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Detecting recent crop phenology dynamics in corn and soybean cropping systems of Kentucky

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Abstract: Accurate phenological information is essential for monitoring crop development, predicting crop yield, and enhancing resilience to cope with climate change. This study employed a curve-change-based dynamic threshold approach on NDVI (Normalized Differential Vegetation Index) time series to detect the planting and harvesting dates for corn and soybean in Kentucky, a typical climatic transition zone, from 2000 to 2018. We compared satellite-based estimates with ground observationsand further performed trend analysis for crop phenological stages over the study period to analyze their relationships with climate change and crop yields. Crop planting dates were delayed for corn and soybean by 0.01 and 0.07 days/year, respectively. Corn harvesting dates were also delayed at a rate of 0.67 days/year, while advanced soybean harvesting occurred at a rate of 0.05 days/year. The growing season length has increased considerably at a rate of 0.66 days/year for corn and was shortened by 0.12 day/year for soybean. Sensitivity analysis showed that planting dates were more sensitive to the early-season temperature, while harvesting dates were significantly correlated with temperature over the entire growing season. In terms of the changing climatic factors, only the increased summer precipitation was statistically related to the delayed corn harvesting dates in Kentucky. Further analysis showed that the increased corn yield was significantly correlated with the delayed harvesting dates (1.37 Bu/acre per day) and extended growing season length (1.67 Bu/acre per day). Our results suggested that crop phenological trends, particularly corn harvesting, were mostly impacted by changes in seasonality (summer precipitation) rather than long-term climate change in Kentucky over the study period. We also highlighted the critical role of changing crop phenology in constraining crop production, which should be given more emphasis on optimizing crop management practices.

Keywords: Crop phenology; MODIS NDVI; Climate change; Agricultural yield; Food security

1. Introduction

Vegetation phenology is defined as the development, differentiation, and initiation of plant organs [1]. Accurate retrieval of crop phenology information is a prerequisite for evaluating crop adaptation to climate change, modeling agricultural ecosystem carbon exchange, and predicting future agricultural production [2-5]. The Intergovernmental Panel on Climate Change has reported a change in global mean temperature of 1.5°C above pre-industrial levels, along with changes in precipitation and an increased frequency of extreme climate events (IPCC, 2018). This shift in climate may bring varying degrees of impacts on agricultural ecosystems at different temporal and spatial scales. Crop phenology is closely related to climate change and is a critical indicator of optimum yield [6-7]. Therefore, it is essential to consider changes in crop phenology when assessing climate impacts on agricultural productivity, carbon cycling, and land-atmosphere feedbacks [8-9].

Many studies have shown that the climate impacts on agricultural ecosystems are reflected in variation in crop phenology, such as the advanced or delayed planting and harvesting dates [10-12]. For example, He et al. [13] reported that soybean planting dates were delayed by an average of 1.78 days/decade, and the growing season length was shortened by an average of 1.16 days/decade during 1981 - 2010 across the major soybean-producing areas in China. Climate warming is a primary factor that drives phenological shifts [14], with temperature responses varying with crop types, locations, and study periods [15-16]. A handful of studies have investigated the responses of crop phenology to historical climate change at regional to global scales. For example, Estrella et al. [17] reported that maize sowing dates in Germany advanced in response to March - May temperature increases at a rate of 0.60 day/°C for maize and 4.15 day/°C for oats. Based on corn phenology observations collected from agro-meteorological stations in China, Tao et al. [18] reported that the growing season lengthened during 1981 - 2009 due to combined effects of warming temperature, changing field practices, and shifting varieties. Model simulation results from Tubiello et al. [19] have shown that predicted warmer temperatures accelerated plant phenology and further shortened the crop growing period, which resulted in crop yield reduction and potential food insecurity. In addition, other climatic factors such as precipitation could also determine the planting date more directly than the temperature in some regions [20-21]; however, few studies have explored the crop phenological changes and their relations with precipitation.

Remote sensing imagery can be considered an essential tool that complements field-based data collection approaches [22]. Numerous studies have reported the use of satellite-based Normalized Differential Vegetation Index (NDVI) and Enhanced Vegetation Index (EVI) for detecting crop phenology [23-25]. Some studies have shown good performance in identifying phenological stages of specific crop types using pre-defined VI thresholds [26]. For example, Sakamoto et al. [27] used a two-step filtering approach to detect the phenological stages of corn and soybean and achieved high accuracies at the site and region levels. Huang et al. [28] applied dynamic thresholds to VI time-series to detect the start and end of the season of different crop types and obtained higher accuracies compared to the results of commonly used 20% or 50% thresholds.

Kentucky is a traditional agricultural state, with corn and soybean being major crops. As a typical climatic transition zone, agriculture in Kentucky faces mixed climates that blend northern and southern weather patterns. A recent study showed that no significant seasonal changes in temperature were found over the last 100 years, especially during the crop growing season in this region [29]. Although crop phenological changes such as earlier planting dates have been widely reported under a warming climate [17-18, 30], the associated spatial patterns are highly varied [31-32]. Uncertainties remain about how crop phenology has changed over areas like Kentucky, where temperature trends were generally flat over the past decades.

In this study, we adopted a curve-change-based dynamic threshold approach to detect the planting and harvesting dates for corn and soybean using MODIS NDVI time series and ground observations in Kentucky from 2000 to 2018. Based on the crop phonological estimations, we also generated the temporal trends of crop phenology and quantified its responses to climatic factors (i.e., temperature and precipitation) and the correlations with crop yields. The objectives of the study are 1) to identify phenological dates of corn and soybean using MODIS NDVI time series in Kentucky from 2000 to 2018; 2) to evaluate the estimated crop phenological stages using ground data at the state and county levels; 3) to characterize the temporal trends of crop phenological stages for corn and soybean in Kentucky during the study period; 4) to examine the correlations between crop planting/harvesting dates and temperature/precipitation variations; 5) to analyze the effects of crop phenological change on crop yields.

2. Materials and Methodology

2.1. Study Area

In this study, we focused on the Commonwealth of Kentucky (36° 30' N to 39° 9' N and 81° 58' W to 89° 34' W) (Figure 1). In general, Kentucky has a humid subtropical climate that is characterized by hot summers and cold to mild winters, with an oceanic climate found in the highlands of the southeast. The mean annual temperatures in Kentucky range from 11.67°C in the northeast to 15°C in the southwest. The annual precipitation is 1143 mm. The northern region receives 965.2 mm of precipitation annually, less than that in the south (1270 mm). Crops in Kentucky are predominantly corn and soybean, which account for more than 90% of total cropland in the state.

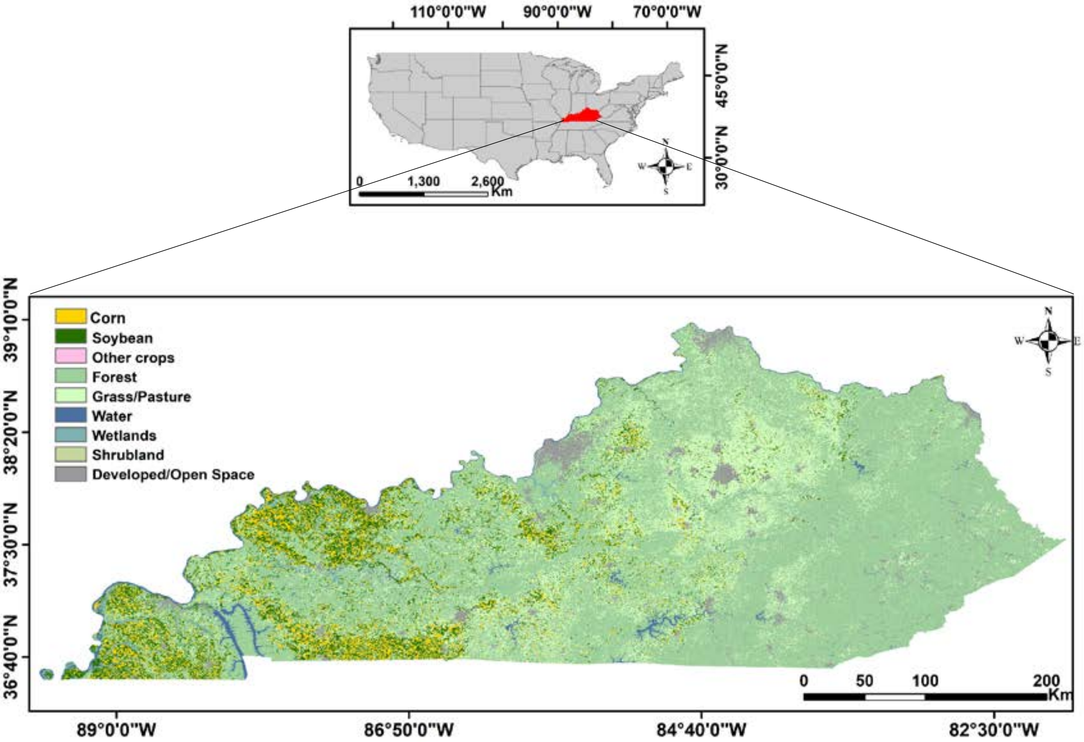

Figure 1. Maps of the study area (Kentucky, overview, and CDL (Cropland Data Layer is derived from USDA NASS)).

