

PaddockTS: paddock-level satellite time series analysis of agroecosystem dynamics

John T. Burley^{1,*}, Yasar Adeel Ansari¹, Christopher Bradley¹, Alex Norton^{1,2}, Justin Borevitz¹

¹ Research School of Biology, Australian National University, Acton, ACT 2601, Australia

² CSIRO Environment, Aspendale, VIC, Australia

Submitter ORCID: <https://orcid.org/0000-0003-4702-5056>

* Corresponding author: john.burley3000@gmail.com

1 September 2026

Abstract

PaddockTimeSeries (PaddockTS) is an open-source data analysis pipeline that aligns Earth observation data with agricultural fields, or paddocks—the core land management units where agricultural decisions are made and outcomes such as yield, phenology, productivity, and soil condition are recorded. PaddockTS enables scalable agricultural monitoring and research on how land management and environmental variation shape agroecosystem dynamics. For a user-defined location and date range in Australia, PaddockTS delineates paddock boundaries from Sentinel-2 time-series imagery using geospatial segmentation or accepts user-provided boundaries, aggregates Sentinel-2 satellite time series within them, and returns analysis-ready datasets and graphics describing vegetation dynamics and derived seasonal features. It also retrieves environmental covariates, including terrain, soil, weather, and water-balance variables. By summarising vegetation dynamics at the paddock level, PaddockTS makes Earth observation data easier to integrate with management records, environmental conditions, and agricultural and ecological outcomes. Its outputs enable comparisons across paddocks, years, and environmental gradients and provide analysis-ready inputs for agroecosystem modelling and machine-learning prediction tasks. PaddockTS can be used as a programmable Python workflow for reproducible research or through a web interface for exploratory analysis without coding.

Software repository: <https://github.com/johnburley3000/paddocktimeseries>

Interactive web tool: <https://www.paddocktimeseries.net/>

Statement of need

Satellite data are increasingly used to map crops, detect agricultural management and plant phenology, and estimate field-level productivity and yield (Burke and Lobell 2017; d’Andrimont et al. 2020; Van Tricht et al. 2023; Xie et al. 2024). Their repeated, globally consistent observations create opportunities to compare how agroecosystems respond to management and environmental variation across large areas, complementing the scope of purpose-built agronomic experiments (Cambron et al. 2024; Hu et al. 2024; Weiss et al. 2020). Such comparisons are important for evaluating how agricultural management in different contexts affects productivity, resilience to climate extremes, and carbon stocks (Guan et al. 2023; Lobell et al. 2025; Nouri et al. 2021; Zhou et al. 2022).

Realising this potential requires satellite observations to be organised at spatial scales appropriate to research questions or applications. Remote-sensing analyses commonly operate at the pixel level or more broadly across land-use categories or administrative regions. However, practices such as sowing, grazing, fertilisation, irrigation, and harvest—and associated records of crop development, soil properties, and yield—are often organised by paddock. Paddock-level summaries therefore provide a complementary scale of analysis that aligns satellite time series with the spatial units in which management is applied and outcomes are commonly recorded. Converting dense satellite archives into standardised paddock-level time series also makes comparisons more tractable at continental or global scales.

PaddockTS addresses this need by providing a reproducible workflow for generating paddock-level time series and derived features together with relevant environmental covariates. It is intended for researchers conducting agroecosystem monitoring, comparative analysis, machine learning, and process-based modelling, as well as practitioners seeking interpretable summaries of satellite and environmental data that complement local knowledge. The current implementation focuses on Australia because it builds on Australian Earth observation and environmental datasets, while its modular architecture supports extension to other regions and data sources.

State of the field

PaddockTS builds on several open-access Earth observation datasets and analytical tools. It retrieves Sentinel-2 NBART surface reflectance through Digital Earth Australia (Dhu et al. 2017; Geoscience Australia 2022) and environmental covariates from Copernicus DEM, SILO, SLGA, and OzWALD (European Space Agency 2022; Jeffrey et al. 2001; Dijk et al. 2018; Viscarra Rossel et al. 2015). It also applies established spectral indices, an Australian fractional-cover model (Scarth et al. 2010, 2022), and established approaches for estimating phenology metrics (Jönsson and Eklundh 2004; Trotter and Robinson 2021).

