

Solar and sensor geometry, not vegetation response, drive satellite NDVI phenology in widespread ecosystems of the western United States

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Abstract

Satellite-derived phenology metrics are valuable tools for understanding broad-scale patterns and changes in vegetated landscapes over time. However, the extraction and interpretation of phenology in ecosystems with subtle growth dynamics can be challenging. US National Park Service monitoring of evergreen pinyon-juniper ecosystems in the western US revealed an unexpected winter-peaking phenological pattern in normalized difference vegetation index (NDVI) time-series derived from Moderate Resolution Imaging Spectroradiometer (MODIS) imagery. In this paper, we assess the validity of the winter peaks through ground-based observation of phenology and examination of solar and satellite geometry effects. To test the premise of a true vegetation response, we analyzed NDVI values extracted from a time series of ground-based digital camera ('phenocam') images collected September 2017 to December 2018 in a pinyon-juniper woodland in Arizona, US. Results show pinyon and juniper growth peaked in the warm season, as did the other species in the phenocam field of view. NDVI time series from four other sensors (Landsat 7, Sentinel-2, VIIRS, and Proba-V) confirmed that winter peaks in this ecosystem are not limited to MODIS products. Examination of NDVI time series (2003-2018) derived from daily 250-m MODIS data in the broader pinyon-juniper ecosystem revealed that solar-to-sensor angle, sensor zenith angle, and forward/back-scatter reflectance explained >80% of intra-annual variability. Solar-to-sensor angle exerted the greatest control, and the direction of its correlation (positive) was the opposite of that which would be expected if it were driven by vegetation greenness. Solar-to-sensor angle is controlled seasonally by solar zenith angle and daily by variations in satellite overpass geometry. We mapped winter peaks across the western US in Google Earth Engine using 500-m MODIS MCD43A4 data, which correct for reflectance differences caused by view angle. In areas where winter vegetation peaks are ecologically improbable (i.e., locations with sub-freezing December temperatures), consistent

winter peaks (≥ 14 years in 2003 to 2018) are widespread in both pinyon-juniper and non-pinyon-juniper conifer ecosystems; winter peaks are common (≥ 5 years in 2003 to 2018) across areas of shrubland. We attribute winter peaks to the positive correlation of NDVI with solar-to-sensor angle and solar zenith angle in combination with sparse, vertically oriented evergreen vegetation canopies. Increasing shadow visibility has been shown to increase overall NDVI, and the prevalence of the winter peaking in evergreen western sparse canopy ecosystems is consistent with this hypothesis. The extent of winter peaking patterns may have been previously overlooked due to temporal compositing, curve fitting, and incomplete snow screening.

Keywords: phenology; MODIS; NDVI; phenocam; pinyon-juniper; Google Earth Engine; Landsat; Sentinel; VIIRS

1. Introduction

Temporal, spatial, and taxonomic patterns in plant phenology provide keys to understanding how ecosystems interact with climate, assessing systemic vulnerabilities, and measuring climate change in ecologically relevant terms. The tight coupling of phenology with climate (Cleland et al., 2007; Lieth, 1974) and its usefulness for tracking species-level trends in vegetation composition and abundance (Bradley, 2014; Wallace et al., 2016) make phenology a critical component of ecological monitoring efforts. In the US National Park Service (NPS), phenometrics derived from satellite data (i.e., Land Surface Phenology (LSP); Reed et al., 2009; White et al., 2009) have emerged as valuable tools for tracking climate-forced ecosystem changes. The NPS employs field-based phenology and LSP measures to identify deviations from ecological baselines and to guide management decisions in a variety of park ecosystems (Miller-Rushing et al., 2011), such as the pinyon-juniper ecosystem currently monitored at Grand Canyon

National Park (GCNP-PJ). Most of the 289 natural resource parks in the NPS Inventory & Monitoring Program are now at the extreme warm end of their historical (1901-2012) temperature distributions, and are projected to experience continued warming and precipitation changes in the future (Monahan et al., 2016). Information about coupled climate-phenology response allows resource managers to, for example, identify the most effective time to apply herbicides on invasive species (Wallace et al., 2016), model and anticipate mule deer migration and reproductive success (Stoner et al., 2016), and predict the timing of signature park events such as wildflower blooms (Miller-Rushing et al., 2011).

