



Advancements in Crop Phenological Stage Mapping Using Satellite Imagery and Spectral Analysis: A Review

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Abstract. Crop phenology has become an important part of crop mapping, yield prediction and for better agricultural decisions for such as irrigation, fertilization and crop drought control. The satellite sensors such as sentinel-2 and landsat-8/9 can be used to obtain high resolution imagery that can be used for larger field area for crop analysis by using vegetation indices and time series analysis. The present study is a systematic review approach for automated crop phenological stages based on satellite imagery and spectral signature. It discusses techniques like preprocessing and feature selection based on vegetation indices and temporal curves with help of different machine learning and deep learning techniques. This analysis indicates how the time-series data and smoothing methods are crucial in deriving dependable phenological measures like Start of Season (SOS), Peak of Season (POS), and End of Season (EOS). This study also highlights benefits and drawbacks of current methodological approach by giving future research direction for multi-source data integration with real time monitoring system with generalized models of various agricultural conditions.

Keywords: Crop phenology, NDVI, ML, Spectral Feature Extraction

1 Introduction

The study of crop development which is the time of major plant growth stages, including germination, vegetative growth, flowering and maturity is vital in contemporary agriculture as it is referred to as crop phenology [1]. Proper understanding of these stages assists in proper management of crops such as timing of irrigation, application of fertilizers, pest control and estimating the yields. Knowledge about the phenological patterns also helps farmers and researchers to evaluate the health of crops and react to environmental stress. With climate variability and rising food demand, crop phenology monitoring has emerged as a critical measure towards enhancing productivity and achieving sustainable agricultural practices [2].

The past few years have seen the progress of remote sensing technologies that have greatly increased capability to monitor crops on large spatial and temporal scales. Multispectral data with high resolution is available on satellite platforms like Sentinel-2, Landsat, and MODIS and can be used to track changes in crop conditions over the growing season [3]. These data sets allow the derivation of vegetation indices and time profiles, which are directly related to the dynamics of crop growth. Remote sensing provides affordable, consistent and repeatable monitoring over large agricultural areas, compared to the traditional field-based observations [4].

In spite of these improvements, detecting phenological stages [1] of crops by means of satellite information is a complicated process particularly when done by hand or using traditional methods. The growing access to time-series satellite data has generated a requirement in the automated procedures that have the ability to effectively process big information and deliver precisely on phenological shifts [5]. While there will be less manpower needed to accomplish the same tasks, automation will also increase consistency and the capacity to scale, and can be integrated into real-time agricultural monitoring systems. The application of both machine learning and data-based approaches have a role in improving the capacity to simulate complex crop development temporality further [6].

Phenological stage detection methods have a number of limitations with regard to traditional methods, which mainly rely on field surveys and visual observation. These are labor and time consuming to execute and more so, are restricted to a smaller geographical area [7]. They are also prone to human error, and cannot track temporal changes and therefore are difficult to record dynamic changes in crop development [8]. Even semi-automatic methods that are based on basic threshold of vegetation indices cannot be generalized to other crops, regions and environments. The shortcomings of these limitations show the necessity of solutions that are more robust, scalable and automated [7][8].

Therefore, the aim of this review paper is to critically assess the methods available for automated mapping of phenological phases of crops using satellite images and spectral curve analysis. This paper includes systematic review of different methodology based on PRISMA framework. It includes spectral indices based, crop type and machine learning and deep learning based analysis of different phenological study. It also follows with future scope for automated phenology mapping system in consideration of current studies.

2 Recent Developments in Phenological Monitoring through Remote Sensing

Recent research indicates the growing importance of remote sensing in the greatly enhanced accuracy and scalability of crop phenology monitoring. As an illustration, time-series vegetation indices calculated using Sentinel-2 data were shown to be able to successfully measure important phenological changes, including the onset and the end of the growing season, in one of the studies of the author for remote Sensing crop phenology. Their paper highlighted that the high temporal observations can be very useful in

crop growth dynamics detection than single-date imagery [9]. Likewise, the second author vegetation index phenology study indicated that such indexes as NDVI and EVI are closely related to crop development phases and could be utilized to track seasonal fluctuations in various agricultural areas [10].