Paddock segmentation presents a distinct challenge within this workflow and is an active area of research in satellite remote sensing (Corley et al. 2026; Muhawenayo et al. 2026). Recent approaches increasingly use time-series satellite data to exploit differences in vegetation trajectories and management timing (Watkins and Niekerk 2019; Yan et al. 2024), although performance remains dependent on agricultural context, imagery, and model parameterisation (Ferreira et al. 2025). Because paddocks are transient in time and are not always clearly defined spatial units, particularly in heterogeneous cropping–pasture landscapes, this motivates flexible workflows that support different automated segmentation approaches as well as user-supplied polygons to define paddocks.

PaddockTS’s contribution is to integrate otherwise separate capabilities into a scalable workflow for time-series analysis of agroecosystem dynamics, with paddocks as the core spatial unit of analysis. It complements increasingly available field-boundary predictions (e.g., Robinson et al. 2026) and benchmarking datasets (e.g., Kerner et al. 2024). It differs from platforms that support data access and custom processing but do not provide this domain-specific workflow and its standardised outputs by default (Gorelick et al. 2017; Haan et al. 2023).

Software design

Workflow architecture

PaddockTS is organised as a modular workflow that coordinates data acquisition, paddock delineation, time-series construction, seasonal feature extraction, and visualisation (Figure 1). Each analysis is defined by an immutable query object, called `troi`, specifying the time and region of interest. Maintained in the separate `troi` package, this object provides a consistent identity for data retrieval and caching across related geospatial packages.

Workflows begin from either a user-defined region with automated paddock delineation or user-supplied paddock polygons. Processing steps can be run as a complete pipeline or independently, with cached intermediate products allowing analyses to resume without recomputation.

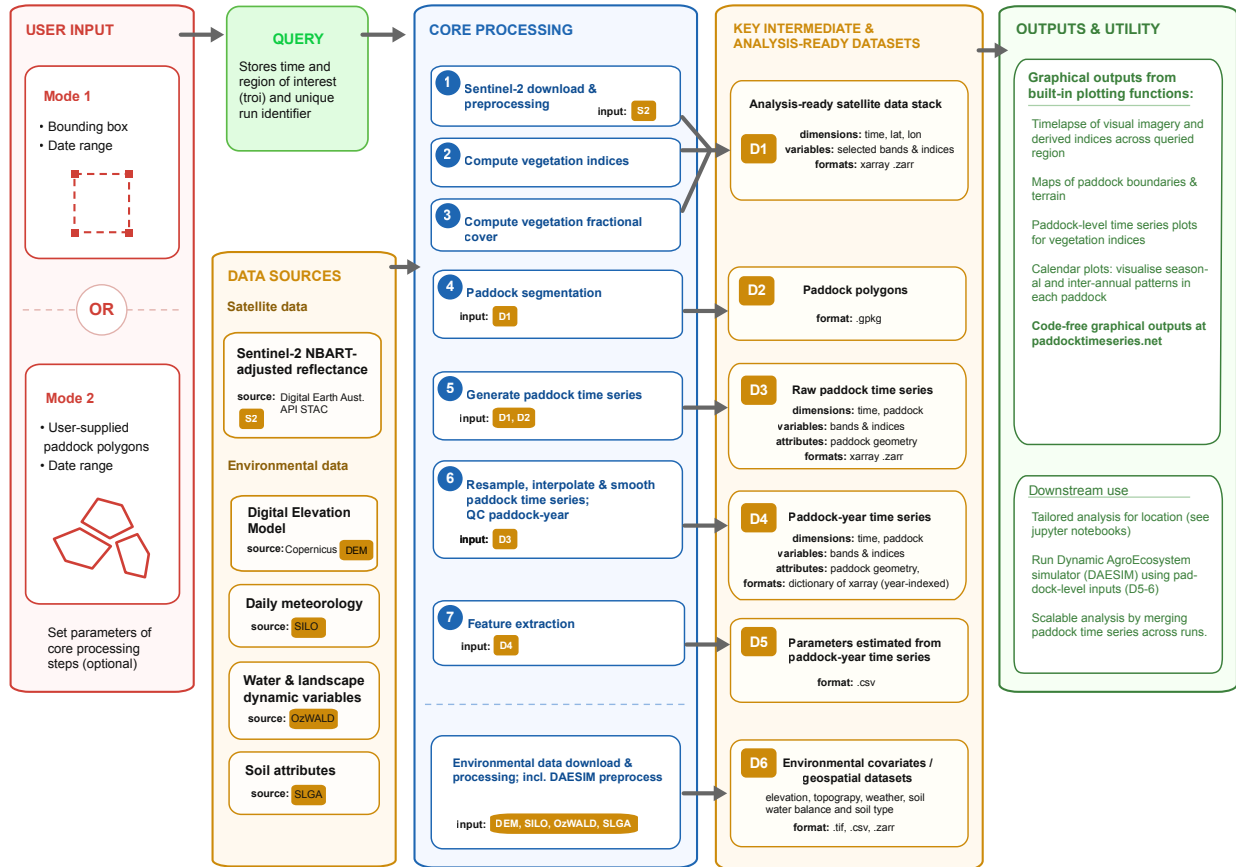


Figure 1: PaddockTS architecture and typical workflows.

