*remote sensing*

*Editorial*

# Remote Sensing of Land Surface Phenology: Editorial

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**Citation:** Ma, X.; Jin, J.; Zhu, X.; Zhou, Y.; Xie, Q. Remote Sensing of Land Surface Phenology: Editorial. *Remote Sens.* **2022**, *14*, 4310. https://doi.org/10.3390/rs14174310

Received: 25 August 2022
Accepted: 29 August 2022
Published: 1 September 2022



## 1. Background

Land surface phenology (LSP) is an important research field in terrestrial remote sensing and has become an indispensable approach in global change research, as evidenced by many important scientific findings supported by LSP in recent decades. LSP involves the use of remote sensing to monitor seasonal dynamics in vegetated land surfaces and to retrieve phenological metrics (transition dates, rate of change, annual integrals, etc.). LSP is an essential indicator of global change and has played a pivotal role in shaping our understanding about how terrestrial ecosystems are responding to climate change and human activities. Both regional and global LSP products have been routinely generated and played prominent roles in modeling crop yield, ecological surveillance, identifying invasive species, modeling the terrestrial biospheric processes, and assessing global change impacts on urban and natural ecosystems.

Recent advances in field and spaceborne sensor technologies, as well as data fusion techniques, have enabled novel LSP retrieval algorithms that refine LSP retrievals at even higher spatiotemporal resolutions, providing new insights into ecosystem dynamics. Meanwhile, rigorous assessment of the uncertainties in LSP retrievals is undergoing, and efforts to reduce these uncertainties are also forming an active research field. In addition, open-source software and hardware are being developed and have greatly facilitated the use of LSP metrics by scientists beyond the remote-sensing community. As such, we organized this Special Issue to cover the latest developments in sensor technologies, LSP retrieval algorithms and validation strategies, and the use of LSP products in a variety of fields. The objective of this Editorial is to offer the readers an overview of the latest developments in the LSP field and facilitate the distribution of the scientific knowledge from this Special Issue.

## 2. Papers in the Special Issue

The 15 papers published in this Special Issue represent diverse themes in the LSP research field (see Table 1). Figure 1 presents the major keywords contained in the abstracts of the papers. Although natural ecosystems were mostly studied [1–3], urban [4,5] and agricultural ecosystems [6] were also considered in the as an important field of LSP applications. High-altitude and high-latitude ecosystems gain particular attention in this Special Issue, likely due to the sensitivity of these ecosystems to climate change [7–12]. Most studies have a temporal scale greater than a decade, with a few having used NOAA/AVHRR data of longer than three decades [10,13]. Additionally, it can be seen that the use of cloud-based remote-sensing big data analytics facilities such as Google Earth Engine (GEE) have also been adopted by several studies (e.g., [7–9]). While a majority of the papers focused on scientific applications, some studies also looked at the theoretical aspect of LSP such as the scaling effect [13]. Data-wise, most studies used vegetation indices due to their long-term continuity; a few papers also exploited the potential of emerging proxies such as solar-induced chlorophyll fluorescence (SIF) [14]. Lastly, half of the studies published in this Special Issue used some type of ground phenology data, including phenocam, traditional phenology observations, and eddy–covariance flux towers.

**Table 1.** Publication summary of the Special Issue.

| Publication | Topic | Satellite Data | Inclusion of Ground Phenology Data | Target Ecosystems | Temporal Scale | Analytic Platform |
|---|---|---|---|---|---|---|
| Kim et al. [4] | Impact of urbanization on phenology | MODIS EVI | Yes (phenocam) | Urban, rural, and natural | 2016 | Local |
| Wang et al. [8] | Mechanism and impact of climatic and soil factors on the phenology of alpine ecosystems | MODIS NDVI | Yes (phenology stations) | Alpine meadow and alpine steppe | 2001–2018 | GEE |
| Ma et al. [7] | Phenological trends of GPP dynamics in the Arctic | MODIS GPP | Yes (Fluxnet) | Arctic ecosystems | 2001–2019 | GEE |
| Zhang et al. [6] | Crop phenology and yield prediction | MODIS NDVI, EVI, and LAI | No | Maize | 2010–2015 | Local |
| Ji et al. [5] | Urban heat island effect on spring phenology | MODIS EVI, LST, Phenology | No | Urban, rural | 2006–2018 | Local |
| Guo et al. [9] | Mountain phenology response to meteorological drivers | MODIS NDVI | No | Mountainous ecosystems | 2001–2019 | Local |
| Chen et al. [13] | Scaling effect of LSP over complex terrain | MODIS NDVI, GIMMS3g NDVI | Yes (phenology stations) | Grassland, cropland, and forests | 1982–2020 | Local |
| Yang et al. [10] | Turning points of grassland autumn phenology | GIMMS3g NDVI | No | Alpine meadow, forests, and shrublands | 1982–2015 | Local |
| Guo et al. [15] | Snow phenology and its environmental drivers | MODIS Snow Cover, NDVI | No | Forest, cropland | 2001–2018 | GEE |
| Medeiros et al. [3] | Caatinga phenology and environmental drivers | MODIS EVI | No | Caatinga | 2000–2019 | GEE |
| Wang et al. [14] | Comparison of LSP from SIF and EVI | MODIS EVI, GOSIF (Reconstructed OCO-2 SIF) | No | Terrestrial ecosystems in China | 2003–2016 | Local |
| Costa et al. [2] | Phenology of GPP and WUE | MODIS GPP | Yes (Fluxnet) | Tropical forest, caatinga, and cerrado | 2009–2016 | Local |
| Liu et al. [11] | Phenology responses to snow seasonality | MODIS Snow Cover | No | Mountainous ecosystems | 2002–2020 | Local |
| Cui et al. [12] | Phenology response to soil moisture and temperature | MODIS NDVI | Yes (phenology stations) | Mountainous ecosystems | 2001–2020 | Local |
| Costa et al. [1] | Phenology of ecosystem productivity in dry tropical forest | MODIS GPP, MODIS NDVI and EVI | Yes (Fluxnet) | Caatinga (dry tropical forest) | 2014–2015 | Local |


