



A review of remote sensing applications in flower phenology detection

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The shift in flowering phenology with plants blooming earlier due to climate change, disrupts the synchronization between plants and pollinators by creating temporal and spatial mismatches. Monitoring these shifts is essential, and remote sensing has become an invaluable tool for detecting flowering periods over vast areas. Despite the technological advancements, there remains a significant gap in comprehensive reviews that explore the use of remote sensing in flowering phenology and its impact on pollination ecology. Therefore, this study aims to review and summarize research on the remote sensing of flowers, with a particular focus on key techniques used to analyze flowering phenology. We categorized the application of remote sensing in the field of flowering phenology into four groups based on the type of data used: optical, Synthetic Aperture Radar (SAR), Unmanned Aerial Vehicle (UAV), and PhenoCam-based applications. In each section, we have reviewed and provided a summary of the studies conducted in this field, with a particular focus on those that primarily examine canola crop flowering. In conclusion, our findings reveal that Optical remote sensing, proves effective in capturing detailed imagery of flowering events, while SAR technology offers robust, all-weather monitoring capabilities. UAV-based remote sensing provides high-resolution, site-specific data, although it is constrained by operational limitations. PhenoCams offer valuable long-term monitoring but lack the spatial resolution for detailed analysis. Each remote sensing approach has distinct advantages and limitations, underscoring the need for integrated methods to improve flowering phenology assessments and enhance agricultural monitoring.

Keywords: climate change, optical, PhenoCams, plants, pollination, Synthetic Aperture Radar, Unmanned Aerial Vehicle

Introduction

Agricultural practices occupy about one-third of the Earth's land surface (Foley et al. 2005; Pye-Smith et al. 2022) and are a significant contributor to the degradation and fragmentation of natural habitats globally (Foley et al. 2005; Keenan et al. 2015; Rahimi and Dong 2022; Rands et al. 2010). To satisfy the demands of the projected global population by 2050, agricultural output must double (Bruinsma 2009; Tilman et al. 2011). In 2018, Africa faced significant food insecurity (Food and Agriculture Organization 2019), while India alone accounted for a quarter of the global food-insecure population (Mughal and Fontan Sers 2020). Concurrently, there is an increasing trend toward urbanization, with 56% of the world's population currently residing in urban areas (Department of Economic and Social Affairs 2018; Seto and Ramankutty 2016). It is estimat-

ed that by 2030, urban land will expand by an additional 1.2 million square kilometers, potentially encroaching on fertile agricultural lands near urban centers (Hou et al. 2021; Seto et al. 2012).

In 2015, the global community, represented by all United Nations Member States, adopted 'The 2030 Agenda for Sustainable Development.' This initiative was designed to foster peace, prosperity, and sustainability for people and the planet. Central to this agenda are 17 sustainable development goals, including a key goal to eradicate hunger, ensure food security, enhance nutrition, and promote sustainable agriculture (General Assembly 2016). However, a report from the Food and Agriculture Organization in July 2021 indicated that the world is not on course to meet this goal by 2030, with projections suggesting that the number of people suffering from hunger could exceed 840 million (www.un.org). The world must transform the food and ag-



riculture systems to adequately feed the current 690 million hungry people and an anticipated additional 2 billion by 2050 (www.un.org). The 2021 report on global food security and nutrition highlighted that even before the COVID-19 pandemic, progress toward eliminating hunger and malnutrition by 2030 was off track (UNICEF 2021).

The Millennium Ecosystem Assessment of 2005 (Millennium Ecosystem Assessment 2005) revealed a global decline in ecosystem services, with an almost 60% reduction in those evaluated and up to 70% specifically in regulating services like pollination. Presently, agriculture's dependence on pollinators has intensified, leading to an increased need for more cultivated land, especially in developing countries. This indicates that as reliance on pollination services grows, there is a corresponding demand for expanding agricultural areas, particularly in less economically developed regions (Aizen et al. 2008; Bentrup et al. 2019; Potts et al. 2016). However, climate change is projected to increase by 1.5 to 5.8 degrees Celsius by the end of the 21st century (Pachauri et al. 2014). This temperature rise is known to impact pollination by disrupting plant-pollinator interactions (Chakraborty et al. 2021). These disruptions can occur through temporal (phenological) and spatial (distributional) mismatches, potentially altering the availability of mutualistic partners (Gérard et al. 2020; Hegland et al. 2009; Jordano 2016; Rafferty 2017; Schweiger et al. 2010).

Such mismatches can lead to the formation of new mutualistic networks between plants and pollinators (Biella et al. 2017). Spatial mismatches can be predicted using species distribution models for interacting species pairs (Devoto et al. 2007; Filazzola et al. 2021; Rahimi et al. 2022; Rahimi and Jung 2024c, 2024d; Schleuning et al. 2016). Temporal mismatches occur when the flowering period of plants and the activity periods of their pollinators are no longer synchronized (Rahimi and Jung 2024e; Straka and Starzomski 2014). This misalignment can reduce pollination efficiency, leading to lower crop yields and diminished food supply (Smith et al. 2015). Such mismatches are particularly critical for pollinator-dependent crops that form the backbone of global agricultural systems (Rahimi and Jung 2024b). However, not all plants respond uniformly to climate change (Brooker 2006; Inouye 2022; Kelly and Goulden 2008). While many studies report earlier flowering due to rising spring temperatures, some early-spring flowering angiosperms have been observed to bloom later. This delayed flowering could result from complex interactions between temperature, photoperiod, and other environmental factors, highlighting the need for nuanced phenological monitoring to understand species-specific responses (Gusain et al. 2024).