Earth observation and environmental data processing and caching

Sentinel-2 NBART surface-reflectance data are accessed from Digital Earth Australia through the independently maintained [pysentinel2](#) package. Raw reflectance bands and Fmask classifications are stored in a sparse, spatially indexed Zarr data cube. For each request, only missing date/location chunks are downloaded. Overlapping or adjacent queries can therefore reuse locally available observations. Cloud and shadow masking uses a configurable procedure within [pysentinel2](#), allowing independent testing and development. Cleaned reflectance data are then used to calculate spectral indices and vegetation fractional cover, which are also cached for downstream analyses.

Terrain, soil, weather, and water-balance data are retrieved through dedicated packages for Copernicus DEM, SLGA, SILO, and OzWALD. These packages apply source-appropriate spatial and temporal caching and return products aligned to the query region and period. Because some environmental datasets are substantially coarser than Sentinel-2 imagery, they are treated as contextual or modelling covariates rather than assumed to represent within-paddock variation.

Paddock segmentation

The default workflow applies a Fourier transform to the normalised difference water index (NDWI) time series to produce a three-band image summarising temporal variation, which is supplied to SAMGeo for segmentation ([Kirillov et al. 2023](#); [Wu and Osco 2023](#)). As in other time-series-based approaches, this representation identifies spatial units with relatively consistent temporal dynamics that differ from their immediate surroundings. Candidate paddock boundaries may vary with the query date range, reflecting both genuine changes in land management and uncertainty in the segmentation, including omission and commission errors. PaddockTS therefore treats automated segmentation as a pragmatic means of approximating field boundaries at scale rather than as a definitive representation of management units. Predicted polygons can be filtered geometrically and by vegetation-index trajectories to reduce commission errors. Applications requiring reliable boundary accuracy should evaluate segmentation results against appropriate reference data or substitute user-provided boundaries.

Paddock time series and seasonal features

Paddock polygons are aligned to the Sentinel-2 grid to aggregate median reflectance, spectral-index, and fractional-cover values by paddock and acquisition date. The resulting series can be resampled, interpolated, smoothed, and quality checked using configurable settings, while both observed and processed trajectories are retained. Processed time series are also divided into paddock-year datasets containing calendar-date and day-of-year coordinates. Processed NDVI trajectories for each paddock-year are passed to PhenoloPy to estimate the start, peak, and end of the growing season.

Data products and visual outputs

PaddockTS preserves outputs from multiple processing stages, including satellite reflectance, paddock polygons, paddock-by-time and paddock-year datasets, seasonal features, and environmental covariates. These analysis-ready data products are used by PaddockTS to generate maps, animations of satellite imagery, annotated paddock calendars, landscape-scale time-series summaries, environmental diagnostics, and phenology plots. Persistent paddock identifiers allow time series and derived features to be joined with user-provided attributes and observations, such as crop type, management activities, yield, or soil measurements.

Demonstration

The workflow was applied to a mixed cropping–grazing landscape near Milgadara, New South Wales, Australia, where paddock boundaries and management histories were available. [Figure 2](#) compares user-provided paddock boundaries to those detected by PaddockTS using 2018–2025 Sentinel data. Paddock-level time series of vegetation fractional cover reveal contrasting trajectories among paddocks and years, which can be viewed alongside weather and soil-moisture conditions ([Figure 3](#)). At the individual-paddock scale, calendar plots arrange satellite observations by week and year, allowing vegetation development and management transitions to be interpreted alongside user-provided crop labels ([Figure 4](#)). Paddock-year vegetation-index trajectories can also be converted into seasonal features, including the estimated start, peak, and end of the growing season ([Figure 5](#)). Together, these outputs demonstrate how PaddockTS supports movement between landscape-scale comparison, detailed inspection of individual paddocks, and analysis-ready seasonal features.