Synoptic, broad-scale LSP measures are most useful when they can be linked to well-characterized and ecologically relevant biophysical phenomena. In deciduous ecosystems, the contrast between seasonal leaf-on and leaf-off conditions is represented as distinct changes in satellite-derived greenness measures. The timing of these transitions (i.e., “start of season” and “end of season”) are convenient temporal benchmarks for quantifying the effect of warming temperatures on the initiation and length of growing seasons around the globe (e.g., Badeck et al., 2004). Analogous extractions of phenometrics from evergreen reflectance profiles are challenging because of the lack of pronounced seasonal cycles in canopy biomass. Cloud cover and satellite noise can mask the more subtle variations in coniferous vegetation signals (Hmimina et al., 2013; Moulin et al., 1997; Zhang et al., 2006) and extrinsic phenomena such as snow seasonality in boreal forests can obscure green-up and senescence timing (Jin et al., 2017; Jönsson et al., 2010; Walther et al., 2016).

Patterns in reflectance are also controlled by the complex interplay of solar zenith angle, sensor view angle, and forward/back-scatter view (i.e., sensor azimuthal relation to the sun) with the

non-Lambertian reflective character of vegetated surfaces (Colwell, 1974; Middleton, 1992; Ranson et al., 1986). The quantitative summary of canopy reflection parameters under solar-sensor geometry conditions is given by the bidirectional reflectance distribution function (BRDF) (Bréon and Vermote, 2012; Huete et al., 1992). Numerous studies have documented the effects of these factors on measured spectral reflectance from vegetation canopies, with sometimes asymmetrical responses about nadir or conflicting directions of correlation caused by different vegetation canopy textures, correlated aspects such as atmospheric haze with solar zenith angle, spectral range, and how closely the field of view was restricted to nadir (Berglund and Mace Jr, 1976; Middleton, 1992). Increased solar zenith angles result in greater proportions of shaded vegetation within the sensor field of view. The higher sensitivity of red wavelengths than near-infrared (NIR) to changing fractions of sunlit and shaded vegetation (Walter-Shea et al., 1997) means that shaded areas affect the widely used normalized difference vegetation index (NDVI) (Tucker, 1979):

$$(\rho_{NIR} - \rho_{red})/(\rho_{NIR} + \rho_{red}) \quad (1)$$

where ρ_{NIR} is reflectance in the NIR band, and ρ_{red} is reflectance in the red band. Although the overall magnitudes of both red and NIR reflectance decrease when highly layered green vegetation intercepts incident light, the NIR reflectance drops proportionally less (Gao et al., 2000; Ranson et al., 1986). The result is that NDVI values are generally higher at increased solar zenith angle, given the increase in vegetation shadows and interactions with soil (Fensholt et al., 2010; Huete et al., 1992; Park, 2013; Zhang et al., 2015).

The azimuthal relation of the sensor to the sun is another contributing factor to the anisotropic behavior of canopy reflectances. Forward and back scatter describe situations in which the sensor view either opposes or is aligned with the incident illumination, respectively. Under forward-

scatter conditions the sensor perceives a more heavily shaded landscape. Spectral path lengths through the canopy are also longer, leading to increased absorption of red wavelengths relative to NIR and higher NDVI (Middleton, 1992). Conversely, the more directly illuminated vegetation layers viewed under back-scatter conditions yield lower NDVI values (Ranson et al., 1986). Individual plant structure and/or density of overall vegetation canopy are controlling factors on the magnitude of this effect. Sparser vegetation canopies also show a more pronounced backscattering effect due to the greater exposure of the soil background (Kimes, 1983; Walter-Shea et al., 1992). Huete et al. (1992) tested solar and sensor angle effects using a ground-based system in a southern Arizona (US) grassland; they found that back scatter resulted in increased NDVI for a given solar angle. Numerous subsequent studies have confirmed the dependence of reflectances or derived vegetation indices on solar angle, sensor angle, and background reflectance (e.g., Bhandari et al., 2011; Fensholt et al., 2010; Goodin et al., 2004; Myneni et al., 1995; van Leeuwen et al., 1999) and quantified the extent to which the effects were mediated by vegetation type (Walter-Shea et al., 1992), canopy density (Kimes, 1983; Ma et al., 2019; Walter-Shea et al., 1992; Walter-Shea et al., 1997), and vegetation index (Bhandari et al., 2011; Moura et al., 2012; Sims et al., 2011; Yang et al., 2012).