Since the 1960s, spring activities such as vegetation growth and flowering have consistently begun earlier (Craufurd and Wheeler 2009; Defila and Clot 2001; Ha-

munyela et al. 2013; Menzel 2000; Piao et al. 2019; Roetzer et al. 2000; Studer et al. 2005; Studer et al. 2007; Walther et al. 2002). This trend underscores the importance of timely and accurate tracking of flowering periods across various spatial scales. Peak flowering times are crucial for assessing crop growth and predicting yields (d'Andrimont et al. 2020; Panetta et al. 2018; Sulik and Long 2016; Zhang et al. 2023). It's essential to measure the degree of temporal synchrony between pollinators and pollinator-dependent crops to identify areas at risk of pollinator shortages (Aizen et al. 2019; Carrasco et al. 2021; Giannini et al. 2017; Giannini et al. 2020; Marshall et al. 2023; Polce et al. 2014). Phenological monitoring is conducted through field observations and remote sensing (Rahimi and Jung 2024a, 2024f). Field observations record the timing of significant events like bud burst, leaf unfolding, flowering, and leaf color change (Schwartz 2003). In contrast, remote sensing offers improved spatial and temporal continuity and is more cost-effective, making it a preferred method for regional to global studies (John et al. 2020; Shen et al. 2014).

To assess the temporal mismatch between pollinators and flowering plants, particularly in pollinator-dependent crops, we need detailed information on the flowering phenology of plants, including the start, peak, and end of flowering. For pollinators, it's essential to have data on their physiology, lifespan, and the timing of their first emergence, peak activity, and final day of activity (Kudo and Ida 2013; Petanidou et al. 2014). With this information, we can evaluate the degree of temporal alignment between flowers and pollinators. Recently, there has been a significant focus on estimating the flowering phenology of crops, forest trees, and wildflowers. Some studies have concentrated on identifying the start and end of crop flowering, while others have focused on detecting flowers in grasslands or flowering trees in forests, developing new methods and vegetation indices to distinguish flowering plants and analyze their phenology. However, a review summarizing these studies is lacking, and it appears that many researchers are unaware of the relevance of such work in the field of pollination ecology. This study aims to firstly provide concise and valuable information on flowering plants, pollinator-dependent crops, and the role of insect pollinators in food security, and secondly review and summarize studies on remote sensing of flowers, focusing on key remote sensing techniques, for analyzing flowering phenology.

Methods

We conducted a literature search using the ISI Web of Science, focusing on studies published between 2000 and 2024. Our search employed the following string: (Remote sensing* OR Satellite images* OR Multispectral* OR Synthetic Aperture Radar (SAR)* OR Hyperspectral* OR Phe-

nocam* OR Unmanned Aerial Vehicle (UAV)*) AND (Flower phenology*). This yielded nearly 194 articles, which were narrowed down to 126 unique articles after removing duplicates. We specifically targeted studies that aimed to detect the flowering time of plants or crops, or that identified any phenological phases of flowers. After reviewing the titles and abstracts, we identified 48 articles that were aligned with our research objectives and recorded their key findings. To systematically analyze the methods and their effectiveness in assessing flowering phenology, we categorized the results into four general sections: optical, SAR, UAV, and PhenoCam-based approaches.

Network Visualization

We performed a network analysis using the *igraph* package (Csardi and Nepusz 2006) in R to visualize the relationships between frequently occurring keywords in the titles (> 2 times) of the selected papers. The network was constructed by treating keywords as nodes and their co-occurrences within paper titles as edges, forming connections. To group the keywords, we applied a community detection algorithm based on the Louvain method (Blondel et al. 2008), which identifies clusters of closely connected nodes within the network. This method ensures that keywords with stronger co-occurrence patterns are grouped into distinct communities, reflecting thematic areas within the reviewed studies. The groups were color-coded to enhance interpretability and represent specific research focuses, such as remote sensing techniques, phenology monitoring, and crop-specific studies.

Results

Optical-based applications

Optical or multispectral remote sensing captures reflected or emitted electromagnetic radiation across the visible, near-infrared (NIR), and short-wave infrared (SWIR) wavelengths. Unlike active sensors, such as SAR, optical sensors are passive and rely on sunlight as the illumination source, making them sensitive to atmospheric conditions and diurnal variations (Zhu et al. 2018). These sensors provide valuable spectral information, enabling the identification and monitoring of vegetation and flowering phenology over large spatial extents. While this study does not focus on the technical aspects of optical remote sensing, previous research has extensively examined its capabilities, including the temporal and spatial resolutions of optical satellites such as Sentinel-2, Landsat, and MODIS (Chen et al. 2019; Dixon et al. 2021; Gim et al. 2020; John et al. 2020; Shin et al. 2023; Soubry et al. 2021; Zhang et al. 2022b). Table 1 summarizes key applications of optical remote sens-

ing in studying flowering phenology.