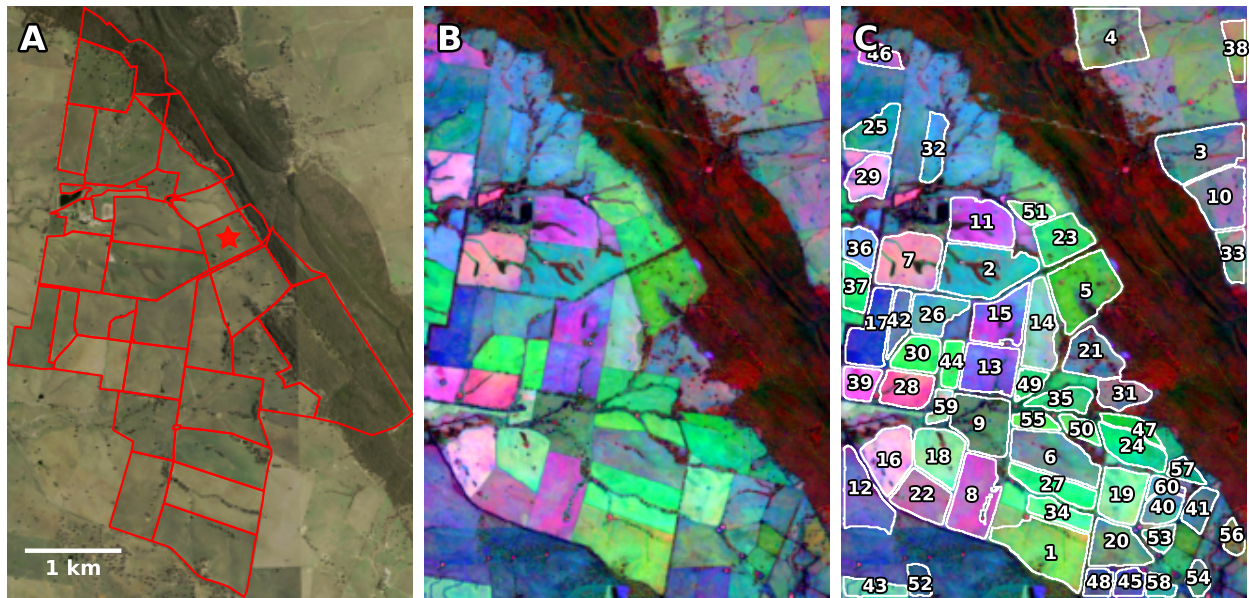


Figure 2: Paddock boundaries for the PaddockTS demonstration landscape near Milgadara, New South Wales, Australia. (A) User-provided paddock boundaries overlaid on aerial imagery. (B) False-colour representation of the Sentinel-2 NDWI time-series Fourier transform (2018–2025) used for segmentation; (C) resulting candidate paddock boundaries numbered from largest to smallest.

Research impact statement

PaddockTS is being used to characterise vegetation dynamics across Australian cropping regions and investigate how management and environmental variation influence productivity and resilience to climatic extremes. Its standardised paddock-level time series support comparisons within and among years across broad bioclimatic gradients, provide imagery and structured inputs for machine-learning applications, and are being integrated with the DAESim process-based agroecosystem model ([Taghikhah et al. 2022](#)). This integration enables satellite-observed vegetation trajectories to be compared with modelled dynamics and supports efforts to distinguish environmental constraints from management-related effects.