2.2. Datasets

2.2.1. Ground Data

We acquired crop planting and harvesting dates of corn and soybean in Kentucky at both the state and county levels. Crop reports released by USDA National Agricultural Statistics Service (NASS) provided the state-level progress of crop phenology information of Kentucky from 2004 to 2018 (https://www.nass.usda.gov/Publications/National_Crop_Progress). The dates of 80% progress of planting and harvesting stages of corn and soybean were extracted from the crop progress and condition graphs in the crop reports using the Web Plot Digitizer (https://automeris.io/WebPlotDigitizer). We also obtained 5-year averaged crop planting and harvesting dates from the same data source. The state-level crop yields were from the USDA survey data (https://quickstats.nass.usda.gov/). The county-level crop phenology datasets were from the Kentucky Hybrid Corn Performance Tests (http://cvt.ca.uky.edu/) and Kentucky Soybean Variety Performance Tests (https://pss.ca.uky.edu/extension/soybean-variety-trials). These tests offered annual planting and harvesting dates of corn and soybean from 2000 to 2018.

Table 1. Description of datasets used in this study.

	Heading dates	Planting dates	Harvesting dates

Phenology descriptions	The peak (DOY) of NDVI time series	The peak (DOY) of the 2nd derivative	The peak (DOY) of the 2nd derivative
Corn: 2000-2004	[143, 254]	[106, 143]	[254, 320]
Corn: 2005-2009	[152, 249]	[101, 152]	[249,314]
Corn: 2010-2014	[161, 251]	[100, 161]	[251, 319]
Corn: 2015-2019	[151, 248]	[98, 151]	[248, 301]
Time ranges	[143, 254]	[98, 161]	[248, 320]
Soybean: 2000-2004	[172, 262]	[113, 172]	[262, 313]
Soybean: 2005-2009	[179, 261]	[121, 179]	[261, 305]
Soybean: 2010-2014	[183, 265]	[112, 183]	[265, 332]
Soybean: 2015-2019	[179, 261]	[125, 179]	[261, 302]
Time ranges	[172, 265]	[112, 183]	[261, 332]

2.2.2. MODIS Data

In this study, the MODIS NDVI time-series calculated from the MCD43A4 product (version 6, ftp://ltdr.nascom.nasa.gov/allData) was used to detect the planting and harvesting dates of corn and soybean in Kentucky from 2000 to 2018 [33]. MCD43A4 provides 500-m and daily surface reflectance of seven bands in a Sinusoidal projection system, available from February 2000 to the present.

The crop classification maps from NASS Cropland Data Layers (NASS-CDL) (https://nassgeodata.gmu.edu/CropScape/) were used to identify specific locations of corn and soybean fields. The NASS-CDL classifies specific crop types and provides multi-year crop classification maps at 30 m resolution for the conterminous United States. This classification map is available from 2008 to 2018 for Kentucky.

We used gridded monthly air temperature and precipitation from Daymet to examine the relationships between climate change and crop phenological development [34], which include minimum/maximum temperature and precipitation at a 1km spatial resolution (https://daymet.ornl.gov/). We calculated the monthly average air temperature based on the maximum and minimum temperatures.

2.3. Methodology

2.3.1. Time Series Data Processing

Google Earth Engine (GEE) was used to process MODIS daily reflectance data. The NDVI was calculated from the reflectances of the RED and NIR bands as follows [35]:

$$NDVI = \frac{\rho_{NIR} - \rho_{RED}}{\rho_{NIR} + \rho_{RED}} \quad (1)$$

where ρ_{RED} and ρ_{NIR} are band 1 (0.620–0.670 µm) and band 2 (0.841 – 0.876 µm) reflectances from the MODIS product, respectively.

It was necessary to smooth the time-series data using smoothing functions before extracting phenological dates. The smoothing methods should take the noise bias caused by snow or clouds into account and be able to handle missing data. Here, the NDVI time series were smoothed by the Harmonic analysis method. The algorithm can smooth and reconstruct remotely sensed VI time-series while reducing the influence of clouds at the pixel level [36].

2.3.2. Detection of Crop Planting Dates, Harvesting Dates, and Crop Growth Period

In this study, the definitions of crop phenological stages were from USDA NASS (https://www.nass.usda.gov/Publications/National_Crop_Progress/terms_definitions). We considered the silking stage of corn and the blooming stage of soybean as heading dates, respectively. We used a curve-change-based dynamic threshold approach on NDVI time-series to identify crop planting and harvesting dates for corn and soybean in Kentucky from 2000 to 2018.

The corn and soybean areas were extracted using the NASS-CDL maps from 2008 to 2018. The original 30-m CDL maps were aggregated into 500-m maps with the percentages of corn or soybean areas being calculated in each 500 m pixel, respectively, to match the size of the MODIS pixel. Pixels with individual crop (corn or soybean) percentage larger than 50% were retained for crop phenology detection. Previous studies have shown that the NDVI increases with leaf green-up during the spring season and decreases with leaf senescence in the fall [37-38]. As VI values in croplands generally exceed 0.4 at peak growth [39], spurious peaks were discarded if the corresponding NDVI values were less than 0.35. We then set a threshold of 0.35 to limit the cropland, i.e., the pixels with the maximum NDVI values less than 0.35 were excluded as non-cropland cover types [40].

For each crop pixel at a given year, the first and the second derivatives of the NDVI curve were defined by the following equations:

$$f(x_i)' = \frac{f(x_i) - f(x_{i-1})}{1} \quad (2)$$

$$f(x_i)'' = \frac{f(x_i)' - f(x_{i-1})'}{1} \quad (3)$$

where f' and f'' are the first- and second-order derivatives of the smoothed NDVI time-series (f), i is the time sequence number of values in the smoothed NDVI time-series (2, 3 …365), 1 is the time step of NDVI time series, and f is the smoothed NDVI time series.

We then identified crop phenological dates based on the characteristics of the derivatives:

Heading dates:

Previous studies have shown that the maximum NDVI was found to occur around the heading dates [41]. We used the point at the NDVI peak to capture crop heading dates and constrained the valid range according to the five-year averaged planting dates from the crop reports dataset (Table 1).

$$\begin{cases} f(x_i)' > 0 \\ f(x_{i+1})' < 0 \\ f(x_{i+1}) \geq 0.35 \\ a < Peak(heading\ dates) < b \end{cases} \quad (4)$$

where f' is the first-order derivative of the NDVI curve; f is smoothed NDVI curve; i means the ith of NDVI/NDVI′ values in the time-series (1, 2, 3…365), a and b are the upper and lower boundaries of the valid time range for NDVI peak, respectively.

Table 1. Parameters thresholds derived from the crop reports dataset used for crop phenology detection.

Phenology descriptions	Heading dates	Planting dates	Harvesting dates
	The peak (DOY) of NDVI time series	The peak (DOY) of the 2nd derivative	The peak (DOY) of the 2nd derivative
Corn: 2000-2004	[143, 254]	[106, 143]	[254, 320]
Corn: 2005-2009	[152, 249]	[101, 152]	[249,314]
Corn: 2010-2014	[161, 251]	[100, 161]	[251, 319]
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Soybean: 2015-2019	[179, 261]	[125, 179]	[261, 302]
Time ranges	[172, 265]	[112, 183]	[261, 332]

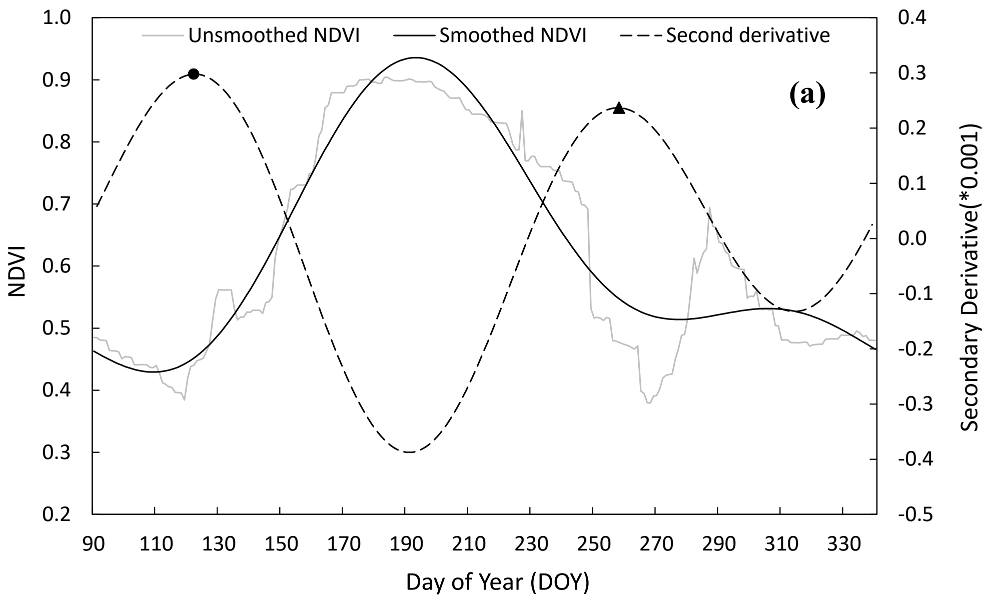
Planting dates:

The NDVI curve shows lower values before crop planting when agricultural lands are plowed or cultivated (Figure. 2). After the crop planting, photosynthetic activity starts with plant expanded leaves, and thereby, the NDVI curve begins to increase. It is reasonable to expect the NDVI value of the planting date is located at the low point at the early stage of the NDVI curve. We, therefore, applied the peak of the second-order derivative of the NDVI curve (before the heading date) to detect the crop planting date. Then the crop planting time was defined at the date when the second derivative of the NDVI curve reaches the first peak before the heading dates. The crop planting dates were constrained within the time range of 40 - 120 days before the heading dates based on the Corn and Soybean Production Calendar in Kentucky (https://simpson.ca.uky.edu/files/corn_and_soybean_production_calendar.pdf). Besides, we also used more accurate ranges to filter out all possible outlier estimates according to the 5-year averaged phenology derived from the crop reports dataset (Table 1).