SAR-based applications

SAR is an active remote sensing technology that emits microwave signals and measures their backscatter to capture detailed surface information. Unlike passive optical methods that depend on sunlight, SAR operates independently of weather and lighting conditions, making it effective for all-weather, day-or-night monitoring (Bhogapurapu et al. 2021; Wang et al. 2015). Its ability to penetrate cloud cover, vegetation, and soil to varying depths (depending on the wavelength) makes SAR particularly valuable in regions with frequent cloud cover or for applications requiring structural and moisture-related data. This unique capability has positioned SAR as a critical tool for monitoring phenology under challenging conditions (Liu et al. 2019; Lopez-Sanchez et al. 2012). Table 2 summarizes key SAR-based applications in studying flowering phenology.

UAV-based applications

UAV remote sensing employs UAVs equipped with sensors and cameras to acquire high-resolution imagery of the Earth's surface. Its exceptional spatial resolution allows for detailed and site-specific monitoring, often exceeding the capabilities of satellite or airborne platforms (Osco et al. 2021). UAVs can be equipped with various sensors, including hyperspectral imagers, which offer narrow, contiguous wavelength bands (~10 nm) compared to the broader bands of multispectral sensors (~100 nm), enabling precise detection of subtle spectral variations (Chen et al. 2017). This versatility makes UAVs invaluable for fine-scale phenological studies. Table 3 summarizes key UAV-based applications in monitoring flowering phenology.

PhenoCam-based applications

PhenoCam-based applications utilize automated digital cameras specifically designed for long-term monitoring of vegetation phenology. Unlike general digital repeat photography, which encompasses a wide range of camera types and technologies, PhenoCams are specialized systems that capture time-lapse images at regular intervals (Jose et al. 2023). Typically mounted on towers or other fixed structures, these cameras provide continuous observations of plant and ecosystem changes, making them invaluable for tracking phenological events over time (Crimmins and Crimmins 2008; Mann et al. 2022; Nijland et al. 2013). Their ability to capture temporal data complements other remote sensing methods by offering high temporal resolution, particularly for localized studies. Table 4 summarizes key PhenoCam-based applications in monitoring flowering phenology.

Table 1 The summary of optical-based applications in flower phenology

| Study | Plant | Location | Data | Goal | Key results |
|-------------------------|---|-------------------|---|--|--|
| Bogawski et al. 2019 | <i>Betula pendula</i> <i>Roth</i> | Poland | Landsat, MODIS | Spatial pattern of flowering onset | Birch trees in urban areas began flowering significantly earlier than those in rural areas |
| Chen et al. 2019 | Almond | USA | PlanetScope, Sentinel-2, Landstat | Developing an Enhanced Bloom Index (EBI), based on the multispectral remotely sensed data | EBI enhanced the signals of flowers and reduced the background noise from soil and green vegetation |
| Forsström et al. 2019 | Lingonberry, blueberry | Finland | FieldSpec Pro FR | Mapping of the spatial distribution of understory species | Lingonberry and blueberry can be identified by their spectral signatures if ground reference data are available over the entire growing season |
| Chávez et al. 2019 | Wildflowers | Chile | AVHRR | Identifying blooming deserts | They detected the looming deserts as positive NDVI anomalies |
| Paz-Kagan et al. 2019 | <i>Acacia salicina</i> , <i>Acacia saligna</i> | Israel | Airborne sensors, WorldView-2 | Identification and mapping | Acacia can be monitored based on unique phenological signals |
| d'Andrimont et al. 2020 | Rapeseed | Germany | Sentinel-2 | Developing a method to automatically calculate peak flowering | A novel methodology was proposed to map oil seed rape flowering phenology |
| Han et al. 2021 | Rapeseed | Germany | Sentinel-2, Landsat 8 | Introducing a new spectral index | The Normalized Rapeseed Flowering Index (NRFI) for identifying the flowering |
| Dixon et al. 2021 | <i>Corymbia calophylla</i> | Australia | Drone, PlanetScope | Creating extensive maps of flowering patterns | The new method predicts the proportion of flowering at the pixel level throughout the entire flowering period |
| Torgbor et al. 2022 | Mango | Ghana | Sentinel-2 | Identification phenological stages | Flowering peaks in June/July |
| Ashourloo et al. 2022 | Rapeseed | Iran, USA | Sentinel-2 | Introducing an automatic method for rapeseed mapping | The proposed index for differentiating canola from other crops |
| Rahman et al. 2022 | Avocado | Australia | Sentinel-2 | Identification phenological stages | The lowest EVI values were recorded during the flowering stage |
| Yi et al. 2022 | Sunflower | China | Sentinel-2 | Early-season identification and mapping | The sunflower crops were identified early, during the flowering stage in late July |
| Domingo et al. 2023 | <i>Acacia dealbata</i> | Spain | Sentinel-2 | Distinguishing and mapping the spatial extent | A flowering period was identified in March that was effective for <i>A. dealbata</i> discrimination |
| Dixon et al. 2023 | <i>Corymbia calophylla</i> | Australia | PlanetScope | Assessing the impact of fire on the flowering patterns | Fire events decreased the proportion of flowering trees |
| Xiong et al. 2023 | Chestnut | China | Sentinel-2 | Distribution mapping | Random forest ranked highest accuracy for mapping |
| Zang et al. 2023 | Rapeseed | China | Sentinel-2 | Introducing an automatic method for rapeseed mapping | With the proposed method, China rapeseed was mapped during 2017–2021 |
| Tao et al. 2023 | Rapeseed | China | Sentinel-2 | Introducing a new index for mapping winter rapeseed | The phenology-Based Winter Rapeseed Index (PWRI) effectively distinguished between winter rapeseed and winter wheat |
| Shao et al. 2023 | Rapeseed | China, Germany | Sentinel-2 | Introducing a Yellowness Index for rapeseed mapping | The proposed NYI exhibited the potential to capture yellow-flowering |
| Sun et al. 2024 | Rapeseed | China | Sentinel-2 | Exploring the effectiveness of a deep learning-based algorithm for detecting the early flowering stage | The PSPNet model, equipped with a ResNet-50 backbone, successfully fulfilled the requirements for precise classification |
| Fernando et al. 2024 | Rapeseed | Canada | PlanetScope | Forecasting rapeseed yield | The final model exhibited the potential of medium-resolution satellite imagery for yield prediction |

