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Does any phenological event defined by remote sensing deserve particular attention? An examination of spring phenology of winter wheat in Northern China

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ABSTRACT

Phenology is often considered the "leading indicator" of ecological responses to climate change, and therefore it is important that researchers have accurate methods to track phenological changes. Remote sensing has been widely used to study phenological responses to climate change. However, land surface phenology observed by remote sensing is fundamentally different from that observed in the field, which raises the difficulty in understanding and validating phenological change observed using remote sensing. In this study, we revisited the criteria of "good" phenological events and argued that the relationship between phenology and climate factors is one of the most important meanings of phenological studies. Instead of validating remotely sensed phenology by its consistency with field observations, this study aims to judge different possible definitions of phenological events based on remote sensing by their temperature sensitivity and correlation. Using the winter wheat zone in northern China as the study area, we compared the temperature correlation and sensitivities of winter wheat phenology date derived from different methods: the relative threshold method with different thresholds, and the curvature method, based on remotely sensed data. Our results show that there is no distinct phenological event that is overwhelmingly more sensitive or correlative than any others. Therefore, there are no particular phenological events that deserve emphasis when exploring the relationship between phenology date and the pre-season temperature. Instead, the phenological stage (i.e. the threshold of relative threshold method) that is most sensitive or correlative to pre-season temperature varies spatially, showing a good latitude gradient. On an average, the thresholds of the most correlative and sensitive phenological stages to pre-season temperature decreased by 9.92% and 14.69% per latitudinal degree, respectively. The results indicate that the traditional emphasis on discrete phenological events could miss the phenological stages that are most sensitive and correlative to pre-season temperature, thereby resulting in a limited understanding of phenological responses to climate change.

1. Introduction

Phenology, commonly refers to the timing of recurring biological life cycle, has attracted increasing attention due to its sensitivity to climate change (Schwartz, 2013). Many studies have reported that global warming has shifted the date of phenological events, like the advancement of spring phenology and postponement of autumn phenology (Menzel and Fabian, 1999; Cleland et al., 2007; Piao et al., 2019). Accordingly, significant efforts have been devoted during the past few decades in phenological monitoring (Zhang et al., 2003; Brown et al., 2016; Templ et al., 2018) and exploring the relationship between the phenology shifting and climate change (Menzel et al., 2006; Piao

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et al., 2006; Richardson et al., 2006; Shen, et al., 2011).

Researchers typically monitor vegetation phenology in two ways: field observation and remote sensing. Field observation is the traditional method that documents the timings of key phenological events that have clear physiological significance like bud burst, leaf unfolding, flowering and leaf coloring (Schwartz, 2013). Unfortunately, the sparse and uneven spatial distribution of ground stations limits the potential to explore the spatial distribution of phenological responses to climate change (Liu et al., 2017; Piao et al., 2019). Moreover, differences in observation criteria, methods, and observers hardly guarantee spatio-temporal consistency and data quality (Guo et al., 2016; Piao et al., 2019). Phenology observed by remote sensing (also named as land surface phenology, or LSP) overcomes the aforementioned shortcomings and thus has been widely applied in studies ranging from regional to global scale thanks to its better space–time continuity and a lower cost (e.g. Myneni et al., 1997; Zhang et al., 2004; Shen et al., 2014). However, there are intrinsic discrepancies between the dates of phenological events detected by remote sensing and field observations (Friedl et al., 2006; White et al., 2009). Sharp phenological transitions at the individual plant level are blurred in the remotely sensed time-series data due to the coarse spatial resolution of satellite sensors with significant mixed pixel effect (White et al., 2009; Chen et al., 2018) and due to time-series preprocessing functions such as smoothing or fitting (Henebry and De Beurs, 2013). Accordingly, the key phenological events defined by remote sensing (e.g. green-up onset, senescence onset) are sometimes criticized as “ill-defined” events with no clear physiological significance (Henebry and De Beurs, 2013). Such fundamental discrepancies between satellite and field observations raises the difficulty in understanding and validating the phenology change observed by remote sensing (White et al., 2009).

