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Impacts of land cover and land use change on long-term trend of land surface phenology: a case study in agricultural ecosystems

Xiaoyang Zhang[1,2], **Lingling Liu**[1,2] **and Geoffrey M Henebry**[3,4]

[1] Geospatial Sciences Center of Excellence, South Dakota State University, Brookings, SD 57007, United States of America
[2] Department of Geography, South Dakota State University, Brookings, SD 57007, United States of America
[3] Center for Global Change and Earth Observations (CGCEO), Michigan State University, East Lansing, MI 48823, United States of America
[4] Department of Geography, Environment, and Spatial Sciences, Michigan State University, East Lansing, MI 48824, United States of America

E-mail: Xiaoyang.Zhang@sdstate.edu

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Abstract

Vegetation phenological trends during last few decades have been frequently reported and these trends are commonly assumed to result from climate change. With the widespread influence of both human activities and natural processes, however, land cover and land use change (LCLUC) has dominated across various ecosystems in more than one-third of world's land surface. LCLUC could lead to changes in vegetation types and species composition at local to regional scales. Thus, we hypothesize that LCLUC can significantly influence phenological trends at an ecosystem scale. Here we tested this hypothesis in agricultural ecosystems composed of various crop types spanning the Midwest of the United States by analyzing satellite-observed land surface phenology from 1982 to 2014. Greenup onset dates in croplands occurred later at rates ranging from 0.18 to 0.67 d yr^{-1} at the state scale. This trend was due to significant areal increases in corn (maize) and soybean that have later emergence coupled with areal decreases in wheat and oats that have earlier emergence, despite a trend of warmer spring temperatures that aid earlier crop emergence. Overall, considering the long-term directional change in greenup onset dates across these croplands, two-thirds was attributable to LCLUC and one-third to climatic variation. This finding indicates that extensive LCLUC can be the primary driver of satellite-observed phenological trends, especially in intensively managed agricultural landscapes.

1. Introduction

Phenology is a sensitive and robust indicator of biological responses to climate change (IPCC 2014). Long-term records of plant phenology have contributed greatly toward the understanding of biological responses to climate change from local to global scales. Species-specific phenological data have indicated that terrestrial ecosystems across the planet are being modified in response to climate change (Parmesan and Yohe 2003, Cleland *et al* 2007, Korner and Basler 2010, Walther 2010). These data generally lack consistent temporal and/or spatial sampling designs; thus, it is challenging to use ground observations of plant species phenology for the monitoring of phenological shifts between ecosystems or across regions. Consequently, there is a great need to characterize accurately how ecosystems respond to climatic change.

Remote sensing has been shown to be an useful tool to characterize seasonal dynamics of the vegetated land surface from local to regional (Melaas *et al* 2018) to continental and global scales (Zhang *et al* 2007, de Jong *et al* 2011, Melaas *et al* 2013). It provides spatio-temporally consistent observations across a large geographical coverage; thus, remote sensing is an ideal tool for exploring the impacts of climatic change on ecosystems. Indeed, long-term land surface phenology as observed from satellite sensors has revealed that vegetation growth has generally been starting earlier in spring and ending later in autumn across the mid-to-high latitudes of the Northern Hemisphere (Myneni *et al* 1997, Zhou *et al* 2001, de Beurs and Henebry 2004, Zhang *et al* 2007, de Jong *et al* 2011). Such shifts in land surface phenology were commonly attributed to the influence of climatic change across different scales (Myneni *et al* 1997, Richardson *et al* 2013).

Satellite-observed phenology characterizes the seasonal dynamics of the vegetated land surface at spatial resolutions from sub-moderate (~30 m), moderate (~500 m), and coarse (>1000 m) (White *et al* 2009, Melaas *et al* 2013, Gao *et al* 2017, Zhang *et al* 2018). These pixels, particularly at moderate to coarse resolutions, usually consist of a mixture of multiple plant species as well as non-vegetated background materials that influence the seasonal pattern of satellite-derived greenness (de Beurs and Henebry 2004). Within a pixel footprint, phenological events associated with different species can vary by three weeks or more (Lechowicz 1984, Augspurger *et al* 2005, Richardson and O'Keefe 2009, Zhang *et al* 2017), where the phenological difference could be enlarged with the alteration of plant species during certain periods (Gerstner *et al* 2014). The variation of plant species mixture in a pixel, which happens across almost all scales, is primarily driven by land cover and land use change (LCLUC), which includes (a) natural processes, such as climate extremes and disturbances (landslides and avalanches, volcanic eruptions and ashfall, tsunamis and storm surge, wildfires, and outbreaks of pests and disease); (b) direct human activities on the landscape, such as agricultural, forestry, grazing management practices, urbanization, reservoir construction, and coastal modification; and (c) indirect human activities affecting the landscape, such as modifications to hydrological routing and flow and soil quality (Turner and Meyer 1991). Among these drivers, direct human activities play a critical role, having modified one-third to one-half of the planetary land surface and transformed at least another one-third of the terrestrial biosphere into rangelands and seminatural anthromes (anthropogenic biomes), i.e. human-dominated biomes (Vitousek *et al* 1997, Ellis 2011). As a result, invasive plant species have occurred worldwide (Mack *et al* 2000, Bradley *et al* 2010, Turbelin *et al* 2017) and crop species diversity has widely decreased (but in some cases increased locally) over past few decades (Aguilar *et al* 2015). All these LCLUC processes can result in substantial variation of plant community composition and abundance within a moderate to coarse resolution satellite pixel as well as within the regional context.

In this paper, we seek to quantify the degree of influence of LCLUC on long-term phenological trends at a regional scale. We assume that variation in cropland ecosystems could provide a clear signal, since agriculture is now the dominant force behind many environmental threats (Foley *et al* 2011). Globally, agriculture occupies about 38% of the Earth's land surface: 12% as croplands and 26% as grazing lands (Foley *et al* 2011). Changes in agricultural practices should show significant impacts on phenological trends, particularly where large-scale agriculture is intensive and mechanized. Although agricultural management practices are largely related to shifts in land use change instead of conversion between land cover types, land use change can have the same functional impacts on phenology as land cover change. Thus, the term of LCLUC is used in this study for easy illustration. We characterized long-term trends of land surface phenology derived from the Advanced Very High Resolution Radiometer (AVHRR) for 1982–1999 and the Moderate Resolution Imaging Spectroradiometer (MODIS) for 2000–2014 in the cropland-dominated region across the Midwest of the USA. Further, the cropland greenup onset trends derived from the long-term satellite data were statistically correlated to climate variation and LCLUC datasets. Finally, the greenup trends were decomposed into the proportion of change attributable to climatic variation and to LCLUC.