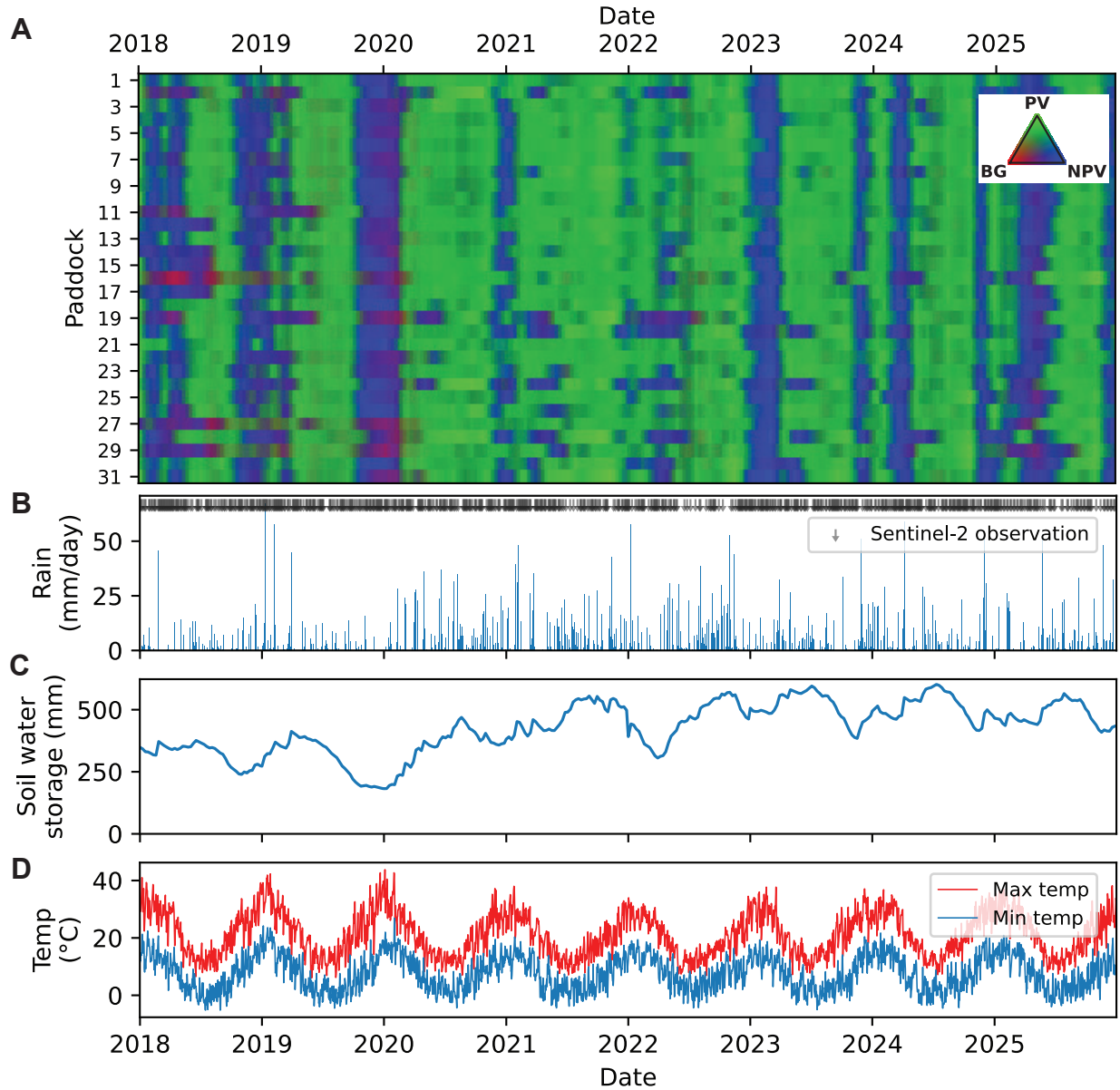


Figure 3: (A) Paddock-level temporal variation in vegetation fractional cover for the 31 largest paddocks identified in the demonstration run. The colour scale represents the predicted fractional contributions of bare ground (BG; red), photosynthetic vegetation (PV; green), and non-photosynthetic vegetation (NPV; blue). Paddock identifiers correspond to [Figure 2C](#). (B–D) Contextual rainfall, soil-moisture and temperature data, and timing of Sentinel-2 observations.

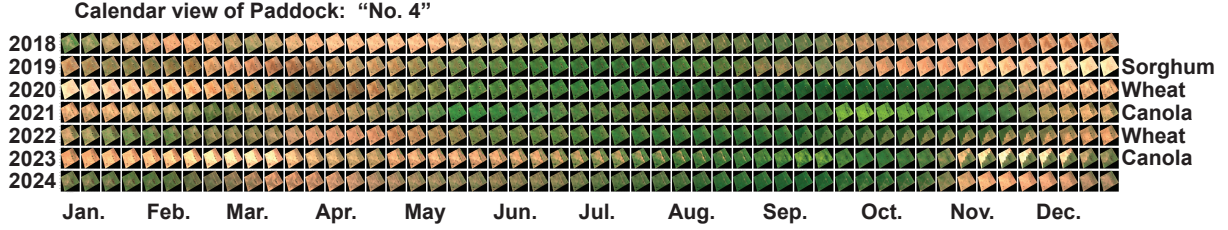


Figure 4: “Calendar view” of an example paddock from the demonstration with recorded crop rotations, marked by a red star in Figure 2A. Sentinel-2 thumbnail images show RGB derived from the temporally resampled, interpolated, and smoothed series. Seasonal variation in plant development and senescence is evident, such as canola flowering visible in 2021 and 2023.