Confronting with such dilemma in phenology study by remote sensing, we reviewed the definition and fundamental meaning of the commonly used phenological events. Leopold and Jones (1947) systematically summarized the characteristics of “good” phenological events, which are simplified in Table 1 (Henebry and De Beurs, 2013). Most of these points except (2) and (7) can be satisfied both by field and remote sensing observations. Henebry and De Beurs (2013) argued that remote sensing observation cannot satisfy the point (2) (“sharp/distinct”) due to mixed pixel effect and smoothing of time-series. In our opinion, however, the “sharp/distinct” characteristics typically used to minimize observers’ errors might not be necessary when using remote sensing, considering that remotely sensed data is continuous and objective. Although uncertainty or inconsistencies exist among different processing methods, they can be trackbacked through investigating the processing chain (e.g. Shen et al., 2013; Liu et al., 2017). Thus, in this study we target the point of (7) “evidence of newness” as the key concept to be reconsidered. Leopold and Jones (1947) explained “evidence of newness” as “stories” told by certain phenological events. One of the most important stories is the relationship between the date of phenological event and climate factors. For example, green-up date (GUD) is particularly concerned because spring phenology is more sensitive to climate change than others (Badeck et al., 2004; Niu et al., 2013). Thus, phenology is often considered as the “leading indicator” of ecological responses to climate change (USA National Phenology Network, 2019). From this perspective, we attempt to judge the performance of commonly defined phenological events from remote sensing with the principle of “leading indicator” of climate change.

Using the winter wheat zone in Northern China as a case study, we investigated whether there is a particular event derived from remote sensing observation that is most sensitive or correlative to pre-season temperature. Winter wheat was selected for our study for two reasons. First, temperature is the primary controller of spring phenological change for winter wheat (Wang et al., 2008), considering that good farming management would simplify the relationship between phenology and climate factors (e.g. irrigation could compensate the insufficient rainfall). Second, the long-term and wide wheat cultivation offers continuous spatiotemporal observations of both phenological records and climate data in this area.

Table 1
Comparison of field and remote sensing observations of “good” phenological events.

Characteristics of “good” phenological events	Field observation	Remote sensing
low labor cost/simple to observe	√	√
Sharp/distinct to minimize error among observers	√	?
Common/abundant	√	√
High degree of accessibility	√	√
Reliability of recurrence	√	√
Continuity	√	√
Evidence of newness	√	?
Locally-determined dynamics	√	√
Prior knowledge exists to identify the unusual	√	√

2. Material and methods

2.1. Study area and data

The study area is primarily located in the North China Plain (Fig. 1). The Plain is the main wheat production zone in China and accounts for 44% of the total wheat planting area and 60% of the total wheat production of China (Ren et al., 2008). Within the study area, winter wheat is usually sowed in late-September–October and harvested in late-June–July the following year. Crops follow several key phenological stages: sowing, seedling, tiller, green-up, jointing, heading, grouting, maturity, and harvesting.

Climate data from 1981 to 2015 in this area were archived at 324 national meteorological stations, among which 130 stations are located near winter wheat cropland (Fig. 1). The daily climate data of these 130 stations (temperature, sunshine duration and precipitation) were downloaded from the Chinese Meteorological Agency. In addition, winter wheat phenological data, GUD, jointing date (JD) and heading date (HD), were documented in 54 stations (agro-meteorological experimental stations). The third generation NDVI dataset produced by Global Inventory Modeling and Mapping Studies (GIMMS3g) (https://ecocast.arc.nasa.gov/data/pub/gimms/3g.v1/) was collected for deriving winter wheat phenology considering its long-term observation records. This dataset, obtained from Advanced Very High Resolution Radiometer (AVHRR) instruments onboard the NOAA satellites (Tucker et al., 2005), has been corrected for radiometric calibration, orbital drift, view geometry, volcanic aerosols, and other effects unrelated to vegetation change. Thus, the GIMMS3g NDVI dataset with a temporal resolution of 15 days was widely used for detecting the phenology dates for vegetation from regional to global scales (e.g. Shen et al., 2014; Liu et al., 2017).

A winter wheat map at 20 m resolution created by a recent study (Dong et al., 2020) was used to determine the winter wheat pixels at 8 km spatial scale. Considering the change of winter wheat distribution during the study period, a manual discrimination procedure was further conducted to confirm the stable winter wheat pixels near the meteorological stations.

2.2. Methodology

This study aims to investigate whether there is a spring phenological event deserving particular attention by comparing temperature correlations and sensitivities of the phenology dates derived by different methods. The main flowchart of this study is illustrated in Fig. 2.