Harvesting dates:

Plant leaves continue to wither and die during the harvesting season. Crop canopy can be harvested in this stage. Correspondingly, the NDVI value decreases to the lowest point when the crop is harvested from fields. The peak (after the heading date) of the second-order derivative of the NDVI curve can catch the lowest value of NDVI at the last period of the NDVI curve (Figure 2). Here we used this transition point to detect the crop harvesting date. Similarly, the harvesting dates were constrained to occur within the time range of 30 - 110 days after the heading date according to the crop calendar in Kentucky. Similarly, we retained estimates that fall into the valid time range as determined by the 5-year averaged harvesting dates (Table 1).

Subsequently, crop growing season length was calculated for each pixel using the time difference between planting and harvesting dates.



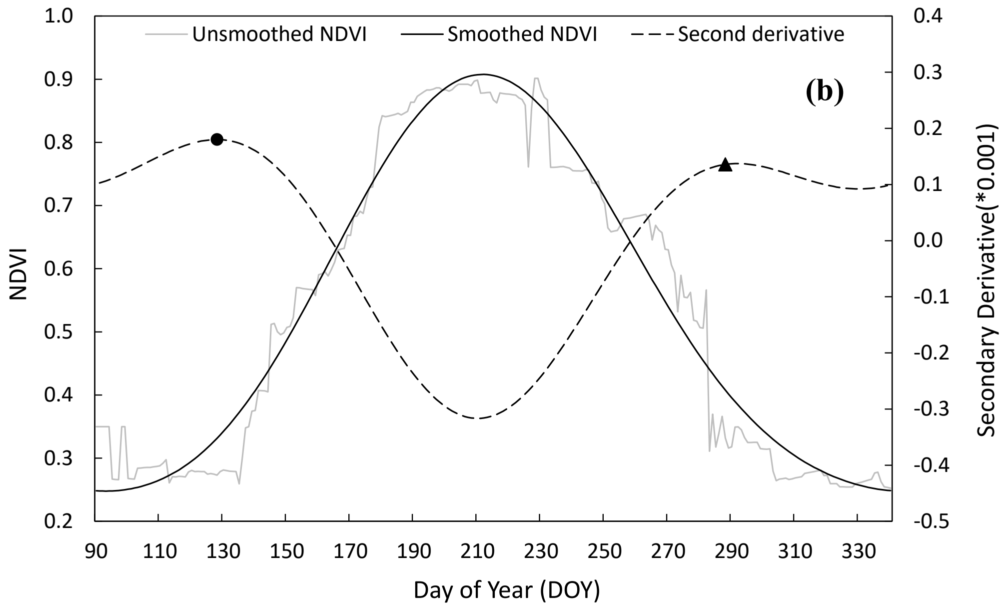


Figure 2. NDVI curves and second derivative of smoothed NDVI for (a) corn and (b) soybean with key points for planting and harvesting dates (● Planting date, Second derivative peak; ▲ Harvesting date, Second derivative peak. Pure pixels were selected in study area based on CDL map).

2.3. Evaluation and Trend Analysis

At the state level, we calculated the dates when the areas of estimated phenological dates occupied 80% of the total planting areas across the whole state for corn and soybean. For county-level evaluation, the mean values of the estimations were calculated for corn (68 counties) and soybean (74 counties) in top producer counties. The coefficient of determination (R^2) and root mean square error (RMSE) were used to evaluate the accuracy of the estimated crop phenology compared with the ground data at both the state and county levels.

$$R^2 = \frac{\sum_{i=1}^{n}(x_i - \bar{x})^2 (y_i - \bar{y})^2}{\sum_{i=1}^{n}(x_i - \bar{x})^2 \sum_{i=1}^{n}(y_i - \bar{y})^2} \quad (5)$$

$$RMSE = \sqrt{\frac{1}{n} * \sum_{i=1}^{n}(y_i - x_i)^2} \quad (6)$$

where n represents the number of samples. y_i and x_i are the ground data and remote sensing estimates, respectively.

Linear regression analysis was applied for generating the changing trends of the phenological estimations at the state level over the study period. We also used the Mann–Kendall test [42-43] and the Sen's slope estimator [44] to analyze the temporal trends of phenological stages at the pixel scale. During the process, pixels with more than 12 years being identified as an individual crop (corn or soybean) were included in the Mann-Kendall test. The analytical method was implemented using the R computing environment [45].

The temporal patterns of climatic factors and crop yields were investigated using linear regression analysis, as well as their relationships with the crop phenology. The Pearson correlation coefficient was adopted to describe the sensitivity of crop phenology to climate change. A paired t-test was used to determine statistical significance. Climatic factors include minimum, maximum, average temperatures, and accumulated precipitation during three seasons (spring: March-May, summer: June-August, fall: September-November) and the whole crop growing period.

3. Results

3.1. Evaluation of Simulated Crop Phenology

3.1.1. State-level Evaluation

The state-level evaluation results showed that crop phenology estimated by remote sensing was at a high level of agreement with the crop reports from the survey data (Figure 3). The estimated harvesting dates closely matched those from the crop reports, with R^2 of 0.92 and 0.90 for corn and soybean, respectively (Figure 3b). The R^2 of the estimated planting dates of corn and soybean against survey data was 0.87 and 0.79, respectively. Notably, the accuracy of the estimated harvesting dates of soybean was the highest, with an RMSE of 3.34 days. The RMSE value of corn harvesting dates was 3.82 days. The accuracies of the estimated planting and harvesting dates of corn were 3.70 and 6.05 days, respectively (Figure 3a).

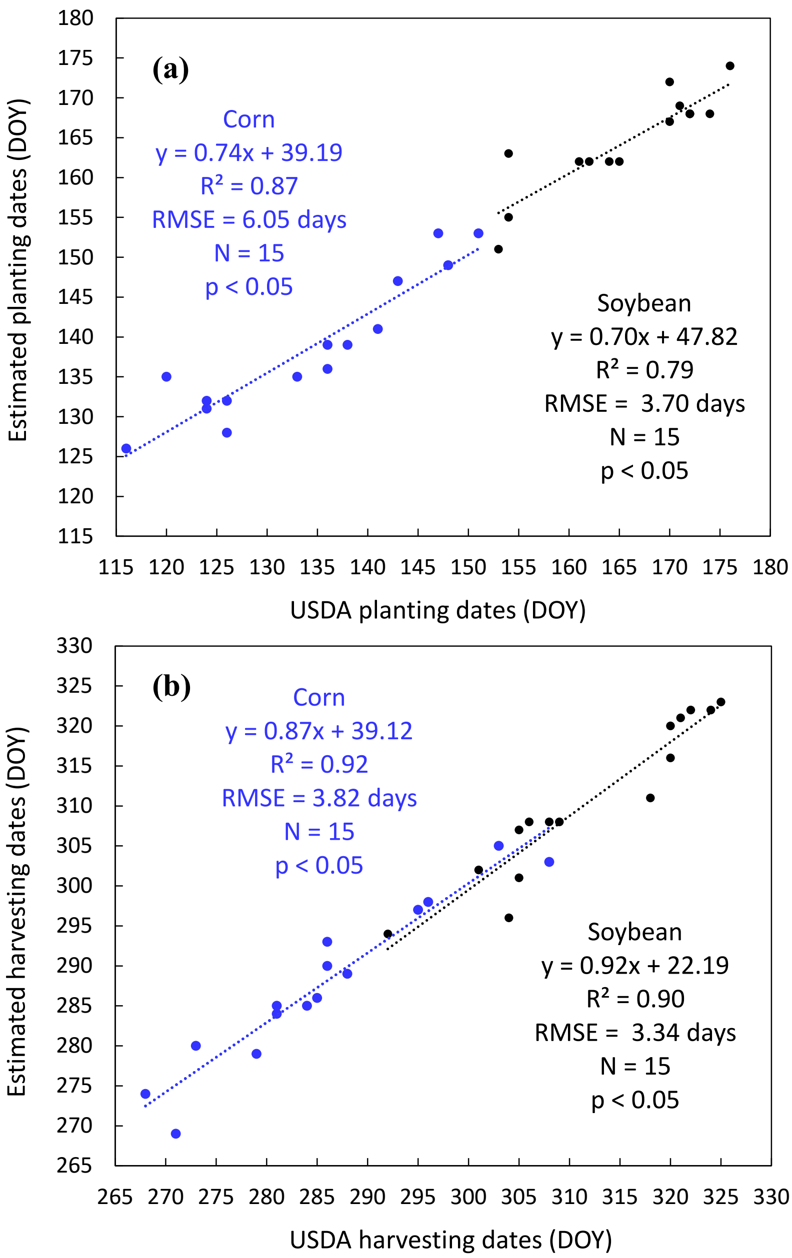


Figure 3. Evaluation of estimated crop phenology at the state level (N is 15 years, blue for corn and red for soybean; a. planting dates; b. harvesting dates).

