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# PS3: The Pheno-Synthesis software suite for integration and analysis of multi-scale, multi-platform phenological data

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ABSTRACT

Phenology is the study of recurring plant and animal life-cycle stages which can be observed across spatial and temporal scales that span orders of magnitude (e.g., organisms to landscapes). The variety of scales at which phenological processes operate is reflected in the range of methods for collecting phenologically relevant data, and the programs focused on these collections. Consideration of the scale at which phenological observations are made, and the platform used for observation, is critical for the interpretation of phenological data and the application of these data to both research questions and land management objectives. However, there is currently little capacity to facilitate access, integration and analysis of cross-scale, multi-platform phenological data. This paper reports on a new suite of software and analysis tools – the "Pheno-Synthesis Software Suite," or PS3 – to facilitate integration and analysis of phenological and ancillary data, enabling investigation and interpretation of phenological processes at scales ranging from organisms to landscapes and from days to decades. We use PS3 to investigate phenological processes in a semi-aride, mixed shrub-grass ecosystem, and find that the apparent importance of seasonal precipitation to vegetation activity (i.e., "greenness") is affected by the scale and platform of observation. We end by describing potential applications of PS3 to phenological modeling and forecasting, understanding patterns and drivers of phenological activity in real-world ecosystems, and supporting agricultural and natural resource management and decision-making.

## 1. Introduction

Phenology is the study of recurring plant and animal life-cycle stages (Lieth, 1974). Classic examples of phenological events include leafing and flowering of plants, maturation of agricultural crops, emergence of insects, and migration of birds and mammals. These seasonal dynamics show high sensitivity to environmental variation and scale (e.g., Liang and Schwartz, 2009; Morisette et al., 2009) and across observing

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systems (Browning et al., 2015; Richardson et al., 2017), making phenological records important in the study of climate change and its effects on living systems (Parmesan, 2007). Documentation of patterns and trends in phenology has increasingly contributed to climate change research, including applications in national climatological assessments and indicator systems (e.g., U.S. Environmental Protection Agency, 2016, Kissling et al., 2018, Lipton et al., 2018, Weltzin et al., 2020).

Because of its broad and interdisciplinary scope (Schwartz et al., 2013), phenological information is highly relevant to a wide range of environmental applications (Enquist et al., 2014), including many aspects of land management such as forestry (Lausch et al., 2018), agriculture (Hufkens et al., 2019), wildland fire management (Emery et al., 2020) and conservation of biodiversity, ecosystems and ecosystem services (Weiskopf et al., 2020). Phenology science is also important in the rapidly evolving field of terrestrial animal migration ecology (Aikens et al., 2020; Berman et al., 2020). At the same time, from an Earth system perspective, phenology is a critical component of terrestrial biosphere models because it plays an important role in regulating land-atmosphere interactions and feedbacks (Richardson et al., 2012, 2013).

The relevance of phenology to site-level management decisions and global-scale models highlights the fact that phenological processes operate across spatial and temporal scales that span orders of magnitude – from leaf to globe, and from days to seasons (Cleland et al., 2007). Consideration of the scale at which phenological observations are made is critical for the interpretation of phenological data, and the application of these data to both research questions and land management objectives (Berman et al., 2020). First, variation in phenological responses across species or functional groups can lead to substantial variation in phenology within natural communities (Browning et al., 2015) or across landscapes (Klosterman et al., 2018; Waller et al., 2018), particularly in heterogeneous environments (Browning et al., 2017; Liu et al., 2019). Second, phenological transition dates (e.g., spring onset) derived from satellite vegetation indices (e.g., Normalized Difference Vegetation Index; NDVI) may lag behind underlying biological phenomena (e.g., spring budburst or leaf-out) and may be comparatively insensitive to other phenomena (e.g., flowering or fruiting). Phenological models such as the extended spring indices (Schwartz et al., 2013), while useful for predicting broad-scale patterns and long-term trends (Monahan et al., 2016), may be imperfect proxies at the site level (Richardson et al., 2019) or across taxa (Gerst et al., 2020). Third, differences between local climate and microclimate can complicate the interpretation of satellite observations and highlight the importance of understanding the ultimate drivers of fine scale phenological variation (Fisher et al., 2006). Finally, on-the-ground, organism-level observations of phenological events may not provide the broad-scale perspective or frequency of observations necessary to interpret whole-ecosystem data on productivity or carbon and water fluxes for which scale-relevant observations are needed (Richardson, 2019).

The variety of spatial scales at which phenological processes operate and can be observed is reflected in the range of methods for collecting phenologically relevant data and programs focused on these collections (Jones et al., 2010; Morisette et al., 2009). However, there is little capacity to facilitate integration, let alone analysis, of cross-scale multi-platform phenological data (Richardson et al., 2017). Unlocking the full potential of the growing array of diverse phenology-related dataset can be enhanced through tools that allow researchers to access, integrate, and analyze data from multiple programs and platforms and across a variety of spatiotemporal scales and resolutions.

Here, we report on a new suite of software and analysis tools to facilitate cross-scale and cross-platform integration of phenology-relevant data, which we term the “Pheno-Synthesis Software Suite,” or PS3. PS3 was developed to address integration and synthesis across several existing dataset and the related phenology programs. The phenology datasets include field-based observations at a local scale, near-surface imagery at a canopy level/catchment scale, satellite imagery observed at a 30-250 m pixel resolution, and climate-derived products at 2.5 km resolution (Fig. 1, Table 1). We first provide background information on these datasets, and then describe the constellation of software. To demonstrate the utility of these tools for facilitating multi-scale analysis, we provide an example from phenological observations in an arid environment.

## 2. Materials and methods

### 2.1. Ground-based phenology observations

#### 2.1.1. USA National Phenology Network protocols and data

The USA National Phenology Network (USA-NPN; Schwartz et al., 2012) is the primary source of in situ (ground-based) organismal phenology data in the United States. The data maintained by the USA-NPN are contributed by professional and volunteer observers across the country (Rosemartin et al., 2014; Table 1, Fig. 1) based on rigorous, scientifically vetted “status and intensity” protocols established by the USA-NPN and widely adopted by the research community (Denny et al., 2014). “Status” protocols require observers to indicate the presence or absence of phenological phases, or phenophases, such as the presence of leaves or fruits on individual plants repeatedly over the course of a season. The protocols also incorporate measures of abundance that reflect the count of elements (e.g., number of fruits) present on an individual plant, as well as measures of intensity that reflect proportional expression of a phenophase (e.g., percent of fruit that are ripe, or proportion of canopy with green leaves) (Denny et al., 2014).