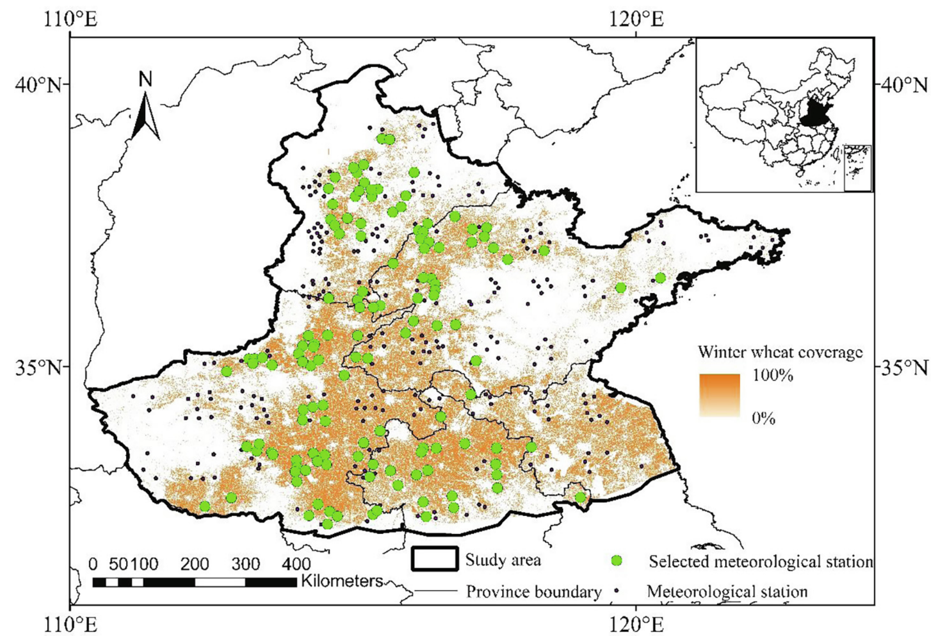

Fig. 1. Study area and location of meteorological stations.

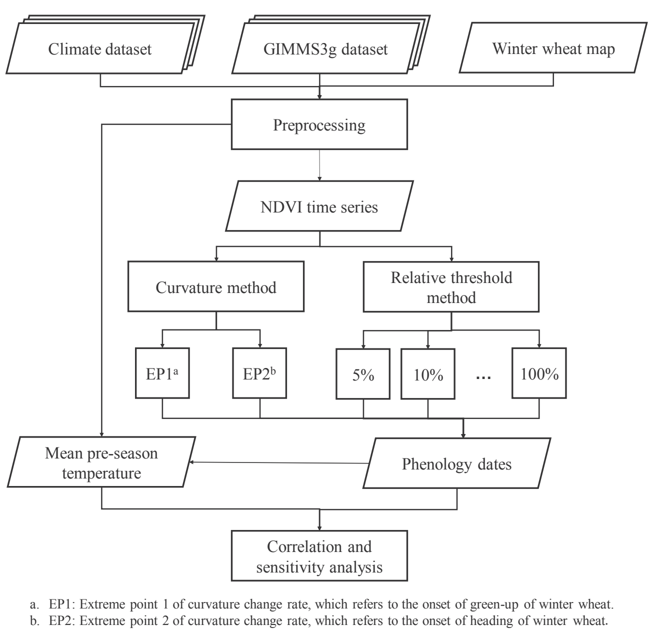

Fig. 2. Flowchart of the study.

2.2.1. Data preprocessing

Data preprocessing was conducted to extract and smooth the NDVI time series of stable winter wheat pixels around each meteorological station. First, a snow-free procedure (Zhang et al., 2007; Guo et al., 2016) and iterative Savitzky-Golay filter (Chen et al., 2004) were employed to generate high-quality daily NDVI time series data. Second, the stable winter wheat pixels (keeps unchanged during 1981–2015) were determined manually by referencing the annual NDVI curves and the winter wheat map at 20 m resolution (Dong et al. 2020). Here, winter wheat cropland nearby the 130 meteorological stations were selected as study sites. Five stable winter wheat pixels were identified manually for each site. Finally, the NDVI time series of winter wheat in each site was calculated by averaging NDVI time series of five stable winter wheat pixels.

2.2.2. Determination of spring phenology dates for winter wheat by remote sensing

Spring phenology (from green-up onset to heading) typically receives more attention than other phenological events in remote sensing research, partly because the crop development is dominated by greenness increasing in this period (Guo et al., 2019) and partly because spring phenology is more sensitive to temperature than others (He et al., 2015). Therefore, the NDVI segment between the spring's valley before green-up and the main peak corresponding to the heading stage

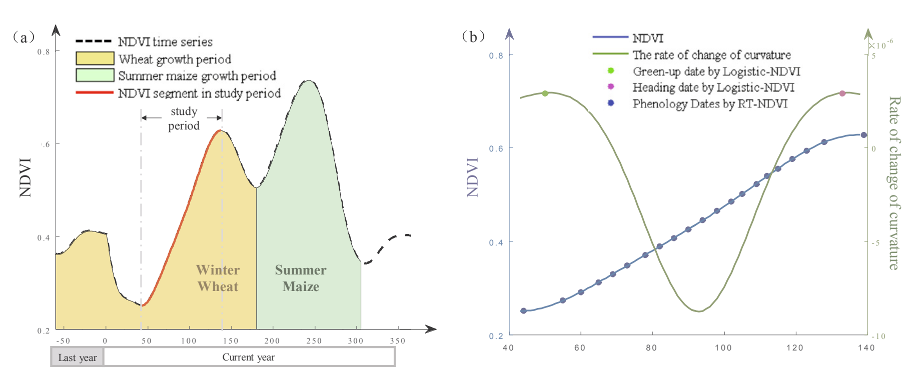

Fig. 3. NDVI curve of winter wheat pixel (a) and phenology dates detected by relative thresholds and the curvature method (b).