Table 2 The summary of Synthetic Aperture Radar (SAR)-based applications in flower phenology

| Study | Plant | Location | Data | Goal | Key results |
|-------------------------|-------------------|----------|------------------------|---|--|
| Cable et al. 2014 | Rapeseed, Soybean | Canada | RADARSAT-2 | Investigating the impact of acquisition time and incidence angle on various SAR polarimetric | Each crop exhibited a characteristic rise and fall in backscatter response |
| Wiseman et al. 2014 | Rapeseed, Soybean | Canada | RADARSAT-2 | Investigating the relationship between RADARSAT-2 polarimetric SAR responses and the dry biomass of rapeseed and soybean | Polarimetric SAR responds to the accumulation of dry biomass |
| McNairn et al. 2018 | Rapeseed | Canada | RADARSAT-2, TerraSAR-X | Estimating canola growth stages | The new crop growth stage indicator and identified SAR polarimetric parameters were sensitive to phenological changes |
| Bhogapurapu et al. 2021 | Rapeseed | Canada | Sentinel-1 | Introducing three polarimetric descriptors as pseudo-scattering-type parameter (θ_c), pseudo scattering entropy parameter (Hc), and co-pol purity parameter (mc) | During the transition from the leaf development stage to the flowering stage, the θ_c parameter shifted by approximately 17° |
| Löw et al. 2021 | Rapeseed | Germany | Sentinel-1 | Identification of the phenological phases of rapeseed | By combining, polarimetric Alpha and Entropy, and backscatter (VV/VH) measurements, they detected phenological stages |
| Liu and Zhang 2023 | Rapeseed | China | Sentinel-1 | Developing a comprehensive approach for rapeseed mapping | The first publicly available 10-meter resolution product for rapeseed distribution in China |
| Zhao et al. 2023 | Rapeseed | China | Sentinel-1 | Exploring rapeseed characteristics by analyzing backscattering profiles | Backscattering features during the flowering to maturity stages were particularly influential, leading to higher classification accuracy |
| Qadir et al. 2023 | Sunflower | Ukraine | Sentinel-1 | Monitor sunflower phenology by analyzing a time series of backscattering coefficients | Two key phases were identified: the beginning of flowering (BoF) and the end of flowering (EoF) |

Results Summary

The review of remote sensing methods for analyzing flowering phenology—optical, SAR, UAV, and PhenoCam—reveals a diverse array of capabilities and limitations, highlighting the strengths and challenges inherent to each technique. Optical methods, evaluated across 20 studies, stand out for their high spatial resolution and efficacy in mapping flowering periods and spatial distributions. SAR methods, covered in 8 studies, offer significant advantages in all-weather monitoring, capable of penetrating cloud cover and capturing data irrespective of lighting conditions (Table 5). UAV methods, discussed in 16 studies, provide high-resolution and site-specific data that is invaluable for detailed flower detection and phenological stage mapping. UAVs offer flexibility in application and high spatial resolution, which is beneficial for capturing nuanced plant health and phenology data. PhenoCam methods, explored in 4 studies, are notable for their long-term monitoring capabilities and effectiveness in capturing continuous temporal data on flowering events.

Geographically, North America has seen widespread adoption of all methods, reflecting a broad application of remote sensing techniques across various environments.

Europe has focused predominantly on optical and PhenoCam methods, leveraging their strengths in spatial and temporal analysis. In contrast, Asia has shown a significant emphasis on UAV studies, highlighting the region's interest in high-resolution, site-specific data. Each method's challenges—ranging from atmospheric interference for optical methods, complex data processing for SAR, high costs for UAVs, to spatial resolution limitations for PhenoCam—underscore the need for continued research and development. Future directions include enhancing data integration across methods, improving algorithmic approaches, and expanding research to encompass a wider geographic scope to address these challenges comprehensively and advance the field of flowering phenology analysis.