3.1.2. County-level Evaluation

The county-level assessment appeared to show lower accuracies compared to the state-level assessment (Figure 4). The evaluation results showed that the estimated crop phenological dates were, in general, later than those observed from field tests. Overestimations were larger in estimated planting dates than harvesting dates for both corn and soybean. The RMSE values of corn planting and harvesting dates were 10.84 and 10.93 days, respectively. For soybean, the RMSE of harvesting dates was 9.17 days, and the RMSE value of planting dates was 12.26 days.

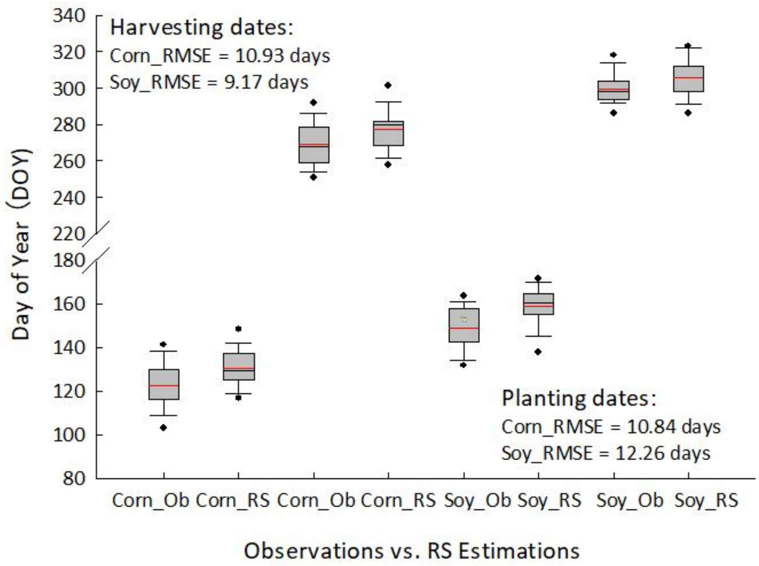
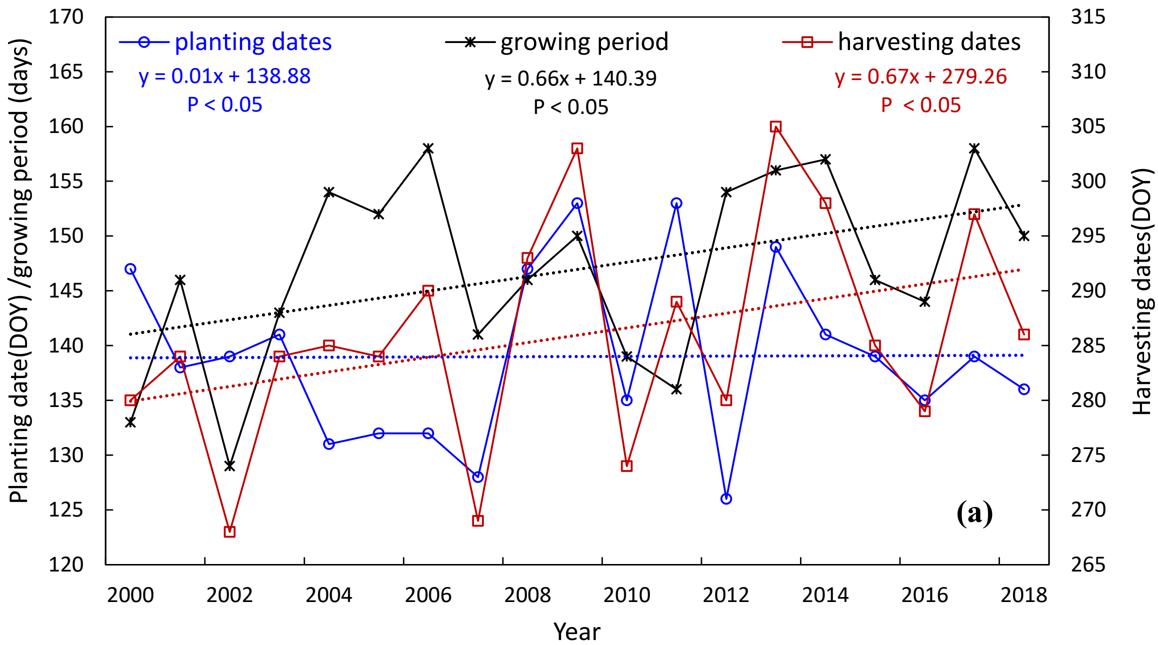


Figure 4. Comparison between the estimated and observed crop phenology at the county level (Red line represents the mean values of each group; Black points represent the values of 5th and 95th of each group; Corn_Ob and Soy_ob represent phenological observations from field tests; Corn_RS and Soy_RS represent phenological estimations from remote sensing).

3.2. Changing Trends of Crop Phenology

Significant phenological trends were found for corn and soybean at the state level in Kentucky over the study period (Figure 5). The crop planting dates were slightly delayed by 0.01 days/year for corn and 0.07 days/year for soybean. Corn harvesting dates were delayed by an average rate of 0.67 days/year, while a slightly advanced pattern (0.05 days/year) in the soybean harvesting dates was detected. The inter-annual variation in the crop growing season length was related to the changing planting and harvesting dates. For soybean, a slightly shortening trend was found at a rate of 0.12 days/year, i.e., 2.28 days over the entire study period. However, the corn growing season experienced an increasing tendency by an average rate of 0.66 days/year, i.e., 12.54 days over the study period.



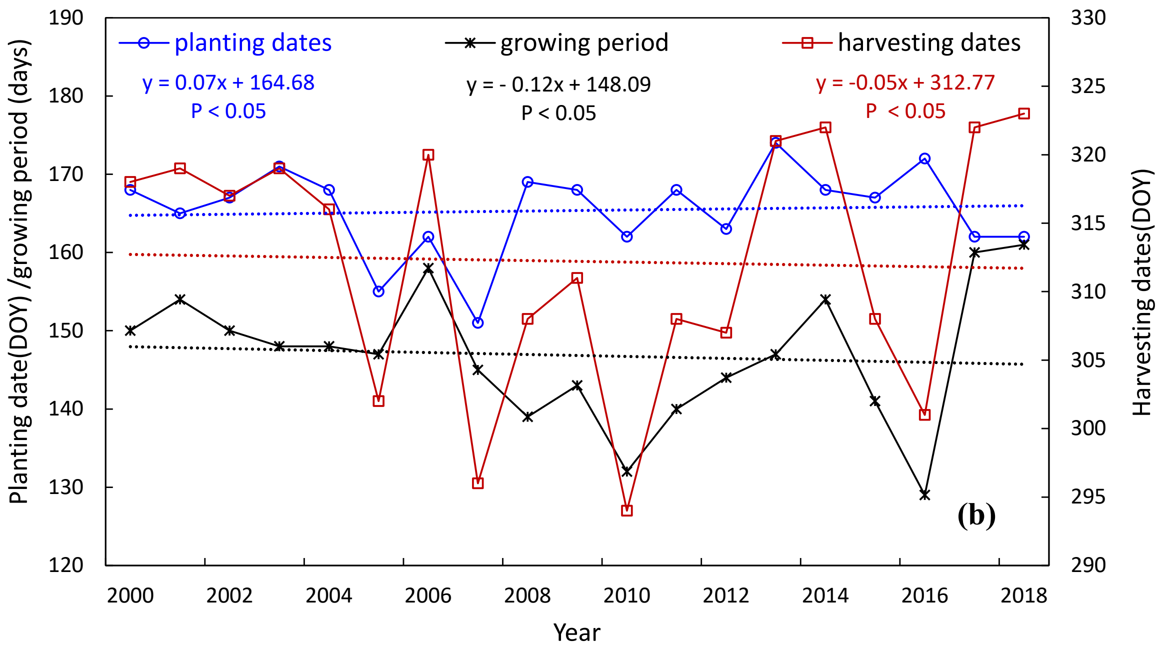


Figure 5. Linear regression analysis for trends of phenological stages in Kentucky, 2000-2018 ((a) corn, (b) soybean).

In addition, widespread negative tendencies were detected for the phenological estimations of corn and soybean from pixel to pixel in Kentucky from 2000 to 2018 (Figures 6 and 7). For corn, the p-values in Figures 6 (b, d, and f) showed that more than one-fifth of corn production areas experienced significant phenological changes. All significant pixels were scattered across the corn production areas. From the statistics (histograms in Figures 6a, c, and e), pixels with unchanged slopes (slope = 0) accounted for the largest proportion (77.10%) of all significant pixels (red color). Figure 6a indicated the corn planting dates had evident negative trends over the study area (18.43% of the significant pixels). However, for corn harvesting dates, comparable proportions of significant trends were displayed with negative (8.28%) and positive slope values (6.05%). In Figure 6e, the growing season length was shortened at most corn production areas (18.43%).

Larger proportions of significant trends were found in soybean planting and harvesting dates compared with those of corn (Figures 7b and d). A quarter of pixels with statistically significant trends ($P < 0.05$) were observed in soybean growing season length. Similarly, pixels with significant unchanged trends (slope = 0) made up to 50% of total significant values (red color) in soybean planting dates, harvesting dates, and growing season length (histograms in Figures 7a, c, and e). An advanced pattern was detected in soybean harvesting dates with a high proportion of negative values (33.79%) (Figure 7c). However, pixels with extended growing season length accounted for 14.18% of the areas with significant trends.