This paper explores the validity of phenometrics extracted from a largely evergreen, semiarid ecosystem for natural resource monitoring purposes. The NPS Southern Colorado Plateau Network (SCPN) collects species-specific vegetation monitoring data in more than 400 plots across 15 ecosystems to identify trends in vegetation (DeCoster et al., 2012) and uses remote sensing data to identify phenology trends in 19 arid and semiarid park units across the southwestern US (Thoma et al., 2017). SCPN derives LSP phenometrics (e.g., timing and amplitude of annual and seasonal peak values) from time series of daily 250-m MODIS Aqua and

Terra NDVI data per network imagery protocols (Norris, 2020). In dryland areas, precipitation patterns influence the strength and timing of herbaceous response (Breshears and Barnes, 1999; Rich et al., 2008). Many of the SCPN ecosystems of interest display NDVI patterns that are consistent with moisture-driven growth cycles: low cold-season (November - March) NDVI, marked spring green-up, and flat or decreasing NDVI until a late-summer increase due to monsoonal rains (Thoma et al., 2017). In contrast, the GCNP-PJ ecosystem shows an unusual pattern of consistent cold-season NDVI peaks, implying a surge of plant productivity and greenness during the winter (Fig. 1). Examination of MODIS-NDVI patterns at point locations within pinyon-juniper and ecologically similar ecosystems on the Colorado Plateau revealed similar patterns of varying consistency throughout the MODIS era. This phenomenon has been observed previously in other satellite-data time series. Walker et al. (2012, 2014) identified unusually late peaks in MODIS-based observations in pinyon-juniper and higher elevation ponderosa pine (*Pinus ponderosa*) ecosystems in central Arizona. Snyder et al. (2019) observed Landsat-derived winter NDVI peaks in a pinyon-juniper woodland in central Nevada; these patterns conflicted with the warm-season NDVI peaks derived from repeat photography collected by a networked digital camera (hereafter “phenocam”; Richardson et al., 2009; Sonnentag et al., 2012) in the same ecosystem. Huang et al. (2009) presented MODIS-derived NDVI data for pinyon-juniper ecosystems across northern Arizona and southern Utah that clearly displayed early or late annual peaks. None of the studies accounted for the idiosyncratic phenological behavior of the pinyon-juniper class.