Table 6 summarizes the spectral bands commonly used in remote sensing for flowering phenology detection, highlighting their characteristics, associated vegetation indices, and applications. The Visible (Red) band (620–750 nm) is sensitive to chlorophyll absorption and is effective in isolating flowering signals, with indices like the Enhanced Bloom Index (EBI) and NDVI reducing background noise from vegetation and soil. The NIR band (750–900 nm) reflects strongly in healthy vegetation, aiding in differentiating flowers from surrounding vegetation and supporting

Table 3 The summary Unmanned Aerial Vehicle (UAV)-based applications in flower phenology

| Study | Plant | Location | Data | Goal | Key results |
|----------------------------|---------------------------------|-------------|------------------------------|--|--|
| Ge et al. 2006 | <i>Centaurea solstitialis</i> | USA | Spec ProFR | Investigating the spectral reflectance of various flowering stages | Spectral differences between simulated flowering stages varied by spectral regions and phenological stages |
| Gai et al. 2011 | Wildflowers | Canada | ASD FieldSpec-3 | Measuring the reflectance spectra of flowers | The linear unmixing model is an effective method for estimating the coverage of grassland flowers |
| Landmann et al. 2015 | Wildflowers | Kenya | AISA/Eagle | Creating the first map of flowering and short-term floral cycles | Overall mapping accuracy was higher during the peak flowering period |
| Sulik and Long 2016 | Rapeseed | USA | ASD FieldSpecPro™ | Detecting phenological stages | They developed a Normalized Difference Yellowness Index (NDYI) |
| Ma et al. 2019 | Rapeseed | China | ASD FieldSpec 4 | Winter rapeseed biomass estimation | Results indicated that rapeseed biomass could be reliably estimated by canopy hyperspectral data |
| Mahmud et al. 2020 | <i>Solidago altissima</i> | Japan | ASD Field Spec 4 | Mapping an invasive | Detection of <i>S. altissima</i> distribution was possible using a high-resolution satellite image |
| Neumann et al. 2020 | <i>Calluna vulgaris</i> | Germany | DJI Phantom 4 Pro drone | Quantifying spatial patterns of phenology | Calluna life-cycle phases can be spatially differentiated into pioneer, building, and mature phases in UAV imagery |
| Stanski et al. 2021 | <i>Eriophorum vaginatum</i> | Canada | Phantom 4 Advanced Pro drone | Developing a method for detecting tundra plant species' flowers | R-CNN architecture was capable of <i>E. vaginatum</i> flower species detection and counting |
| Zhang et al. 2022a | Rapeseed | China | Rededge-MX | Enhancing a shape-model method for extracting phenological stages | Among vegetation indices, Clred-edge achieved the greatest accuracy in estimating the phenological stage dates |
| Gallmann et al. 2022 | Wildflowers | Switzerland | DJI Matrice 600 PRO | Flower Mapping in Grasslands | Some flowers were detected poorly due to reasons such as lack of enough training data, and appearance changes due to phenology |
| Athira et al. 2023 | Wildflowers | India | Ocean Optics USB | Quantifying diverse floral colors across landscapes | The research introduced a novel approach that utilizes floral spectral reflectance data to study subtle changes in the landscape |
| Lee et al. 2023 | Tropical trees | USA | DJI Phantom Pro 4 drone | Developing an advanced method integrating the Residual Networks 50 (ResNet50) | The deep learning method achieved high accuracy in classifying flowers |
| Zhang et al. 2023 | Apple | Netherlands | Phantom4 RTK, | Introducing an innovative approach for quantifying flower intensity using single raw aerial images | The method was successful in the tree-level flower cluster estimation derived |
| Kopec' et al. 2023 | <i>Echinocystis lobata</i> | Poland | HySpex VNIR | Assessing the impact of acquiring synchronized on-ground data and hyperspectral data | Mapping an annual vine using remote sensing and machine learning is possible and highly effective |
| Thoday-Kennedy et al. 2023 | Safflower | Australia | RedEdge-M multispectral | Identifying the onset of flowering | Early flowering genotypes often had lower peak NDVI values and a slower decay rate |
| Gupta et al. 2024 | <i>Heterotheca subaxillaris</i> | Israel | DJI Phantom 4 | Developing a methodology to identify and map | Random forest classification approach, achieving a remarkable 97.4% accuracy in identifying <i>H. subaxillaris</i> |

indices such as NDVI and the Normalized Rapeseed Flowering Index (NRFI) in agricultural applications. The SWIR band (1,300–2,500 nm) is sensitive to vegetation water content and physiological changes, with the Normalized Difference Water Index (NDWI) monitoring water stress and

its impact on flowering behavior. Together, these spectral bands provide critical insights into flowering phenology across diverse environments and crops.

Table 4 The summary PhenoCam-based applications in flower phenology

| Study | Plant | Location | Data | Goal | Key results |
|----------------------------|---|-----------|--------------------------|--|---|
| Nijland et al. 2013 | <i>Hedysarum alpinum</i> | Canada | Pentax K100D digital SLR | Exploring whether time-lapse photography could be used to monitor the phenological development of a forest stand | Repeat photography and image analysis were effective in detecting all key phenological events |
| Mann et al. 2022 | <i>Dryas octopetala</i> , <i>Dryas integrifolia</i> | Greenland | TimelapseCam Pro | Introducing a method for automated monitoring of flowering phenology | The convolutional neural network was effective in collecting flower phenology data |
| Funada and Tsutsumida 2022 | Cherry | Japan | - | Developing a deep-learning model using 'YOLOv4' to detect cherry blossoms from street-level photographs | The object-detection model achieved an overall accuracy of 83% |
| Andreatta et al. 2023 | Wildflowers | Germany | TLC 100, Brinno | Developed a workflow for extracting flowering phenology in grassland species mixtures using | The random forest classifiers demonstrated high accuracy in predicting the cover of wildflowers |