2. Materials and methods

2.1. Phenological metrics in croplands from AVHRR and MODIS data

Time series of daily satellite data were collected from two sensors for 1982 through 2014 in this study. The AVHRR Long Term Data Record (LTDR) from 1981 to 1999 provided daily surface spectral reflectance at a spatial resolution of 0.05 degrees (~5 km), which was derived from a set of AVHRR sensors on the NOAA-7, NOAA-9, NOAA-11, NOAA-14, and NOAA-16 satellites (Vermote and Saleous 2006). This dataset was calibrated to be continuous with MODIS data by a NASA-funded MEASURES project (http://vip.arizona.edu/viplab_data_explorer). Additionally, the MODIS dataset at Climate Modeling Grid (CMG) provided daily surface reflectance at a spatial resolution of 0.05°, covering the period of 2000–2014. From the daily red and near infrared reflectance, we calculated the long-term daily two-band enhanced vegetation index (EVI2) (Huete *et al* 2006, Jiang *et al* 2008). EVI2 remains functionally equivalent to the enhanced vegetation index (EVI) despite the removal of the blue band, and it retains advantages over the NDVI (Huete *et al* 2002). Specifically, EVI2 reduces sensitivity to soil, non-photosynthetically active vegetation (i.e. litter, woody tissues, etc) and atmospheric effects, but still remains sensitive to changes in canopy structure and density in cases where NDVI loses sensitivity (Huete *et al* 2002, Rocha and Shaver 2009). We further generated a time series of 3 d EVI2 composited from daily data for croplands in the Midwest, where croplands were determined using the MODIS IGBP land cover type (Friedl *et al* 2010).

The EVI2 time series from AVHRR and MODIS data was used to identify the timing of onset of greenness increase (called 'greenup onset' henceforth) from 1982 to 2014 in this study. There are many methods available for detecting land surface phenology. These methods commonly remove abiotic impacts by smoothing or fitting the temporal vegetation index using moving-window averages (Reed *et al* 1994), Fourier harmonic analyses (Moody and Johnson 2001), asymmetric Gaussian function-fits (Jonsson and Eklundh 2002), piece-wise logistic functions (Zhang *et al* 2003), Savitzky–Golay filters (Chen *et al* 2004), quadratic models based on degree-day accumulations (Henebry and de Beurs 2013), polynomial (or spline-based) curve fitting (Bradley *et al* 2007), and shape model fitting (Sakamoto *et al* 2010). The smoothed or fitted time series of vegetation index is then used to identify the start of a vegetation growing season using methods that include threshold-based techniques (Fischer 1994, White *et al* 1997, Jonsson and Eklundh 2002), harmonic analyses (Jakubauskas *et al* 2001, Moody and Johnson 2001), and inflection point estimates within the time series of vegetation indices (Moulin *et al* 1997, Zhang *et al* 2003). Because different assumptions are involved, various phenological detection methods can produce considerable discrepancies using the same data (White *et al* 2009, de Beurs and Henebry 2010).

We detected crop greenup onset using the hybrid piecewise logistic model-land surface phenology detection (HPLM-LSPD) algorithm (Zhang *et al* 2003, Zhang 2015). This HPLM-LSPD has been demonstrated effective in depicting the temporal trajectory of land surface phenology across various ecosystems (Zhang *et al* 2003, Ahl *et al* 2006, Richardson *et al* 2006, Zhang *et al* 2006, Liang *et al* 2011). It is because the HPLM-LSPD algorithm minimizes snow and cloud contaminations explicitly, describes either symmetric or asymmetric vegetation greenness development, assigns each model parameter to a biophysical meaning related to vegetation greenup, and identify phenological transition dates without predefined thresholds (Zhang 2018). Briefly, observations of clouds and snow cover were removed from the temporal daily EVI2 data according to quality assurance flags in the AVHRR LTDR and MODIS CMG datasets. Snow contamination in a pixel-based annual time series was replaced using the background EVI2 value, which represented the minimum EVI2 that reflects soil and evergreen vegetation (Zhang 2015). Temporal data gaps caused by clouds were filled by linear interpolation using neighboring good quality data. The EVI2 time series for individual pixels was smoothed using a Savitzky-Golay filter (Chen *et al* 2004) followed by a running local median filter using a window of five 3 d lengths. Each smoothed EVI2 time series was then modeled using the hybrid piecewise logistic function. Phenological transition dates within a growing season were identified using the rate of change in the curvature of the modeled curves (Zhang *et al* 2003).

2.2. Crop area and phenology

Data on crop progress at the state level are available at the USDA (US Department of Agriculture) National Agricultural Statistics Service (NASS) website (http://nass.usda.gov/). Surveys are conducted weekly by NASS to provide state-level information on acreage planted, acreage harvested and yield for a variety of crop types. We used data for both the planted crop area and crop progress (timing of emergence for areal proportion of crop). These data have been compiled based on surveys collected from random samples of farms. We obtained the data for barley, corn (maize), oats, soybeans, sorghum, and wheat from 1982 to 2014 for twelve states in the US Midwest: North Dakota (ND), South Dakota (SD), Nebraska (NE), Kansas (KS), Minnesota (MN), Iowa (IA), Missouri (MO), Wisconsin (WI), Illinois (IL), Michigan (MI), Indiana (IN), and Ohio (OH). However, crop progress data were mainly available after 1999, and the crops surveyed varied by state.

2.3. Climate data

We used the 3 h surface temperature data at a spatial resolution of 32 km (approximately 0.25°) between 1982 and 2014 from the NCEP (National Centers for Environmental Prediction) North America Regional Reanalysis (NARR) (Mesinger *et al* 2006) to investigate the crop responses to climatic change. The NARR dataset was produced using a fixed assimilation/forecast model, which blends a variety of observational data into model output containing 45 vertical layers over a mesh across North America. It provides a detailed reanalysis of meteorological and surface variables and is the most accurate and consistent long-time series of dataset that covers all of North America (Mesinger *et al* 2006). From this dataset, we calculated monthly temperature for the individual states.