Furthermore, recent studies have also been geared towards combining spectral curve analysis with other advanced modeling approaches to automated phenology mapping. The time-series phenology mapping of the authors revealed that the use of smoothing algorithm and extraction of phenological measures like start of season (SOS), peak of season (POS) and end of season (EOS) increases classification accuracy. Their results indicate that integrating machine learning models and satellite time-series data can offer a powerful model to monitor crops at scale [11]. Taken together, these papers show that there is a definite trend towards automated, data-intensive methods of detecting phenological stages, which supports the argument that remote sensing is essential to precision agriculture. In addition, the above research papers we have conducted study where we identified crop specific sensors and technical analysis for crop phenology which is characterized in detail in table 1.

Crop Type	Sensor/Satellite	Technique Used	Result / Accuracy	Ref.
Winter Wheat	NDVI Time-Series Data	Savitzky–Golay filtering, threshold-based phenology extraction, hierarchical classification	Extraction accuracy: 94.92%, Spatial accuracy: 93.26%, Kappa: 0.9228	[12]
Wheat	UAV Imagery	FS-CS feature selection, multi-level Relevance Vector Machine (mRVM)	Stage classification accuracy ranged from 0.22–0.93	[13]
Corn, Soybean	Harmonized Landsat & Sentinel-2 (HLS)	Two-step RGDD-based phenology framework	Corn: $R^2 = 0.90$, MAE = 2.7 days; Soybean: $R^2 = 0.87$, MAE = 2.5 days	[14]
Soybean	MODIS NDVI	Phenological metric extraction from NDVI time series	Strong agreement with DERAL reference data	[15]
Cotton	Sentinel-2	Random Forest with optimized phenological and harmonic features	OA > 98%, Kappa > 0.96, $R^2 > 0.96$	[16]
Cotton	Sentinel-1, Sentinel-2, PhenoCam	Color-based phenology algorithm	Overall accuracy: 95%	[17]
Corn, Soybean	Sentinel-2	Crop-specific spectral indices with unsupervised classification	Average OA: 88.90%, F1-score: 0.88	[18]
Corn	Optical VIs, SAR, Meteorological Data	PSI feature selection with Random Forest layered strategy	RMSE = 8.74 days, explained 96% spatial variation	[19]
Potato	Sentinel-1, Sentinel-2	NDVI, fAPAR, IRECI2, VH/VV integration	Overall $R^2 = 0.80$; RMSE = 12–17 days	[20]
Potato	Sentinel-2	Potato Early Mapping Index (PEMI)	OA: 88.67%–97.00%, F1: 79.57%–94.12%	[21]
Rice, Sunflower	Satellite NDVI Data	Phenology-based yield prediction models	Review-based qualitative analysis; no specific accuracy provided	[22]
Corn, Soybean	Time-series Remote Sensing Data	WISE phenology-normalized attention-based 1D CNN	>90% OA end-of-season, 85% OA during growing season	[23]

Table 1. Literature Survey based on Crop Type and Techniques

3 Methodology

To ensure transparent and well-structured methodology a systematic literature survey is done based on PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) framework as represented in figure 1. Literature study related to satellite remote sensing, crop phenology, time series analysis, spectral signature, machine learning and deep learning based data was collected from different sources like MDPI, Elsevier, Springer, IEEE, Taylor & Fancies and some other journals published between 2023-2026. Keywords such as “crop phenology”, “crop phenotyping”, “remote sensing”, “Sentinel-2”, “Landsat”, “machine learning”, “deep learning”, “NDVI”, and “spectral signature” were used during the search process. Initially, 152 records were identified, from which 28 duplicate studies were removed. Due to insufficient data availability or not related to our scope 68 studies excluded from 124 screened articles. After that 56 full text articles were assessed and from which 22 excluded because of incomplete phenological analysis, lack of performance metrics, or insufficient experimental validation. At the end 34 articles were included for detailed analysis in this review.