Table 5 A summary comparison of reviewed methods

| Method | Number of studies | Key focus areas | Examples of key findings |
|----------|-------------------|--|---|
| Optical | 20 | Flowering onset, bloom indices, phenological stages, spatial distribution | <ul style="list-style-type: none"> - Enhanced Bloom Index (EBI): Improved detection of flowering events by reducing background noise from vegetation and soil - Effective Mapping: Successfully mapped flowering periods and spatial distribution across different environments - Phenological Indicators: Various indices like NDVI and specific bloom indices were used to assess and monitor flowering stages |
| SAR | 8 | Growth stages, phenological phases, polarimetric response | <ul style="list-style-type: none"> - Growth Stage Indicators: Identified distinct SAR parameters sensitive to phenological changes, such as the θ_c parameter shift during flowering - Phenological Phases: Detailed mapping of growth stages and phenological phases using SAR's ability to capture changes in vegetation structure |
| UAV | 16 | Reflectance spectra, flower coverage, phenological stages, high-resolution mapping | <ul style="list-style-type: none"> - High-Resolution Mapping: UAVs provide detailed, high-resolution imagery for precise flower detection and mapping, though detection accuracy can vary - Reflectance Spectra: Effective in assessing spectral differences between flowering stages and vegetation types - Variable Detection: Challenges with variable detection due to changing phenological states and the need for extensive training data |
| PhenoCam | 4 | Phenological monitoring, automated detection, time-lapse photography | <ul style="list-style-type: none"> - Long-Term Monitoring: Effective for monitoring flowering events over time with high temporal resolution - Automated Detection: Convolutional neural networks and deep learning models achieved high accuracy in detecting and classifying flowering phenology - Event Detection: Successful in capturing key phenological events using repeat photography and time-lapse techniques |

SAR: Synthetic Aperture Radar; UAV: Unmanned Aerial Vehicle.

Table 6 Summary of spectral band characteristics, vegetation indices, and flowering detection applications

| Spectral band | Wavelength range (nm) | Characteristics | Vegetation indices | Relevance to flowering detection |
|---------------------------|-----------------------|--|--|---|
| Visible (Red) | 620–750 | Sensitive to chlorophyll absorption; highlights flowering signals against green vegetation | Enhanced Bloom Index (EBI), NDVI | Effective in identifying flowering onset and reducing soil/vegetation background noise (Chen et al. 2019) |
| Near-Infrared (NIR) | 750–900 | Reflects strongly in healthy vegetation, differentiating it from flowers or soil | NDVI, Normalized Rapeseed Flowering Index (NRFI) | Aids in mapping flowering phenology, particularly in agricultural landscapes like rapeseed fields (Han et al. 2021; Zang et al. 2023) |
| Shortwave infrared (SWIR) | 1,300–2,500 | Sensitive to vegetation water content; highlights physiological changes during phenological stages | Normalized Difference Water Index (NDWI) | Tracks water stress and phenological changes affecting flowering behavior (Chávez et al. 2019) |

ronments.

Several studies (e.g., Ashourloo et al. 2022; Chen et al. 2019; d'Andrimont et al. 2020; Han et al. 2021; Shao et al. 2023; Tao et al. 2023; Zang et al. 2023) have introduced new methodologies for automatic crop mapping or spectral indices tailored for specific crops or conditions, such as the EBI and the NRFI. These indices are innovative and offer potential improvements in accuracy. However, the generalizability of these indices to other crops or environments remains uncertain and should be further validated.

These studies also highlight how flowering phenology can be effectively monitored across various climates and plant species, from birch trees in urban Poland to rapeseed in China. However, results vary depending on the region and plant species, suggesting that local environmental conditions significantly influence the success of these methods. For instance, the spatial resolution required to map rapeseed in dense agricultural landscapes might differ from that needed to detect flowering in sparsely distributed wildflowers in Chile (Chávez et al. 2019). There is also a consistent finding that optical methods can successfully identify and map flowering stages (e.g., Dixon et al. 2021; Domingo et al. 2023). However, the accuracy and precision of these detections often depend on the availability of ground truth data (Forsström et al. 2019). The need for extensive ground validation is a recurring theme, which could limit the scalability of these methods in regions where such data are not readily available.

These studies primarily focus on Europe, China, and the USA, with fewer studies in tropical or arid regions. Moreover, common crops like rapeseed are frequently studied, while other economically important or ecologically significant species receive less attention. This indicates a potential bias in research that could overlook critical phenological changes in underrepresented areas and species. Many studies use time-series data to capture phenological changes (e.g., Sentinel-2 data in multiple studies). However, the temporal resolution may not be sufficient to capture rapid phenological events, such as sudden flowering onset triggered by specific climatic conditions. The studies show significant potential for practical applications in agriculture and ecology, such as forecasting crop yields (Fernando et al. 2024) and assessing the impact of environmental factors like fire (Dixon et al. 2023). These applications highlight the value of optical methods in managing and adapting to environmental changes. However, the translation of these methods into operational tools for farmers or land managers is not thoroughly discussed in most studies, which could limit their real-world impact.