2.4. Evaluation of crop greenup onsets calculated from EVI2

Crop phenology detected from satellite greenness provides an indirect estimate of physiological crop growth stages (Gao *et al* 2017). The crop greenup onset derived using the HPLM-LSPD has been evaluated in previous studies, showing that the greenup onsets were strongly correlated to NASS crop emergence dates for specific crops at 30 m (Gao *et al* 2017) and pure crop pixels (500 m) (Liu *et al* 2018), although a lag was observed between the satellite detections and NASS measurements. Similarly, phenological timings for corn and soybean in the Central US have been reliably retrieved from satellite observations at 250 and 500 m resolution using methods such as the shape model filtering approach (Sakamoto *et al* 2010, Zeng *et al* 2016, Sakamoto 2018).

Because phenology detections were performed for ~5 km pixels in this study, all the pixels were the mixture of various crop types. Thus, it was impossible for us to directly validate the crop phenology detections. Alternatively, we evaluated the interannual variation of the 5 km greenup onsets using the NASS crop progress. Specifically, the crop greenup onset at the state level was averaged and statistically correlated to the timing of crop emergence for 10% and 50% crop progress stages (in NASS crop areas), separately. We also calculated the long-term mean absolute difference (MAD) between the greenup onset dates and the NASS crop progress reports.

2.5. Long-term trends and interannual variation in greenup onset, croplands, and spring temperature

The trends and interannual variation in satellite-derived greenup onset dates were analyzed for individual states in order to match the spatial resolution of the NASS data. Analysis at the state level is reasonable because satellite footprints are sufficiently coarse to characterize the phenology of crop mixtures, and detailed spatial patterns of crop type are not available from the NASS surveys. Analysis of crop growth at the state level is similar to the examination of phenological variation within an ecoregion (Dannenberg *et al* 2018). The ecoregion maybe an ideal unit to provide localized patterns of ecosystem changes because it delineates areas that share common climatic characteristics, vegetation properties, and seasonal variation in vegetation greenness (Olson *et al* 2001, Hargrove *et al* 2009). However, crop progress reports are not conducted for ecoregions. Therefore, we investigated long-term variations and trends of greenup onset, area of croplands, and spring temperatures at the scale of individual states.

Linear regression was used for two purposes: (1) to identify any long-term trends for greenup onset, area of croplands, and spring temperatures; and (2) to characterize the relationship between crop greenup onset and the influences of LCLUC and climate change. Prior to estimation of the regression trend, the greenup onset time series needed slight adjustments to reduce the possible impacts of sensor differences. Although the AVHRR data were calibrated to be continuous with the MODIS data (Yoshioka *et al* 2012), inconsistencies may remain in some pixels because the MODIS data are of higher quality, which could affect trend estimation (de Beurs and Henebry 2005). To minimize such an impact, this method assumed that the timing of greenup onset in 1999 and 2000 predicted separately from the models of linear temporal trends from 1982 to 1999 (AVHRR) and from 2000 to 2014 (MODIS) should be identical. Their difference, if any, was used to adjust the greenup onset detected from the AVHRR data to be comparable to the MODIS detections.

Multiple linear regression was conducted to examine the relative contributions of crop type change and climatic variation on the trend of greenup onset timing in croplands. The independent variables of temperature and planted crop areas have widely varying means and variances, so the resulting coefficients cannot be compared directly. So we calculated the standardized regression coefficients to attribute the contribution of climatic variation and LCLUC to the greenup onset timing in each state. The standardized regressing coefficients (or beta weight) were calculated using the following formula (Nathans *et al* 2012):

$$\frac{Y-\overline{Y}}{S_Y} = \beta_1^* \frac{X_1-\overline{X_1}}{S_{X_1}} + \beta_2^* \frac{X_2-\overline{X_2}}{S_{X_2}} + \ldots + \beta_n^* \frac{X_n-\overline{X_n}}{S_{X_n}},$$

where Y is greenup onset timing, $X_1, X_2, \ldots X_n$ are the parameters related to LCLU change and climate variability, S indicates standard deviation, $\overline{Y}$ and $\overline{X}$ are mean value, and β^* are the standardized coefficients.

We calculated standardized coefficients for monthly temperatures in spring (as a proxy for climatic variation), and planted area of major crop types (as a proxy of LCLUC) for individual states when the timing of crop greenup onset was chosen as a dependent variable. Standardized coefficients for independent variables are comparable: they all refer to a change of one standard deviation (increase or decrease) in the timing of greenup onset. The rank of standardized coefficients in their absolute values provides an initial rank ordering (relative importance) of the contribution of climate variation and LCLU change to the crop greenup timing. The relative ratio of standardized coefficients indicates the ratio of their contributions to the models (Nathans *et al* 2012); thus, the relative percentage of contribution was determined using standardized coefficients of individual variables divided by the sum of the standardized coefficients. The percentage of contribution attributed to LCLUC was determined by the variation in planted crop area and to climatic variation by change in spring temperature.

3. Results

3.1. Variation in crop emergence timing

NASS crop progress reports show that the timing of crop emergence varied greatly depending on crop type and state (figure 1). For specific crop type, the areal proportion of crop emergence indicated that timing could vary by more than two months within a state. The emergence timing generally occurred earliest for oats (late March or early April), followed by spring wheat, corn (maize), barley, sorghum, and soybean. However, it also varied largely across states. Note that winter wheat emerged (not shown in figure 1) before November in the previous year and started to turn green once the snow had melted and warmer temperature returned in the spring, thereby displaying the earliest spring greenup.