The USA-NPN’s in situ phenology data are also available in progressively wider spatial extent from “individual phenometrics” to”site phenometrics” data, which yield estimated phenophase onset and end dates for individual plants or for multiple individuals of a species at a site, and”magnitude phenometrics” data, which provide measures of the extent to which a phenophase is expressed across multiple individuals or sites over a specified time interval (Rosemartin et al., 2018).

The USA-NPN’s phenology data total over 23 M records of phenological status for ~1400 species collected at over 15,000 sites across the United States for the period 2009-2020. These data have contributed to over 100 scientific publications, with applications including the identification of drivers of phenology in select species (Gerst et al., 2017; Mazer et al., 2015), the development of predictive models of phenology (Crimmins et al., 2017a; Elmendorf et al., 2019), and the detection and control of invasive plants (Wallace et al., 2016) and animals (Crimmins

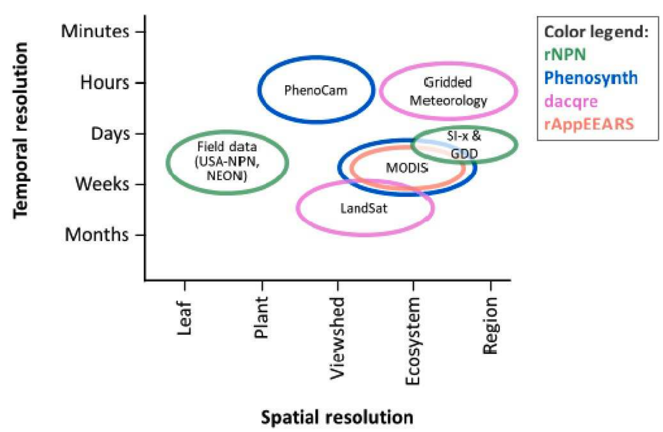


**Fig. 1.** A graphical representation of the approximate spatial and temporal resolution of the phenologically relevant dataset accessed through PS3. The colour of the oval surrounding the dataset name indicates the specific software used to access those data. (While there is not a blue circle around Landsat, Phenosynth does access Landsat-derived land cover data, it does not access Landsat vegetation time series data.) (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

**Table 1**
Suite of phenologically relevant dataset available for integration in PS3, including data sources, type of observation, potential application and utility, temporal and spatial scales, and component software used to access and analyze the data.

| Dataset | Description | Utility | Period of availability | Temporal frequency | Spatial scale | Data Provider | Related PS3 software |
|---|---|---|---|---|---|---|---|
| Ground-based phenology observations | in-situ phenology observations from the USA National Phenology and NEON programs | Phenological stages of individual plant species | 2009-present | Days to weeks | Individual organism | USA National Phenology Network (and NEON via USA NPN) | rNPN |
| Near-surface imagery | Near surface, tower-based imagery | Canopy-scale perspective | 2005-present | 15 to 30 min | Viewshed (sub-landscape to landscape) | Phenocam Network | Phenosynth |
| Satellite-based land surface phenology | Satellite-based (e.g. Landsat, MODIS) vegetation indices and land surface phenology (LSP) metrics | Globally-consistent information on plant dynamics | Variable, depending on sensor | Days to weeks | Ecosystem | Land Processes Distributed Archive Archive Center | Phenosynth with AppEEARs4R |
| Gridded climate data | Historical temperature and precipitation interpolated from observations | Links between plant phenology and variations in weather and climate | 1979-present (gridMET) 1980-present (Daymet) | Daily | Ecosystem/ Region | gridMET and DayMet via Google Earth Engine | dacqre |
| Gridded phenological indices | Spring Index (SI) and Accumulated Growing Degree Days (AGDD) | Predictor of phenological transitions | 1981-present | Daily | Ecosystem/ Region | USA National Phenology Network | rNPN |

et al., 2020).

### 2.1.2. National Ecological Observatory Network protocols and data

The National Ecological Observatory Network (NEON) is a National Science Foundation (NSF)-sponsored continental-scale observation facility designed to collect long-term open access ecological data to better understand how ecosystems in the United States (U.S.) are changing in the face of several environmental drivers (Keller et al., 2008). NEON collects plant phenological data following the USA-NPN's "status and intensity" protocols across all terrestrial sites within the network (Denny et al., 2014; Elmendorf et al., 2016). NEON's data are fully integrated into the USA-NPN's phenology database, enabling users to access, explore, and visualize integrated USA-NPN and NEON data using tools on the USA-NPN website (NEON, 2020). NEON phenology observations have the benefit of the additional rich set of biophysical observations obtained at each NEON site: these ancillary site-level meteorological and ecological data enable analysis of the relationships between plant-level phenology and meteorological and environmental forcing functions (Elmendorf et al., 2016).

## 2.2. Near-surface imagery

Most vegetation types exhibit seasonal or interannual variation in photosynthetic activity, and some (e.g., deciduous shrubs and trees, grasses) have distinct life cycles marked by the growth and senescence of leaves. Associated changes in biochemistry affect reflectance of electromagnetic radiation from foliage on the land surface that can be measured using remote sensors. The timing of these recurring changes in reflectance is called land surface phenology (LSP; de Beurs and Henebry, 2010, Henebry and de Beurs, 2013, Hanes et al., 2014). LSP can be determined from ground-based (i.e., near-surface) or satellite-based remote sensing platforms.

The PhenoCam network is a near-surface network of canopy-level digital cameras distributed across a range of ecoregions, climate zones, and plant functional types in North America (Richardson et al., 2007, 2017; Fig. 1, Table 1). PhenoCam imagery is obtained by cameras mounted on poles or towers 1–10 m above the ground or canopy surface. This orientation provides a canopy-scale perspective while retaining the capacity to resolve individual organisms. Because PhenoCam imagery has digital and physical characteristics similar to imagery obtained from airborne or satellite platforms and sensors, it can serve as a link between ground observations and satellite or airborne remote sensing (Berman et al., 2020; Keenan et al., 2014; Richardson et al., 2009; St. Peter et al., 2018).