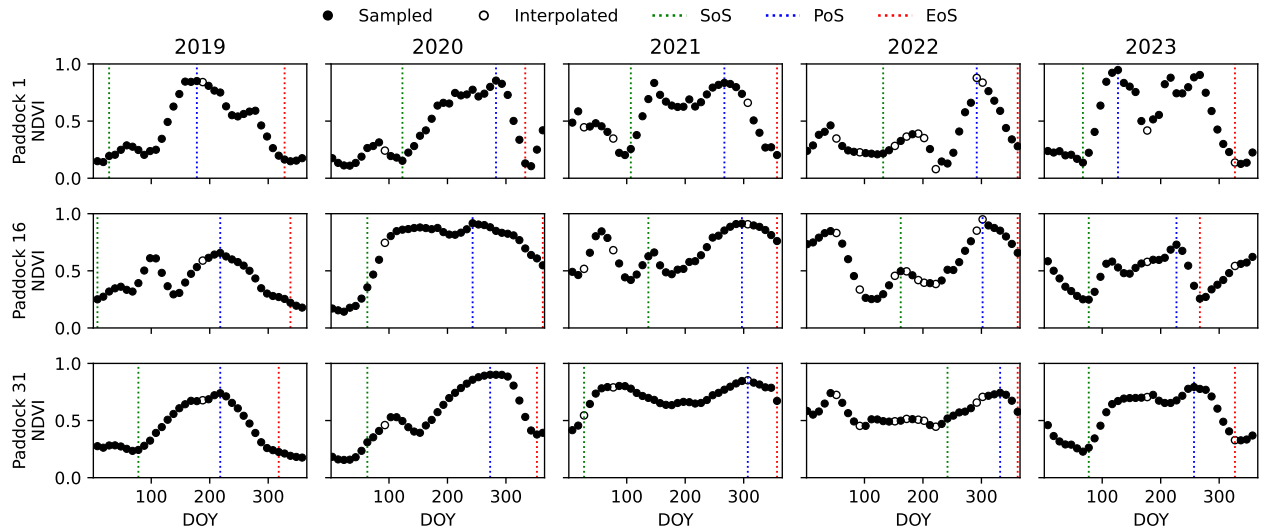


Figure 5: Examples of seasonal features estimated from paddock-level vegetation trajectories. Panels show processed NDVI time series for selected paddock-years at Milgadara, with start of season (SoS), peak of season (PoS), and end of season (EoS) indicated.

At smaller spatial scales, PaddockTS has been applied with Australian land-management organisations, including the Mulloon Institute and Soils For Life, to examine vegetation responses where novel management practices and paddock configurations are being trialled to improve climate resilience. In these applications, user-provided paddock boundaries are used to compare vegetation dynamics in treatment and reference areas while controlling for environmental variation. Together, these applications demonstrate the utility of PaddockTS for large-scale comparative research and for complementing experimental research involving paddock-level treatments.

AI usage disclosure

Generative AI tools (ChatGPT, OpenAI; Claude, Anthropic) were used to assist in developing PaddockTS code and this manuscript. All AI-assisted outputs were critically reviewed, edited, tested, and validated by the authors. The authors made all scientific, conceptual, and software-design decisions and take full responsibility for the accuracy and integrity of the submitted work.

Acknowledgements

This work was supported by the National Environmental Science Program and computational resources provided by the National Computational Infrastructure (NCI Australia). We thank Geoscience Australia, Digital Earth Australia, and the developers of the open-source software used in this work.

References

- Burke, Marshall, and David B. Lobell. 2017. “Satellite-Based Assessment of Yield Variation and Its Determinants in Smallholder African Systems.” *Proceedings of the National Academy of Sciences* 114 (9): 2189–94. <https://doi.org/10.1073/pnas.1616919114>.
- Cambron, Taylor W., Jillian M. Deines, Benjamin Lopez, Rohan Patel, Sheng-Zhe Liang, and David B. Lobell. 2024. “Further Adoption of Conservation Tillage Can Increase Maize Yields in the Western US Corn Belt.” *Environmental Research Letters* 19 (5): 054040. <https://doi.org/10.1088/1748-9326/ad3f32>.
- Corley, Isaac, Hannah Kerner, Caleb Robinson, and Jonathan Marcus. 2026. *Fields of the World: A Field Guide for Extracting Agricultural Field Boundaries*. <https://doi.org/10.48550/arXiv.2602.08131>.
- d’Andrimont, Raphaël, Marijn Taymans, Guido Lemoine, Andrej Ceglar, Mihail Yordanov, and Marijn van der Velde. 2020. “Detecting Flowering Phenology in Oil Seed Rape Parcels with Sentinel-1 and -2 Time Series.” *Remote Sensing of Environment* 239: 111660. <https://doi.org/10.1016/j.rse.2020.111660>.
- Dhu, Trevor, Ben Dunn, Bronwyn Lewis, et al. 2017. “Digital Earth Australia – Unlocking New Value from Earth Observation Data.” *Big Earth Data* 1 (1–2): 64–74. <https://doi.org/10.1080/20964471.2017.1402490>.
- Dijk, Albert van, David Summers, Luigi Renzullo, and Marta Yebra. 2018. *OzWALD Gridded*