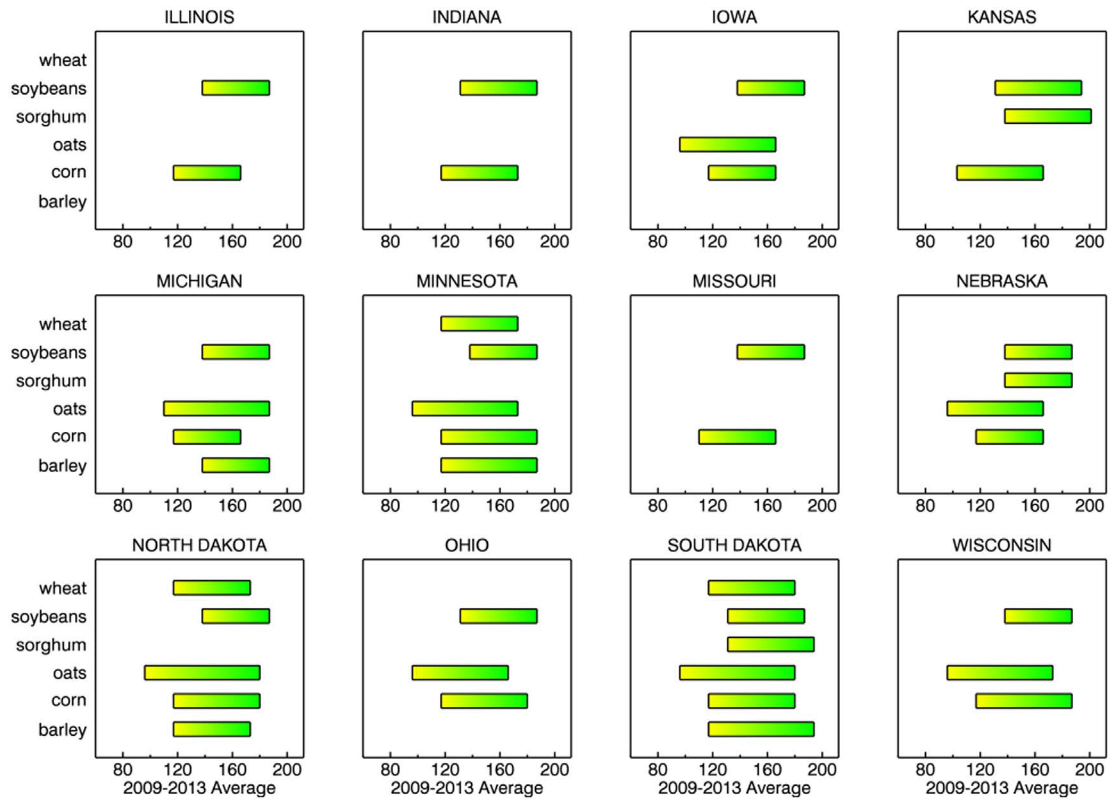

Figure 1. Cumulative areal proportion of crop emergence varying with time (day of year) averaged from 2009 to 2013. The color legend indicates cumulative areal proportion from 0% (yellow) to 100% (green). The emergence data are not available for some crop types in some states.

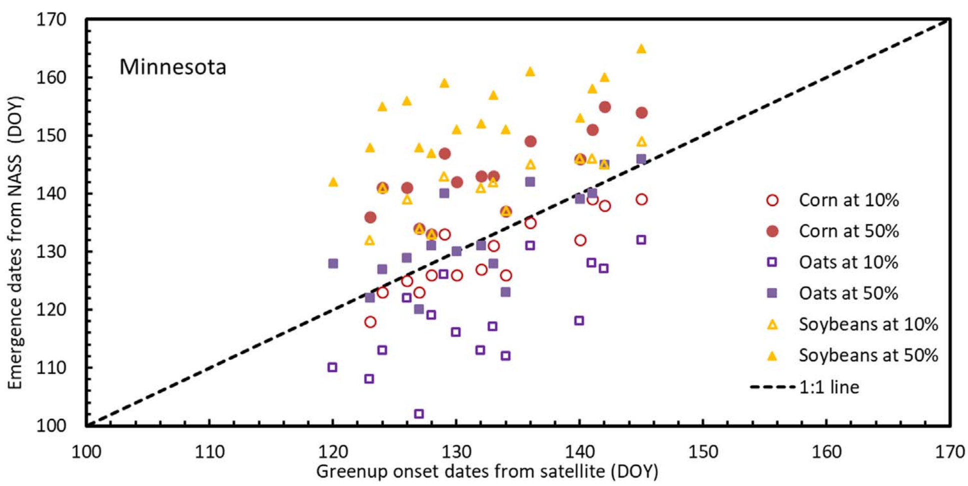

Figure 2. Comparison between satellite greenup onset and emergence timing at 10% and 50% crop progress stages in Minnesota.

3.2. Evaluation of satellite-detected greenup onset

Satellite greenup onsets reflected well the timing of crop emergence from NASS crop progress. This correspondence was evident in the Pearson correlation of interannual variations between satellite greenup onsets at croplands and NASS crop emergence timing from 1999 to 2014 (figure 2 and table 1). The greenup onset significantly correlated to the interannual variation in the timing at both 10% and 50% crop progress stages. However, the strength of the correlation varied across states and crop type: it was higher in Minnesota, Iowa, and North Dakota (mostly $r > 0.7$); whereas, it was lower in Illinois, Indiana, and Kansas (mostly $r < 0.6$, table 1). Similarly, the differences between greenup onset and emergence timing was varied by state and crop types. For example, in Minnesota, greenup onset was (1) 14 d (MAD) later than the 10% oat progress timing and similar to the 50% oat progress timing with a MAD of 4 d, (2) 4 d later and 11 d earlier than the 10% and 50% corn progress

Table 1. Pearson correlation coefficients (r) of greenup onset dates from satellite observations with crop emergence timing at 10% and 50% crop progress stages from NASS observations from 1999 to 2014 ($p < 0.1$). 'n/a' indicates either no significant correlations or no NASS data available. ND-North Dakota, SD-South Dakota, NE-Nebraska, KS-Kansas, MN-Minnesota, IA-Iowa, MO-Missouri, WI-Wisconsin, IL-Illinois, MI-Michigan, IN-Indiana, and OH-Ohio.