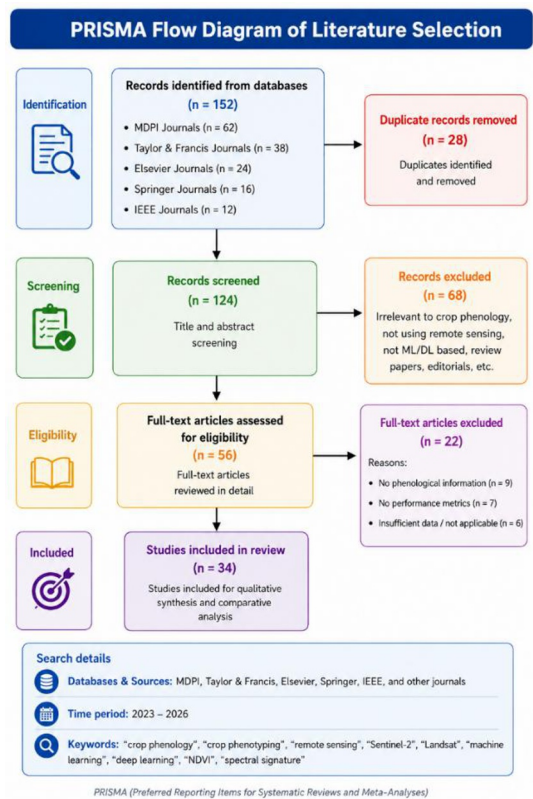


Fig. 1. PRISMA Flow Diagram

On the basis of the extensive literature review, a generalized and efficient automated crop phenological stage mapping methodology has been discovered as depicted in figure 2. The methodology is a combination of satellite-based time-series analysis, spectral curve modeling and machine learning to effectively determine crop growth stages.

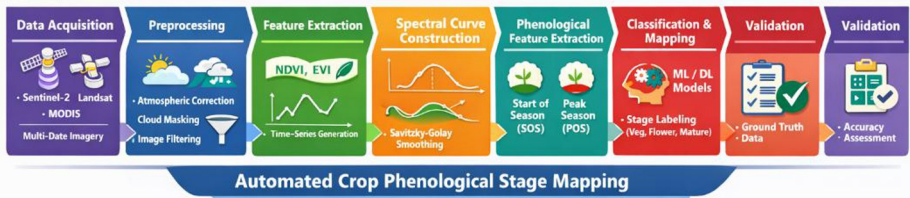


Fig. 2. Proposed Methodology

3.1 Data Acquisition:

Multispectral data through satellites are obtained by satellites like Sentinel-2, Landsat and MODIS. Sentinel-2 is the most popular of these because it has a high spatial and temporal resolution, which is why it can be used to monitor crops in detail [3]. The data is taken in several dates throughout the crop growing season. Such temporal range choice is necessary to be able to capture all the phenological stages, starting with the early growth and ending with maturity, which can be analyzed with the help of time-series analysis [3][24].

3.2 Preprocessing:

The obtained satellite data is preprocessed to guarantee consistency and reliability. Atmospheric correction is used to eliminate the effects of atmospheric interference and get real values of surface reflectance. To remove cloud and shadow-based pixels that may otherwise skew the outcome of analysis, cloud masking techniques are applied to detect and remove them. Also, image filtering is done to minimize noise and enhance the overall quality of the dataset, to provide smooth transitions in data between the times [25].

3.3 Feature Extraction:

During this step, significant vegetation indices of NDVI, EVI, and other spectral indicators are obtained based on the satellite images. They are extremely sensitive indices to vegetation health and can be used to represent crop growth conditions. These indices are calculated at every time step and put together to produce a time-series dataset, which is the temporal change in crop development over the growing season [26].

