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RESEARCH ARTICLE

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A tool for crop phenology metrics analysis from big Earth observation data

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ABSTRACT

Phenological metrics are a set of measurements obtained from Earth observation (EO) satellite image time series that allow the estimation of phenological stages. These include indicators like the start of the greening season, the onset of senescence, and the growing season length. They are useful for crop monitoring. Today, large volumes of images are produced and made available by different EO satellites. These large EO data sets pose a challenge for storage and processing systems, exceeding the capacity of personal computers to handle them. This paper presents a free and open-source tool for phenological metrics analysis from large EO image collections that runs on server-side infrastructure and does not require local data downloads. The Web Crop Phenology Metrics Service (WCPMS) is the core of this tool, designed to estimate phenological metrics as a web service. The tool extracts phenological metrics associated with spatial locations, based on the Brazil Data Cube (BDC) platform. It calculates phenological metrics from data cubes of distinct remote sensing image collections. The potential of the tool is shown through an experiment estimating soybean sowing dates using phenological metrics compared with field data obtained in the Central-South region of Brazil.

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Big data; phenological metrics; Python package; remote sensing; spatio-temporal analysis; satellite image time series; web service

1. Introduction

Phenology is the part of biology that studies the cyclical processes of living beings and analyzes how they are influenced by seasonal and interannual variations in climate or habitat (Lieth, 1974). Remote sensing researchers have been studying how to obtain plant phenology from satellite image data since the early 1980s. They have developed phenological metrics to estimate phenological stages based on Earth observation (EO) image time series, mostly vegetation index (VIs) time

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series (Zeng et al., 2020). These include indicators mainly obtained using curve filtering, fitting, and threshold techniques applied to vegetation indices (Jönsson & Eklundh, 2004; Rodigheri et al., 2023; You et al., 2013). Some examples of phenological metrics are the start of the greening season (SOS), the peak of the growing season (POS), the onset of senescence or end of the season (EOS), and the growing season length (LOS). They are useful for crop monitoring and mapping applications (Bolton & Friedl, 2013; Jonsson & Eklundh, 2002; Rodigheri et al., 2023).

Satellite-based phenology research uses multispectral imagery and Vegetation Indices like the Normalized Difference Vegetation Index (NDVI) to monitor large-scale plant life cycles globally (Studer et al., 2007). It is crucial for the better development of crop models and crop monitoring research. An important step is the validation of satellite-derived phenological metrics, such as the Start of Season (SOS). For modeling, this procedure compares *in-situ* observations of specific plant events, like early leaf emergence, with remote sensing data to ensure the accuracy and reliability of remote sensing of phenology (Gong et al., 2024; Santana et al., 2025).

Several methodologies have been proposed to estimate phenological metrics, leading to the development of different software tools and packages such as CropPhenology (CP) (Araya et al., 2018), Digital Earth Australia (DEA) (Geoscience-Australia, 2024), TIMESAT (TS) (Jonsson & Eklundh, 2002), Greenbrown (GB) (Forkel & Wutzler, 2015), and Phenex (Lange & Doktor, 2017). However, the unprecedented and growing volume of satellite images currently available, often referred as 'big EO data' presents significant computational and data management challenges for many of these traditional software tools and packages.

Today, large volumes of images are produced by EO satellites and are freely available to society. In 2023, Landsat Collection 2 had more than 10.2 million images and 9 petabytes (Crawford et al., 2023). These large EO data sets pose a challenge for storage and processing systems, exceeding the capacity of personal computers to handle them. This requires a paradigm shift by moving away from traditional local processing approaches. To address this challenge, novel software platforms have been developed to store, access, and analyze big EO data in cloud computing environments (Gomes et al., 2020). These platforms provide services that can process data sets on server-side infrastructure, without having to move them across the network (Camara et al., 2016; Gomes et al., 2024; Xu et al., 2022). Some examples of these platforms that allow the extraction of phenological metrics from time series of satellite images are Google Earth Engine (GEE) and Sentinels for Common Agricultural Policy (Sen4CAP). GEE is a cloud computing geospatial analysis platform that incorporates a multi-petabyte catalog of satellite imagery and geospatial datasets (Amani et al., 2020; Gorelick et al., 2017). Researchers use GEE for crop phenology studies (Descals et al., 2021; Dong et al., 2016; Nietupski et al., 2021; Santana et al., 2025). Sen4CAP is a platform that encapsulates an EO data processing system and a visualization tool for CAP monitoring based on Sentinel-1, Sentinel-2, and Landsat 8 time series (De Vroey et al., 2021). GEE is not free and open-source. The open-source aspect is important as it allows the scientific community to extend the functionalities and implement new features. Sen4CAP is no longer funded by ESA, with code repositories outdated and unmaintained. Despite advances in cloud computing, big EO data, and the estimation of phenological metrics using satellite image time series, there is no free and open-source tool available that integrates these areas to extract phenological metrics associated with spatial locations running in a server-side infrastructure.

This paper presents a free and open-source tool for large-scale analysis of phenological metrics extracted from big EO data. The proposed tool was developed as a component of the Brazil Data Cube (BDC) platform. BDC produces Analysis Ready Data (ARD) and multidimensional data cubes from big EO data for the entire Brazilian territory (Ferreira et al., 2022). To date, the BDC project has produced more than 2 petabytes of ARD and EO data cubes for Brazil from images of the satellites Sentinel-2, Landsat Collection 2, CBERS-4/4A, AMAZONIA-1, and others. The proposed tool is based on the Web Crop Phenology Metrics Service (WCPMS) and three other modules (1) multiple clients to access the WCPMS, such as Python clients and a QGIS plugin; (2) a local Python client; and (3) graphical interfaces for the web systems BDCExplorer and TerraCollect.