The PhenoCam archive includes data from >650 cameras, with images and derived data products displayed in near-real time on the project website. The archived images—mostly obtained since 2015, but with time series for some cameras extending to 2005 or earlier—provide a permanent record that can be visually inspected to determine the phenological state of the vegetation at any point in time. Quantitative data on the colour of vegetation, a proxy for its phenological state, can also be calculated from the imagery. Relative greenness (i.e., Green Chromatic Coordinate, or GCC) is extracted using simple image processing methods (Sonnentag et al., 2012), and time series data are derived at 1- and 3-day timesteps (Seyednasrollah et al., 2019) along with phenophase transition dates corresponding to start and end of a seasonal cycle (Klosterman et al., 2014).

NEON has deployed PhenoCams at each of its sites using the PhenoCam network's prescribed camera configuration and protocol (PhenoCam, 2020a, 2020b). In short, each NEON site deploys two cameras, one just above ground level and the other near the top of the instrumentation tower, oriented in a manner to include, where feasible, the in situ field transects within the camera field of view. The ancillary meteorological and ecological information at each NEON site enables analysis of the relationships between PhenoCam-derived data and meteorological and environmental forcing functions.

## 2.3. Satellite-based land surface phenology

In addition to being derived from near-surface imagery, LSP can also be calculated from time series of vegetation indices derived from land surface reflectance data obtained from satellite-based sensors (de Beurs and Henebry, 2010; Hanes et al., 2014). Satellite-based LSP data provide estimates of vegetation phenology on landscape to global scales, typically at pixel sizes of 250 m to 1000 m. At this scale, phenological observations can be more readily compared to gridded climate data and can facilitate understanding as to how living systems interact with climate.

Operational Moderate Resolution Imaging Spectroradiometer (MODIS) LSP products are frequently used for regional, continental, and global scale LSP analysis (Ganguly et al., 2010; Moon et al., 2019). MODIS vegetation indices, including Normalized Difference Vegetation Index (NDVI) and the Enhanced Vegetation Index (EVI) (Huete et al., 2002), are used to construct phenological metrics – or phenometrics – (e.g., start of season) from time-series datasets (Friedl and Sulla-Menashe, 2019, Fig. 1, Table 1). Data from the MODIS-like Visible Infrared Imaging Radiometer Suite (VIIRS) were not the focus of the current study. We recognize that PS3 capabilities will need to leverage VIIRS data in the future as MODIS data streams are discontinued.

### 2.4. Gridded climate data

Because plant life-cycle events are driven by meteorological and climatological conditions such as temperature and precipitation (Kathuroju et al., 2007; Menzel et al., 2005), these physical data can be used to assess and predict phenological status and trends across scales from organisms to landscapes and ecosystems (Schwartz, M.D. ed., 2013). Links between plant phenology and variations in weather (short term, days to weeks) and climate (long term, years to centuries) can also feed back to the atmosphere and climate system, and influence ecological interactions at different scales (individual to community to ecosystem) and trophic levels (producers to consumers) (Morisette et al., 2009). Thus, basic meteorological data, particularly air temperature and precipitation, are essential for interpreting short- and longer-term variation in phenology and for developing predictive models. The Gridded Surface Meteorological dataset (gridMET; Abatzoglou, 2013) and the Daymet dataset (Thornton et al., 2018) are made available through PS3 (Fig. 1, Table 1).

### 2.5. Gridded phenological indices

To complement field-based observations, the USA-NPN offers a growing suite of raster map products for the conterminous U.S. and Alaska indicating the phenological status of organisms and seasonal phenomena (Crimmins et al., 2017b). These products include daily accumulated growing degree day (AGDD) maps and extended spring indices (SI-x) which indicate the onset of the spring growing season (Schwartz, 1997; Schwartz et al., 2013). SI-x products span the period from 1880 to present. Real-time and recent (1981-present) data layers and short-term forecasts are available at resolutions of 2.5 km and 4 km (Crimmins et al., 2017b; Fig. 1, Table 1).

## 3. Software to access and integrate phenological data

Each of the datasets described above has been used as part of prior phenological analyses. However, comparatively few studies have leveraged their combined value, likely because of the effort required to access, harmonize and integrate the many layers. Here we describe PS3 – designed to facilitate such analyses. The following section illustrates the value of data integration via a case-study for a dryland ecosystem. Each element of the software suite provides access to one or more of the dataset listed above and provide tools for visualizing these data. Greenwave package (Section 3.5) provides tools for analyzing a time series data (e.g. NDVI) and possible covariates (e.g. climate variables).

Code and more detailed information for each tool are described on the NASA Earthdata Bitbucket repository (NASA Earthdata BitBucket: https://git.earthdata.nasa.gov/projects/APIS/repos/pheno-synthesis-software-suite). The repository describes the five code packages described below (Sections 3.1–3.5) and includes a sixth directory containing code snippets related to the case study below (Section 4).

### 3.1. rNPN

The **rNPN** package (Marsh et al., 2020) was created to allow improved access to the USA-NPN and NEON observational products (Section 2.1) and gridded data products (Section 2.5) by directly importing USA-NPN's web services data into R. Broadly, this package streamlines and improves end-user accessibility to USA-NPN data products individually and collectively. Important features include the ability to stream responses from the server in real-time and the ability to intersect point observations with raster data products.