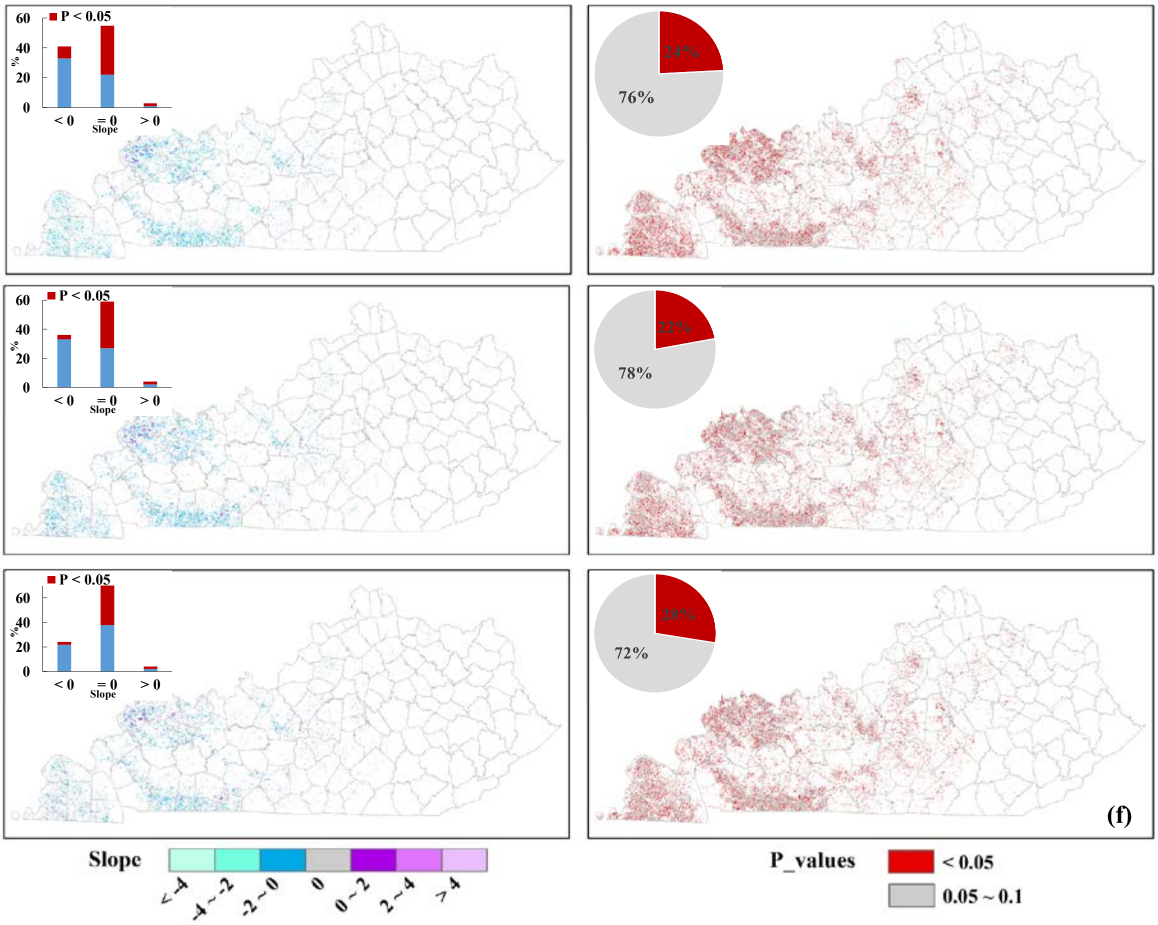


Figure 6. Slope and P values of planting dates ((a), (b)), harvesting dates ((c), (d)), and growing season length ((e), (f)) of corn in Kentucky, 2000 – 2018 (Slope: change rate of crop phenological dates; P values: the confidence of trend analysis; pixels with less than 12 years being identified as corn, which were not included in the Mann-Kendall statistical test).

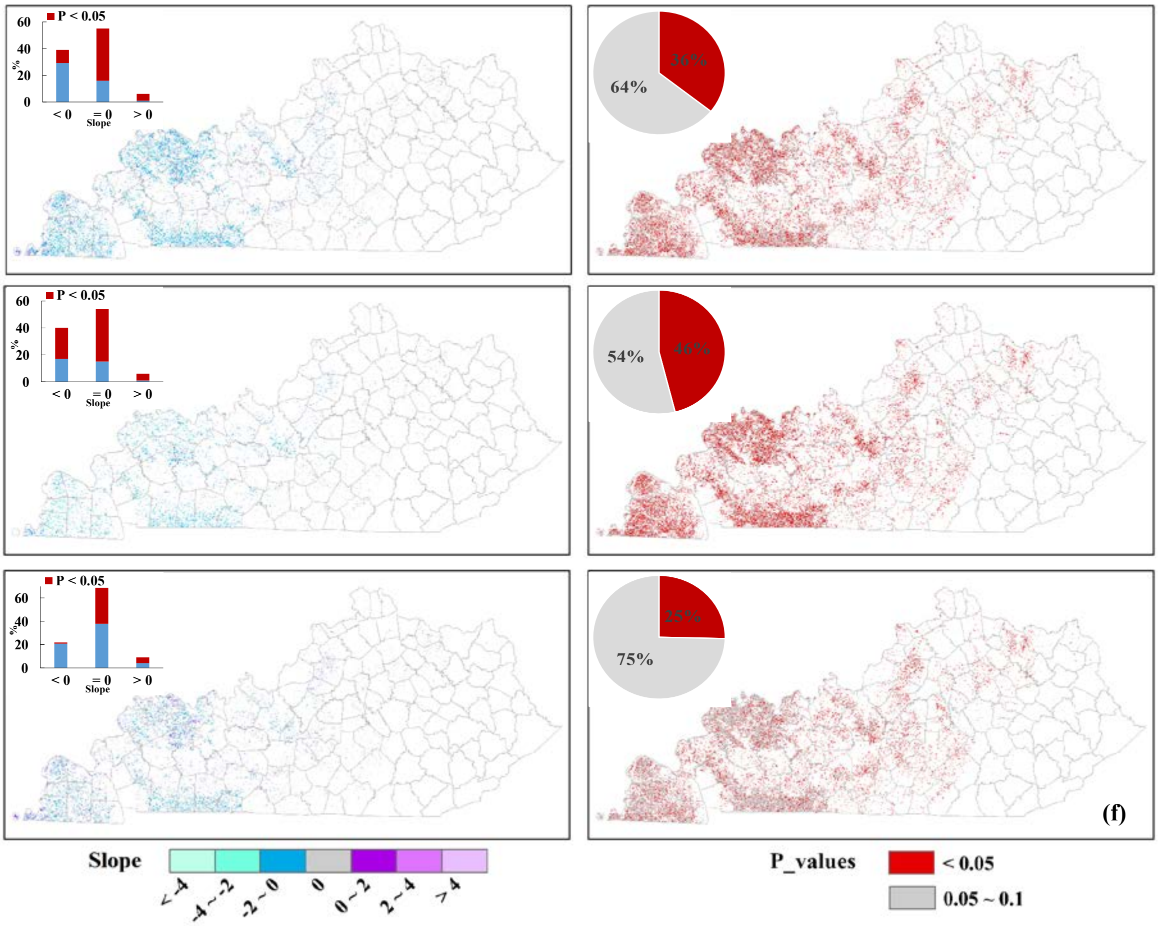


Figure 7. Slope and P values of planting dates ((a), (b)), harvesting dates ((c), (d)), and growing season length ((e), (f)) of soybean in Kentucky, 2000 – 2018 (Slope: change rate of crop phenological dates; P values: the confidence of trend analysis; pixels with less than 12 years being identified as soybean, which were not included in the Mann-Kendall statistical test).

3.3. Trends of Climatic Factors and Its Correlation with Crop Phenology

Maximum temperatures decreased in three seasons and ranged from -0.001 to -0.01 °C/year in Kentucky from 2000 to 2018 (Table 2). Warming trends in minimum and average temperatures were observed, ranging from 0.03 to 0.05 °C/year and from 0.01 to 0.03 °C/year, respectively. Specifically, the minimum temperature during the growing season showed a significant increasing trend with a rate of 0.05 °C/year. Accumulated precipitation increased overtime in all seasons in Kentucky. Notably, significant increasing precipitation in summer occurred at a rate of 5.40 mm/year. Historical climate records showed that summers from 2014 to 2018 are among the ten wettest summers over the last 30 years in Kentucky (http://kyclimate.org/climtrends.html). Thus, over the years tested, the summer climate trended wetter in Kentucky.

Table 2. Trends of seasonal climatic factors in Kentucky, 2000 - 2018.

Seasons	Tmax		Tmin		Tavg		Prec	
	Trends (°C/year)	r	Trends (°C/year)	r	Trends (°C/year)	r	Trends (mm/year)	r
Spring	-0.01	-0.05	0.03	0.16	0.01	0.05	3.58	0.21
Summer	-0.001	-0.003	0.04	0.28	0.02	0.13	5.40*	0.41
Fall	-0.01	-0.03	0.04	0.22	0.02	0.09	0.64	0.04
Apr-Oct	0.01	0.08	0.05**	0.54	0.03	0.31	8.41	0.32

Note: Trends are significant with *P < 0.10, **P < 0.05. Tmax, Tmin, Tavg, and Prec represent the maximum temperature, minimum temperature, average temperature, and precipitation, respectively.