2. Material and methods

2.1. Crop phenology extraction workflow

This section outlines the four main steps required for crop phenology extraction from satellite images: (1) Preprocessing; (2) Image time series extraction; (3) Image time series processing; and (4) Phenology extraction (Figure 1). The first step is to download satellite images. If these images are not Analysis Ready Data (ARD), users must perform atmospheric and radiometric corrections. Following this, the images must be stacked temporally. The next step is the extraction of the time series, which serves as the primary input for crop phenology extraction algorithms. The algorithms focus mostly on the extraction of phenology from image time series rather than the full workflow, which includes the preprocessing step, shown in

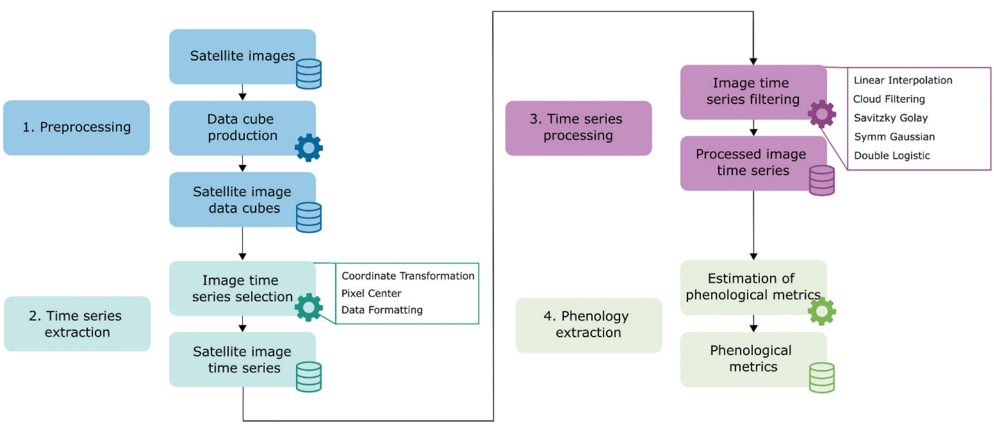

Figure 1. The main stages in the on-premises crop phenology extraction workflow from satellite images: (1) Preprocessing; (2) Time series extraction; (3) Time series processing; and (4) Phenology extraction.

Figure 1. Araya et al. (2018) state that users of the CropPhenology (CP) package are responsible for acquiring and preparing the image time series on their local machines. The process of extracting seasonality information relies on mathematical fitting and filtering procedures. These methods often employ techniques such as function fitting (e.g., Savitzky–Golay, Gaussian, or double logistic models) to model noisy vegetation index data. The presence of clouds and cloud shadows reduces image usability, posing challenges for remote sensing applications (Zhu et al., 2018). When working with image time series, approaches to dealing with clouds and shadows include temporal filters, masking, and temporal image compositions, such as data cubes or data fusion (Chatenoux et al., 2021; Ferreira et al., 2020; Gao et al., 2020; Graesser et al., 2022; Hird & McDermid, 2009; Killough et al., 2021; Liang et al., 2024; Zhou et al., 2016; Zhu et al., 2015). Finally, crop phenology extraction is performed by analyzing the vegetation curve. This multi-step workflow highlights the significant computational and data management burdens placed on users, underscoring the need for more streamlined, server-side solutions.

2.2. Packages for extracting crop phenology

This section details different existing packages for phenological metrics extraction, describing how they work and match with the crop phenology extraction workflow shown in Figure 1. The packages described in this section were selected based on the study by Rodigheri et al. (2023), which evaluated them for crop phenology extraction. Rather than developing novel algorithms, we opted to integrate existing ones into the proposed tool. This strategy allows us to leverage established methodologies, ensuring robustness and accuracy, while focusing our development efforts on the innovative server-side architecture designed for large EO data sets. For the first version of the proposed tool, we decided to use the Phenolopy package. However, the proposed tool is modular and all the algorithms listed in this section can be integrated into it.

2.2.1. CropPhenology (CP)

It is an R package that uses vegetation index time series to obtain crop phenology (Araya et al., 2018). The package extracts 15 phenological metrics that are presented on Table 1. It was designed for interoperability with other R packages, enabling users to customize their phenology extraction workflows, including image pre- and post-processing and analysis.

The CP package offers a comprehensive suite of phenological metrics commonly found in the literature. However, its narrow scope within the phenology extraction workflow (Figure 1) is a limitation. Its functionality is limited to the phenology extraction stage. Users are responsible for acquiring and preparing the image time series on their local machines, as well as for handling any pre- or post-processing functionalities. According to Araya et al. (2018), this design choice emphasizes metric extraction, granting users the flexibility to apply their preferred smoothing techniques before utilizing the package's core functions.

Table 1. Phenological metrics extracted by CropPhenology.

Acronym	Metrics
OnsetV	Onset NDVI[a] value
OnsetT	Onset time
MaxV	Maximum NDVI value
MaxT	Time of maximum NDVI
OffsetV	Offset NDVI value
OffsetT	Offset time
LengthGS	Length of growing season
BeforeMaxT	Length of growing season before MaxT
AfterMaxT	Length of growing season after MaxT
GreenUpSlope	Growth rate between Onset and MaxT
BrownDownSlope	Growth rate between MaxT and Offset
TINDVI	NDVI area
TINDVIBeforeMax	NDVI area between Onset and MaxT
TINDVIAfterMax	NDVI area between MaxT and Offset
Asymmetry	Measure of asymmetry

[a]Normalized Difference Vegetation Index.

2.2.2. Digital Earth Australia (DEA) tool

The DEA is a Python package that brings together satellite imagery, cloud computing, open-source systems, and open data based on the Digital Earth Australia project (Geoscience-Australia, 2024). Due to its petascale EO data catalog, the Open Data Cube of the DEA tool has simplified access to satellite data. The package, through its xr_phenology function, extracts 11 phenological metrics (Table 2). The package was developed to work with xarray, a multi-dimensional array package. This structure is widely used to create virtual satellite image data cubes.

The DEA tool, benefiting from its built-in integration with Open Data Cube, covers all the main stages of crop phenology extraction (Figure 1).

2.2.3. TIMESAT (TS)

TS is a software package developed in Fortran and Matlab for estimating phenological metrics from EO time series (Jonsson & Eklundh, 2002). A key strength of TS is its comprehensive coverage of both time-series processing and phenology extraction stages. Its functionalities are also available in other programming languages, including R [via rTIMESAT (Kong, 2021)] and Python [via Phenolopy (Trotter & Robinson, 2021)].

Table 2. Phenological metrics extracted by the DEA tool.

Acronym	Metrics
SOS	DOY[a] of start of season
POS	DOY of peak of season
EOS	DOY of end of season
vSOS	Value at start of season
vPOS	Value at peak of season
vEOS	Value at end of season
Trough	Minimum value of season
LOS	Length of season (DOY)
AOS	Amplitude of season (in value units)
ROG	Rate of greening
ROS	Rate of senescence

[a]Day Of the Year

Table 3. Phenolopy phenological metrics.

