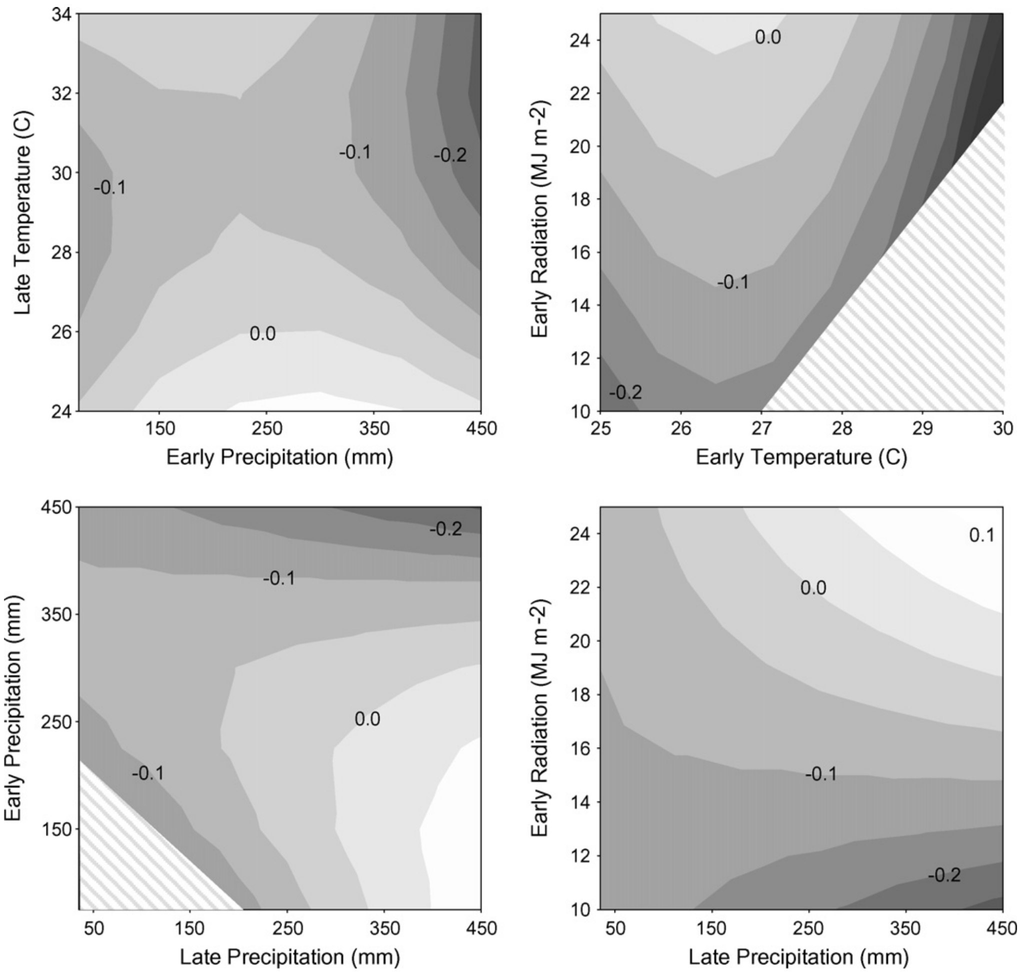

Fig. 5. Corn yield fraction (yf) as a function of weather variables, estimated using Eq. (1) (contour intervals of 0.05). Average values for weather variables are used in Eq. (1) computation of yf except where adjusted as shown. Data are not available for the conditions of high early temperature and low early radiation; data are not available for the conditions of low late precipitation and low early precipitation.

$p = 0.027$); and qbo_d^2 correlates positively with Ltemp ($r = +0.38$; $p = 0.007$). The correlation between nao and Erad could be related to cloud cover (Warren et al., 2007). The correlation between soi and Lprecip may be consistent with low magnitude SOI for two consecutive months associated with a high probability of exceeding median rainfall for the following months in the north-central U.S. (Stone et al., 1996). The QBO has been reported to impact the incidence of extreme temperature events in the wintertime (Thompson et al., 2002) and surface UV radiation (Zerefos et al., 1998). Long-term surface UV radiation data in the U.S. corn-belt is available starting around 1997; as more data is collected, future research may detect a correlation with QBO.

We classified about 50% of Eq. (2) annual yf estimates as neutral and the rest as either high or low (Fig. 4b). The "high", "low", "neutral" classification system used does not appear unrepresentative of the range of possible splits (Fig. 7). This pattern was applied to the observed yield fractions (yf) for the "six county" area, which results in a mean yf difference between high and low yielding years of 0.19 (or 19%; $p = 0.0001$; Table 3). The difference between the high and low median yf for this area is 0.15 (or 15%;

Table 3
Observed mean and median corn yield fractions (yf) for different areas in Iowa grouped by high, low, and neutral*.

