Challenges in remote sensing of vegetation phenology

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Received: November 22, 2023; Accepted: April 28, 2024; Published Online: May 15, 2024; https://doi.org/10.59717/j.xinn-geo.2024.100070

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Citation: Shen M., Zhao W., Jiang N., et al., (2024). Challenges in remote sensing of vegetation phenology. The Innovation Geoscience 2(2): 100070.

Large-scale vegetation phenological changes, with substantial impacts on land surface and atmospheric processes, are crucial for understanding responses and feedbacks of terrestrial ecosystems to climate change. Remote sensing technologies monitor timings of spring greenness increase and autumnal greenness decline (i.e., the start and end of vegetation growing season, also known as land surface phenology) mainly using satellite-derived vegetation index (VI) time series[1] (Figure 1), offering valuable insights into the spatiotemporal variations of vegetation phenology over the last 40-50 years. Despite recent thorough reviews on remote sensing methods for phenology,[1] some issues have been overlooked.

PREPARATION OF HIGH-QUALITY VEGETATION-INDEX TIME SERIES

In practice, vegetation phenological metrics are determined using high-quality VI time series. Nevertheless, generating such data faces multiple challenging issues.

First, snow or ice during periods of snowmelt in early spring and autumn snowfall causes abrupt changes in traditional VIs, introducing biases in vegetation phenology detection. To mitigate snow interference, many studies have replaced snow-contaminated VI values with snow-free median values during the non-growing season for deciduous plants (Figure 1). However, this method is less accurate when snow-contaminated data are misidentified or when snow-free winter background VI values are unavailable. Other studies have introduced snow-free VIs to address this issue such as the Normalized Difference Phenology Index (NDPI) and the Normalized Difference Greenness Index (NDGI). NDPI was designed to minimize reflectance differences between soil and snow but did not consider the interference of dry vegetation on the NDPI values during the non-growing season. In contrast, NDGI was developed, promising for detecting vegetation phenology in snowy middle and high latitude regions. However, caution is advised in applying NDGI to ecosystems with significant multiple scattering (e.g., forests). Despite these efforts, addressing snow's impact on phenology estimation remains a challenge, necessitating further research.

Second, the lack of reliable cloud and aerosol flags impedes accurate reconstruction of VI time series, impacting phenology detection (Figure 1). Simulations demonstrate that with accurate flags for cloud and aerosol contaminations, VI time series can be accurately reconstructed unless prolonged continuous contaminations occur. However, current VI products' labeling for cloud and aerosol contaminations (CACs) contains uncertainty, complicating accurate VI reconstruction. Excessively smoothed VI time series could introduce errors and obscure true phenological changes. This effect could be further amplified when contaminations on VI interact with true VI value drops (e.g., decreased greenness due to crop harvest). Future research should improve the detection of CACs to address this issue.

Third, VI data from Advanced Very High-Resolution Radiometer (AVHRR) observations since the early 1980s, sometimes combined with MODIS VI time series, have been widely employed to assess vegetation phenology changes over the past 40 years. However, caution is needed due to differences between AVHRR2 and AVHRR3, discrepancies between MODIS and AVHRR, as well as sensor degradation and orbit drift effects. These differences may affect the accuracy of VI in depicting vegetation greenness over a long time and thus on the assessment of phenological changes. Although efforts have been made to mitigate these temporal issues and generate long (~40 years) VI time series, their suitability for extracting extended phenology time series requires careful evaluation.