Acronym	Metrics
vPOS	Peak of season value
tPOS	Peak of season time
vMOS	Middle of season value
tMOS	Middle of season time
vVOS	Valley of season value
tVOS	Valley of season time
BSE	Base
vSOS	Start of season value
tSOS	Start of season time
EOS	End of season
LOS	Length of season
ROI	Rate of increase
ROD	Rate of decrease
AOS	Amplitude of season
SIOS	Short integral of season
LIOS	Long integral of season
SIOT	Short integral of total
LIOT	Long integral of total
NOS	Number of seasons

2.2.4. Phenolopy

Phenolopy is a Python package for analyzing EO time series to investigate dynamic vegetation properties (Trotter & Robinson, 2021), based on TS (Jonsson & Eklundh, 2002). A key advantage of Phenolopy is its versatility, allowing application to any satellite imagery stack. Developed with xarray integration, the package extracts 19 distinct phenological metrics (Table 3).

The phenolopy package has demonstrated usability and performance in phenological metrics extraction. It extends the capabilities of tools like TS by supporting three key workflow stages: time-series extraction, time-series processing, and phenology extraction. Its versatility stems from its applicability to any satellite imagery stack, enabling direct extraction of phenological metrics from virtual data cubes. Consistent with EO data handling practices, phenolopy's xarray integration makes it suitable for direct interaction with satellite image data cubes.

2.2.5. Greenbrown (GB)

GB is an R package that provides functions for analyzing trends, detecting changes, and identifying phenological events in gridded time series from satellite images or climate model simulations (Forkel & Wutzler, 2015). Like the DEA tools, GB's utility extends beyond phenological metrics extraction; it is a versatile library encompassing 74 functions for land surface phenology and trend analysis. Specifically, its Phenology function calculates 12 annual metrics of vegetation phenology (Table 4).

The GB package has functions for phenological detection in climate model simulations. The package covers two of the four stages: the time series processing and phenology extraction (Figure 1).

2.2.6. Phenex

Phenex is an R package for phenological analysis and spatial analysis of phenological data sets (Lange & Doktor, 2017). The package includes functions for data correction, data modeling, correlation analysis, moving averages and other tasks. The package, through its

Table 4. Phenological metrics extracted by GB.

Acronym	Metrics
sos	Start of season
eos	End of season
los	Length of season
pop	Position of peak value
pot	Position of trough value
mgs	Mean growing season value
peak	Peak value
trough	Trough value
msp	Mean spring value
mau	Mean autumn value
rsp	Rate of spring greenup
rau	Rate of autumn senescence rates

phenoPhase function, extracts six phenological metrics based on NDVI time series (Table 5). The Phenex package covers both stages: the time series processing and phenology extraction.

Table 5. Phenological metrics extracted by Phenex.

Acronym	Metrics
max	DOY with highest NDVI value
maxval	The highest modelled NDVI value
min	DOY with lowest NDVI value
minval	The lowest modelled NDVI value
greenup	DOY of the greenup takes place
senescence	DOY of the senescence takes place

2.3. Agriculture monitoring as a service

The need of big EO data management and processing promotes the transition of agricultural monitoring from on-premises applications to services based on cloud computing. A key solution for this transition is the Software as a Service (SaaS) model—a paradigm where applications are hosted by providers and accessed by users online (Knorr, 2006; Sun et al., 2007). Challenges such as processing big data come from several fronts, where the volume of data exceeds the capacity of personal machines to store and process it (Gomes et al., 2020). Some initiatives that enable the extraction of phenological metrics from large volumes of data are FORCE (Framework for Operational Radiometric Correction for Environmental monitoring), an all-in-one processing engine for medium-resolution Earth Observation image archives (Frantz, 2019); SPIRITS (Software for the Processing of Image Remote sensing Ingestion and Time-Series analysis), a specialized tool for measuring key information of vegetation from remote sensing images (Rembold et al., 2015); and the EO4PM (Earth Observation for Phenological Metrics) a process chain that combines all stages of phenology extraction to generate phenological metrics for analysis from Sentinel-2 MSI time series (Filipponi et al., 2022).

There are also initiatives using large volumes of EO data for crop applications, such as Sen4CAP, a platform that encapsulates an EO data processing system and a visualization tool for CAP monitoring (De Vroey et al., 2021). The Sen4CAP EO system processing chain generates products for agriculture monitoring from Sentinel-2, Sentinel-1, and Landsat 8 time series.

Sen4CAP is part of the Copernicus Data Space Ecosystem, a set of independent processing modules orchestrated by a data-driven approach (De Vroey et al., 2021). It was designed to enable collaboration between the public sector and the private sector, which aligns with our use case.

Sen4CAP, within the Copernicus Data Space Ecosystem, is a solution for the European Common Agricultural Policy. The tool proposed in this paper is a solution for Brazilian agricultural monitoring, based on the Brazil Data Cube cloud computing platform. The proposed tool connects phenological metric analysis to a large catalog of satellite images. Leveraging a cloud computing approach, we take advantage of large EO data sets, such as remote sensing data cubes, and estimate phenological metrics using established algorithms, which can be shared or updated. The tool also benefits from being open-source, allowing the scientific community can refine and update it.

3. A tool for crop phenology metrics analysis

3.1. Requirements

The tool proposed in this paper was designed based on a group of functional requirements (FR), collected through a series of meetings in the context of a joint project to monitor rural credit operations with the Central Bank of Brazil (BCB) and the Brazilian Federal Court of Accounts (TCU) (de Queiroz et al., 2025).

- FR1: Users should be able to calculate phenological metrics without needing to generate ARD images and data cubes or extract image time series on their personal computer.
- FR2: Users should be able to calculate phenological metrics by providing the following parameters: image collection, band, latitude, longitude, start date, and end date.
- FR3: The phenological metrics tool should make its functionalities available as a web service, suitable for big EO data handling.
- FR4: The crop phenology web service should use an existing and extensible algorithm for phenology extraction, supporting future modifications or additions.
- FR5: Users should be able to access the functions for calculating phenological metrics via Python clients.
- FR6: Users should be able to calculate phenological metrics and analyze them through graphical interfaces integrated with BDC web applications BDCExplorer and TerraCollect.
- FR7: The tool should have access to all BDC image collections and data cubes.