Area	Category mean			Means comparison *p*-value			Category median			*p*-value
	High	Neutral	Low	h, n	n, l	h, l	High	Neutral	Low	h, l
"six county"	−0.02	−0.09	−0.21	0.0461	0.0079	0.0001	−0.03	−0.09	−0.18	0.0007
State (Iowa)	−0.03	−0.10	−0.19	0.0892	0.0548	0.0008	−0.02	−0.08	−0.14	0.0007
Story	−0.04	−0.07	−0.24	0.4277	0.0023	0.0003	−0.06	−0.08	−0.15	0.0082
Boone	−0.02	−0.10	−0.24	0.0381	0.0242	0.0001	−0.03	−0.11	−0.16	0.0082
Hamilton	−0.02	−0.10	−0.22	0.0320	0.0108	0.0001	−0.01	−0.07	−0.17	0.0001
Webster	−0.02	−0.09	−0.21	0.0263	0.0120	0.0001	−0.03	−0.09	−0.17	0.0007
Humbolt	−0.03	−0.09	−0.19	0.1316	0.0378	0.0008	−0.02	−0.08	−0.18	0.0007
Wright	−0.02	−0.10	−0.20	0.0288	0.0408	0.0001	−0.03	−0.11	−0.18	0.0001
Calhoun	−0.05	−0.13	−0.21	0.0334	0.1174	0.0006	−0.06	−0.13	−0.20	0.0082
Kossuth	0.00	−0.08	−0.16	0.0634	0.1126	0.0012	−0.01	−0.07	−0.14	0.0007

* The Tukey–Kramer test was used for means comparisons of the corn yield fraction (yf) transformed to achieve a normal distribution ($yf\_t = [yf + 3]^8/8$). The one-sided median test was used for median comparison between "high: and "low" corn yield fraction (yf). The symbols "h", "n", and "l" indicate high, neutral, and low.

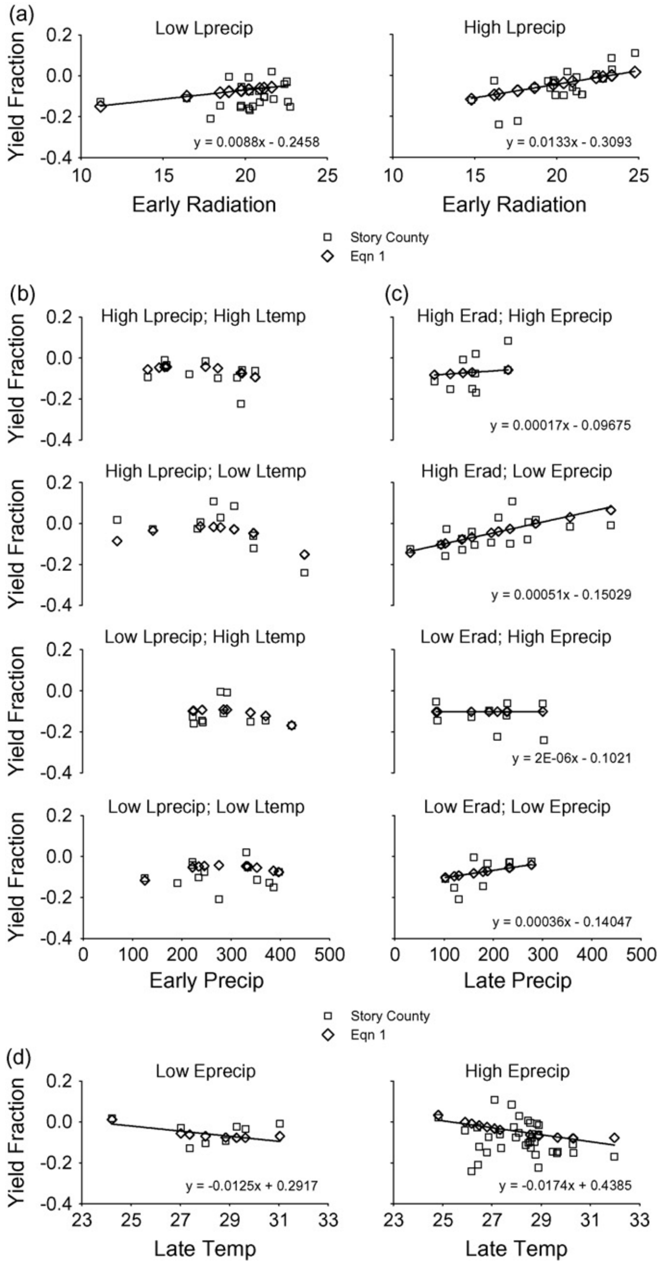

Fig. 6. Story County and Eq. (1) estimated corn yield fraction (yf) as a function of weather. The estimated yf was calculated with median weather variables for the given figure except where adjusted according to x-axis variable. The linear trend through the Eq. (1) predicted yf is presented (except for Eprecip) along with the associated equation of the linear trend. (a) yf as a function of Erad for the lowest and highest Lprecip. (b) yf as a function of Eprecip for the lowest and highest Lprecip and Ltemp. (c) yf as a function of Lprecip for the lowest and highest Erad and Eprecip. (d) yf as a function of Ltemp for the lowest and highest Eprecip.