### 3.2. phenoSynth

**phenoSynth** is an open-repository R-Shiny interface that integrates PhenoCam and MODIS datasets and allows users to visualize, interact with, and download co-located phenological data across multiple sources. **phenoSynth,** through **AppEEARs4R** (described below) can extract MODIS NDVI and EVI time series (Friedl and Sulla-Menashe, 2019), as well as the MODIS land-cover products (Sulla-Menashe et al., 2019) and the Multi-Resolution Land Characteristics (MRLC) Consortium land cover products (Wickham et al., 2014). This web-based tool advances cross-scale analyses by displaying the geospatial location and field of view for any PhenoCam site relative to the associated MODIS 250 m pixel. The geospatial information (and related accuracy) are inherited from the original dataset. **phenoSynth** allows users to select any number of individual MODIS pixels and pull those remotely sensed indices of phenology in concert with PhenoCam GCC. The tool allows users to interactively evaluate agreement in phenological indices and time series across datasets and spatial scales, then download data for further investigation in any platform of their choice. In many cross-scale comparisons it is common to simply pull remotely sensed pixels which overlap a PhenoCam's location. However, for quality control of GCC timeseries, PhenoCam region of interest (ROI) often consist of a select number of trees or shrubs, or cover multiple plant functional types, including those not widely present at a landscape-scale. To address scale mismatch **phenoSynth** highlights MODIS pixels whose land-cover classification matches that of a PhenoCam ROI vegetation-type, and also assesses vegetation heterogeneity within a MODIS pixel via the LandSat National Land Cover Database (Homer et al., 2020). **phenoSynth** allows users to select any number of individual MODIS pixels and pull those remotely sensed indices of phenology in concert with PhenoCam GCC. The tool allows users to interactively evaluate agreement in phenological indices and time series across datasets and spatial scales, then download data for further investigation in any platform of their choice. By integrating phenological data from multiple platforms into the same interface and demonstrating their coherence or overlap, **phenoSynth** supports investigations of phenological response at regional and continental scales, with concrete applications for validation, ecological forecasting, and modeling.

### 3.3. AppEEARs4R

The Application for Extracting and Exploring Analysis Ready Samples (AppEEARS; AppEEARS Team, 2020) offers users a way to perform data access and transformation processes for gridded dataset archived at the Land Processes Distributed Active Archive Center (LP DAAC; https://lpdaac.usgs.gov/). AppEEARS enables users to subset data spatially, temporally, and by layer, greatly reducing the volume of data downloads. For phenological applications, AppEEARS provides access to hundreds of datasets from multiple missions, including the operational MODIS LSP products as well as the MODIS NDVI and EVI time series. **AppEEARs4R** is an R package for AppEEARS functionality that allows data end users to request and interact with data available through the AppEEARS interface. The library provides a wrapper to all endpoints available in the AppEEARS REpresentational State Transfer (REST) Application Program Interface (API) and a unifying function that coordinates the entire process of requesting and retrieving data.

### 3.4. dacqre

The Data ACQuisition and REtrieval software (**dacqre**) toolkit extracts geospatial datasets relevant for phenological modeling from the Google Earth Engine (GEE) data catalog and allows retrieval within the Google Cloud Platform (GCP) bucket storage. GEE provides access to over twenty petabytes of Earth data across forty years. The utility of **dacqre** includes 1) leveraging Google's web services and related dataset, 2) easy integration with existing GEE tools and developer communities, which can raise awareness of phenological products to a broader community; and 3) allowing access to the many assets on GEE not being served operationally in other phenology data systems, but which serve as potentially valuable covariates in understanding phenology.

### 3.5. Greenwave

**Greenwave** is an R package that was developed to fit the annual vegetation greenness curve, or "green wave" (sensu Schwartz, 1998) to LSP time series data, and to derive predictions of phenological parameters from the modeled curve. **Greenwave** can fit models to near-surface vegetation greenness data from PhenoCams as well as satellite data from LANDSAT, MODIS, and Sentinel. It can also be extended to any vegetation index (e.g. the Enhanced Vegetation Index, EVI). The approach used by **Greenwave** differs from previous modeling efforts (summarized in de Beurs and Henebry, 2010) in that it is built on a probabilistic *generative* model (McElreath, 2020) for both prediction (e.g., predicting the green wave at an unsampled site, or forecasting into the future) and for inference (e.g., understanding the specific drivers behind phenological parameters of interest). The approach builds on earlier work by Senf et al. (2017), which modeled greenup. It extends that work by modeling the complete annual cycle, including the "brown down" phase in which vegetation greenness decreases back down to baseline levels as the fall and winter seasons progress. The approach differs from previous methods that use more empirical curve-fitting algorithms (e.g., splines). Such non-generative models lack an ability to make predictions about the expected value of new observations and, as such, cannot support forecasting or the incorporation of covariates. The parameters used to fit a **Greenwave** model to the annual time series can be translated into phenological metrics, such as the start and end of season, peak greenness, and duration of green-up and brown-down. The Bayesian approach used to fit the **Greenwave** models also provides uncertainty estimates for each phenological metric. Additional details on the underlying mathematics and parameters of the **Greenwave** model can be found in the Supplemental Information (S1).

## 4. Case study: an application of PS3 in a dryland ecosystem

In this section, we present an example application of PS3 for a well-instrumented dryland grass/shrub ecosystem in the Chihuahuan Desert in the southwestern U.S. Using some of the data streams described in section 2, we demonstrate how some of the tools described in section 3 can be used to acquire, integrate, and analyze phenology observation in this area. The results illustrate how phenological parameters vary relative to the spatial scale of observations and the temporal scale of meteorological conditions. We then discuss how scale and ecological processes can interact, and how multi-scale phenological inference can be used to better understand, characterize, and manage dryland and other ecosystems (Section 5).

### 4.1. Study site

The Jornada Experimental Range (JER), located in the Chihuahuan Desert near Las Cruces, New Mexico, U.S., is a low-diversity, mixed perennial grassland and evergreen/deciduous shrubland (Browning et al., 2015). Long-term (1930–2008) local average precipitation is 232.2 mm with 62% of that occurring from July to October (Browning et al., 2012). Both precipitation seasonality along with storm size and duration influence soil water available to plants via the pulse reserve paradigm (Loik et al., 2004; Reynolds et al., 2004). Evidence that fire was historically common in this region of the Chihuahuan Desert is scant (Buffington and Herbel, 1965).

The site, which has been managed by the US Department of Agriculture's Agricultural Research Service (USDA-ARS) since 1912, is a node of the Long-Term Ecological Research (LTER) network, the Long-Term Agroecosystem Research (LTAR) network, and NEON, all of which include standardized observations of plant or landscape phenology across multiple observing platforms. We chose this site in part because it is well-instrumented, has a long history of applied and experimental research, and because interpretation of phenological processes is typically challenging in dryland ecosystems, especially those with strongly contrasting plant functional types.