3.2. Software as a service

To follow the cloud computing paradigm and the SaaS model, we designed part of the proposed tool with components running on both the server side and part to run on the client side. As the SaaS model typically involves distributed data and logic, interoperability with external data services is crucial. Consequently, the proposed tool is integrated with the BDC Web Time Series Service (WTSS) (Ferreira et al., 2020). This integration provides seamless access to the BDC project's comprehensive image collection catalog, enabling the retrieval of satellite image time series via standard Web (GET) requests. For the initial version of the proposed tool, we utilized the Phenology library. This choice was made based on the study by Rodigheri et al. (2023), which identified TIMESAT as one of the packages that showed promising results for crop phenology extraction. We selected Phenolopy because it is built upon the concepts and methodology behind the TIMESAT software. However, it is important to highlight that the proposed tool is modular, allowing other algorithms to be integrated as needed.

3.3. Architecture

The architecture of the proposed tool for phenological metrics analysis from big EO data comprises four modules (Figure 2). The server-side component of our tool is the Web Crop Phenology Metrics Service (WCPMS). WCPMS enables analysts to compute phenological metrics directly from satellite image data cubes, eliminating the need to download large

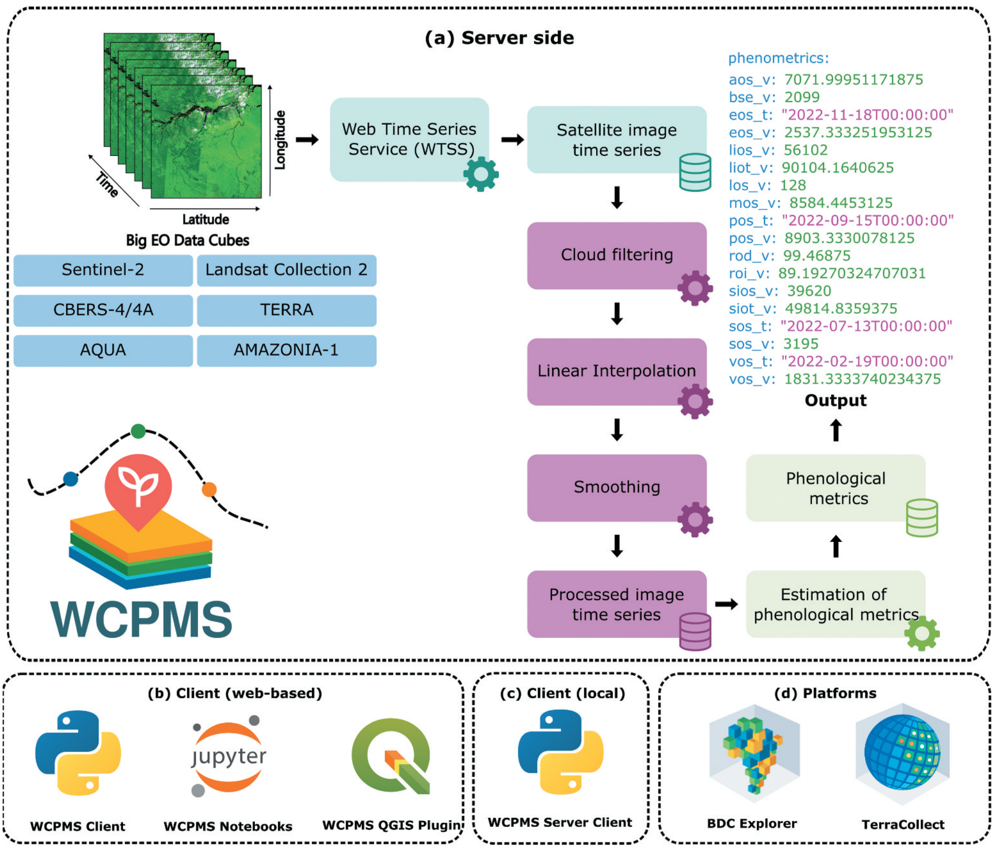

Figure 2. Architecture of the crop phenology analysis tool. Module (a), the server-side component, includes layers for time series extraction from EO data cubes, cloud filtering, linear interpolation, smoothing, and phenological metrics calculation. Module (b) is composed of web-based clients, and module (c) consists of a local client. Module (d) comprises graphical components for the BDC web systems.

EO data sets to their own computers. Our primary objective was to establish an entirely server-side workflow, consolidating metric extraction libraries and time series access within the cloud environment. To achieve this, we leveraged the Phenolopy library as a service and WTSS to extract image time series from data cubes. The proposed tool uses the EO data cubes produced in the Brazil Data Cube platform (Ferreira et al., 2020) and its services to extract image time series from these data cubes. The tool handles data structuring, filtering, and phenological metrics computation, with all processes running server-side on the Brazil Data Cube cloud infrastructure.

The second module encompasses web-based clients, providing diverse interfaces for accessing WCPMS. This group includes the WCPMS Python client, the WCPMS notebook gallery, and the WCPMS QGIS plugin. These clients collectively enable analysts to leverage the tool for metric analysis directly from satellite image data cubes, offering access through a Python library, ready-to-use notebooks, or a QGIS plugin interface. The third module comprises the WCPMS Server Python client, a client designed to calculate phenological metrics directly on data arrays of satellite time series. It processes all pixels within the array using parallel computing. This module provides analysts with the flexibility to apply the full WCPMS methodology and processing capabilities to their own satellite time series. The fourth module comprises graphical components designed for integration with the BDC's web systems, namely BDCExplorer and TerraCollect. BDCExplorer is a web application for visualizing image collections, data cubes, classifications, and mosaics produced by the BDC project. TerraCollect is a web platform for collecting land use and land cover samples.