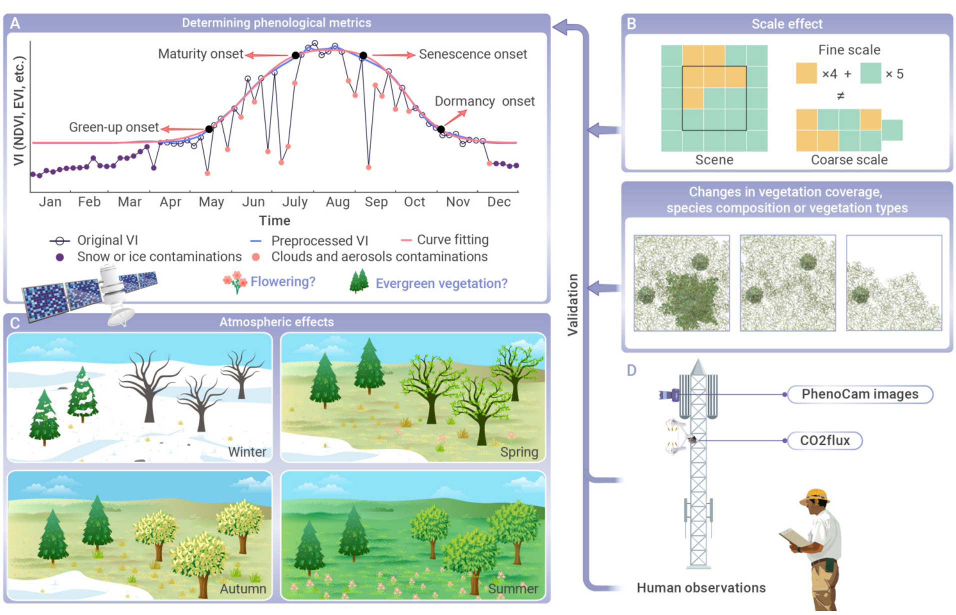

Figure 1. Schematic diagram for the remote sensing of vegetation phenology (A) improving quality of vegetation index (VI) time series and determinations of typical phenological metrics; (B) scale effect in phenology, coarse-pixel phenological metric differing systematically from the mean of fine-pixels; (C) changes in vegetation coverage, species composition or vegetation types that could lead to variations in remotely sensed phenology without true phenological changes; (D) validation of satellite phenology from VI and solar-induced chlorophyll fluorescence against human-observed phenology of a few individual plants, phenology from phenocam images, and phenology of gross primary production from CO_2 flux.

IMPROVING TEMPORAL AND SPATIAL RESOLUTIONS

The detection of vegetation phenology from satellite data in diverse landscapes, such as urban and fragmented croplands, demands both high frequency and high spatial resolutions. Earth observation satellites often face a trade-off between these aspects. Data fusion, which integrates data from multiple satellites with different frequencies and resolutions, is increasingly used for vegetation phenology detection.[2] Despite its potential benefits, several issues persist. The reliability of phenology detection from fused data is uncertain when critical periods are affected by cloudy data. Preprocessing before fusion, especially normalizing differences in reflectance caused by bidirectional effects, is often overlooked. Challenges remain in handling pixels with multiple vegetation types with distinct phenology patterns, like different crops. Although deep learning-based optical and radar data fusion gains traction, it lacks generalization for large-scale applications due to intrinsic differences between these data types. Rigorous validation is essential before implementing data fusion for vegetation phenology detection at finer resolutions.

Recently, there have been new remote sensing technologies that can improve temporal resolution: Synthetic Aperture Radar (SAR) and geostationary satellites. SAR time series offer valuable means to monitor vegetation phenology in cloudy areas as they penetrate clouds and reflect changes in vegetation status. Two primary methods are used: first, extracting feature points like inflection points from SAR time series or radar VI time series; second, employing machine learning, such as random forest or supporting vector machine, on the SAR time series to estimate phenology. However, SAR signals differ from optical data and may not capture certain phenological stages that lack distinct canopy structure changes. Future research should improve the understanding of the relationship between SAR signals and canopy development throughout the growing season. Geostationary meteorological satellites offer new opportunities to estimate vegetation phenology with frequent observations (every 5-10 minutes), enhancing access to cloud-free optical data and complementing polar-orbiting satellites for phenology monitoring in cloudy regions. However, these satellite images are limited by coarse spatial resolution, regional coverage (e.g., Himawari-8 covers only the Asia-Pacific), and extensive pre-processing for generating ready-for-analysis datasets (e.g., atmospheric and geometric corrections).

DETERMINING PHENOLOGICAL METRICS

In many studies, annual VI time series are fitted to functions like Logistic functions to determine phenological metrics. However, there is no universal function suitable for all vegetation types with varying shapes. Even if a fitting function exists, irregular changes in VI trajectories due to disturbances like harvests or stress pose fitting challenges. Changes in vegetation types within a year also complicate fitting. To tackle this, some methods focus on capturing local phenological characteristics in VI time series, such as local fitting and shape-model fitting. Nevertheless, their effectiveness depends on handling noise in the data, as these local-fitting methods are sensitive to it.