Research at JER focuses on providing data, tools, and methods for understanding changes in grassland and shrubland ecosystems and for predicting the dynamics of future ecosystem states in response to changing climate and land use (Bestelmeyer et al., 2018; Browning et al., 2015). In this dryland system, knowledge of ecological structure and function (e.g., soil composition, biodiversity, carbon cycling) and applications such as land management (e.g., grazing practices, grassland restoration) benefit by understanding how phenological processes interact with meteorological and climatological conditions, at spatial scales ranging from individual plants to landscapes and at temporal scales ranging from days to decades (Browning et al., 2015). This example explores phenological patterns of co-existing grass and shrub plant functional groups at a range of spatial scales over a six-year period (2014–2020). The study area map with MODIS land cover classifications, the location of the PhenoCam sites, the ROIs for each PhenoCam field of view, and the MODIS pixel locations for the grassland and shrubland cover types are shown in Fig. 2.

### 4.2. Data acquisition and processing

The **rNPN** package was used to extract a time series of phenophase status and intensity for the warm-season bunchgrass black grama (*B. eriopoda*) and the deciduous shrub honey mesquite (*P. glandulosa*) at the JER study area (Fig. 2B). We used **phenoSynth** to extract time series of GCC from three PhenoCams based on ROIs focused on grass and shrub plant canopies within each PhenoCam viewshed (Fig. 2C). We also used **phenoSynth** to extract NDVI time series data from six contiguous MODIS pixels (to reduce interpixel variation caused by landscape heterogeneity), within shrubland or grassland vegetation types based on the MODIS landcover product, adjacent to two of the PhenoCam sites (Fig. 2B). For each site, we used **dacqre** to extract a time series of gridded climatological data (daily maximum temperature, daily precipitation). Finally, we fit the **Greenwave** model to the grassland and shrubland PhenoCam GCC and the MODIS NDVI time series. Additional information on data extraction and analysis for this case study are in the NASA Earthdata Bitbucket repository (https://git.earthdata.nasa.gov/projects/APIS/repos/pheno-synthesis-software-suite).

One drawback of using remotely sensed imagery for phenological research is the mixing of target and non-target signals within the relatively large footprint of the pixel (Henebry and de Beurs, 2013). In our case study, the signal in a MODIS pixel is a mix of photosynthetically active and senescent leaves from grasses and shrubs, woody material, and soil. The target-to-noise ratio is further diminished by artifacts including atmospheric constituents, sensor degradation, and viewing and illumination geometry. For the PhenoCam signal we were able to overcome or diminish these issues by using relatively narrow ROIs from the PhenoCams, and by aggregating multiple images collected each day to a 3-day product that minimizes the influence of variation in weather and illumination geometry on the retrieved phenological signal (Richardson et al., 2018; Sonnentag et al., 2012). There was no evidence of PhenoCam sensor degradation over the 6 years of observation, as baseline values were stable over time (Richardson et al., 2018).

### 4.3. Observed phenological patterns and related drivers in a dryland ecosystem

PS3 facilitated data access, extraction, compilation, integration, and analysis to enable a system-level assessment of phenological drivers and responses in a dryland ecosystem based on multi-scale, multi-platform

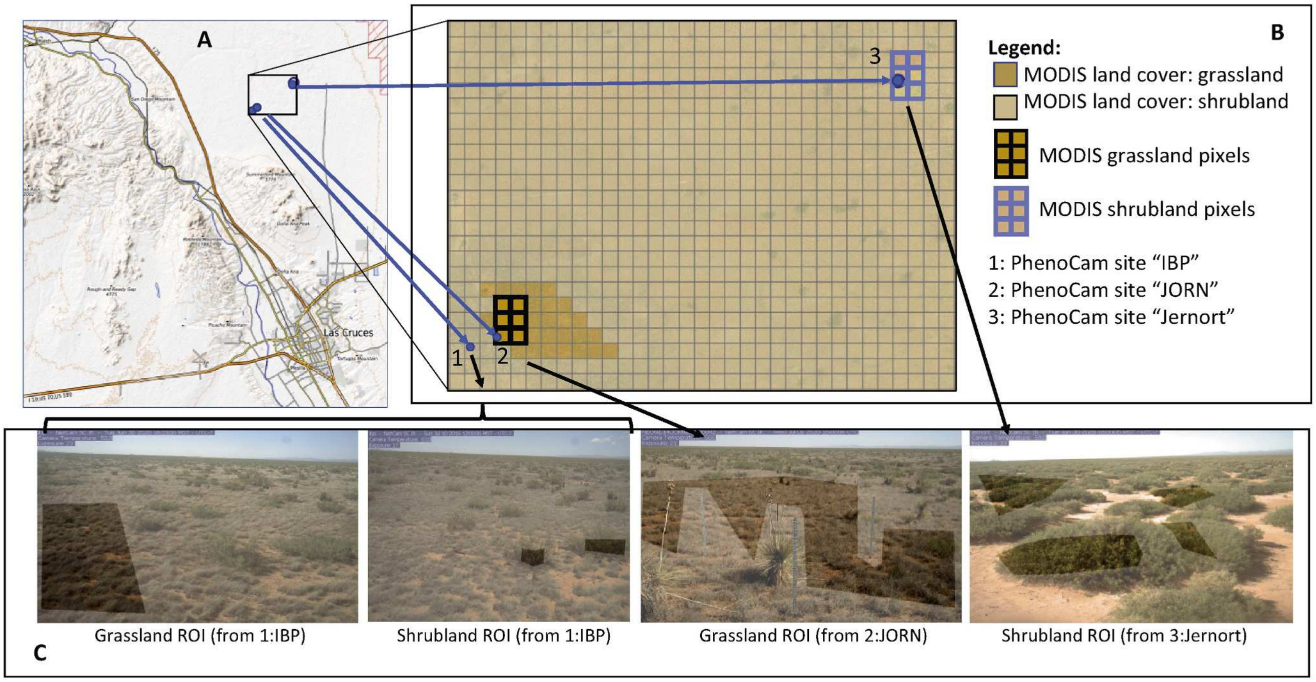


**Fig. 2.** A) Location of study area in New Mexico, USA; B) MODIS landcover classification, location of 3 PhenoCam sites, and position of MODIS pixels within each landcover type used for determination of NDVI; and C) representative PhenoCam images showing the grassland and shrubland ROI for determination of GCC.

phenological and climatological data (cf Browning et al., 2015). Concurrent consideration of each of the four datasets – in situ grass and shrub species canopy greenness estimates, near-surface grass and shrub canopy greenness response, satellite-based surface reflectance from grassland and shrubland cover types, and climatological trends – revealed nuances in phenological profiles for grasses and shrubs depending on temporal and spatial scales of observation and inference (Fig. 3).