	Corn		Oats		Soybean	
State	10%	50%	10%	50%	10%	50%
IA	0.73	0.82	0.44	0.78	0.62	0.70
IL	n/a	n/a	n/a	n/a	0.56	n/a
IN	0.51	n/a	n/a	n/a	0.42	n/a
KS	n/a	0.55	n/a	n/a	n/a	n/a
MI	0.61	0.64	n/a	n/a	0.59	0.41
MN	0.90	0.80	0.70	0.67	0.80	0.72
MO	n/a	n/a	n/a	n/a	0.43	0.48
ND	0.76	0.77	0.44	0.53	0.83	0.71
NE	0.50	0.46	n/a	0.71	0.57	n/a
OH	0.58	0.45	0.53	0.46	n/a	0.40
SD	0.60	0.50	0.44	0.53	0.45	0.45
WI	n/a	0.75	0.70	0.81	0.50	0.69

timing, respectively, and (3) 7 d and 21 d earlier than the 10% and 50% soybean progress timing, respectively (figure 2).

3.3. Spatial patterns and long-term trends of crop greenup onset

Spatial patterns of crop phenology retrieved from MODIS data between 2000 and 2014 indicate that the crop greenup onset mainly followed a latitudinal gradient with later onset dates at more northern locations (figure 3(a)). Crop greenup onset occurred in late February and March in southern tier of the study area, in late March and April in the eastern area, and in May over the northwestern area (particularly in ND, SD, MN, and northern area of IA and NE). However, the timing of crop greenup onset in northern IL, IN, and OH was much later than that in the more northern area (southern WI and MI). This interrupted gradient resulted from the large area (>42%) of soybean planted in IL, IN, and OH since soybean was planted and germinated later (figure 1).

Trend analysis reveals the spatial pattern of a significant trend ($p < 0.1$) of crop greenup onset in individual satellite pixels from 1982 to 2014 (figure 3(b)). A later trend with a rate of generally less than 0.3 d yr^{-1} appeared in most parts of the region, particularly in ND, SD, NE, MN, and IA. The rate of later trend was reduced to less than 0.15 d yr^{-1} in states farther east (WI, IL, MO, and MI), where an earlier trend was also observed in many pixels.

3.4. Impacts of climate change and planted crop areas on interannual crop greenup onset

Interannual variation in the date of crop greenup onset was a function of both climatic variation and agricultural practices. The crop greenup onset date as derived from MODIS data between 2000 and 2014 shows the interannual variation (measured as temporal standard deviation) mainly ranged from 4 to 12 d across the study area (figure 4). However, the timings of greenup onset in 2012 were advanced by more than 10 d in most areas (20 d in some areas of the Western Corn Belt) for an average of 13 d earlier across all states compared with the long-term mean (figure 5). The interannual variation in phenology was revealed to be the response to both climatic variation and LCLUC within a state, which was evident in South Dakota, for example, where corn (maize) and soybean have recently become dominant crops (figure 6). In 2012, spring temperatures in South Dakota were 7.8 °C, 3.0 °C, and 1.1 °C higher than the 2000–2014 average in March, April, and May, respectively. The EVI2 curves shifted 12.1 d earlier in 2012 compared to the long-term average (figure 6(a)). On the other hand, in years when the spring (March–May) temperatures were similar, such as in 2001 and 2014 (figure 6(b)), a later greenup onset of 12 d in 2014 relative to 2001 was observed. This difference of greenup onset corresponded to an areal increase in corn (maize) and soybean (later emergence) and an areal decrease in wheat and oats (earlier emergence), where total croplands were also expanded (figure 6(c)).

Long-term trends across the Midwest states exhibited substantial variation from 1982 to 2014 concerning greenup onset, crop area planted, and spring temperatures (table 2). South Dakota again provides a good example to illustrate the interannual variation: spring temperatures displayed no significant trend in any month, but there were significant increasing trends for the area planted to both corn (maize) and soybean, and decreasing trends for the area planted to wheat, oats, and barley (figure 6 and table 2). Similar patterns appeared across the other Midwest states. Overall linear trends for individual states were significantly later with a rate of 0.31–0.67 d yr^{-1} for the crop greenup onset, while the trend varied considerably for the area planted to specific crops depending on crop types (table 2). The area planted to oats or wheat (earlier emergence crops) was significantly reduced across every state (except for wheat in WI). Area planted to barley or sorghum exhibited either significantly decreases or no significant trends, varying among states. In contrast, the area planted to corn (maize) or soybean (later emergence crops) strongly increased with trends varying from 1.1 $\times$ 10^4 to 11.9 $\times$ 10^4 acres yr^{-1} for corn (maize), and 3.5 $\times$ 10^4 to 15.8 $\times$ 10^4 acres yr^{-1} for soybean. However, those trends in crop area were not significant in MI and WI for corn (maize) or in IL for soybean only. Nevertheless, spring temperatures exhibited significantly increased trends only in April (table 2).

Statistical analyses reveal that both magnitude and direction of the timing of greenup onset were significantly affected by crop area and spring temperature (table 3). Pearson correlation coefficients (r) show that

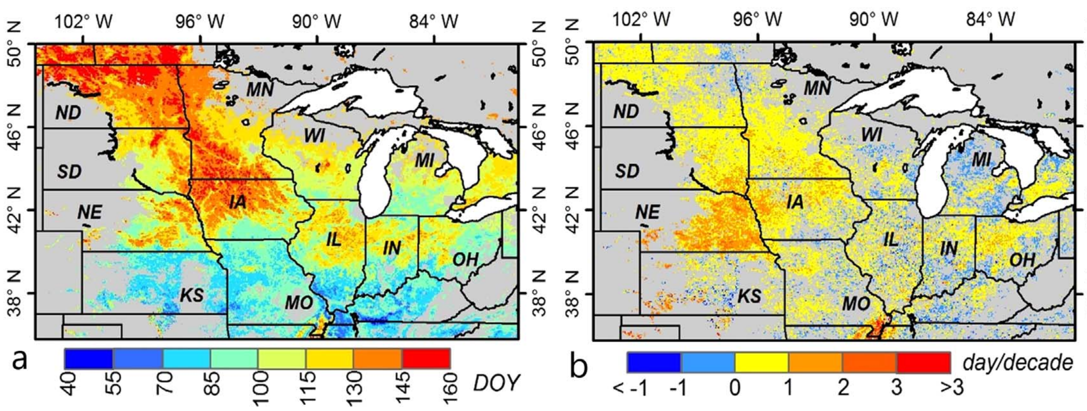

Figure 3. Spatial pattern of the timing of greenup onset in croplands calculated from satellite data at a spatial resolution of 0.05°: (a) mean values from 2001 to 2014; and (b) trends between 1982 and 2014 (significant level >90%). The gray color indicates either no significant trend or the area is not cropland.