SAR-based applications

These studies primarily utilize SAR data from RADAR-SAT-2 and Sentinel-1, with some incorporating TerraSAR-X. SAR offers unique advantages, such as the ability

to penetrate cloud cover and provide data under all weather conditions, which is particularly beneficial for monitoring phenology in areas with frequent cloud cover. However, SAR data are more complex to interpret compared to optical data, requiring advanced processing techniques. The reliance on different SAR sensors across studies is both a strength (diversity of data) and a potential limitation (differences in data consistency and resolution). Several studies (Cable et al. 2014; McNairn et al. 2018; Wiseman et al. 2014) have focused on polarimetric SAR, which analyzes different polarization states of the radar signal. This approach is effective for distinguishing between different crop types and detecting phenological changes. The introduction of novel polarimetric descriptors (Bhogapurapu et al. 2021) adds value by enhancing the sensitivity of SAR data to phenological stages. However, the complexity of polarimetric analysis may limit its accessibility for broader applications without specialized expertise.

The studies consistently show that SAR data are effective in identifying key phenological stages in crops like rapeseed and soybean. For example, McNairn et al. (2018) and Löw et al. (2021) successfully used SAR to detect stages of rapeseed growth. Zhao et al. (2023) further confirm the capability of SAR in distinguishing flowering to maturity stages with high classification accuracy. This consistency underscores SAR's robustness in phenological monitoring. However, the results are highly dependent on the specific SAR parameters and polarimetric techniques used, suggesting a need for standardization.

While SAR-based methods have been widely tested in Canada and China, their application to different crops (e.g., sunflower in Ukraine) shows variability in effectiveness. For instance, while rapeseed phenology is well-documented, the identification of sunflower phenological stages in Ukraine highlights different backscattering responses, emphasizing the need to tailor SAR analysis to specific crop types and regional conditions. The studies focus predominantly on rapeseed, with only one study (Qadir et al. 2023) extending the application to sunflower. This narrow focus limits the generalizability of the findings to other crops with different phenological patterns. Expanding SAR-based research to a wider variety of crops could enhance our understanding of its applicability across diverse agricultural landscapes. Also, while Sentinel-1 offers frequent revisits and high spatial resolution, there are still limitations in capturing rapid phenological changes. The temporal resolution may be insufficient for crops with short flowering periods, leading to potential gaps in data. The reliance on SAR alone might also overlook the benefits of integrating with optical data to provide a more comprehensive phenological assessment.

UAV-based applications

These studies have utilized a wide range of UAV plat-

forms and sensors, from simple RGB cameras (e.g., DJI Phantom series) to advanced hyperspectral sensors (e.g., HySpex VNIR). This diversity allows for a broad exploration of UAV applications in flower phenology, capturing different aspects of plant development. However, the variation in sensor types and resolutions complicates the comparison of results across studies, as different sensors have unique strengths and limitations. Several studies, such as those by Ge et al. (2006) and Sulik and Long (2016), focus on spectral reflectance data to identify phenological stages or develop indices like the Normalized Difference Yellowness Index (NDYI). While spectral analysis is powerful for detecting subtle phenological changes, it often requires high-quality, consistent data, which may not always be available, particularly in diverse and complex field conditions.

More recent studies (Gupta et al. 2024; Lee et al. 2023; Stanski et al. 2021) incorporate advanced machine learning models, such as R-CNN architecture and Random Forest classifiers, to enhance the accuracy of flower detection and classification. These approaches represent a significant advancement in UAV-based phenology, offering precise, automated analysis. However, they also require substantial computational resources and expertise, potentially limiting their accessibility for broader applications. The studies consistently demonstrate that UAVs are effective tools for identifying and mapping phenological stages. For example, Zhang et al. (2022a) found that the CIred-edge vegetation index was highly accurate in estimating phenological stage dates for rapeseed, while Neumann et al. (2020) successfully quantified spatial patterns of phenology in *Calluna vul-*

garis using UAV imagery. These findings underline UAVs' potential in fine-scale phenological monitoring, especially in heterogeneous landscapes.

Despite the overall success, some studies, such as Gallmann et al. (2022), report challenges in accurately detecting certain flower species. Issues like insufficient training data and changes in flower appearance due to phenology highlight the limitations of current UAV-based methods. This indicates a need for more robust, adaptable models that can account for such variability. While the studies cover a range of locations and plant species, there is a noticeable concentration on certain crops, such as rapeseed and wildflowers. This focus limits the generalizability of the results, as different crops and regions may exhibit different phenological patterns and responses to UAV-based monitoring. Expanding the research to include a wider variety of crops and ecosystems would enhance the understanding and applicability of UAV technology in phenology.