3.3.1. Web Crop Phenology Metrics Service (WCPMS)

The WCPMS is a web service, a type of software designed to facilitate the communication between different applications over the internet. Through WCPMS, analysts can provide a spatial location and obtain the corresponding phenological metrics using image time series. The WCPMS receives as input: collection, band, start_date, end_date, freq, latitude and longitude. The collection parameter designates the target satellite image data cube for time series extraction, while the band parameter specifies the particular spectral band to be extracted. The remaining parameters define the temporal period of the time series (start_date and end_date), the desired data cube frequency (freq), and the spatial location for time series extraction (latitude and longitude). For additional information related to the WCPMS, the official documentation is available for reference (https://wcpms.readthedocs.io/en/latest/). WCPMS also includes optional parameters for filtering and phenological metric estimation; if these are not specified, default values are used. WCPMS has specific data connectivity requirements to function correctly. One primary dependency is the WTSS, which accesses satellite images in Cloud Optimized GeoTIFF (COG) format and retrieves image time series for WCPMS. The system then performs time series processing and phenological metrics extraction. A key advantage of WCPMS is its approach to handling clouds and cloud shadows, which includes smoothing filters, cloud masking, and the use of data cubes. The phenometrics process receives parameters using query string, fetches the time series, and extracts phenology data from it (Listing 1).

Listing 1. WCPMS query and response.

```
#request
https://data.inpe.br/bdc/wcpms/phenometrics?collection=S2-16D-2&latitude
    =-11.739646939&longitude=-45.75273513&start_date=2021-01-01&end_date
    =2021-12-31&freq=16D&band=NDVI

#response
  {
    "phenometrics": {
      "aos_v": 8046.0,
      "los_v": 96.0,
      "eos_t": "2021-10-17T00:00:00",
      "eos_v": 1396.0,
       [...]
      "pos_t": "2021-09-15T00:00:00",
      "pos_v": 9222.0,
      "sos_t": "2021-07-13T00:00:00",
      "sos_v": 1176.0,
      "vos_t": "2021-07-13T00:00:00",
      "vos_v": 1176.0
    },
    "timeseries": {
      "timeline": [
        "2021-01-01",
        "2021-01-17",
        "2021-02-02",
        [...]
        "2021-11-17",
        "2021-12-03",
        "2021-12-19"
      ],
      "values": [
        8029,
        9210,
        8251,
        [...]
        2404,
        2580,
        5927
      ]
    }
}
```

3.3.2. WCPMS Python client

The Python client, implemented as the wcpms.py library, serves as a key module for facilitating crop phenology extraction operations within our tool. This library was developed from scratch to be interoperable with other Python libraries, enabling users to integrate established libraries into their own workflows for pre- or post-processing and analysis. Its user-friendly design further encourages the scientific community to extend its functionalities and implement new features. The Python client works by allowing the researcher to define the data cube they want to use via the cube_query method and then extract phenological metrics for a point (latitude and longitude), using the get_phenometrics method.

3.3.3. WCPMS Python server client

The tool also includes a standalone Python client, named wcpms_server. This library was developed to enable the calculation of phenological metrics, directly on data arrays of satellite time series. It encapsulates the entire processing chain developed for the WCPMS layer system, including satellite image time series extraction from EO data cubes, cloud filtering, linear interpolation, smoothing, and phenological metrics calculation. This provides analysts the flexibility to apply the WCPMS methodology and processing capabilities to their own image time series. The wcpms_server main method is calc_phenometrics_cube; it takes a DataArray from a vegetation index or any stacked satellite image and computes the phenological metrics for all image time series using parallel computing. The library supports xarray objects, so it is compatible with any satellite imagery formatted as an xarray.

3.3.4. WCPMS BDCExplorer component

Another component of the tool within the platform group is the graphical interface for the WCPMS. The BDC web applications, such as BDCExplorer and TerraCollect, integrate this component. The interface of BDCExplorer with the WCPMS graphical component is shown in Figure 3. This component enables analysts to select a specific location on the map via the interface's bottom-left corner. Upon activation, BDCExplorer's central graphics tab opens, allowing users to visualize both the phenological metrics and the corresponding image time series for the selected point.

To ensure consistency between the BDCExplorer and TerraCollect platforms, we adopted a unified development strategy using the Angular web framework. The WCPMS visualization tool was implemented as a reusable, modular component, allowing it to be integrated into different applications with minimal configuration. This module has been released as an open-source library, ng-wcpms, designed to facilitate adoption by other developers.

Figure 3. Interface of BDCExplorer, the BDC web platform for the visualization and retrieval of satellite image collections, with the WCPMS component. At the bottom, the graph displays the phenological metrics (SOS, POS, EOS, VOS, planting period) over the NDVI and the smoothed NDVI time series for the point selected on the map.

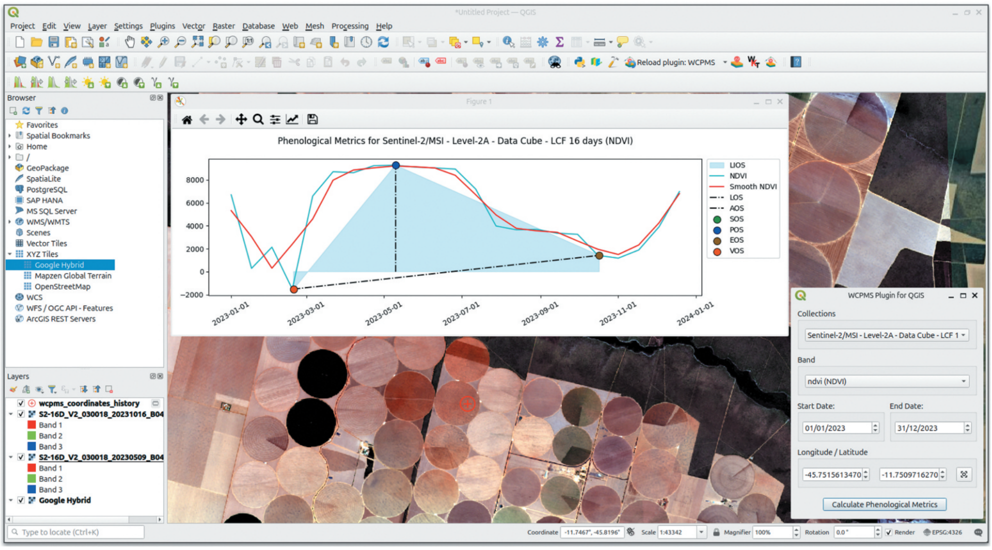

Figure 4. WCPMS QGIS plugin. The WCPMS graph display phenological metrics (SOS, POS, EOS, VOS, planting period), NDVI and smoothed NDVI time series data.

3.3.5. WCPMS QGIS plugin

Similar to the graphical interface, another component of the tool is the WCPMS QGIS plugin. Implemented as a QGIS plugin, it aims to extract phenological metrics using WCPMS within the established QGIS system. The WCPMS QGIS plugin works just like the Python client; it requires the selection of a collection, band or vegetation index, start date, and end date. After that, the analyst can use the point button to mark a location on the map.