**Figure 1.** Cloud of the words contained in the abstracts of the papers published in the Special Issue "Remote Sensing of Land Surface Phenology". The bigger the size, the higher the frequency of each word.

## 3. Outlook to the Future

As elaborated in the Call of Papers of this Special Issue, our hope was to not only summarize the ongoing diverse LSP developments but also boost discussions on prospects in LSP research. With the 15 selected papers, we believe that this aim should have been accomplished. Based upon the new knowledge we gained from this Special Issue, we hereby offer our perspective on future research directions in the LSP field:

First, improving the quality of the input satellite observations remains important as it lays the foundation for any downstream phenology retrieval and applications. From the sensor perspective, the improvement in sensor performance including spatial, spectral, and temporal resolutions is the direction of the development of new-generation remote-sensing data sources. From the methodological perspective, data fusion can effectively regulate the inherent contradiction between "spatial resolution and temporal resolution" of satellite remote-sensing observation, and realize the simultaneous improvement in spatial resolution and temporal resolution. In addition, with the development of remote-sensing sensor technology, more spaceborne platforms are becoming available, such as geostationary satellites that can observe the full disk of the Earth every 10–15 min, leading to much-improved temporal resolution that is capable of the near-real-time monitoring of vegetation dynamics [16–18]. Meanwhile, dozens or even hundreds of micro-/nanosatellites can form a constellation to significantly increase the spatial coverage and spatial–temporal resolution through a multisatellite synergetic approach. A relatively successful case is the PlanetScope constellation, which has launched more than 200 micro-/nanosatellites so far, providing seamless multispectral observation data at a global scale with a daily temporal resolution and 3 m spatial resolution, significantly improving the capability of resolving the fine details of global phenology change [19,20].

Second, the LSP retrieval workflow needs to be refined including the development of a more generalized algorithm. An often-encountered challenge in remote-sensing phenology applications is the fact that different data sets do not share the same processing algorithm, which makes it difficult to analyze and compare the results from different studies. Therefore, it is an important future direction for remote-sensing phenology to develop a versatile algorithm that can adapt to different circumstances.

Third, like many other remote-sensing subjects, validation is the essential component in any satellite phenology product development. A key issue here is the scale mismatch challenge [21,22]. Scale matching is not only the matching of spatial scales but also the matching between ground-based phenology metrics (e.g., budburst, flowering, leaf-coloring, etc.) and satellite-based metrics (e.g., SOS, EOS, POS, etc.) [23,24]. Therefore, it is critical to advance the theory and method that can resolve scale mismatch issues so that ground and satellite observations can be used in a more tandem manner [25,26]. The use of UAV observations and tower-mounted cameras can, to a certain extent, remediate the scale mismatch issue [27,28]. Meanwhile, considering the complexity of scale effects, computer simulations based on 3D radiative-transfer modelling can be used as a powerful tool to explore the scale effects or mixed image effects in vegetation phenology remote-sensing monitoring [29]. In addition, for low- and medium-resolution remote-sensing phenology products (e.g., MODIS/VIIRS), it is difficult even for UAVs or phenocams to provide validation data at the comparable pixel scale, in which case indirect "validation" can be performed using higher-spatial-resolution satellite data [30].

**Author Contributions:** Conceptualization, all authors; writing—original draft preparation, all authors; writing—review and editing, all authors. All authors have read and agreed to the published version of the manuscript.

**Funding:** This study is supported by National Natural Science Foundation of China (No. 42171305, Principal Investigator: X. Ma; No. 41971374, PI: J. Jin); Natural Science Foundation of Gansu Province, China (No. 21JR7RA499, PI: X. Ma); the Open Fund of State Key Laboratory of Remote Sensing Science (NO. OFSLRSS202229, PI: X. Ma); the Open Fund of the State Key Laboratory of Resources and Environmental Information System (No. 4 of the 2022 Round, PI: X. Ma); the Open Fund of Key laboratory of Geographic Information Science (Ministry of Education), East China Normal University (KLGIS2022A02, PI: X. Ma); Fundamental Research Funds for the Central Universities (No. lzujbky-2021-ct11, PI: X. Ma). Q. Xie acknowledges support from University of Technology Sydney Chancellor's Postdoctoral Research Fellowship and University of Technology Sydney Faculty of Science Seed Funding (Round 2 in 2021).

**Acknowledgments:** The authors would like to thank Xiaoyu Zhu and Yuhe Zhao for their help in collecting information and creating the word cloud graph.

**Conflicts of Interest:** The authors declare no conflict of interest.

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