PhenoCam-based applications

These studies leverage PhenoCams and time-lapse photography as primary data collection tools for monitoring phenological changes in various plant species. These methods offer a cost-effective and accessible approach to capturing continuous phenological data over time, with particular strength in visualizing changes that occur gradually, such as flowering events. For instance, Nijland et al. (2013) successfully utilized time-lapse photography to monitor phenological events in *Hedysarum alpinum*, demonstrating the method's effectiveness in detecting key phenological stages. More recent studies, such as Mann et al. (2022)

Table 7 Summary of strengths, limitations, challenges, and future directions for each method

| Method | Strengths | Limitations | Challenges | Future directions | Suitable for |
|----------|---|---|---|---|---|
| Optical | High spatial resolution; effective for large-scale mapping and detecting flowering events. | Sensitive to atmospheric conditions and vegetation cover; may require ground truthing. | Atmospheric interference, need for extensive ground validation. | Development of more robust indices and integration with complementary data types. | Large-scale mapping, bloom indices, spatial distribution studies. |
| SAR | All-weather capabilities; provide detailed growth stage indicators. | Complex data processing; is less effective for detecting detailed flowering events. | Complex processing and limited resolution for small-scale flowering detection. | Improvement in spatial resolution and better integration with optical data. | Biomass estimation, growth stage monitoring, phenological phase detection. |
| UAV | Very high-resolution, site-specific data; flexible and adaptable. | High operational costs; weather-dependent; challenges in consistent detection accuracy. | Cost, weather dependence, and variability in detection due to changing phenological states. | Reduction in costs, improvement in algorithms, and expansion of applications. | Precise flower detection, detailed phenological stage mapping, and site-specific studies. |
| PhenoCam | Provides long-term, high-frequency monitoring; effective for phenological events over time. | Limited spatial coverage; less effective for mapping large areas. | Limited resolution and applicability to broader spatial scales. | Integration with high-resolution methods and expansion of study areas. | Long-term phenological monitoring and automated detection of flowering events. |

SAR: Synthetic Aperture Radar; UAV: Unmanned Aerial Vehicle.

and Funada and Tsutsumida (2022), incorporate machine learning models, like convolutional neural networks (CNNs) and YOLOv4, for automated phenology monitoring. These models enhance the efficiency and accuracy of data analysis by automating the identification and classification of phenological stages. However, the reliance on advanced algorithms also introduces complexity, requiring significant computational resources and expertise in machine learning.

The studies employ a variety of camera systems, ranging from simple digital SLRs (e.g., Pentax K100D) to specialized time-lapse cameras (e.g., TimelapseCam Pro, Brinno). This diversity allows for flexibility in capturing phenological data across different environments and species. However, the variation in camera quality and setup may affect the consistency and comparability of results across different studies. The studies consistently demonstrate that PhenoCams are effective tools for capturing and analyzing phenological events. For example, Nijland et al. (2013) showed that repeat photography could effectively detect all key phenological events in a forest stand, while Mann et al. (2022) found that a CNN model could effectively collect flower phenology data for *Dryas* species in Greenland. These findings underscore the utility of PhenoCams for detailed phenological monitoring, particularly in remote or challenging environments.

The studies primarily focus on specific regions and plant species, such as *Dryas* in Greenland and cherry blossoms in Japan. While these studies provide valuable insights, the limited geographic and species coverage restricts the generalizability of the findings. Expanding research to include a broader range of ecosystems and plant species would provide a more comprehensive understanding of phenological patterns and responses to environmental changes. The effectiveness of PhenoCam-based phenology monitoring largely depends on the quality of the imagery captured. Variations in lighting conditions, camera angles, and image resolution can impact the accuracy of phenological observations. Finally, we summarized the strengths, limitations, challenges, and future directions of four remote sensing methods—Optical, SAR, UAV, and PhenoCam—while highlighting their suitability for specific applications in phenology studies (Table 7). Table 7 provides a comprehensive comparison to guide the selection of appropriate methods based on research goals and practical considerations.

Conclusion

This study provides a comprehensive review of various remote sensing methods—Optical, SAR, UAV, and PhenoCam—used in flower phenology research. Through a detailed analysis of existing literature, we have identified the

key strengths, limitations, and applications of each method highlighting how they contribute to understanding and monitoring flowering events across different plant species and environments. We aimed to highlight the potential of these remote sensing technologies to capture the flowering times of flowers and pollinator-dependent crops, thereby addressing the temporal mismatches between plants and their pollinators. This review underscores the importance of utilizing remote sensing techniques to better understand and mitigate temporal mismatches between flowering plants and their pollinators, ultimately contributing to more effective conservation and management strategies for pollinator-dependent ecosystems.

Abbreviations

CNNs: Convolutional neural networks
EBI: Enhanced Bloom Index
NDWI: Normalized Difference Water Index
NDYI: Normalized Difference Yellowness Index
NIR: Near-infrared
NRFI: Normalized Rapeseed Flowering Index
SAR: Synthetic Aperture Radar
SWIR: Short-wave infrared
UAV: Unmanned Aerial Vehicle

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Authors' contributions

Conceptualization, ER and CJ; Validation, CJ; Formal Analysis; Investigation, ER; Resources, CJ; Data Curation, ER; Writing – Original Draft, ER; Preparation, ER; Writing – Review & Editing, CJ; Supervision, CJ; Project Administration, CJ; Funding Acquisition, CJ. All authors have read and agreed to the published version of the manuscript.

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Availability of data and materials

A list of studies downloaded from the Web of Science is available at <https://github.com/ehsanrahimi666/Flower-Phenology.git>.

Ethics approval and consent to participate

Not applicable.

Consent for publication

Not applicable.

Competing interests

The authors declare that they have no competing interests.

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