is selected for detecting spring phenology in this study (Fig. 3a). Key phenology dates were identified from this NDVI segment by two widely used methods: the relative threshold method (White et al., 1997) and the curvature method (Zhang et al., 2003). In the relative threshold method, GUD was identified as the day when the NDVI reached a specific percentage of its annual amplitude (White et al., 1997). Different from the previous studies that used only one certain threshold, all possible thresholds ranging from 5% to 100% were employed in this study for a complete comparison (Fig. 3b). For the curvature method, the logistic function was fitted to the NDVI data, followed by the identification of the GUD and HD as the days when the rate of change in the NDVI curvature reached the local maximum (Fig. 3b). In total, 20 phenology dates were derived by the relative threshold method and two phenology dates were derived by curvature method.

2.2.3. Correlation and sensitivity analysis between phenology dates and pre-season temperature

The correlation and regression coefficients between pre-season temperature and phenology dates derived from NDVI time series were compared. Despite other climate factors (e.g. precipitation, sunshine duration) that may influence phenology dates, pre-season temperature is the main controller of spring phenology for winter wheat (Wang et al., 2008). Thus, we focused on pre-season temperature in this study. Considering the pre-season period varies across different areas, we determined the pre-season period uniformly starting from January 1st and ending at the multi-year average (34 years from 1982 to 2015) of spring phenology date for each site (Wang et al., 2015). Pearson correlation and partial correlation analyses were both conducted to analyze the relationship between annual phenology dates and pre-season temperature for each site. The partial correlation analysis with the control variables of pre-season precipitation and sunshine duration was conducted to remove the corresponding effects. The temperature sensitivity (unit: days/°C) was determined as the linear regression coefficient between the annual phenology dates and pre-season temperature. The temperature correlations and sensitivities of phenology dates derived from relative threshold method and curvature method were then compared to check whether a particular event that is most correlative or sensitive to pre-season temperature exists.

3. Results

Fig. 4 compares the correlation and regression coefficients between pre-season temperature and the phenology dates derived from relative threshold method (twenty phenology dates corresponding to 5%, 10% … 100%) and the curvature method (two phenology dates corresponding to two inflection points) for all of the study sites. The result of partial correlation (Fig. 4b) is similar to that of Pearson correlation (Fig. 4a), indicating that the effect of sunshine duration and precipitation could be neglected for the regression analysis between phenology dates and pre-season temperature. Both of the correlation and regression coefficients between pre-season temperature and phenology dates are negative for all of the methods, indicating that increasing temperatures advances the phenology dates throughout the growth period no matter how the phenological event was defined. More importantly, the values of correlation and regression coefficients of different phenology definition methods are comparable, each of which exhibited large variation. Although there is a slight trend that the phenological events in later stages are more sensitive or correlative to pre-season temperature than those in earlier stages, overall, this trend actually varied spatially. When the whole study area was divided into three subzones, we found that the phenological events in earlier stages are more sensitive or correlative to pre-season temperature in the northern zone, whereas the phenological events in the later stages are more sensitive or correlative to pre-season temperatures in the middle and southern zones (Fig. 5). This indicates that none of phenological events defined by remote sensing were especially correlative or sensitive to pre-season temperatures across the whole area among all the competed definitions.

We further examined the phenological event (i.e. threshold of relative threshold method) with the highest correlation coefficient and regression coefficient among the events of all possible thresholds for each site (Fig. 6a-b). As shown in Fig. 6 c-d, it exhibits latitude gradients for the thresholds of the most correlative and sensitive phenological stage, decreasing with increasing latitude (−9.92% and −14.69% per latitudinal degree respectively). This suggests that the phenology of winter wheat in the northern area is more sensitive to pre-season temperatures in its early growth stage, whereas in the southern area is more sensitive in its late growth stage. Thus, there is a potential to analyze continuous phenological processes in order to better capture the spatial pattern of the phenological response to rising temperatures.

