Reply to Reviewer #1' comments

The authors addressed the concerns of the reviewer. The reviewer suggested the acceptance after discussing the following perspectives:

Response: We sincerely thank the reviewer for the continued time and effort devoted to reviewing the manuscript. We also appreciate the recommendation for acceptance and the valuable suggestions provided below.

1. The resolution is a little bit coarse. What are the typical application scenarios?

Response: Thank you for this helpful suggestion. While the dataset is generated at a 500 m spatial resolution, it is well suited for applications that focus on regional and long-term agricultural dynamics. Typical applications include refining remote-sensing phenology products, evaluating the agro-environmental impacts of crop management decisions, improving yield and carbon-cycle modeling, and monitoring management practices such as tillage, cover cropping, and irrigation through the delineation of growing and off-season periods. These application scenarios are discussed in the manuscript (Lines 507–530 and 560–564).

2. What is the potential of hyperspectral and multispectral foundation models in this area?

Response: Thank you for this insightful question. We agree that multispectral and hyperspectral foundation models represent a promising direction for future crop phenology monitoring. We have added a discussion (Lines 540-543) in the manuscript highlighting their potential to learn transferable spatiotemporal representations of crop development from large-scale Earth observation datasets, which may further improve the characterization of crop phenology and the retrieval of planting and harvesting dates (Yang et al., 2024; Li et al., 2026).

Reference:

Yang, Z., Diao, C., Zhao, Y., Liu, Y., Gao, F., 2024. Near real-time crop phenology characterization at field scale through weakly supervised deep learning, in: AGU Fall Meeting Abstracts, AGU Fall Meeting Abstracts. pp. B52C-05.

Li, W., Liang, S., Chen, K., Chen, Y., Ma, H., Xu, J., Ma, Y., Zhang, Y., Guan, S., Fang, H., Shi, Z., 2026. AgriFM: A multi-source temporal remote sensing foundation model for Agriculture mapping. Remote Sensing of Environment 334, 115234. https://doi.org/10.1016/j.rse

Reply to Reviewer #3' comments

I noticed the manuscript has undergone a round of review, and the authors have addressed several concerns. Overall, it has significant improvements and is suitable for the journal's topic. Only a few comments from my side are supplied as follows:

Response: We sincerely thank the reviewer for the positive assessment of our revisions and for recognizing the improvements made to the manuscript. We appreciate the additional comments and have addressed them below.

1. When NDVI approaches zero or becomes negative during senescence or residue phases, HPI can become unstable and affect NHPI min/max and thresholding. Please clarify whether NDVI lower bounds, ratio clipping, or outlier removal are applied and how this influences harvest-date detection.

Response: Thank you for this valuable comment. NDVI values approaching zero or becoming negative can affect the stability of HPI and, consequently, NHPI-based harvest date detection. Therefore, in practice, these potentially problematic observations are removed during the preprocessing stage prior to HPI calculation.

Specifically, outlier removal is performed sequentially using a quality assurance (QA) filter, a spline filter, a median absolute deviation (MAD) filter, and a snow filter before planting and harvesting date retrieval. The QA filter removes observations flagged as poor quality in the satellite product, including those affected by cloud contamination and cloud shadows. As an additional quality-control step, observations with NDVI values below zero are excluded because agricultural fields are generally expected to exhibit non-negative NDVI values throughout the year under crop canopy, bare-soil, and crop-residue conditions. Negative NDVI values are therefore more likely to reflect contamination from water, snow cover, cloud shadows, or other anomalous surface conditions. After the initial quality screening, a spline filter is applied to smooth the NDVI curve and remove observations with residuals exceeding the mean plus/minus three standard deviations. The MAD filter further removes sharp spikes using the median absolute deviation criterion. Finally, the snow filter excludes observations with NDSI values above −0.2 to remove snow-contaminated observations that may not be fully identified by the preceding filtering steps.

To clarify this procedure, we have expanded the description of the preprocessing workflow in Section 2.2.1 (Lines 189-201). The revised text now explicitly describes the NDVI lower-bound filtering and snow-filtering steps applied before harvest date detection, thereby clarifying how anomalous observations are removed prior to HPI and NHPI calculation.

2. Line 263: The calculation of MAE and R2 should be based on the planting and harvesting dates rather than just the harvesting date alone.

Response: Thank you for pointing this out. We have revised the corresponding sentence to clarify that both planting and harvesting dates are used in the calculation of MAE and R^2. The revised text now reads:

“We quantify accuracy using Mean Absolute Error (MAE) and the coefficient of determination (R^2) (Eqs. 4 and 5), based on comparisons between estimated and observed planting or harvesting dates for corn and soybean.” (Lines 285-286)

3. Given typical NDSI ranges, a threshold of -0.2 seems unusually stringent and may exclude many non-snow observations. Please verify this point and explain the selected threshold.

Response: Thank you for this comment. In our workflow, the NDSI filter is used as a quality-control step to minimize the influence of residual snow contamination on the NDVI time series used for NHPI calculation. Since harvest date detection relies on identifying abrupt phenological transitions associated with crop senescence and residue exposure, even a small number of snow-contaminated observations can distort HPI values during the harvest period, propagate errors into the NHPI, and ultimately bias harvest date estimates derived using threshold-based methods. Therefore, we adopted a conservative NDSI threshold (−0.2) to maximize the removal of potentially snow-contaminated observations prior to phenological analysis. This threshold follows the implementation in Liu et al. (2025) and was retained to ensure consistency with the original NHPI framework. We have added a clarification of this rationale in Section 2.2.1 of the revised manuscript (Lines 200–201).

Reference:

Liu, Y., Diao, C., Yang, Z., Mei, W., Guo, T., 2025. A novel normalized harvest phenology index (NHPI) for corn and soybean harvesting date detection using landsat and sentinel-2 imagery on google earth engine. Remote Sensing of Environment 331, 115016. https://doi.org/https://doi.org/10.1016/j.rse.2025.115016