- Environmental Data for Australia*. <https://doi.org/10.4225/08/5a3c52da083b8>.
- European Space Agency. 2022. *Copernicus DEM – Global and European Digital Elevation Model (COP-DEM)*. <https://doi.org/10.5270/ESA-c5d3d65>.
- Ferreira, Lucas B., Vitor S. Martins, Uilson R. V. Aires, Nuwan Wijewardane, Xue Zhang, and Sathishkumar Samiappan. 2025. “FieldSeg: A Scalable Agricultural Field Extraction Framework Based on the Segment Anything Model and 10-m Sentinel-2 Imagery.” *Computers and Electronics in Agriculture* 232: 110086. <https://doi.org/10.1016/j.compag.2025.110086>.
- Geoscience Australia. 2022. *Geoscience Australia Sentinel-2A MSI NBART Collection 3 – DEA Surface Reflectance NBART (Sentinel-2A MSI)*. <https://doi.org/10.26186/146571>.
- Gorelick, Noel, Matt Hancher, Mike Dixon, Simon Ilyushchenko, David Thau, and Rebecca Moore. 2017. “Google Earth Engine: Planetary-Scale Geospatial Analysis for Everyone.” *Remote Sensing of Environment* 202: 18–27. <https://doi.org/10.1016/j.rse.2017.06.031>.
- Guan, Kaiyu, Zhenong Jin, Bin Peng, et al. 2023. “A Scalable Framework for Quantifying Field-Level Agricultural Carbon Outcomes.” *Earth-Science Reviews* 243: 104462. <https://doi.org/10.1016/j.earscirev.2023.104462>.
- Haan, Sander, Jono Harianto, Nicole Butterworth, and Thomas Bishop. 2023. “Geodata-Harvester: A Python Package to Jumpstart Geospatial Data Extraction and Analysis.” *Journal of Open Source Software* 8 (89): 5205. <https://doi.org/10.21105/joss.05205>.
- Hu, Pengfei, Bangyou Zheng, Qian Chen, et al. 2024. “Estimating Aboveground Biomass Dynamics of Wheat at Small Spatial Scale by Integrating Crop Growth and Radiative Transfer Models with Satellite Remote Sensing Data.” *Remote Sensing of Environment* 311: 114277. <https://doi.org/10.1016/j.rse.2024.114277>.
- Jeffrey, Stephen J., John O. Carter, Keith B. Moodie, and Alan R. Beswick. 2001. “Using Spatial Interpolation to Construct a Comprehensive Archive of Australian Climate Data.” *Environmental Modelling & Software* 16 (4): 309–30. [https://doi.org/10.1016/S1364-8152\(01\)00008-1](https://doi.org/10.1016/S1364-8152(01)00008-1).
- Jönsson, Per, and Lars Eklundh. 2004. “TIMESAT—a Program for Analyzing Time-Series of Satellite Sensor Data.” *Computers & Geosciences* 30 (8): 833–45. <https://doi.org/10.1016/j.cageo.2004.05.006>.
- Kerner, Hannah, Snehal Chaudhari, Aninda Ghosh, et al. 2024. *Fields of the World: A Machine Learning Benchmark Dataset for Global Agricultural Field Boundary Segmentation*. <https://doi.org/10.48550/arXiv.2409.16252>.
- Kirillov, Alexander, Eric Mintun, Nikhila Ravi, et al. 2023. *Segment Anything*. <https://doi.org/10.48550/arXiv.2304.02643>.
- Lobell, David B., Stefania Di Tommaso, Qian Zhou, Yizhi Ma, James Specht, and Kaiyu Guan. 2025. “The Mixed Effects of Recent Cover Crop Adoption on US Cropland Productivity.” *Nature Sustainability* 8 (9): 1004–12. <https://doi.org/10.1038/s41893-025-01599-5>.