To confirm the reliability of the observed latitudinal gradient of the most sensitive phenological stages to pre-season temperatures, field observed phenology data was used for comparison. With a similar regression process as described in Section 2.2.3, the temperature-sensitivity of GUD, JD, and HD were calculated for 54 sites with field-observed phenology data. As shown in Fig. 7, although the latitudinal gradient of the most sensitive phenological event (field observed GUD, JD and HD) to pre-season temperature is not as obvious as that shown in Fig. 6, GUD is more likely to be the most sensitive phenological event to pre-season temperature in the northern area, whereas HD is more likely to be the most sensitive one in southern area (Fig. 7b). This result is consistent with the latitudinal gradient observed by remote sensing to some extent. However, the phenological stage with the highest temperature sensitivity was missed for the field observation data because only three phenological events were observed. Instead, remote sensing that observed vegetation growth continuously was able to capture the phenological stage that is most sensitive to pre-season temperature. Therefore, these results not only confirm the reliability of the result derived from remotely sensed data, but also imply a potential of remote sensing to provide more information about the response of the phenological process to climate change than limited phenological events.

4. Discussion

This study suggests that no phenological event defined by remote sensing worth particular attentions in term of temperature sensitivity or temperature correlation. Actually, the phenology dates derived by relative threshold methods with different thresholds showed a high correlation with each other (Table 2), indicating that these derived phenology dates provide similar information when the defined thresholds are closed. As mentioned earlier, mixed pixel effect and time-series smoothing could blur the sharp phenological transition observed at individual plant scale (Henebry and De Beurs, 2013; Chen et al., 2018). From the perspective of temperature sensitivity, another important reason should be noted. The response of vegetation phenology to climate variation is reflected on not only the discrete phenological events, but also the growth process. In general, the response of phenology date to climate factors originates from the response of developmental rate to climate factors. This is usually described with following formula (Chuine et al., 2013).

$$t_p \text{ such that } S_t = \sum_{i=0}^{t} R_t = S^* \tag{1}$$

wheret_p is the date of a specific phenological transition event; S_t is the state of development on day t; R_t is the development rate on day t, which is a function of climate factors. S^* is the critical state required to reach the phenological event (t_p). The state of development (S_t), to a large extent, refers to observed greenness by remote sensing, especially in the period from GUD to HD. Thus, any points in the NDVI curve, other than particular defined point (phenological event), could respond to climate variation. In the traditional field observations, the growth

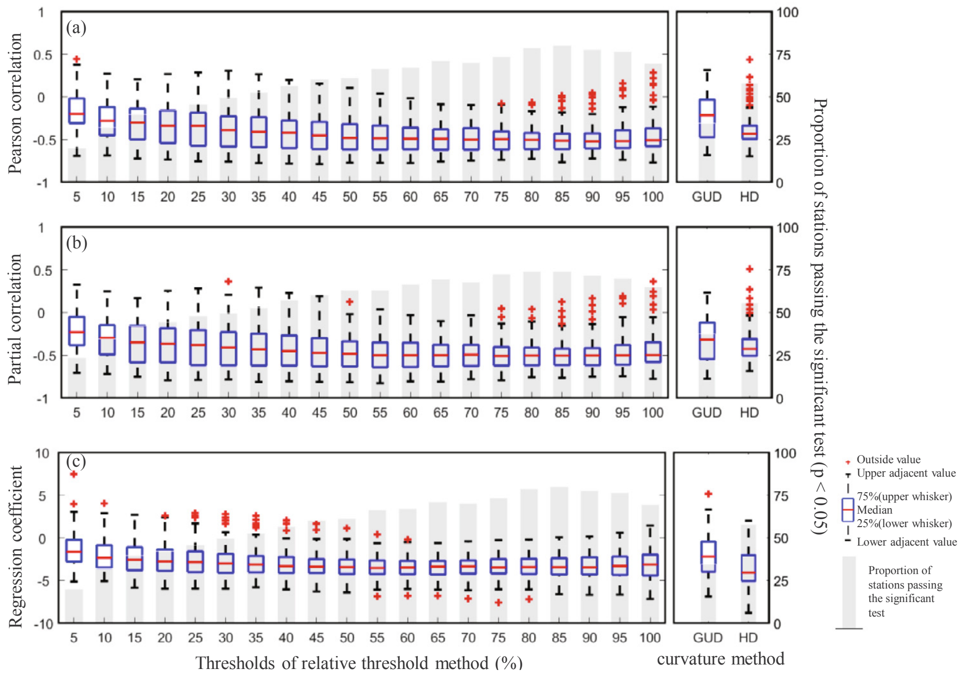

Fig. 4. Correlation/regression coefficients of phenology dates defined by relative threshold methods (from 5% to 100%) and the curvature method (GUD, HD) to pre-season temperature. (a) Pearson correlation; (b) Partial correlation; (c) Linear regression coefficient.

process is neglected to a large extent due to the difficulty in quantifying it by human observation; thus the "sharp/distinct" events are preferred as they are easier to be observed. On the contrary, the growth process represented by greenness is easily observed by remote sensing; whereas the signal of "sharp/distinct" phenological events are blurred. Therefore, it is worth questioning whether the commonly defined phenological events from remote sensing deserve particular attention from the perspective of "leading indicator" of ecological response to climate change.