All datasets demonstrated high interannual variability across the study period. However, interannual variability became less pronounced as the spatial resolution of time series decreased from field observations of individual species to near-surface imagery of canopies to satellite-

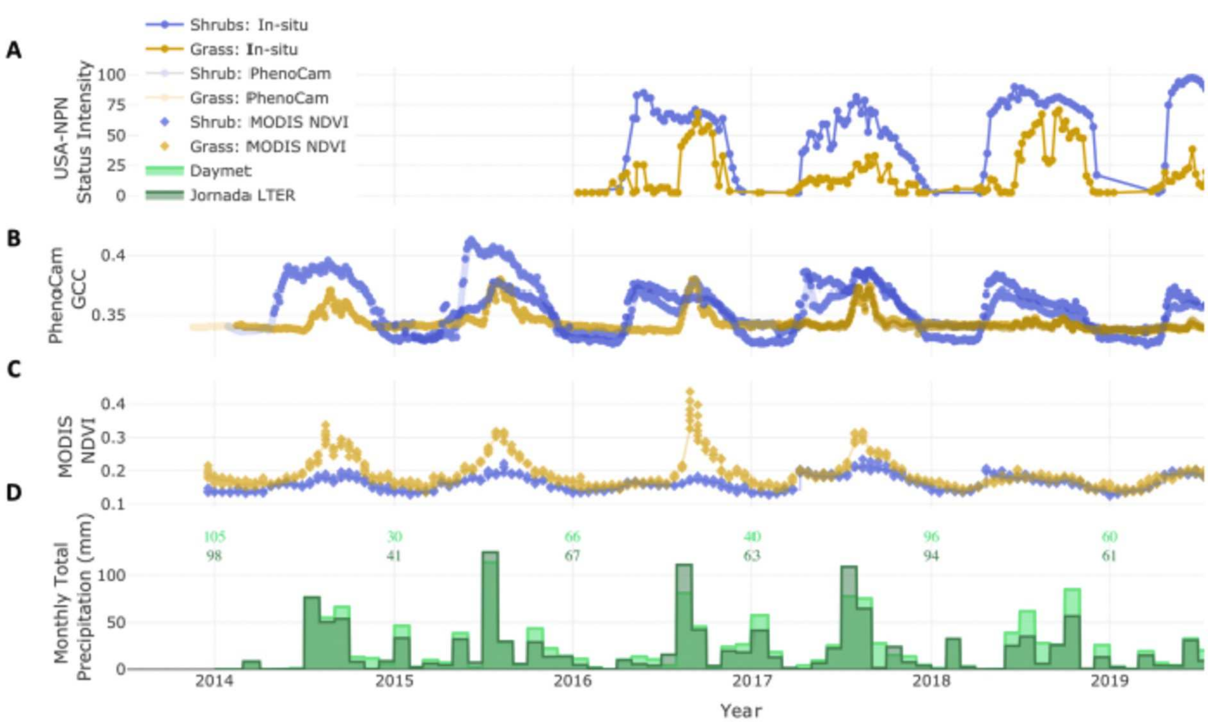


**Fig. 3.** Time series of mean (a) canopy greenness (%) for black grama (*B. eriopoda*; grass) and honey mesquite (*P. glandulosa*; shrub), (b) Green Chromatic Coordinate (GCC) for grass- and shrub-dominated Regions of Interest (ROI) from PhenoCams, (c) Normalized Difference Vegetation Index (NDVI) from MODIS for landcover types of grassland and shrubland, and (d) monthly accumulated precipitation estimated from Daymet and obtained from an in-situ precipitation gage (Jornada LTER). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

based imagery of land-cover types. At the highest resolution, differences in the pattern of responses for black grama and honey mesquite (Fig. 3A) confirm prior reports of the importance of growing-season (summer) precipitation (Fig. 3D) to photosynthetic activity of grasses at this site, whereas the photosynthetic activity of the deciduous shrubs is relatively consistent from year to year (e.g., Browning et al., 2015, 2017). Properties of grasses and shrubs with contrasting root morphologies, provide nuanced responses with respect to timing, duration and size of rainfall events and differences in soil texture and depth (Duniway et al., 2018). The multi-year time series of phenological data along with combined interpolated/gridded and in-situ precipitation (Fig. 3D) offer an opportunity to examine the pulse-reserve paradigm (Loik et al., 2004; Reynolds et al., 2004) at a broader context. In addition, PS3 data integration tools facilitate opportunities to examine the role of winter precipitation on mesquite patch dynamics in landscape change (Browning et al., 2012).

At a slightly lower resolution, GCC from PhenoCam ROIs (Fig. 3B) closely reflected patterns of greenness observed in individual shrub and grass canopies (Fig. 3A). The relatively muted response of grass ROIs in 2018 likely reflects patterns of precipitation in the relatively dry summer season that year (Fig. 3D). At our lowest resolution, NDVI from MODIS pixels (Fig. 3C) for both grass and shrub time series exhibited less temporal variability within any given growing season. For MODIS we also see a damping of the shrub time series which is likely to be a function of the amount of bare soil present in these pixels (Fig. 2).