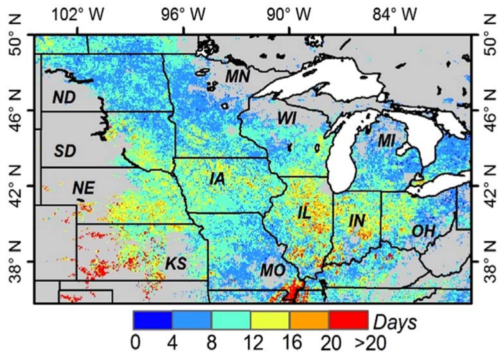

Figure 4. Interannual variation (as standard deviation) in the timing of greenup onset in croplands calculated from MODIS data at a spatial resolution of 0.05° between 2000 and 2014.

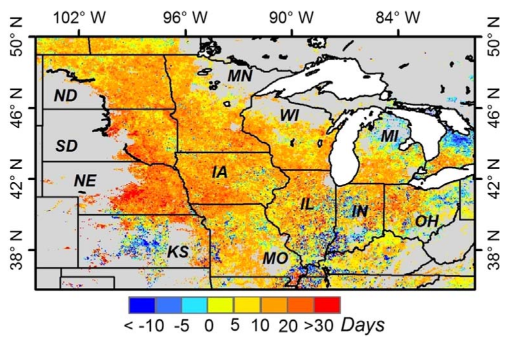

Figure 5. Anomaly of greenup onset in 2012 compared with the average between 2000 and 2014. Positive values indicate earlier timing of crop greenup onset in 2012.

overall greenup onset was positively correlated to the area of corn (maize) and soybean and negatively correlated to the area of barley, sorghum, and wheat. As expected, warmer spring temperature led to earlier onset of crop greenup. Further, the coefficient of determination (R^2, calculated from r in table 3) shows that individual variables of crop areas and spring temperatures could account for as much as 40% of variation in greenup onset date, which presented substantial variation across the states and variables.

3.5. Relative contributions of climatic variation and LCLUC to crop greenup onset date

Change in crop area and variation in climate contributed differently to the observed trend in the timing of crop greenup onset (table 4). The contribution of individual variables based on the standardized coefficients indicates that the planted crop area was the most important contributor to the variation in greenup onset, despite crop areas and types differing by state. Temperature was found to be the more important contributor only in OH (32.3% for March temperature) and IL (36.6% for March temperature).

The relative contribution from climatic variation and from LCLUC was indicated using the total relative contributions from spring temperature and crop area planted, respectively, assuming that the timing of emergent crop greenup onset date was fully controlled by the spring temperature and crop area planted (figure 7). The result indicates that LCLUC and climatic variation equally impacted the variation of greenup onset in OH. The largest difference of contribution appeared in MI where the climatic contribution was as low as 21% while LCLUC accounted for 79%. On average, climatic variation accounted for 34% of the variation in timing of greenup onset and LCLUC accounted for 66% across the US Midwest.

4. Discussion and conclusions

Global climatic change has and will continue to impact ecosystems broadly, and it is a leading driver of phenological shifts observed in the northern mid to high latitudes (IPCC 2014). Ecosystem responses to climatic change at regional and global scales are frequently quantified using satellite-derived land

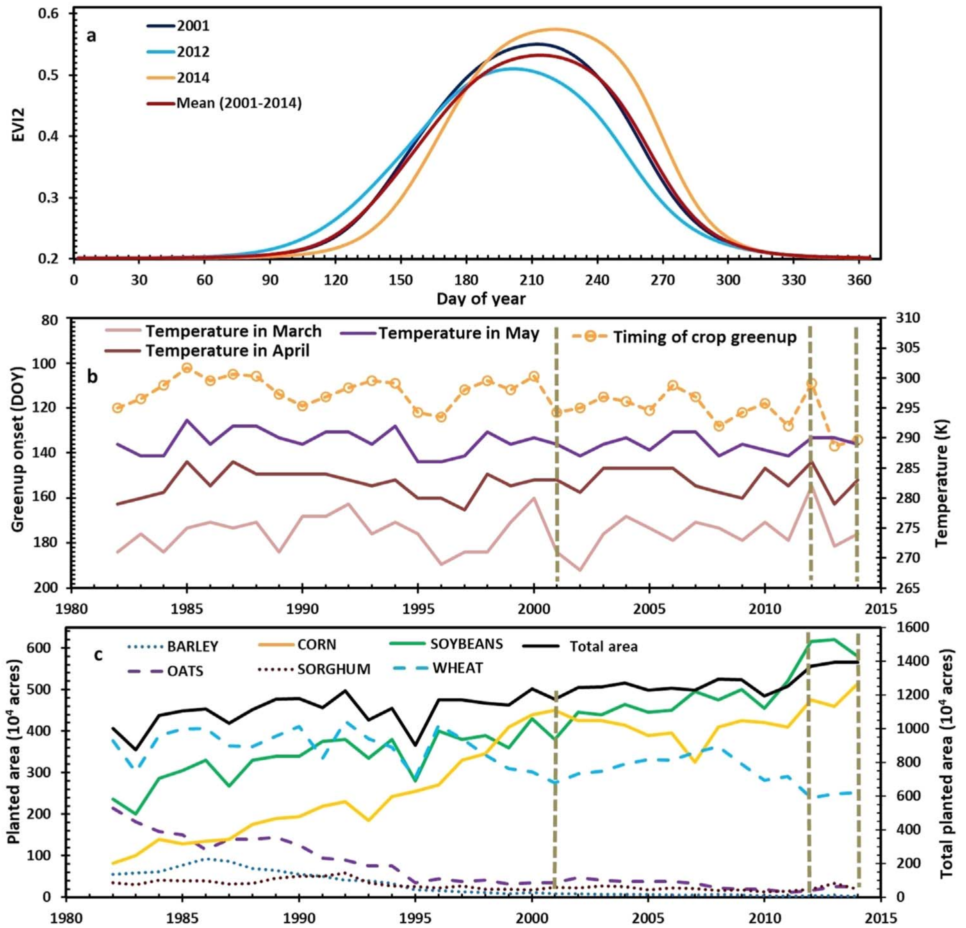

Figure 6. Long-term variation in South Dakota of (a) annual crop temporal trajectories of MODIS EVI2, (b) spring temperatures and the timing of crop greenup onset, and (c) the areas of different crop types. The vertical lines in (b) and (c) indicate the years of 2001, 2012, and 2014 exhibited in (a).