The crop planting/harvesting dates were negatively correlated to three temperature variables and positive to the precipitation for both crops (Tables 3 and 4). Crop planting dates showed significant correlations with the accumulated precipitation in spring. Compared with soybean, corn planting dates were more sensitive to spring temperature. For harvesting dates, higher correlation coefficients with temperature and precipitation were observed for corn and soybean. Significant relationships were found between harvesting and the accumulated precipitation in summer/April - October for corn, and in fall/April - October for soybean, respectively. Corn growing season length exhibited negative sensitivities to temperature variables. Apart from a negative correlation in spring, positive relationships were detected between corn growing season length and the accumulated precipitation. Soybean growing season length was negatively correlated with all climatic factors expect with the accumulated precipitation in fall and April - October. Significant correlations between growing season length and precipitation were mainly concentrated in summer/April - October for corn and in summer/fall for soybean, respectively (Tables 3 and 4).

Table 3. Correlations between corn phenology and climatic variables in Kentucky, 2000 - 2018.

Climate variables in individual seasons	Planting dates		Climate variables in individual seasons	Harvesting dates		Climate variables in individual seasons	Growing season length	
	r	**Response (days/°C; days/mm)**		**r**	**Response (days/°C; days/mm)**		**r**	**Response (days/°C; days/mm)**
Tmax in Spring	-0.56**	-3.95	Tmax in Spring	-0.53**	-4.77	Tmax in Spring	-0.11	-0.82
Tmin in Spring	-0.33	-2.64	Tmin in Spring	-0.27	-2.83	Tmin in Spring	-0.02	-0.19
Tmean in Spring	-0.48**	-3.70	Tmean in Spring	-0.43*	-4.30	Tmean in Spring	-0.07	-0.60
Prec in Spring	0.56**	0.05	Prec in Spring	0.20	0.02	Prec in Spring	-0.28	-0.02
			Tmax in Summer	-0.72***	-7.20	Tmax in Summer	-0.46**	-3.86
			Tmin in Summer	-0.47**	-6.18	Tmin in Summer	-0.38	-4.24
			Tmean in Summer	-0.67***	-8.26	Tmean in Summer	-0.47**	-4.84
			Prec in Summer	0.45*	0.06	Prec in Summer	0.33	0.04
			Tmax in Fall	-0.47**	-3.73	Tmax in Fall	-0.27	-1.81
			Tmin in Fall	-0.20	-2.05	Tmin in Fall	-0.09	-0.77
			Tmean in Fall	-0.41*	-4.32	Tmean in Fall	-0.22	-1.98
			Prec in Fall	0.10	0.01	Prec in Fall	0.07	0.01
			Tmax in Apr-Oct	-0.77***	-9.94	Tmax in Apr-Oct	-0.39*	-4.30
			Tmin in Apr-Oct	-0.36	-6.84	Tmin in Apr-Oct	-0.16	-2.47
			Tmean in Apr-Oct	-0.69***	-12.19	Tmean in Apr-Oct	-0.34	-5.06
			Prec in Apr-Oct	0.47**	0.03	Prec in Apr-Oct	0.17	0.01

Significant level: ***P < 0.01; **P < 0.05; *P < 0.1. Tmin, Tmax, Tavg, and Prec denotes monthly values of maximum, minimum, average temperatures, and cumulative precipitation.

Table 4. Correlations between soybean phenology and climatic variables in Kentucky, 2000 - 2018.

Climate variables in individual seasons	**Planting dates**		**Climate variables in individual seasons**	**Harvesting dates**		**Climate variables in individual seasons**	**Growing season length**	
	r	**Response (days/°C; days/mm)**		**r**	**Response (days/°C; days/mm)**		**r**	**Response (days/°C; days/mm)**
Tmax in Spring	-0.34	-1.71	Tmax in Spring	-0.35	-2.84	Tmax in Spring	-0.15	-1.13
Tmin in Spring	-0.11	-0.64	Tmin in Spring	-0.23	-2.10	Tmin in Spring	-0.17	-1.46
Tmean in Spring	-0.25	-1.37	Tmean in Spring	-0.30	-2.76	Tmean in Spring	-0.16	-1.39
Prec in Spring	0.49**	0.03	Prec in Spring	0.11	0.01	Prec in Spring	-0.20	-0.02
			Tmax in Summer	-0.67***	-5.93	Tmax in Summer	-0.35	-2.93
			Tmin in Summer	-0.48**	-5.59	Tmin in Summer	-0.37	-4.05
			Tmean in Summer	-0.64***	-7.03	Tmean in Summer	-0.39*	-4.04
			Prec in Summer	0.24	0.03	Prec in Summer	-0.03	-0.003
			Tmax in Fall	-0.65***	-4.65	Tmax in Fall	-0.55**	-3.68
			Tmin in Fall	-0.09	-0.82	Tmin in Fall	-0.08	-0.73
			Tmean in Fall	-0.47**	-4.50	Tmean in Fall	-0.41*	-3.60
			Prec in Fall	0.52**	0.05	Prec in Fall	0.54**	0.05
			Tmax in Apr-Oct	-0.69***	-8.00	Tmax in Apr-Oct	-0.38	-4.09
			Tmin in Apr-Oct	-0.23	-3.92	Tmin in Apr-Oct	-0.14	-2.24
			Tmean in Apr-Oct	-0.58***	-9.11	Tmean in Apr-Oct	-0.32	-4.77
			Prec in Apr-Oct	0.49**	0.03	Prec in Apr-Oct	0.21	0.01

Significant level: ***$P < 0.01$; **$P < 0.05$; *$P < 0.1$. Tmin, Tmax, Tavg, and Prec denotes monthly values of maximum, minimum, average temperatures, and cumulative precipitation.

3.4. Trends of Crop Yield and Its Correlation with Crop Phenology

Crop yields showed significant increases in corn (2.19 Bu/acres per year, $p < 0.05$) and soybean (0.75 Bu/acres per year, $p < 0.05$), respectively, in Kentucky over the study period. A more significant increment was found in corn yield. However, we observed that corn yield consistently increased over time except for the sharp decrease in 2012 (68 Bu/acre), dramatically lower than the average corn yield (143 Bu/acre) of the study period. The reduced crop production was relevant to extreme heatwaves and drought during the summer [46].

We further investigated the relationships between the crop phenological dates and crop yields of corn and soybean using the linear regression analysis. Over the 2000 - 2018 period, a significant positive correlation was found between corn growing season length and corn yield, suggesting that a one-day extension of the growing period increased 1.67 Bu/acres ($p < 0.01$) in corn yield. Furthermore, significant responses of harvesting dates to crop yields were detected for corn (trend = 1.37 Bu/acre per day, $p < 0.01$) and soybean (trend = 0.39 Bu/acre per day, $p < 0.05$), respectively.

4. Discussion

4.1. Comparisons of Remote Sensing-Based Crop Phenology with Other Studies

In this study, we detected the crop planting dates, harvesting dates, and growing season length for corn and soybean using an NDVI curve-change-based dynamic threshold approach. The accuracy of crop phenological estimation was comparable with the results in previous studies. For example, using a remote sensing approach, Sakamoto et al. [27] reported the RMSEs of estimated phenological dates ranged from 0.7 to 8.6 days for corn and 1.9 to 14.5 days for soybean. In our study, RMSEs of estimated crop phenological dates were between 3.34 and 6.05 days at the state level and between 9.17 and 12.26 days at the county level. The county-level evaluation showed lower accuracies compared with those of the state-level, which might be related to the evaluation data being from site-level field observations. However, the good performance at the state-level illustrates the potential of the NDVI curve-change-based dynamic threshold approach using MODIS 500-m data to provide a relatively accurate estimate of phenology for corn and soybean.

4.2. Spatial-Temporal Trends of Crop Phenology

We analyzed the state-level linear trends of three estimated crop phenological variables and built their spatial-temporal patterns by the Mann-Kendall test. Many studies have reported that earlier crop planting and extended growing seasons occurred during the past several decades, but the changing trends vary depending on the study period [47-48]. Menzel et al. [49] showed that phenological trends were weaker for the most recent 30-year period (1989 - 2018) compared to the 1976 - 2005 period for both agricultural and wild plants. Kucharik [30] found that the planting date in approximately 75% planted areas of the 12 Corn Belt states was advanced by 0.37 days/year from 1979 to 2005. Notably, Kentucky was among the states with significant changes and was observed with advanced corn planting dates at a rate of 0.8 days/year [30]. Sacks and Kucharik [12] reported that soybean planting dates advanced by 0.49 days/year averaged across the U.S. from 1981 to 2005. However, our study showed a slight delay in crop planting for both corn (0.01 days/year) and soybean (0.07 days/year) at the state level in Kentucky from 2000 to 2018. The changing patterns over different study periods implied that the earlier trend of crop planting season slowed down during the last two decades over the study area. In the U.S. Midwest, soybean is usually planted after completing corn planting. Therefore, delayed corn planting dates might cause delayed soybean planting as well [50]. Sacks and Kucharik [12] also showed that the growing season length of corn and soybean was significantly extended by 0.67 and 0.30 day/year, respectively, in the U.S. during 1981 - 2005. Their findings of the prolonged corn growing season were similar to the results in our study (0.66 days/year).