Overall, the patterns discerned in Fig. 3 reflect differences in methods and scale of observations. Greenness of individual plant canopies may not scale to measures of greenness observed at the resolution of the PhenoCam (e.g., because of background effects) and especially satellite platforms (e.g., because of mixed composition of plant functional types in the pixel). This is illustrated in part by a divergence between grass canopy greenness in 2018 and 2019 relative to GCC and especially NDVI in those years. Early spring (March – May), and summer (July – September) precipitation in 2018 and 2019 were relatively low (Fig. 3D). Moreover, the number of consecutive dry days (with less than 1 mm of precipitation) was recorded as 95d from DAYMET (from day 70 to day 165) and 93d from local rain gage data (from day 70 to 163; Fig. 3D). This suggests that precipitation sufficient for individual plant greenup (Fig. 3A) may have been insufficient for a detectable greenup at the landscape scale (Fig. 3B and C).

We used the **Greenwave** modeling package to fit curves to one grassland and one shrub Phenocam time series, and to one grassland and one shrubland cover type MODIS time series (Fig. 4). The curves fit well, so for each platform and each vegetation type we evaluate three **Greenwave**-derived parameters likely to reflect important phenological transitions: day of year (DOY) for peak greenup, DOY for start of the

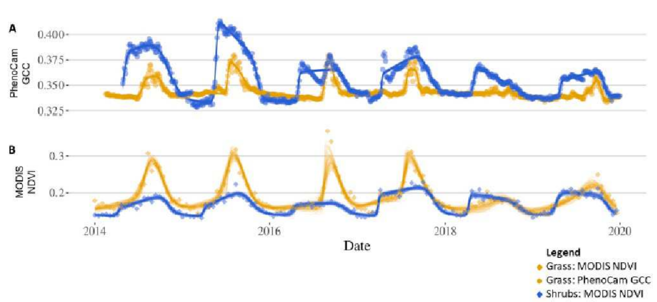


**Fig. 4.** Examples of Greenwave model fits to grass- (gold) and shrub-dominated (blue) sites using time series of vegetation indices from (A) PhenoCam and (B) MODIS. Model fits for all site-sensor combinations, as well as in- and out-of-sample predicted vs observed plots can be found in the code repository. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

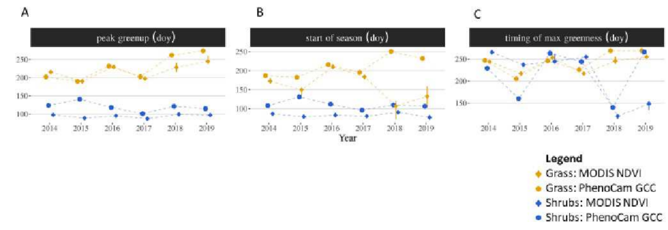


**Fig. 5.** Metrics of seasonality derived using the Greenwave model fits: a) day of the year (DOY) of peak greenup, b) day of the year for the start of the season, and c) day of the year for the timing of maximum greenness. The legend matched the colors and symbols using in Fig. 4.

growing season, and DOY for the time of maximum greenness (Fig. 5).

DOY for peak greenup differed between the plant functional types across all years and showed little dependence on scale (Fig. 5A). Peak greenup of shrubs was relatively consistent across years and was lagged by peak greenup of grasses by about 100d in 2014–2017. Peak greenup of grasses lagged shrubs by about 150d in 2018 and 2019, probably because of relatively low summer precipitation those years (Fig. 3D). DOY for start of season also differed between the two plant functional types and showed little dependence on the scale of observation until 2018 and 2019, again likely because of relatively low precipitation in the spring of these years (Fig. 5B, Fig. 3D). Here we see an interaction between phenological metrics and climate, and the degree to which these metrics responded to climate *depend on the scale of observations*. The drier conditions and lower dynamic range in the time series resulted in much earlier start of season dates from the MODIS time series. As one caveat, prior field observations indicate that grasses and shrubs generally initiate new growth at similar times, but that PhenoCam does not detect grass greenness until canopies reach ca. 25% canopy greenness (Browning et al., 2017); this may extend to MODIS as well. Finally, the timing of maximum greenness showed little difference between the plant functional types and relatively high interannual variability, especially for shrubs (Fig. 5C).

### 4.4. *Interpreting phenological patterns in dryland ecosystems*

The JER use case showcases challenges with detecting phenology in water-limited systems with modest to low vegetation cover (e.g., Smith et al., 2019) that are representative of many western U.S. rangelands (Spiegal et al., 2018). Land managers and producers in western rangelands seek timely and accurate forecasts for primary productivity at a variety of temporal scales (e.g., sub-seasonal to annual) depending on their application. Understanding what drives forage grass production and formulating models to generate seasonal productivity forecasts are high priorities to help producers better manage lands and livestock, fire, or for other management or planning purposes (e.g., conservation, acquisition, fire management). Insights from the use case described in Section 4 confirms and expands on insights from Browning et al. (2017). We confirmed reliability of honey mesquite phenology in wet and dry years, the tightly coupled pattern between black grama phenology and summer precipitation, and a lag in black grama canopy development discerned in the field and using PhenoCam. Inclusion of satellite imagery in our analysis expands on Browning et al. (2017) to indicate that there may be a baseline proportion of fractional cover necessary to detect land surface phenology in below-average rainfall years. Future research could work to identify cover thresholds for detection of LSP across heterogenous landscapes, or the degree to which observations scale across platforms along landscape to regional precipitation gradients.

## 5. Discussion

The PS3 tool suite provides streamlined access to multi-scale, multi-platform phenological data layers and ancillary climatological data layers, greatly reducing barriers to integration and analysis. The multi-scale nature of the data products, integrated with frequently used meteorological and climatological data products, provides an analysis-ready data package suitable for investigating phenological patterns at spatial scales ranging from canopies to communities to landscapes, at temporal scales from days to decades. As described in the following sections, PS3 not only supports data access and integration, but also supports applications related to phenological modeling and forecasting, understanding patterns and drivers of phenological activity in real-world ecosystems, and can support agricultural and natural resource management and decision-making.