Table 2. Trends of greenup onset (d yr^{-1}), planted area (10^4 acres yr^{-1}) of various crop types, and monthly temperature (°C yr^{-1}) from 1982 to 2014. Significance of trends is higher than 90% ($p < 0.1$). 'n/a' indicates either no significant trends or no data available. T3–T5 are the monthly temperature in March, April, and May, respectively. For Kansas, they represent temperatures from February to April because there crop greenup can occur in late February, due to the extensive planting of winter wheat. The abbreviation of states is the same as in table 1.

State	Greenup onset	Planted crop area						Spring temperature		
	Greenup	Barley	Corn	Oat	Sorghum	Soybean	Wheat	T3	T4	T5
IA	0.40	n/a	5.28	−8.32	n/a	6.19	−0.28	n/a	0.06	n/a
IL	0.33	n/a	8.28	−3.72	−0.74	n/a	−3.09	n/a	0.08	n/a
IN	0.34	n/a	1.07	−1.00	n/a	4.22	−2.36	n/a	0.08	n/a
KS	0.44	−0.48	11.87	−0.50	−4.91	7.56	−12.66	n/a	n/a	n/a
MI	n/a	−0.13	n/a	−1.19	n/a	3.64	−0.41	n/a	n/a	n/a
MN	0.48	−4.01	8.46	−5.52	n/a	9.28	−5.07	n/a	n/a	n/a
MO	0.32	n/a	4.91	−0.38	−3.44	1.28	−4.09	n/a	0.08	n/a
ND	0.46	−7.94	7.58	−3.12	n/a	15.82	−7.77	n/a	n/a	n/a
NE	0.67	n/a	9.85	−1.47	−6.11	10.97	−4.21	n/a	0.07	n/a
OH	0.35	n/a	n/a	−1.06	n/a	3.52	−1.66	n/a	0.07	n/a
SD	0.48	−2.61	9.72	−5.19	−0.81	12.58	−3.67	n/a	n/a	n/a
WI	0.31	−0.16	n/a	−3.28	n/a	5.27	0.56	n/a	n/a	n/a

surface phenology because of the advantages of high temporal and spatial resolutions of satellite observations. However, the trend and interannual variation of land surface phenology can be misinterpreted due to our poor understanding of the factors influencing land surface phenology. Taking intensively cultivated croplands as an example, this study has shown that long-term trends in land surface phenology are influenced by both LCLUC and climatic variation, which vary locally and regionally.

Table 3. Pearson correlation coefficients (r, $p<0.1$) of greenup onset dates with crop area and spring temperatures from 1982 to 2014 for individual states across the Midwest US. All variables are the same as in table 2.

State	Barley	Corn	Oats	Sorghum	Soybean	Wheat	T3	T4	T5
IA	n/a	n/a	−0.303	n/a	n/a	−0.329	−0.495	n/a	−0.350
IL	n/a	n/a	n/a	−0.31	n/a	n/a	−0.493	n/a	n/a
IN	n/a	n/a	−0.363	n/a	0.382	−0.316	−0.419	n/a	n/a
KS	−0.336	0.389	−0.328	n/a	0.431	−0.299	−0.324	−0.393	n/a
MI	−0.368	n/a	n/a	n/a	n/a	n/a	−0.459	−0.438	−0.314
MN	−0.591	0.503	−0.447	n/a	0.461	−0.536	−0.469	−0.557	−0.449
MO	n/a	0.304	−0.37	−0.432	n/a	n/a	−0.561	n/a	n/a
ND	−0.617	0.538	−0.474	n/a	0.632	−0.520	−0.457	−0.501	−0.573
NE	n/a	0.500	−0.541	−0.564	0.536	−0.509	n/a	n/a	n/a
OH	n/a	n/a	−0.374	n/a	0.409	−0.338	−0.365	n/a	n/a
SD	−0.522	0.495	−0.393	n/a	0.477	−0.446	−0.345	−0.446	−0.529
WI	−0.379	n/a	−0.360	n/a	0.388	0.373	−0.524	−0.490	−0.409

To extend the time series for analyzing the crop phenological trend and its drivers, this study detected crop greenup onset date using both AVHRR and MODIS data. Although the greenup onset in a coarse resolution pixel (~5 km) is not able to be validated and is not the same as crop specific phenology, the evaluation revealed that the greenup onset date significantly correlated to the timing of crop emergence reported from NASS at the state level, suggesting the greenup onset was reliable to represent interannual variation in the emergence dates of crops. The results from this study are similar to the findings for specific crops at finer spatial resolutions of 30 and 500 m pixels (Gao *et al* 2017, Liu *et al* 2018).

The greenup onset was linearly correlated to monthly temperature to investigate the influence of climate change on crop phenology in this study. This analysis was based on the simple growing degree-day model indicating that the rate of plant development is linearly related to cumulative temperature (Hänninen 1990, Chuine 2000). Of course, the response of crop greenup onset to climatic variables could be more complex. For example, the requirement of accumulated heat units varies for different plant species and some vegetation species have chilling requirements (Cannell and Simth 1983, Murray *et al* 1989). Even so, it is certain that warmer spring temperatures advance the timing of vegetation greenup onset (Friedl *et al* 2014). This advance shift has also been demonstrated here: the greenup onset was advanced 13 d on average for every Midwest state in 2012 when spring temperatures (March–May) were about 3.2 °C higher than average temperature from 2000 to 2014 across the Midwestern US (Ault *et al* 2013). As a result, the simple linear analysis was able to capture the main influence of climate change on greenup onset.