Concern on phenological process instead of discrete events is more suitable for exploring the phenological responses to climate change by remote sensing. In this study, such concern helped to reveal the latitudinal gradient of the most sensitive phenological stage to pre-season temperature. We surmise that such a latitudinal gradient might be attributed to the different temperature stresses on different phenological periods for the winter wheat in different areas. For the northern area, the lower temperature in the early spring is the main limiting factors of the growth of winter wheat, thus the earlier spring phenological stage tends to be more sensitive to pre-season temperatures. For the southern area, in contrast, the temperature is relatively insufficient in the later spring due to the increased rainy days with lower solar radiation compared to the northern area. Thus, the later spring phenological stage is relatively more sensitive to pre-season temperature in the southern area. However, such hypotheses need to be validated by additional data analyses.

Existing studies used different temporal time spans before spring phenology to calculate the pre-season temperature when they examined the response or sensitivity of spring phenology to temperature (Shen et al., 2011; He et al., 2015; Wu et al., 2019). To investigate whether these different time spans in the definition of pre-season temperature affect the observed latitudinal gradient of the most sensitive phenological stages, we recalculated the temperature correlation and

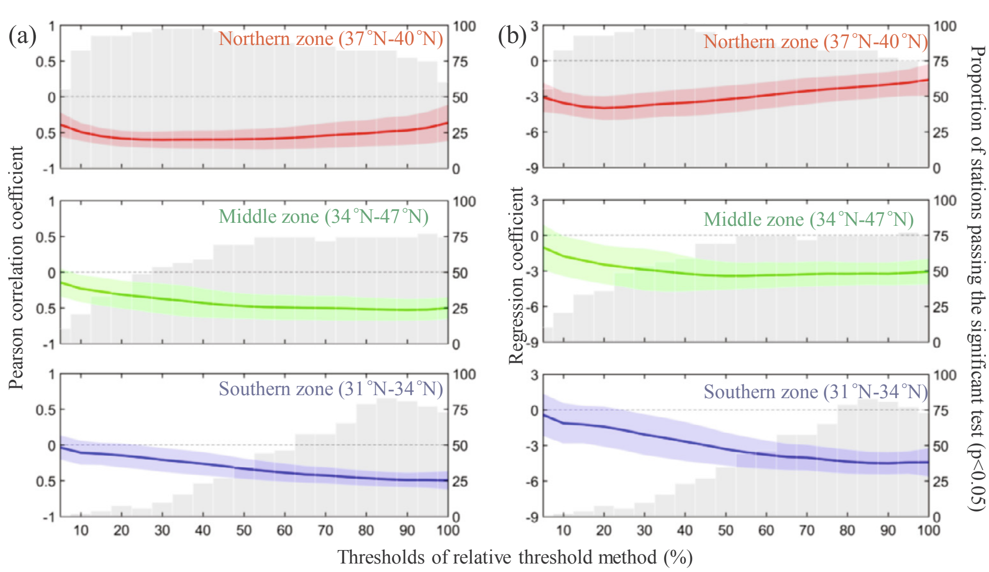

Fig. 5. Correlation (a) and regression (b) coefficients of phenology dates defined by relative threshold methods (from 5% to 100%) to pre-season temperature in three zones. The center line in each subplot represents the regional average coefficient curve and the shadow represents double standard deviation. The gray bar represents the proportion of sites passing the significant test ($p < 0.05$).