Figure 4 shows the plugin's configuration window and the results. It has a control window where a user defines the collection, band, period (start and end date), and point (entered manually or by drawing on the map). The graph window displays the result. For the 1.0 version of the plugin, we decided to implement only the get_phenometrics method, so it is only possible to calculate phenological metrics for a given point.

4. Results

To demonstrate the usability and evaluate the results of the WCPMS tool, two experiments were established. The first experiment presents the application of WCPMS to an entire region, calculating phenological metrics for the total area. The second experiment evaluated the tool's ability to estimate soybean sowing dates using crop phenological metrics and compared the results with field data.

4.1. First experiment: region crop phenology calculation

An experiment was designed to evaluate the capacity of the proposed tool to compute phenological metrics for a specific area using Sentinel-2 images over a year. In this evaluation, we used the Sentinel-2 MSI Level-2A data cube and the Normalized

Difference Vegetation Index (NDVI), although WCPMS accepts any image time series for phenology extraction. This experiment seeks to demonstrate that our tool can perform the extraction of phenological metrics from hundreds of satellite image time series at once for a region, using parallel computing, resulting in a map of phenological metrics.

4.1.1. Study area

The Region crop phenology calculation study area encompasses one Brazilian state: Bahia (BA), specifically the city of Luís Eduardo Magalhaes–Bahia. We used the BDC tiling system, specifically the BDC_SM_V2, grid as the limit for the region calculation. The BDC Small grid is composed of 10,560 x 10,560 cells. It uses the Albers Equal-Area Conic as reference map projection and SIRGAS-2000, the official planimetric datum of Brazil, as the reference geodetic system. We chose a tile that encompasses the region of Luís Eduardo Magalhaes–Bahia, a region with a high incidence of crop areas, allowing better visualization of the phenological metrics spatially.

4.1.2. Experiment methodology

For the region crop phenology calculation, we chose to use the Sentinel-2 MSI Level-2A data cube and the wcpms_server library, which includes the calc_phenometrics_cube, a function designed for region phenology calculation. This function takes an xarray DataArray representing a vegetation index and computes phenological metrics for all embedded image time series.

This capability allows analysts to calculate phenological metrics directly from an xarray DataArray. The function efficiently processes all pixels within the array using parallel computing. We performed the extraction of metrics from a BDC Sentinel-2 data cube for the year 2021, which includes a total of 23 images from 2021-01-01 to 2021-12-31. This data cube is a 16-day best-pixel composition, meaning that every 16 days, all images available for that interval are stacked into a composition based on the least cloud cover (Ferreira et al., 2020). We used the wcpms-phenometrics-region notebook to extract the time series from all pixels in the Sentinel-2 scene, covering 1 year (temporal coverage 16 days) of NDVI data. Figure 5 shows one time step of an input stack NDVI region and on the right the result of the calc_phenometrics_cube function. The resulting DataArray of phenological metrics resembles a 19-layer cube. However, unlike a traditional image data cube where layers represent temporal steps, each layer in this output corresponds to one of the 19 distinct phenological metrics, Table 3.

The experiments were conducted on a custom-built workstation. The system's processing unit was a 10-core Intel Core i5-12600K (3.7 GHz) with 32 GB of DDR5 RAM. For the experiment, a scene from the BDC Small grid ($10{,}560 \times 10{,}560$) was used, i.e., approximately 111,513,600 NDVI time series. A single NDVI image from the BDC is approximately 235 MB; the complete one-year (23 images) used for this analysis totaled 5.4 GB. Using the Cloud Optimized GeoTIFF (COG) format reduced quadrant processing time to 49 minutes, including 46 minutes for data acquisition and 3 minutes for phenological metric computation. Full-scene processing required196 minutes. Although the sowing dates of soybeans across the entire region did not appear promising, mainly because of the noise in the image time series, the computational results were highly satisfactory. Due to parallel processing, the generation of phenological metrics across the extensive region was achieved with high computational efficiency.

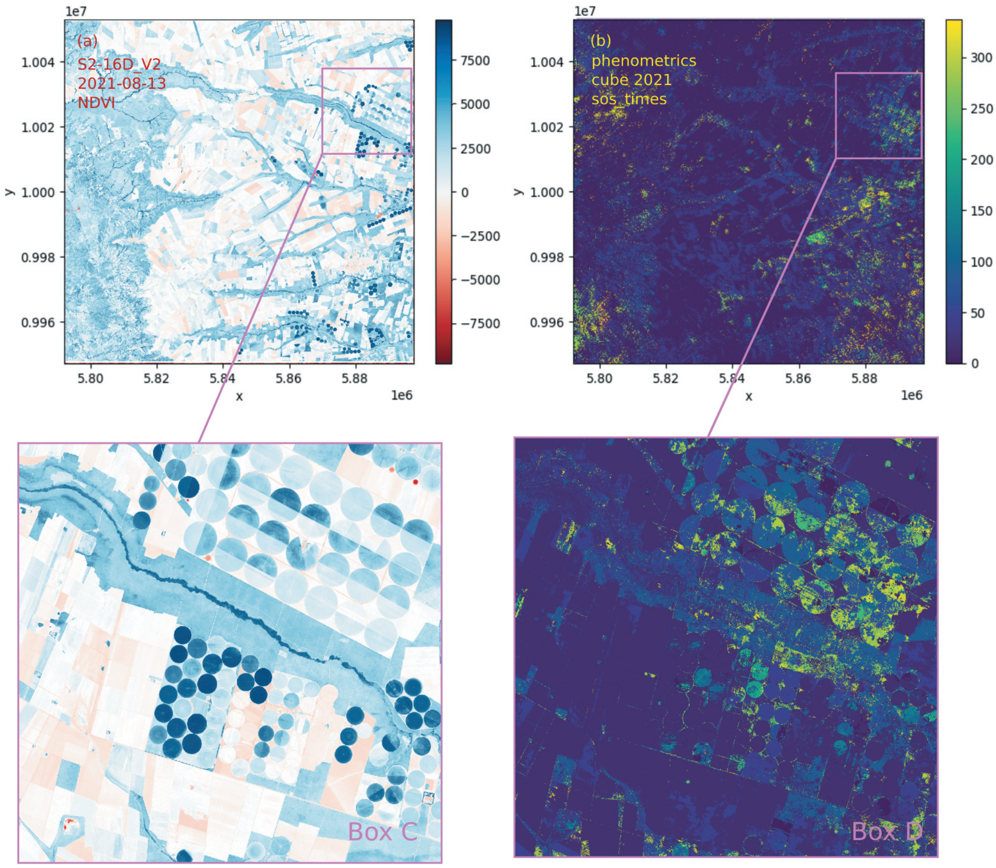

Figure 5. Result of the region crop phenology calculation function from S2-16D_V2 on 2021 near Luís Eduardo Magalhaes–Bahia, Brazil for (a) NDVI image for 2021-08-13 and (b) the phenometrics cube, plotting the metric sos_times in a Julian day in different colors (see scale in panel b). Note that the selected box C and Box D in both panels, a and b is enlarged to show more detailed features for agriculture.