3.4 Spectral Curve Construction:

Spectral curves are constructed within each pixel or agricultural field using the time-series vegetation index data especially NDVI. These curves depict the trend of crop growth with time. Smoothing methods like Savitzky-Golay filter are used in order to improve the quality of these curves and reduce noise. This brings about a more understandable and interpretable depiction of crop growth dynamics [27].

3.5 Phenological Feature Extraction:

Important parameters of phenology are derived based on the smoothed spectral curves. The Start of Season (SOS) is when crop growth begins, the Peak of Season (POS) is when the vegetation is the most active, and the End of Season (EOS) is when the crop is fully matured or is senescent. These characteristics play a vital role in comprehending crop development and can be important inputs to classification models [28].

3.6 Classification / Mapping:

The removed phenological features are then considered as the inputs to the classification models to map the various stages of crop growth. Random Forest (RF) and Support Vector Machine (SVM) machine learning algorithms and Long Short-Term Memory (LSTM) deep learning models are widely used. The models examine temporal trends and label them according to various phenological stages, including vegetative, flowering, and maturity, producing spatial maps of crop development [29].

3.7 Validation:

Lastly, the phenological stage mapping is assessed in terms of accuracy and reliability using validation. This is whereby the model is compared with the ground truth data such as field observations or agricultural records. To measure the performance of the models, standard evaluation metrics like confusion matrix, overall accuracy, precision, recall, and F1-score are employed to guarantee the soundness of the proposed methodology [30].

4 Result and Discussion

The literature review shows that the combination of time-series data on satellite-based time-series and phenological features extraction can greatly enhance crop monitoring and classification. It is possible to capture the dynamics of crop growth at various phenological stages because of the utilization of multispectral imagery, especially that of Sentinel-2. Research indicates that vegetation indices like NDVI, EVI, and enhanced indices like WDRVI have significant correlations with crop development and yield which validates their use in phenological analysis. Also, temporal models, including

double sigmoid functions and harmonic analysis, can be used to accurately determine critical growth transitions like canopy closure, flowering and senescence.

Additional findings show that both feature optimization and time-series analysis are critical in improving the performance of classification. An example is that the combination of phenological features with time-series vegetation indices and terrain parameters results in a significantly better classification accuracy, with overall accuracy values of over 98 percent in a few cases. Optimized feature sets help to reduce redundancy without sacrificing high performance, which proves the significance of feature selection in crop mapping by remote sensing. In addition, smoothing methods like Savitzky-Golay filter enhance the quality of temporal signals, which allows the extraction of phenological measures of SOS, POS, and EOS more accurately.

The figure 3 represents conceptual presentation of spectral signature of crops like potato, cotton, soybean, corn, rice and other crops based on spectral indices over different crop phenological stages.

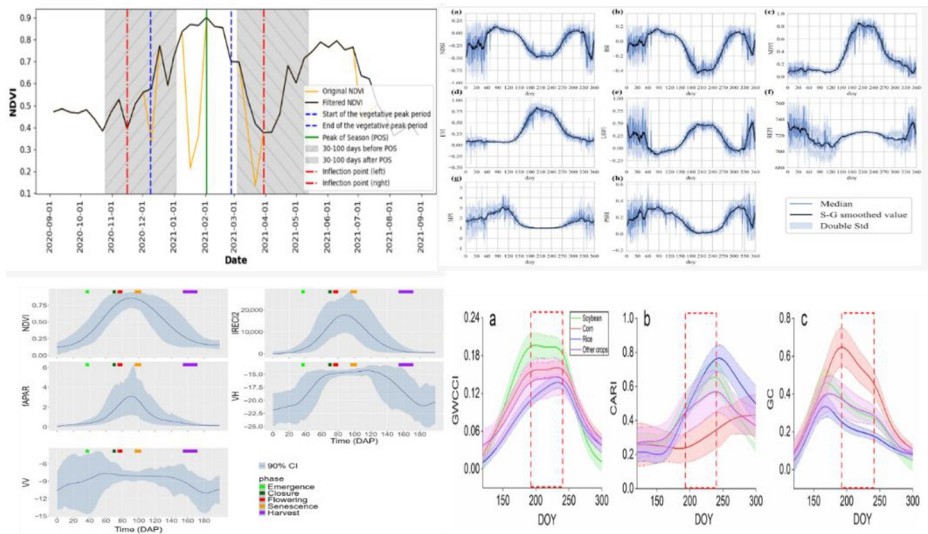


Fig. 3. Conceptual representation of spectral signature transitions during crop phenological stages using remote sensing observations. Adapted from [15],[16],[18] and [20]