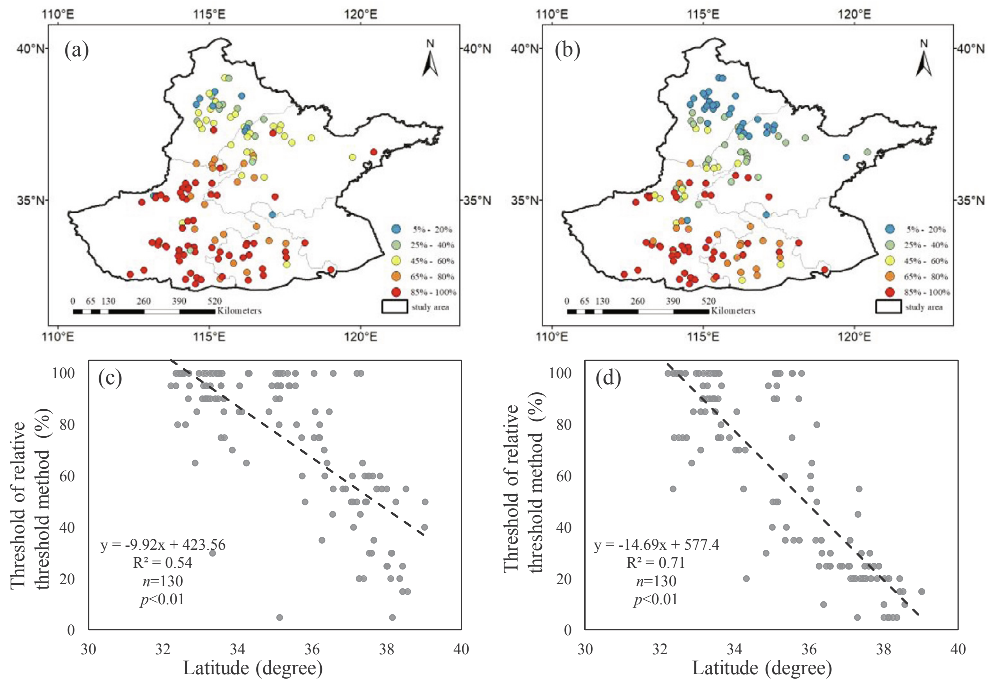

Fig. 6. The spatial distribution of thresholds of the phenological stage with highest temperature correlation (a) and sensitivities (b). The relationship between latitude and the thresholds of the phenological stage with highest temperature correlation (c) and sensitivities (d).

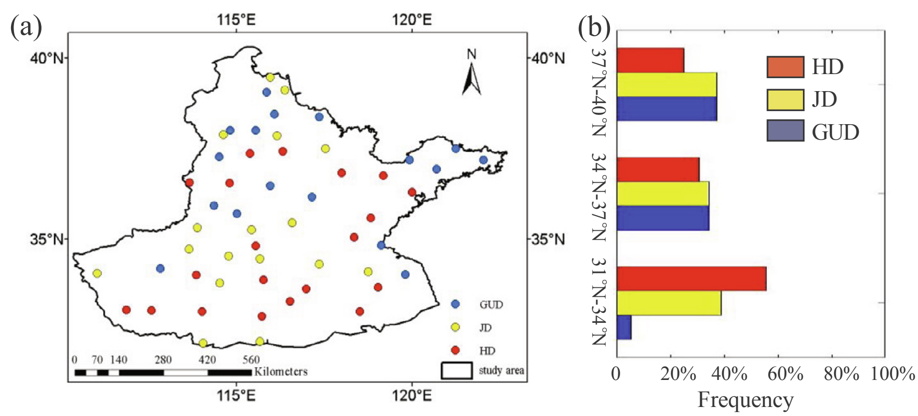

Fig. 7. Spatial distribution (a) and histogram (b) of the most sensitive phenological event to pre-season temperature by using field-observed phenology data.

Table 2
Matrix of correlation coefficients between different phenology dates derived by relative threshold method with different thresholds. All correlations are significant ($p < 0.05$).

	5%	10%	20%	30%	40%	50%	60%	70%	80%	90%	100%
5%	1	0.967	0.892	0.837	0.79	0.752	0.719	0.688	0.658	0.627	0.575
10%		1	0.964	0.922	0.88	0.844	0.81	0.778	0.747	0.713	0.657
20%			1	0.986	0.958	0.929	0.899	0.868	0.836	0.801	0.737
30%				1	0.99	0.971	0.946	0.919	0.89	0.855	0.788
40%					1	0.993	0.977	0.955	0.93	0.897	0.827
50%						1	0.993	0.978	0.958	0.928	0.859
60%							1	0.994	0.979	0.954	0.886
70%								1	0.994	0.975	0.913
80%									1	0.991	0.939
90%										1	0.967
100%											1

Value	Color
[0.50,0.80)	
[0.80,0.90)	
[0.90,0.97)	
[0.97,0.99)	
[0.99,1.00]	