$p = 0.0007$; Table 3). The mean yf difference when removing the polynomial component (i.e., Fig. 2c) only drops from 0.19 to 0.17 and the median yf difference drops from 0.15 to 0.10, confirming that most of the cyclic effect on corn yield is quasi-biennial rather than longer-term. Applying this same pattern to other regional datasets, the yf mean difference between high and low yielding years ranged from 0.16 to 0.22 for the six individual counties, two bordering counties (Calhoun and Kossuth), and the state total ($p < 0.005$ for all datasets; Table 3). Most of the regional data sets also showed significant differences between high and neutral and low and neutral group comparisons ($p < 0.05$; Table 3). In comparison, long-term corn yield differences between La Niña

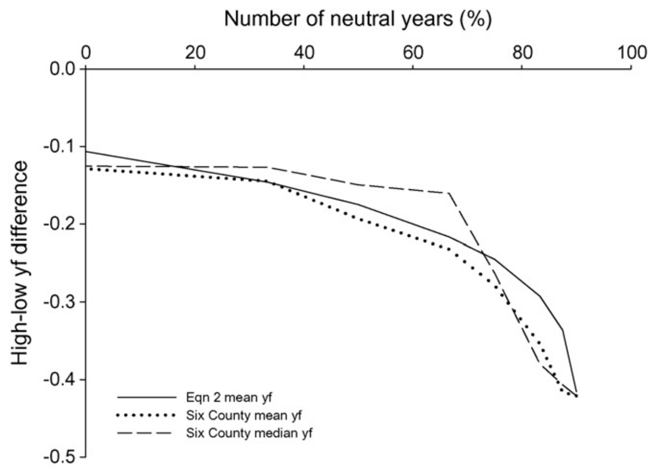

Fig. 7. Difference between "high" and "low" yield fraction (yf) at various categorization of "neutral" years. The yf is Eq. (2) predicted or observed "six county". See text for categorization details.

and El Niño years in the corn-belt are about 10% when nearly 60% of years are classified as neutral (Phillips et al., 1999; Carlson et al., 1996).

3.4. *Spectral analysis of corn yield fraction estimated based on climate indices*

The multitaper power spectrum of the polynomial detrended corn yield fraction series modelled by Eq. (2) over the 1952–2006 interval yields a prominent spectral peak centered at $f = 0.39$ cycles per year (2.6 years; Fig. 3a). The *F*-statistic suggests two significant underlying periods of 2.40 and 2.74 years (frequencies of 0.42 and 0.36 cycles per year; $p < 0.11$; Fig. 3a), which are similar to the peaks of the observed "six county area" corn yield series discussed above (frequencies of 0.43 and 0.38). The two records are highly coherent in the quasi-biennial frequency range (Fig. 3b; approximately 0.4 cycles/years). These results suggest that significant quasi-biennial variability in observed corn yield is related to large scale climate variability.

4. Conclusions

Our results suggest the existence of a quasi-biennial pattern in long-term Iowa corn yields related to large-scale climate variability organized on this timescale. This conclusion should be treated as an impetus for further research. However, we have demonstrated that a statistical model based on underlying climate variables yields skillful predictions of interannual variation in Iowa corn yields. Given the importance of this cereal crop, refined versions of this model might prove to be of economic and environmental significance.

More research is needed partly because our results did not identify a lag-relationship between NAO (compared to corn planting date) and corn yield (Eq. (2)). However, a predictable corn yield pattern with a difference of approximately 19% between high and low yielding years will have economic and production benefits. Stige et al. (2006) suggested that forecasts for NAO and ENSO may help agro-pastoral production in Africa. Jones et al. (2000) reported the potential value of ENSO-only climate forecasts for adjusting corn management practices (planting date, hybrid, N fertilizer amount, planting density) in Tifton, GA was modest at 2% of expected margins. But economic potential was high with more knowledge of the upcoming season's weather with an estimated upper limit of about 25% increase in margins (Jones et al., 2000).

In addition to potential economic and production benefits, tailoring agricultural management to climate forecasts may have a substantial effect on the environment such as N loss. In North Florida, dairy farms could decrease N leaching up to 25% without reducing profit by adjusting management according to ENSO phases (Cabrera et al., 2006). Also, tailoring peanut planting dates to ENSO phases showed at least 10% lower N leaching in about 70% of years (Mavromatis et al., 2002). Reported research is sparse on the impact of adjusting agricultural management to climate forecasts on N loss in the U.S. corn-belt. Small increases in crop N uptake (and corn yield), however, can result in much more substantial decreases in drainage N loss. For example, Malone and Ma (2009) report that 4% greater crop N uptake can result in 30% less N in subsurface drainage in northeastern Iowa. Small changes in nitrogen-containing fertilizer use (e.g., adjusted according to SOI, QBO, and NAO) may substantially reduce nitrate delivery to the Gulf of Mexico (McIsaac et al., 2001). Therefore, refined versions of Eq. (2) may help guide agricultural management decisions that reduce nitrate delivery to streams and improve agricultural profitability within the U.S.

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Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at doi:10.1016/j.agrformet.2009.01.009.

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