- Muhawenayo, Gedeon, Caleb Robinson, Subash Khanal, et al. 2026. *PRUE: A Practical Recipe for Field Boundary Segmentation at Scale*. <https://doi.org/10.48550/arXiv.2603.27101>.
- Nouri, Aidin, Daniel C. Yoder, Mojtaba Raji, et al. 2021. “Conservation Agriculture Increases the Soil Resilience and Cotton Yield Stability in Climate Extremes of the Southeast US.” *Communications Earth & Environment* 2 (1): 155. <https://doi.org/10.1038/s43247-021-00223-6>.
- Robinson, Caleb, Gedeon Muhawenayo, Subash Khanal, et al. 2026. *The First Global Agricultural Field Boundary Map at 10m Resolution*. <https://doi.org/10.48550/arXiv.2605.11055>.
- Scarth, Peter, Robert Denham, and Fiona Watson. 2022. *fractionalcover3: Python Package to Produce Land Cover Fractions from Satellite Imagery*. <https://gitlab.com/jrsrp/themes/cover/fractionalcover3>.
- Scarth, Peter, Achim Roder, and Michael Schmidt. 2010. “Tracking Grazing Pressure and Climate Interaction—the Role of Landsat Fractional Cover in Time Series Analysis.” *Proceedings of the 15th Australasian Remote Sensing & Photogrammetry Conference*. <https://doi.org/10.6084/M9.FIGSHARE.94250>.
- Taghikhah, F., Justin Borevitz, Robert Costanza, and Alexey Voinov. 2022. “DAESim: A Dynamic Agro-Ecosystem Simulation Model for Natural Capital Assessment.” *Ecological Modelling* 468: 109930. <https://doi.org/10.1016/j.ecolmodel.2022.109930>.
- Trotter, Lewis, and Todd Robinson. 2021. *frontiersi/phenology V1.0*. <https://doi.org/10.5281/zenodo.4738425>.
- Van Tricht, Kristof, Jeroen Degerickx, Sander Gilliams, et al. 2023. “WorldCereal: A Dynamic Open-Source System for Global-Scale, Seasonal, and Reproducible Crop and Irrigation Mapping.” *Earth System Science Data* 15 (12): 5491–515. <https://doi.org/10.5194/essd-15-5491-2023>.
- Viscarra Rossel, Raphael A., C. Chen, M. J. Grundy, R. Searle, D. Clifford, and P. H. Campbell. 2015. “The Australian Three-Dimensional Soil Grid: Australia’s Contribution to the GlobalSoilMap Project.” *Soil Research* 53 (8): 845–64. <https://doi.org/10.1071/SR14366>.
- Watkins, Bradley, and Adriaan van Niekerk. 2019. “A Comparison of Object-Based Image Analysis Approaches for Field Boundary Delineation Using Multi-Temporal Sentinel-2 Imagery.” *Computers and Electronics in Agriculture* 158: 294–302. <https://doi.org/10.1016/j.compag.2019.02.009>.
- Weiss, Marie, Frédéric Jacob, and Grégory Duveiller. 2020. “Remote Sensing for Agricultural Applications: A Meta-Review.” *Remote Sensing of Environment* 236: 111402. <https://doi.org/10.1016/j.rse.2019.111402>.
- Wu, Qiusheng, and Lucas Prado Osco. 2023. “samgeo: A Python Package for Segmenting Geospatial Data with the Segment Anything Model (SAM).” *Journal of Open Source Software* 8 (89): 5663. <https://doi.org/10.21105/joss.05663>.

- Xie, Zhi, Yan Zhao, Rui Jiang, et al. 2024. “Seasonal Dynamics of Fallow and Cropping Lands in the Broadacre Cropping Region of Australia.” *Remote Sensing of Environment* 305: 114070. <https://doi.org/10.1016/j.rse.2024.114070>.
- Yan, Shuang, Xiaodong Yao, Jingcheng Sun, et al. 2024. “TSANet: A Deep Learning Framework for the Delineation of Agricultural Fields Utilizing Satellite Image Time Series.” *Computers and Electronics in Agriculture* 220: 108902. <https://doi.org/10.1016/j.compag.2024.108902>.
- Zhou, Qian, Kaiyu Guan, Sheng Wang, et al. 2022. “Recent Rapid Increase of Cover Crop Adoption Across the U.S. Midwest Detected by Fusing Multi-Source Satellite Data.” *Geophysical Research Letters* 49 (22): e2022GL100249. <https://doi.org/10.1029/2022GL100249>.