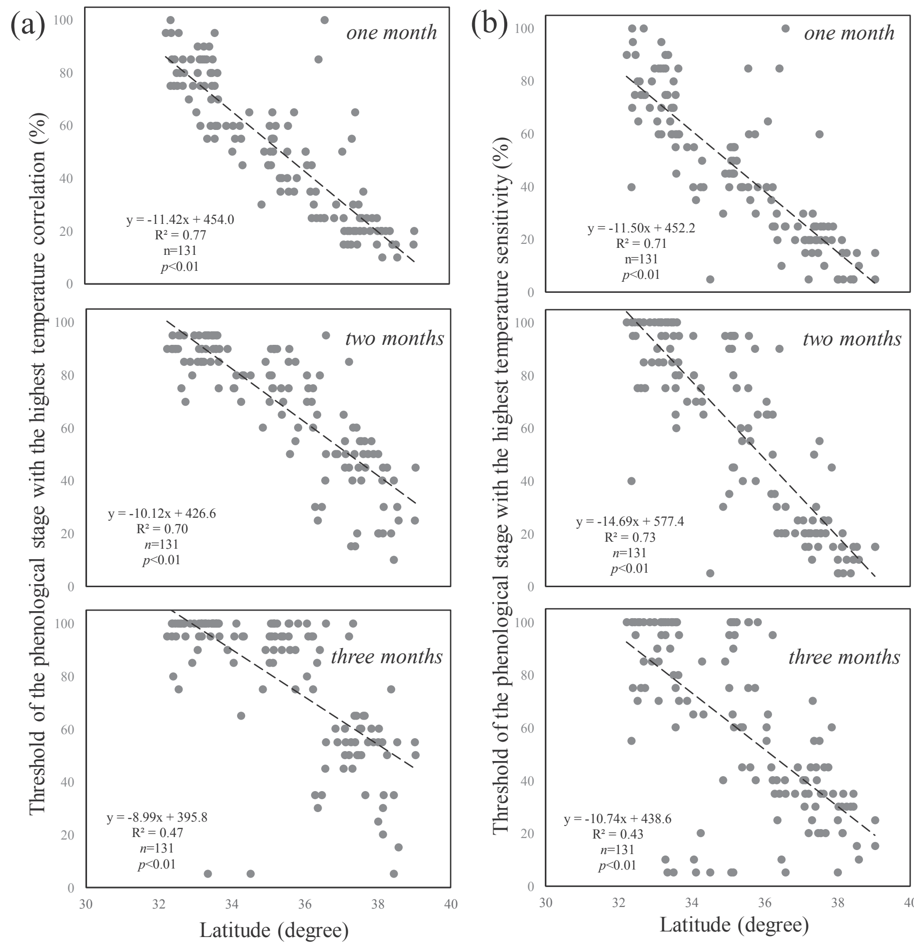

Fig. 8. Latitudinal gradients of the most correlative (a) and sensitive (b) phenological stages to different pre-season temperatures with time spans of one, two and three months before phenology date.

sensitivities by using pre-season temperatures with three different time spans (one, two, and three months before multi-year averaged phenology date). As shown in Fig. 8, the thresholds of phenological stages most correlated and most sensitive to temperature both decreases with latitude for all the three of the stated definitions of pre-season temperature. These results further confirm that the latitudinal gradient of the most sensitive phenological stage is robust to the different definitions of the pre-season temperature.

The 15-day temporal resolution of the composited GIMMS3g NDVI might be another concern. Wang & Zhu (2019) reported an over-estimation of the absolute date of spring phenology with such datasets without consideration of the actual day of observed NDVI. Fortunately, they also mentioned that the temporal variation of phenology date is not affected (Wang & Zhu, 2019). Thus, the calculation of temperature sensitivity or correlation could also be influenced marginally.

Finally, shifting of phenological events are also linked with the carbon cycle, ecosystem functions and community structure (e.g. Richardson et al., 2009; Cleland et al., 2007; CaraDonna et al., 2014; Valdes & Ehrlen, 2017). Thus, it is important to note that this study only proposed an additional perspective for phenological study by remote sensing, rather than denying the importance of particular phenological events. However, it is worth noting that that particular phenological events that occur at the individual plant level will also become increasingly blurred at population levels and community levels, even for the field observation (Inouye et al., 2019).

5. Conclusion

This study examined the temperature sensitivities and correlations of different definitions of phenological events by remote sensing. The results suggest that none of the phenological events defined by remote sensing deserve particular attention when exploring the relationship between phenology and pre-season temperature. Based on the analysis of phenological process, we revealed the latitudinal gradient of the most sensitive phenological event to pre-season temperature, which could help to capture the phenological response to increasing temperature more completely. Thus, we call for more attention to be paid to phenological process instead of phenological events when using remote sensing data. That is, remote sensing, as a continuous observation manner, could better capture the phenological responses to climate change, when focusing on the phenological process (e.g. all of the phenological "events" corresponding to all possible thresholds from 5% to 100%) rather than limited particular events.

CRediT authorship contribution statement

Xuehong Chen: Conceptualization, Methodology, Writing - original draft. **Wenqing Wang:** Data curation, Formal analysis, Visualization. **Jin Chen:** Project administration, Supervision, Writing - review & editing. **Xiaolin Zhu:** Conceptualization, Methodology. **Miaogen Shen:** Methodology, Writing - review & editing. **Liqin Gan:** Validation. **Xin Cao:** Writing - review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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