4.2. Second experiment: estimation of soybean sowing dates

We designed an experiment incorporating field observation datum to estimate soybean sowing dates and evaluate their accuracy using phenological metrics. To do so, we used image time series from the Sentinel-2 Level-2A image collection, the Enhanced Vegetation Index 2 (EVI2) (Jiang et al., 2008), and the SOS metric, which was derived from direct phenology observations in the field. The EVI2 was selected to ensure methodological comparability with Rodigheri et al. (2023), which utilized the same index and field data for phenology estimation.

4.2.1. Study area

The study area for the experiment encompasses regions in four different Brazilian states: Paraná (PR), São Paulo (SP), Goiás (GO), and Minas Gerais (MG). Data for a total of 40 soybean fields for the 2019–2020 growing season were provided by Rodigheri et al. (2023)

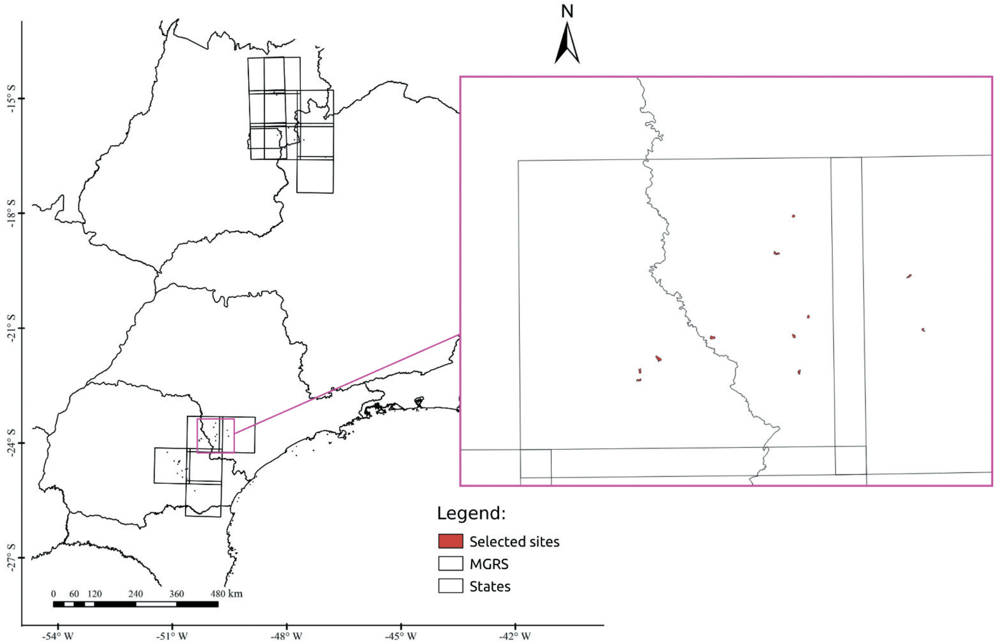

Figure 6. Phenology observation fields in South-Central of Brazil and Military Grid Reference System tiles.

and the ABC Foundation. This data set includes observed sowing and harvest dates. Figure 6 provides an overview of the study area, highlighting the selected field data sites. It also displays the Military Grid Reference System (MGRS) grid, which corresponds to the grid used for the Sentinel-2 image collection data. This layer visually represents the satellite imagery coverage utilized in the evaluation.

4.2.2. Experiment methodology

To estimate soybean sowing dates, we chose to use the Sentinel-2 Level-2A image collection instead of the Sentinel-2 16-day best-pixel composition data cube. Using image collection, we increased the temporal resolution from one image every 16-day to at least one image every 5 days, excluding overlaps. The experiment proceeded as follows: For each of the 40 field datasets, we randomly generated 50 points within the field boundaries. For each point, we obtained the Red and Near-Infrared (NIR) time series values. Then, we calculated the EVI2 (Jiang et al., 2008), as defined by Equation 1, and applied the Savitzky-Golay filter to smooth the time series. From the smoothed EVI2 data, we calculated 19 phenological metrics using WCPMS per point and computed the median SOS metric across the 50 points for each field.

$$EVI2 = 2.5 \times \frac{(NIR - RED)}{(NIR + 2.4RED + 1)} \tag{1}$$

From the resulting list of metrics, we computed the median SOS value. We carried out this process for all 40 fields. We recorded all 50 sos_t metrics for each site, the calculated median, and the field observed data obs_sos.