Meanwhile, we found that soybean experienced a shorter growing season (0.12 days/year) in Kentucky during 2000 - 2018. According to Sacks and Kucharik [12], both corn (1 day/year) and soybean (0.83 days/year) experienced a trend of earlier harvesting in Kentucky over 1981 - 2015. However, our study showed largely postponed harvesting for corn (0.67 days/year) and slightly advanced harvesting for soybean (0.05 days/year) during 2000 - 2018. We also found that the longer corn growing season length could significantly benefit corn yield. The shortened soybean growth period may have undesired consequences for yield but will allow more intercropping or earlier sowing of winter cereals [49]. The advanced harvesting dates and shortened growing season of soybean were probably related to the increasing double cropping system in Kentucky [51].

4.3. Effects of Climate Change and other Factors on Crop Phenology

Temperature is often considered the most critical factor that influences crop phenological change. Many studies suggested advanced trends of crop phenology across the northern hemisphere due to the rising temperatures [52-53]. A long-term study showed that nearly all earlier planting events occurred in warmer years, and more than 80% of them were related to seasonal spring and summer temperatures [17]. In this study, only two climatic variables showed changing trends (minimum temperature in April - October and precipitation in summer from June to August) in Kentucky from 2000 to 2018. From trend analysis, the phenology of corn and soybean was tested with distinctly changing planting, harvesting, and growing season length. Sensitivity analysis showed that crop phenology responded negatively to temperature and positively correlated to precipitation, but no significant response was found with the growing season temperature. The overall analysis revealed that the changing phenology (crop planting and harvesting) was not related to the increasing temperature during April - October.

Climate change raises the question of how field management may need to adapt to the changes in crop phenological development. The trend analysis showed that temperature did not have distinct warming trends in Kentucky over the study period. However, the crop phenology has been observed with significant changes for both corn and soybean. As we discussed, the sensitivity analysis found that only the summer precipitation was significantly related to the delayed corn harvesting dates. The weak linkage between crop phenology and climatic variables indicated that changing phenology is not solely caused by climatic factors. Non-climatic factors (e.g., crop varieties, farmer decisions, cropping systems, and agronomic practices) may also lead to changes in crop phenology [52]. Besides, crop insurance policy is another limiting factor, which restricts the final planting dates for different crop types in different regions [54]. Planting dates falling out of the required period are not covered by insurance, which could influence field activities.

4.4. Effects of Crop Phenological Shift on Crop Yield

Agricultural crop production is closely related to crop phenological change. Previous research presented that the optimum range of crop phenological stages can lead to high crop production [55]. Some studies suggested that warming climate advanced phenological phases and consequently shortened crop growth duration and thereby, might potentially reduce crop yield [2, 19]. However, this study found no significant effects of earlier planting on crop yield in Kentucky. Our result is consistent with Sacks and Kucharik [12], which verified that earlier planting did not show significant effects on crop yields across the U.S. Corn Belt. In addition, we found that planting dates did not show significant correlations with crop yield for both corn and soybean in Kentucky, whereas corn growing season length and harvesting dates contributed to the increased yield during the last two decades. Wu et al. [7] suggested that a longer growth duration might increase agricultural production, which is in agreement with our study. All these findings can be used as a benchmark by farmers to access crop phenology and its associated impacts on crop yield in Kentucky.

4.5. Uncertainty and Expectations

This study detected crop phenological stages using the remote sensing-based method. The robustness of this method is supported by state- and county-level evaluations with ground-based datasets. However, there are still some uncertainties. Firstly, agriculture in Kentucky is mainly concentrated in the north and west regions, while other areas are covered with a high fragmentation of cropland. A 500-m spatial resolution of MODIS products may not accurately capture the crop phenological stages in fragmented areas due to the effects of mixed and perimeter pixels. Data fusion of high-resolution satellite imagery is needed for reducing uncertainties in fragmented areas where mixed cropland pixels are dominant. Secondly, comparisons between county-level satellite-based phenological estimations and site-level field observations might have uncertainties. More ground observations with detailed location information will increase the evaluation accuracy of crop phenology estimations. Thirdly, crop phenology is affected by many non-climatic factors. Thus, there is a need to separate the influences of climatic factors on crop phenological change for further examining the effects of non-climatic factors. Lastly, other crop phenological stages, such as the flowering and grain filling stages, also play critical roles in affecting crop development. Future work should also endeavor to cover more phenological stages to analyze the effects of climate change and improve the capability of crop yield prediction.

5. Conclusions

In this study, using MODIS NDVI time-series and ground datasets, we detected the planting dates, harvesting dates, and growing season length of corn and soybean in Kentucky from 2000 to 2018. We also investigated their dynamic temporal patterns and correlations with climate change and yields. Trend analysis showed that corn experienced delayed planting/harvesting dates and extended growing season length over the study period. However, soybean was found to have delayed planting dates, an advanced harvesting season, and a shortened growing season length. Sensitivity analysis showed that increased seasonal climate temperature could significantly advance the planting and harvesting dates for both corn and soybean. Combining the climate variables and crop phenological patterns revealed that increasing accumulated precipitation in summer was substantially related to the delayed harvesting dates of corn in Kentucky over the study period. This study also suggested that the increasing corn yield had a strong correlation with the delayed harvesting dates and prolonged growing season. No significant correlation was found between climate change and soybean changing phenology. Moreover, changing phenological stages did not contribute to soybean yield. Our findings highlight the future needs to explore the impacts of non-climate-related factors on soybean phenology. The quantitative responses of local crop phenology to climate change and crop yields may provide guidelines for farmers to optimize the field operations.

Author Contributions: Yanjun Yang, Wei Ren, and Bo Tao provided the idea; Yanjun Yang completed most of the statistical analysis, and wrote the paper; Yawen Huang contributed to the data processing with MATLAB; Chris Matocha, Lee, Chad D, Michael Sama, and Bassil El Masri helped to revise the paper and provided a lot of valuable suggestions to the study.

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References

1. Hodges, T. Predicting crop phenology. Crc Press. 1990
2. Anwar, M.R., D.L. Liu, R. Farquharson, I. Macadam, A. Abadi, J. Finlayson, B. Wang, T. Ramilan. Climate change impacts on phenology and yields of five broadacre crops at four climatologically distinct locations in Australia. *Agric. Syst*. **2015**, 132.
3. Liu, L., X. Zhang, Y. Yu, F. Gao, Z. Yang. Real-Time Monitoring of Crop Phenology in the Midwestern United States Using VIIRS Observations. *Remote* Sens. **2018**, 10 (10), 1540.

4. Wang, H., R. Magagi, K. Goïta, M. Trudel, H. McNairn, J. Powers. Crop phenology retrieval via polarimetric SAR decomposition and Random Forest algorithm. *Remote Sens*. *Environ*. **2019**, 231.
5. Yang, L., X. He, F. Shen, C. Zhou, A.X. Zhu, B. Gao, Z. Chen, M. Li. Improving prediction of soil organic carbon content in croplands using phenological parameters extracted from NDVI time series data. *Soil Tillage Res*. **2020**, 196, 104465.
6. Lobell, D.B., G.L. Hammer, G. McLean, C. Messina, M.J. Roberts, W. Schlenker. The critical role of extreme heat for maize production in the United States. *Nat*. *Clim*. *Change*. **2013**, 3(5), 497-501.
7. Wu, D., P. Wang, C. Jiang, J. Yang, Z. Huo, Q. Yu. Measured Phenology Response of Unchanged Crop Varieties to Long-Term Historical Climate Change. *Int. J. Plant Prod*. **2018**, 13, 47-58.
8. Fuhrer, J. Agroecosystem responses to combinations of elevated CO2, ozone, and global climate change. *Agric*. *Ecosyst*. *Environ*. **2003**, 97(1-3), 1-20.
9. Xiao, D., Zhao, Y., Bai, H., Hu, Y., & Cao, J. Impacts of climate warming and crop management on maize phenology in northern China. *J Arid Land*. **2019**, 11(6), 892-903.
10. Abbas, G., S. Ahmad, A. Ahmad, W. Nasim, Z. Fatima, S. Hussain, M.H.U. Rehman, M.A. Khan, M. Hasanuzzaman, S. Fahad, K.J. Boote, G. Hoogenboom. Quantification the impacts of climate change and crop management on phenology of maize-based cropping system in Punjab, Pakistan. *Agric For Meteorol*. **2017**, 247, 42-55.
11. Liu, F., Y. Chen, W. Shi, S. Zhang, F. Tao, Q. Ge. Influences of agricultural phenology dynamic on land surface biophysical process and climate feedback. *J. Geogr*. *Sci*. **2017**, 27(9), 1085-1099.
12. Sacks, W.J. and C.J. Kucharik. Crop management and phenology trends in the U.S. Corn Belt: Impacts on yields, evapotranspiration and energy balance. *Agric For Meteorol*. **2011**, 151, 882-894.
13. He, L., N. Jin, Q. Yu. Impacts of climate change and crop management practices on soybean phenology changes in China. *Sci*. *Total Environ*. **2020**, 707, 135638.
14. Jagadish, S.V.K., R.N. Bahuguna, M. Djanaguiraman, R. Gamuyao, P.V.V. Prasad, P.Q. Craufurd. Implications of High Temperature and Elevated CO2 on Flowering Time in Plants. *Front*. *Plant Sci*. **2016**, 7, 913.
15. Cho, S.J. and B.A. McCarl. Climate change influences on crop mix shifts in the United States. *Sci*. *Rep*. 2017, 7, 40845.
16. Tian, H., W. Ren, B. Tao, G. Sun, A. Chappelka, X. Wang, S. Pan, J. Yang, J. Liu, S. felzer, B., M. melillo, J. Climate extremes and ozone pollution: a growing threat to China's food security. *Ecosystem Health and Sustainability*, **2016**, 2 (1), e01203.
17. Estrella, N., T.H. Sparks, A. Menzel. Trends and temperature response in the phenology of crops in Germany. *Glob*. *Change Biol*. **2007**, 13 (8), 1737-1747.
18. Tao, F., S. Zhang, Z. Zhang, R.P. Rotter. Maize growing duration was prolonged across China in the past three decades under the combined effects of temperature, agronomic management, and cultivar shift. *Glob*. *Change Biol*. **2014**, 20, 3686-99.
19. Tubiello, F.N., M. Donatelli, C. Rosenzweig, C.O. Stockle. Effects of climate change and elevated CO2 on cropping systems: model predictions at two Italian locations. *Eur J Agron*. **2000**, 13, 179-189.
20. Menzel, A. Phenology: its importance to the global change community. *Clim. Change*. **2002**, 54 (4), 379-385.
21. Sacks, W.J., Deryng, D., Foley, J. A., & Ramankutty, N. Crop planting dates: an analysis of global patterns. *Glob*. *Ecol*. *Biogeogr*. **2010**, 19(5), 607-620.
22. Ortiz-Monasterio, J.I. and D.B. Lobell. Remote sensing assessment of regional yield losses due to sub-optimal planting dates and fallow period weed management. *Field Crops Res*. **2007**, 101,80-87.