Machine learning and deep learning methods have demonstrated encouraging outcomes in terms of model performance, in phenological stage identification and crop classification. LSTM networks are better than the traditional models, including RF and SVM, and only LSTM can obtain a classification accuracy of up to 91% because they can recognize the temporal relationship within satellite data. Equally, phenological architectures built on deep learning have demonstrated accuracy of over 96 %, demonstrating their ability to detect complex growth patterns. These results verify that temporal data is critical in the ability to differentiate between crops which have similar spectral properties but vary in their phenological patterns.

Although these developments have been made, a number of challenges still exist in the remote sensing-based phenological mapping. There is a tendency of cloud cover to interfere with optical satellite data and the low frequency of revisiting the same location, thus, making continuous monitoring difficult. Also, inconsistency in the environment, crop management and geographical locations influences generalizability of models. These limitations suggest the need for more robust, multi-source approaches and improved data integration techniques for reliable phenological stage mapping.

5 Future Work

Further studies in automated mapping of crop phenological stages need to be on the incorporation of multi-source information to enhance model robustness and precision [31]. The use of optical satellite data together with SAR data (e.g., Sentinel-1) can address drawbacks associated with cloud cover and enhance temporal consistency in the crop growth monitoring. Moreover, introduction of additional data like climatic parameters (temperature, rainfall) and soil parameters can contribute to the predictive power of the phenological models and help to estimate the yield more accurately [32]. The other direction that is worth pursuing is the creation of improved deep learning frameworks that can be used to borrow more spatial-temporal patterns in crop growing. Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks can be used as hybrid models to enhance the extraction of spatial features as well as modeling of temporal sequences. Moreover, the concept of transfer learning and data augmentation can be investigated to overcome the problem of scarce labeled data, particularly in third world countries [33].

The research can also focus on future studies on real-time and scalable phenological monitoring systems. Typically, with more temporal resolution of satellite observations and an increased data preprocessing methods, it will become possible to detect smaller-duration phenological phases. Besides, studies should be done to come up with generalized models applicable in various crops and geographical locations with minimal recalibration. Lastly, new vegetation indices and new spectral characteristics that are less prone to saturation effects and environmental variability need to be investigated. With the introduction of high-resolution satellite data and new inventions, automated phenological stage mapping will be even more accurate and useful in order to promote sustainable agriculture and precision farming [34].

6 Conclusion

This systematic review reveals the importance of automated mapping of crop phenology stages of crops with different satellite imagery and spectral signatures. The remote sensing technology in combination with satellite sensors like Sentinel-2 or landsat-8/9 also with time series vegetation indices analysis can be proven to be beneficial tool for identifying crop growth dynamics for larger agricultural area and for large temporal scale. For better agricultural decision making and yield prediction spectral signature based on vegetation indices such as NDVI, EVI, SAVI etc. for every growth stage crop

plays a vital role. This review also shows that preprocessing techniques such as cloud masking, image filtering are important for proper feature selection. Machine learning and deep learning models such as random forest, LSTM have capability to discriminate various crop growth stages for different temporal analysis. Despite of improvement there are some issues like data variation, lack of ground truth data and regional generalization of models are also crucial concerns. To overcome this issue it is necessary to come up with multi source data approach like SAR data and climate variables inclusion in analysis, will create more reliable approach. Future study should be aimed at creating a framework in combination of real time crop monitoring with ground truth data. This approach can helps in better crop mapping, yield prediction and minimizing crop losses with enhancing production and achieving suitable agricultural practices across different regions.

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