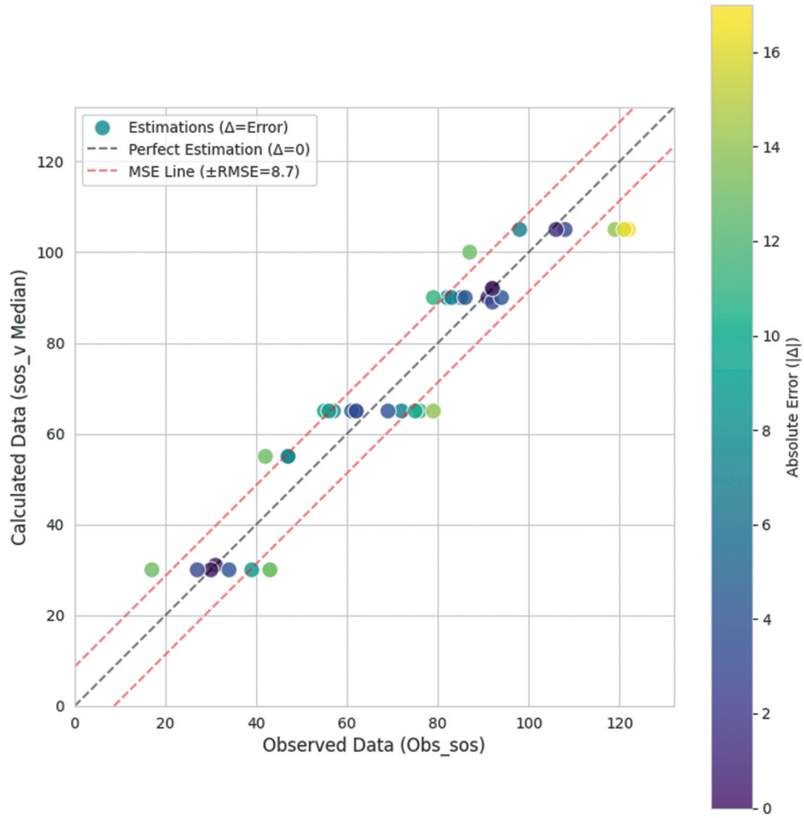

Figure 7. Accuracy evaluation of the SOS metric; the delta is the absolute error, in red the MSE, on the *y*-axis the median of that SOS calculated by the tool and on the *x*-axis the observed data.

An accuracy assessment was conducted using a linear regression (Figure 7) to evaluate the agreement between the crop phenology metric estimates generated by the proposed method and the corresponding field observations. The plot displays the SOS dates for each field as individual data points, with color representing the absolute error relative to the field-reported values.

The experiment we conducted successfully estimated soybean sowing dates in different locations in Brazil. Using field samples, we also assessed the accuracy of the estimates. Despite the small number of field samples, our tool achieved good results. These results underscore that our approach, phenological metrics extraction as a service, can effectively address real crop monitoring problems.

5. Discussion

Region crop phenology metrics calculation is aligned with current research in land use and land cover mapping. These metrics enable the integration of phenological information into mapping workflows, facilitating the identification of single-cropping areas as well as regions with sequential cropping systems—such as soybean/maize rotations, which are common in

Brazil. Furthermore, they support the detection of areas with semi-perennial crops, such as sugarcane (Bendini et al., 2019). The accuracy of such classifications can be further improved by integrating satellite image time series with phenological metrics, benefiting the mapping of both crops (Bendini et al., 2019; Zhang et al., 2017) and natural vegetation (Haddad et al., 2022).

The proposed tool successfully achieved the objective of establishing an entirely server-side workflow for phenological metric extraction, running in a cloud environment without needing local data downloads. By doing so, we reduce data processing time for large-scale EO data access. The existing software tools and packages described in Section 2, CropPhenology (CP) (Araya et al., 2018), Digital Earth Australia (DEA) (Geoscience-Australia, 2024), TIMESAT (TS) (Jonsson & Eklundh, 2002), Greenbrown (GB) (Forkel & Wutzler, 2015) and Phenex (Lange & Doktor, 2017), are offline and rely on the analyst to find a way to retrieve satellite image time series. In contrast, our tool fetches the vegetation index time series on the server-side, representing a significant reduction in phenological metric extraction time. This gain is attributed to our novel large-scale analysis processing architecture, making the analysis of phenological metrics derived from big EO data sets more accessible.

For the soybean-sowing date estimation experiment, the absolute error was calculated as the difference between the estimated Start of Season (SOS) and the observed dates. The resulting Mean Absolute Error (MAE) was 7.23 days, with a median of 7.5 days and a standard deviation of 4.79 days. These results are consistent with findings reported in studies based on Sentinel-2 and MODIS data (de Santana et al., 2024; Rodigheri et al., 2023; Sakamoto et al., 2005, 2010).

6. Conclusion

This paper presented a free and open-source tool for large-scale analysis of phenological metrics derived from big EO data sets that runs on server-side. This allows users to extract these metrics without needing to download big EO data or install software on personal computers. The modules of the proposed tool for phenological metrics analysis are the WCPMS service; multiple clients to access this service, such as Python clients, a gallery of notebooks, and a QGIS plugin; and components for the web systems BDCExplorer and TerraCollect. The tool runs in the Brazil Data Cube platform and delivers phenological metrics analysis using a rich set of data cubes from distinct remote sensing satellite constellations, including Sentinel-2, Landsat Collection 2, CBERS, and AMAZONIA-1, for the entire Brazilian territory.

We demonstrated that our tool was able to perform its core function, phenological metric extraction, through multiple interfaces. Currently, the tool does not support multiple cropping, which refers to the practice of growing two or more crops in sequence in the same field during the same crop year. Studies using different algorithms could help improve the tool's current limitations. Despite this, the tool has already demonstrated its practical value in agricultural policy monitoring, according to recent applications in partnership with the Central Bank of Brazil (BCB) and the Brazilian Federal Court of Accounts (TCU) (de Queiroz et al., 2025).

This tool is a first step towards a system that integrates big EO data processing and agricultural monitoring as well as visualization and analysis components for Common Agriculture Policy (CAP) monitoring for Brazil, based on the BDC platform. Brazilian agriculture holds significant national and international importance, with annual agricultural credit exceeding 500 billion BRL. This system would address the current lack of scalable, cost-effective tools to monitor agriculture, which is essential to support public and private agents in policy control, credit allocation, and large-scale agriculture monitoring efforts.

The source code is publicly available under the following repositories/hosts:
https://github.com/brazil-data-cube/wcpms.py
https://github.com/GSansigolo/wcpms
https://github.com/GSansigolo/tool-for-crop-phenology-paper
https://github.com/brazil-data-cube/wcpms-qgis
https://github.com/brazil-data-cube/ng-wcpms
https://pypi.org/project/wcpms/

Disclosure statement

No potential conflict of interest was reported by the authors.

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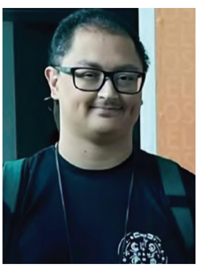

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AI Disclosure statement

The author confirms that no AI or AI-assisted technologies were used in the creation of this work.

Data availability statement

The data that support the findings of this study are openly available on Zenodo at https://doi.org/10.5281/zenodo.17260854, and GitHub at https://github.com/GSansigolo/tool-for-crop-phenology-paper.

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