The current methods for the validation of phenological metrics from remote sensing face several challenges. Firstly, comparing satellite phenology at a pixel level (with spatial resolution ranging from a few hundred meters to kilometers) with observations of a few individual plants on the ground is less effective due to differences in spatial coverage and high variability among ground-level individuals within the area covered by the pixel (Figure 1). Additionally, averaging phenological metrics from all individuals within the ground area cannot effectively validate satellite phenology due to scale effects.[3] In addition, traditional human observations define phenology based on the development of leaves, differing from satellite phenology estimated from VIs that are derived from land surface reflectance. Secondly, validating remote sensing phenology against ground-based Phenocams is hindered by differences in spatial coverage, observation angles, sensor types, and insufficient quality control and calibration of Phenocam images.[4] Lastly, validating remote sensing phenology using phenology derived from gross primary production (GPP) time series fails to capture the essential difference between GPP (representing vegetation function) and VIs (representing structure) that results in large numerical disparities (~1-4 weeks) between the two kinds of phenological metrics parameters. Effective validation requires ground observations for the same VIs as those used for satellite phenology, representing the coverage of satellite sensor pixels.

INTERPRETATION OF CHANGES IN REMOTELY SENSED PHENOLOGY

The "scale effect" in phenology refers to discrepancies in phenological metrics between coarse and fine pixels. Coarse-pixel green-up onset dates could differ systematically from the mean of fine-pixels, appearing earlier or later (Figure 1). This effect hinders the effective cross-scale comparison, assessment, and modeling of phenological changes, as well as the validation of satellite phenology. Simulations with two endmembers (vegetation types) have shown mechanistically that heterogeneity in fine-pixel green-up onset dates led to earlier coarse-pixel onset.[3] Meanwhile, coarse-pixel onset aligned better with fine-pixels showing faster greenness increase from spring to summer.[3] However, the scale effects beyond the green-up onset date in phenology metrics remain unclear. Moreover, it is uncertain whether these findings from simulations using two vegetation types could generalize to scenarios involving multiple types. Furthermore, there is a lack of clear quantification of the scale effect in real remote sensing images for various phenological metrics.

Remote sensing of phenological metrics is primarily used to track changes in vegetation over time. However, alterations in vegetation coverage —even if individual phenology remains constant within a pixel —can cause shifts in these metrics (Figure 1). Similarly, changes in species composition and vegetation types also impact these metrics. Many studies omit these factors when assessing phenological changes and their response to climate change, potentially leading to misleading conclusions, as recently indicated.[5]

PHENOLOGY BEYOND GREENNESS

There is growing interest in phenology beyond land surface greenness, such as photosynthesis and flowering. Remote sensing of solar-induced chlorophyll fluorescence (SIF) has facilitated the detection of GPP phenology. SIF is particularly useful for detecting the phenology of evergreen vegetation which the greenness VIs could not effectively capture (Figure 1). However, GPP phenology based on satellite SIF time series has the following drawbacks compared with vegetation phenology based on traditional VI. Firstly, the fluorescence is a weak signal, and thus the fluorescence inversion is more complicated than the calculation of traditional VI, resulting in coarser and noisier SIF data. Secondly, SIF is affected by many factors and thus may not track GPP changes in some cases. Under strong light conditions, photosynthesis is saturated and the positive relationship between SIF and GPP may be broken. Moreover, water and/or heat stress could affect the relationship between SIF and GPP. Changes in SIF are hence not exactly equivalent to changes in GPP, so SIF-derived phenology may not reflect GPP phenology. Addressing these issues could aid studies on GPP phenology and the onset of leaf senescence (the real but invisible onset of leaf autumn phenology).

The remote sensing of flowering times faces tougher challenges compared to greenness phenology (Figure 1). Firstly, except for a few species, signals from flowers are weak due to low coverage. Secondly, issues arise from mixed-pixel effects and similar spectral features among different species' flowers. Thirdly, the short flowering season often coincides with the rainy season in many areas, limiting the availability of optical remote sensing data.

In summary, several critical issues have been identified that demand attention to improve phenological remote sensing. Addressing these challenges will likely necessitate collaborative endeavors among scholars spanning diverse subfields of the remote sensing community. This collaborative effort should integrate simulation experiments, laboratory and field studies, and the analysis of both human phenological observations and remote sensing data. The complexity and difficulty of these issues underscore the need for a comprehensive approach involving multiple disciplines and observation types to drive advancements in this field.

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DECLARATION OF INTERESTS

The authors declare no competing interests.