23. De Castro, A., J. Six, R. Plant, J. Peña. Mapping Crop Calendar Events and Phenology-Related Metrics at the Parcel Level by Object-Based Image Analysis (OBIA) of MODIS-NDVI Time-Series: A Case Study in Central California. *Remote Sens*. **2018**, 10 (11), 1745.
24. Kotsuki, S. and K. Tanaka. SACRA – a method for the estimation of global high-resolution crop calendars from a satellite-sensed NDVI. Hydrol. *Earth Syst. Sci*. **2015**, 19 (11), 4441-4461.
25. Pan, Y., Y. Nie, C. Watene, J. Zhu, F. Liu. Phenological Observations on Classical Prehistoric Sites in the Middle and Lower Reaches of the Yellow River Based on Landsat NDVI Time Series. *Remote Sens*. **2017**, 9(4), 374.
26. Boschetti, M., D. Stroppiana, P.A. Brivio, S. Bocchi. Multi-year monitoring of rice crop phenology through time series analysis of MODIS images. Int. J. *Remote Sens*. **2009**, 30 (18), 4643-4662.
27. Sakamoto, T., B.D. Wardlow, A.A. Gitelson, S.B. Verma, A.E. Suyker, T.J. Arkebauer. A two-step filtering approach for detecting maize and soybean phenology with time-series MODIS data. *Remote Sens*. *Environ*. **2010**, 114, 2146-2159.
28. Huang, X., Liu, J., Zhu, W., Atzberger, C., Liu, Q. The Optimal Threshold and Vegetation Index Time Series for Retrieving Crop Phenology Based on a Modified Dynamic Threshold Method. *Remote Sens*. **2019**, 11(23), 2725.
29. Gil-Alana, L.A. and L. Sauci. US temperatures: Time trends and persistence. *Int J Climatol.* **2019**, 39(13), 5091-5103.
30. Kucharik, C.J. A Multidecadal Trend of Earlier Corn Planting in the Central USA. *J. Agron*. **2006**, 98 (6), 1544-1550.
31. Chen, M., Griffis, T. J., Baker, J., Wood, J. D., Xiao, K. Simulating crop phenology in the Community Land Model and its impact on energy and carbon fluxes. J. Geophys. *Res*. *Biogeosci*. **2015**, 120 (2), 310-325.
32. Piao, S., X. Wang, T. Park, C. Chen, X. Lian, Y. He, J.W. Bjerke, A. Chen, P. Ciais, H. Tømmervik, R. R. Nemani. Characteristics, drivers and feedbacks of global greening. *Nat. Rev*. *Earth E*nviron. **2019**, 1, 14-27.
33. Thompson, J.A. and D.J. Paull. Assessing spatial and temporal patterns in land surface phenology for the Australian Alps (2000–2014). *Remote Sens. Environ*. **2017**, 199, 1-13.
34. Thornton, P.E., M.M. Thornton, B.W. Mayer, Y. Wei, R. Devarakonda, R.S. Vose, R.B. Cook. Daymet: Daily Surface Weather Data on a 1-km Grid for North America, Version 3, in ORNL DAAC, Oak Ridge, Tennessee, USA. 2014.
35. Rouse Jr, J.W., Haas, R. H., Deering, D. W., Schell, J. A., & Harlan, J. C. Monitoring the Vernal Advancement and Retrogradation (Green Wave Effect) of Natural Vegetation. [Great Plains Corridor]. 1974.
36. Zhou, J., L. Jia, M. Menenti. Reconstruction of global MODIS NDVI time series: Performance of Harmonic ANalysis of Time Series (HANTS). *Remote Sens. Environ*. **2015**, 163, 217-228.
37. Ren, J., Campbell, J. B., & Shao, Y. Estimation of SOS and EOS for Midwestern US Corn and Soybean Crops. *Remote Sens.* **2017**, 9 (7), 722.
38. Xu, X., C. Conrad, D. Doktor. Optimising Phenological Metrics Extraction for Different Crop Types in Germany Using the Moderate Resolution Imaging Spectrometer (MODIS). *Remote Sens*. **2017**, 9 (3), 254.
39. Galford, G.L.; Mustard, J.F.; Melillo, J.; Gendrin, A.; Cerri, C.C.; Cerri, C.E. Wavelet analysis of MODIS time series to detect expansion and intensification of row-crop agriculture in Brazil. *Remote Sens. Environ*. **2008**, 112(2), 576-587.
40. Li, L., M. Friedl, Q. Xin, J. Gray, Y. Pan, S. Frolking. Mapping Crop Cycles in China Using MODIS-EVI Time Series. *Remote Sens*. **2014**, 6 (3), 2473-2493.
41. Sakamoto, T., M. Yokozawa, H. Toritani, M. Shibayama, N. Ishitsuka, H. Ohno. A crop phenology detection method using time-series MODIS data. *Remote Sens*. *Environ*. **2005**, 96, 366-374.

42. Alcaraz-Segura, D., E. Chuvieco, H.E. Epstein, E.S. Kasischke, A. Trishchenko. Debating the greening vs. browning of the North American boreal forest: differences between satellite datasets. *Glob. Change Biol*. **2010**, 16 (2), 760-770.
43. Gilbert, R.O. Statistical methods for environmental pollution monitoring. John Wiley & Sons. 1987.
44. Sen, P.K. Estimates of the regression coefficient based on Kendall's tau. *J Am Stat Assoc*, **1968**, 63, 1379-1389.
45. Breiman, L. Random forests. Machine learning, 45, 5-32. 2001
46. Boyer, J. S., Byrne, P., Cassman, K. G., Cooper, M., Delmer, D., Greene, T., Gruis, F., Habben, J., Hausmann, N., Kenny, N. Lafitte, R. The US drought of 2012 in perspective: A call to action. *Glob. Food Sec*. **2013**, 2 (3), 139-143.
47. Piao, S., Q. Liu, A. Chen, I.A. Janssens, Y. Fu, J. Dai, L.Liu, X. Lian, M. Shen, X. Zhu. Plant phenology and global climate change: Current progresses and challenges. *Glob. Change Biol*. **2019**, 25, 1922-1940.
48. Shen, Y. and X. Liu. Phenological Changes of Corn and Soybeans over U.S. by Bayesian Change-Point Model. *Sustainability*. **2015**, 7, 6781-6803.
49. Menzel, A., Y. Yuan, M. Matiu, T. Sparks, H. Scheifinger, R. Gehrig, N. Estrella. Climate change fingerprints in recent European plant phenology. *Glob. Change Biol*. **2020**, 26(4), 2599-2612.
50. Irwin, Scott H., Darrel L. Good, and Mike Tannura. Forming expectations about 2008 US corn and soybean yields—application of crop weather models that incorporate planting progress. No. 1633-2016-135081. 2008.
51. Egli, D.B. Soybean yield trends from 1972 to 2003 in mid-western USA. *Field Crops Res*. **2008**, 106 (1), 53-59.
52. Nguyen-Sy, T., W. Cheng, K. Tawaraya, K. Sugawara, K. Kobayashi. Impacts of climatic and varietal changes on phenology and yield components in rice production in Shonai region of Yamagata Prefecture, Northeast Japan for 36 years. *Plant Prod. Sci*. **2019**, 22, 382-394.
53. Hughes, L. Biological consequences of global warming: is the signal already apparent? *Trends Ecol. Evol.* **2000**, 15(2), 56-61.
54. Du, X., H. Feng, D.A. Hennessy. Rationality of Choices in Subsidized Crop Insurance Markets. *Am J Agric Econ*. **2016,** 99, 732-756.
55. Knott, C., J. Herbek, J. James. Early Planting Dates Maximize Soybean Yield in Kentucky. *Crop. Forage Turfgrass Manag*. **2019**, 5(1), 1-6.