Similarly, this study directly associated the greenup onset with the crop areas planted to explore the LCLUC impact at the state level. Indeed, croplands have expanded in recent years by converting wetlands (Johnston 2013, 2014) and grasslands (Wright and Wimberly 2013, Lark *et al* 2015, Wright 2015). The new croplands have been mainly used for planting corn and soybean because of new federal policies, changes to commodity markets, and increased demand for biofuels (Hertel and Beckman 2011, Lark *et al* 2015, Wright 2015), such as in South Dakota (figure 6(c); Nguyen *et al* 2019). Because the emergence timing in corn and soybean is much later relative to that in barley, oats, and wheat as shown in NASS crop progress reports, the areal expansion of corn and soybean could have a large impact on the greenup onset date at the state level. The average date of greenup onset detected using ~5 km pixels over croplands may not be necessary to represent well the emergence timing for all crop types because the aggregation of phenological timing from fine to coarse resolutions is not straightforward (Zhang *et al* 2017). However, the linear analysis could statistically assess the proportional impact of crop types on the greenup onset at a large extent.

Furthermore, although the greenup onset date at the state level could be influenced by multiple interacting factors, the standardized regression procedure provides a simple approach to partition the amount of variation observed in the satellite-detected greenup onset to either climatic variation (as observed spring temperatures) or to LCLUC (as reported crop area planted). This approach could significantly improve our understanding of the long-term trend of land surface phenology and provide new insights on the decoupling of climatic change impacts on phenological trends from the influences of LCLUC.

The impact of LCLUC on land surface phenology can also be supported by the finding in burned forest areas where land cover types converted from forests before wildfires to shrublands after wildfires and the greenup onset shifted from a delaying trend to an advancing trend in the burned areas (Wang and Zhang 2017). This contrast in phenological timing results from changes of plant species composition in vegetation community (a type of LCLUC). Such phenological impacts could widely exist because the plant species composition has possibly been altered at local

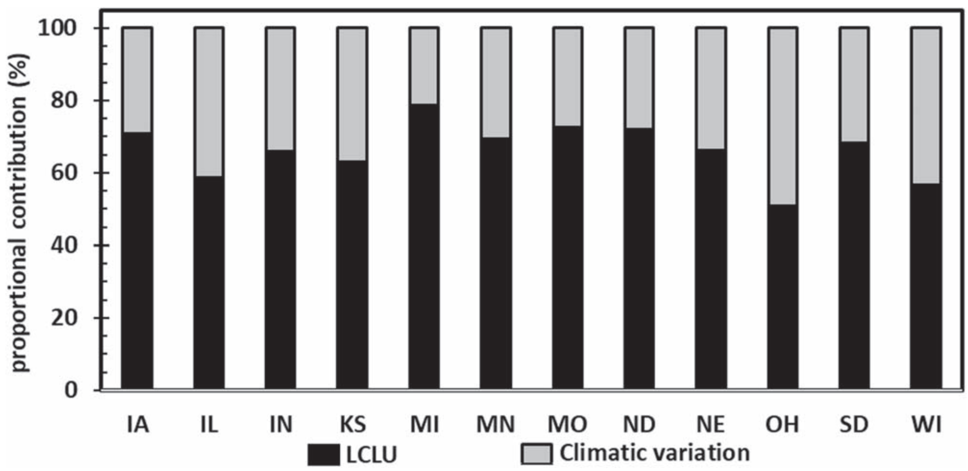

Figure 7. Proportional contribution of LCLUC and climatic variation to the observed variation in crop greenup onset date at state scale.

Table 4. Relative contribution (%) of LCLU change (crop area) and climate variables (spring temperature) to the variation of greenup onset in croplands, which was determined based on the standardized coefficients. Large relative contribution represents high rank order. All variables are the same as in table 2.

	Barley	Corn	Oats	Sorghum	Soybean	Wheat	T3	T4	T5
IA	n/a	22.0	22.0	n/a	0.5	26.5	18.2	7.2	3.8
IL	n/a	6.9	13.9	17.9	5.9	14.0	36.6	1.1	3.7
IN	n/a	9.8	15.6	n/a	14.1	26.3	22.3	8.1	3.8
KS	8.6	10.9	12.4	n/a	20.4	10.7	11.2	20.2	5.6
MI	33.2	6.1	7.1	n/a	29.3	3.1	14.7	5.3	1.2
MN	23.4	1.6	0.8	n/a	21.4	22.1	11.3	12.8	6.6
MO	n/a	12.8	13.0	28.5	6.9	11.4	22.6	2.7	2.3
ND	12.3	7.3	24.6	n/a	24.3	3.5	4.9	10.4	12.6
NE	n/a	23.7	6.5	12.9	4.9	18.3	20.3	1.7	11.7
OH	n/a	n/a	21.5	n/a	4.7	24.6	32.3	11.8	5.2
SD	7.5	25.8	10.6	11.4	1.5	11.3	9.2	6.4	16.3
WI	6.6	10.9	6.8	n/a	28.0	4.4	20.9	22.0	0.5

scales across the globe: more than one-third of the planetary land surface has undergone LCLUC during past several decades (Mack *et al* 2000, Bradley *et al* 2010, Ellis *et al* 2013, Turbelin *et al* 2017). Indeed, various aspects of LCLUC within a region can exert influences—both advancing and delaying greenup onset, for instance—on long-term phenological trends to some degree. The evaluation framework proposed here provides a path towards enhancing our understanding of the fact that the long-term trend of land surface phenology can often show inconsistences with patterns of climatic variation (White *et al* 2009, de Jong *et al* 2011), and to disentangle the relative impacts of climatic variation and LCLUC on long-term phenological trends across ecosystems (White *et al* 2005).

In conclusion, the LCLUC over the Midwest US, where the area planted to corn (maize) and soybean has increased substantially during recent decades, has shaped interannual variation and trends in greenup onset, while climatic factors still play a significant role on timing of crop spring greenup. This finding suggests that extensive LCLUC could be a leading driver of observed phenological shifts, overriding the impact of climatic variation at a regional scale. LCLUC has been occurring across the planet during the past several decades and will continue into the future, and it will influence on phenological trends and complicate the detection and quantification of climate change impacts on phenology at ecosystem and regional scales.

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ORCID iDs

Xiaoyang Zhang https://orcid.org/0000-0001-8456-0547

Geoffrey M Henebry https://orcid.org/0000-0002-8999-2709

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