### 5.1. Data accessibility and integration

The case study presented here suggest ways that PS3 can help realize synergy between otherwise disparate datasets to build a better understanding of how phenological processes relate to the spatial scale of the ecological system, the observation platform, and intra- and interannual variation in climatological drivers. This kind of analysis can also provide insight into the root causes of high vs. low agreement (e.g., landscape heterogeneity, representativeness) between fine-scale ground observations and coarse-scale remote sensing (Richardson et al., 2018). As the spatial and temporal resolution of satellite imagery continues to improve (e.g., PlanetScope, Harmonized Landsat-Sentinel), and as centimeter-scale imagery from low-flying unmanned aerial systems (UASs) becomes increasingly available, questions about how scale, resolution, and extent of observations affect estimated phenological transition dates and seasonal trajectories become increasingly relevant (Klosterman et al., 2018; Liu et al., 2019). PS3 helps lower a previously formidable barrier to empirical phenological analysis by harmonizing protocols within and across platforms, thereby enabling intercomparison of data from individual organisms (≈0.1–10 m) to satellite pixels (≈10–1000 m).

### 5.2. Phenological modeling and forecasting

The ability to integrate diverse phenological datasets—ground observations, near-surface remote sensing, and satellite remote sensing—and rigorous Bayesian model parameterization using PS3 also has the potential to advance the growing field of phenological modeling and forecasting. The **Greenwave** model presented here adds to the growing library of open-source phenology modeling packages that have been made publicly available in recent years (Ault et al., 2015; Hufkens et al., 2018; Senf et al., 2017; Taylor, 2018). Combined, the tools represented in the PS3 suite make it substantially easier for users lacking modeling and parameter optimization expertise to engage in phenological modeling, which is one avenue by which the environmental controls on vegetation phenology can be investigated.

Phenological models are typically calibrated to long-term or spatially extensive ground observations or experimental datasets (Hänninen et al., 2019). These models are increasingly being used to make predictions about how the nonlinear and potentially interacting effects of future climate change (e.g., rising temperatures, altered precipitation regimes) may impact the seasonality of vegetation in different ecosystems (Chen et al., 2016; Hufkens et al., 2016; White et al., 1997). Bayesian methods are now commonly used for phenological model calibration because this approach permits rigorous quantification of posterior parameter distributions with full characterization and propagation of uncertainties (Seyednasrollah et al., 2020; Shirley et al., 2020). Accounting for these uncertainties is particularly important when the calibrated models are used for forecasting.

A potential application of phenological models stems from potential integration with near-term weather forecasts to generate phenological forecasts that can be used to improve scientific understanding of modeled systems while informing land management decision-making (Bradford et al., 2020; Dietze et al., 2018; White and Nemani, 2006). Prototype systems that integrate phenological models with near-term weather forecasts have been developed for specific agricultural (Bourgeois et al., 2008) and pest management (Crimmins et al., 2020) applications. But, fully operational phenological forecasting systems, producing forecasts of a suite of phenological events at continental scale, remain scarce (Taylor and White, 2020). PS3 can contribute to the development of these systems, and the realization of broadscale phenological forecasts that can be used to inform resource management decision-making (Richardson et al., 2017).

### 5.3. Broader applications to natural resource management

The recognition that phenology is relevant to a variety of agricultural and natural resource management applications dates back at least 50 years (e.g., Lieth and Radford, 1971). First, there is a long history of using phenological models to predict the timing of growth and maturation of agricultural crops, which can improve the efficiency or effectiveness of management activities (Hodges, 1991). Phenological monitoring can also inform the timing of natural resource management activities, such as prescribed fire, herbicide applications, or livestock grazing (Browning et al., 2018; Enquist et al., 2014; Morellato et al., 2016). Similarly, **Greenwave** modeling may enable or improve seasonal forecasts of forage production important for optimal rotational grazing management. In sum, PS3 adds value by reducing barriers to data access, organization, integration and analysis, thus improving the potential for the production and delivery of actionable information to support natural resource decision-making.

## 6. Conclusion

This paper describes several phenologically-relevant datasets, derived from different platforms and available in native form at different spatial and temporal scales. The suite of tools described as PS3 is meant to facilitate easier and more automated access to these data streams. While a more thorough analysis of dryland ecology is outside the scope of this paper, the example presented here demonstrates how the software can be used to compile and analyze information across a range of spatial and temporal scales over multiple years that exhibit heterogeneous climatological conditions. The open-source PS3 will enable researchers to explore such processes in different locations and with more in-depth investigations into what drives phenology at different scales and in different ecosystems. It thus addresses a previously identified need to develop tools to facilitate cross-scale phenological data integration and modeling (Richardson et al., 2017), which can contribute to better management of natural resources in a changing world.

## Author contributions

JTM: Supervision, Conceptualization, Formal analysis, Investigation, Writing – Original Draft, Review, and Editing, Funding acquisition.

KAD: Software, Data Curation, Visualization, Validation, Writing - original draft, Writing – Review & Editing.

JFW: Conceptualization, Funding acquisition, Writing - original draft; Writing - review & editing.

DMB: Conceptualization, Writing - original draft; Writing - review & editing.

RLM: Conceptualization, Data Curation, Software Development.

AMF: Data Curation, Project administration, Writing - review & editing.

LJZ: Conceptualization, Methodology, Software, Formal analysis, Writing - Review & Editing, Visualization.

KDE: Software, Data Curation, Visualization, Validation.

VAL: Conceptualization, Methodology, Software, Writing – original draft; Writing – review & editing.

KLG: Conceptualization, Data Curation, Writing – original draft;

Writing – review & editing.

TMC: Conceptualization, Writing - original draft; Writing - review & editing.

KJ: Conceptualization, Data Curation.

TC: Software, Validation, Data Curation.

BWM: Conceptualization, Writing – Original Draft, Writing – Review and Editing, Funding acquisition.

TM: Conceptualization, Data Curation, Project administration, Funding acquisition.

ADR: Conceptualization, Investigation, Writing – Original Draft, Review, and Editing, Funding acquisition.

NOTE: This draft manuscript is distributed solely for purposes of scientific peer review. Its content is deliberative and predecisional, so it must not be disclosed or released by reviewers. Because the manuscript has not yet been approved for publication by the U.S. Geological Survey (USGS) or U.S. Department of Agriculture (USDA), it does not represent any official USGS or USDA finding or policy.

## Declaration of Competing Interest

None.

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## Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ecoinf.2021.101400.

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