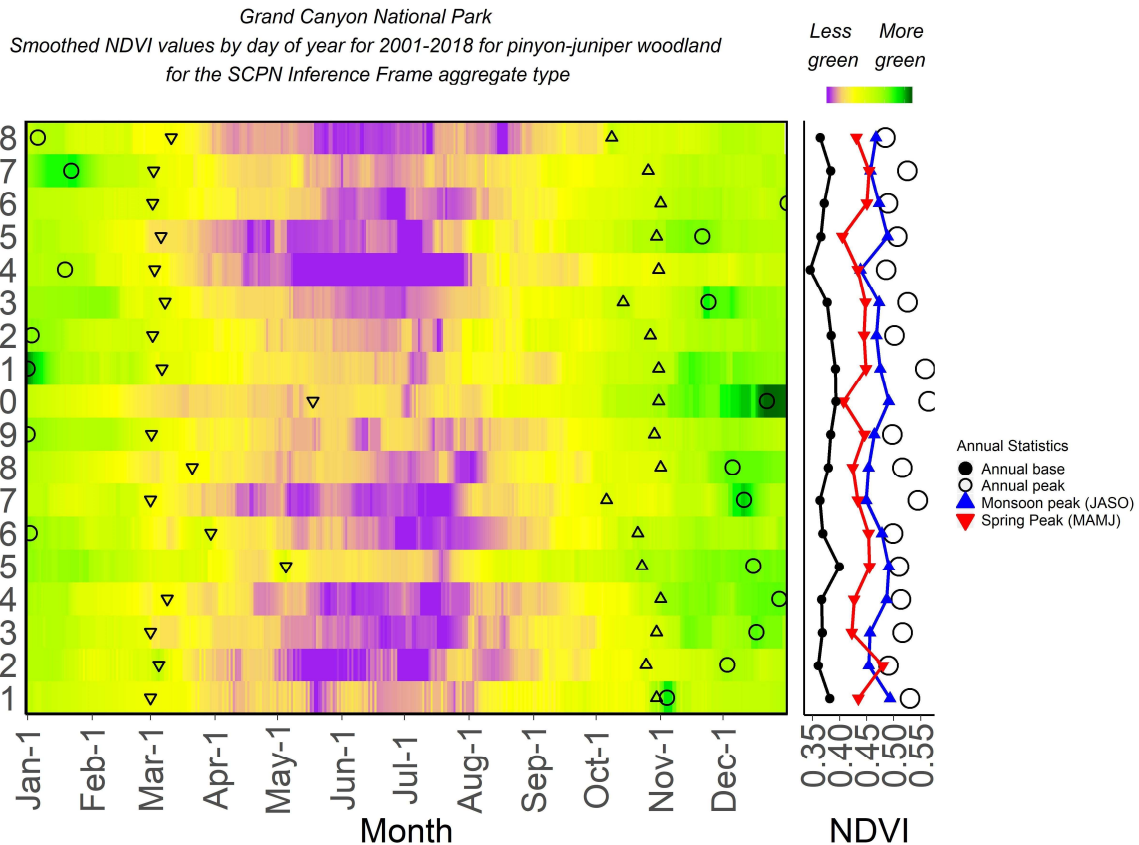


Figure 1. Winter-peaking NDVI phenology observed in the Southern Colorado Plateau Network (SCPN) Grand Canyon pinyon-juniper ecosystem sampling frame, 2001 to 2018. Heatmap shows the intensity and duration of median frame greenness as approximated by NDVI. Marginal plot shows annual, monsoon season (July to October), and spring (March to June) NDVI peaks for each year. Median-smoothed values are derived from daily 250-m MODIS Aqua and Terra imagery (MxD09 product). SCPN methods interpolate between larger gaps of missing values, which most commonly occur during winter due to snow and increased cloud cover. Reprinted from Norris (2020).

The driving force behind the cold-season NDVI peaks is not inherently obvious. Solar and sensor geometry effects are plausible explanatory factors given the wide angle ($\pm 55^\circ$ cross-track) of MODIS viewing properties (van Leeuwen et al., 1999) and the general synchrony of the documented NDVI winter peaks with the lowest solar angles of the year. Nonetheless, the dearth of information about dryland species phenology (Adams et al., 2015) made it ill-advised to

unequivocally rule out a genuine cold-season peak from one or more plant species in the pinyon-juniper ecosystem. Field-based phenological data are not commonly collected for evergreen species because of the subtlety of growth and the lack of visible differences between photosynthetically active and quiescent vegetation. An exception is Snyder et al. (2016), who collected phenocam images in a pinyon-juniper ecosystem in Nevada over the course of a calendar year to determine if pinyon and juniper canopies were phenologically separable. Although the species displayed minimal overall variation in greenness, each showed a clear summer peak. Two field-based studies of juniper phenology were less conclusive about late-season growth because measurements were not made during the winter months (Adams et al., 2015; Herman, 1956). At least one coniferous species has been observed to continue needle and shoot growth throughout the fall (Gaylord et al., 2007), which is a cautionary note for the assumption that growth is limited to warmer months.

Given the possible causes of winter peaks in NDVI, we considered two primary hypotheses:

- 1) At least one species in the GCNP-PJ ecosystem has a peak winter-greening phenological pattern, either in foliage or expressed through a cone, flower, or fruit production that in its reflectance mimics peak winter greening; i.e., *true phenological peak or mimic of winter green*
- 2) Solar-sensor geometry during the winter interacts with the overall mixed canopy height of the woodland structure to increase the NDVI; i.e., *solar angle artifact driven by vegetation structure and forward/back scattering of solar illumination*

The primary objective of this study was to determine the proximate cause of cold-season peaks in the GCNP-PJ ecosystem. We tested the hypotheses using both ground-based and satellite-derived phenology data. To track species-specific phenologies, we installed a phenocam in a representative pinyon-juniper ecosystem and monitored individual plant growth for 16 months,

which included two fall/winter periods. To address the solar-sensor geometry hypothesis, we examined relationships between phenocam-derived NDVI and solar and satellite sensor azimuth and zenith angles. We considered forward/back-scatter influences on both MODIS NDVI data and phenocam NDVI data. We also examined the NDVI patterns of shadowed areas using the phenocam and considered overall reflectance of those areas compared to the integrated signal of the entire terrestrial field of view. Finally, we mapped the occurrence of winter peaks across the continental US West to determine the extent to which this phenomenon can be linked to particular vegetation communities.

2. Methods

2.1 Study site

Ground-based and satellite data were collected within the GCNP-PJ sampling frame located in Grand Canyon National Park (GCNP), Arizona, USA (Fig. 2). The sampling frame (5,598 ha) lies between 1,950–2,050 m elevation on a plateau that descends sharply 1,300 vertical meters to the Colorado River and forms the southern rim of the Grand Canyon. The climate is semiarid, with 38.6 cm of annual precipitation (PRISM Climate Group, 2019) arriving in a predominantly bimodal pattern of winter snow and late-summer rains as part of the North American monsoon (Adams and Comrie, 1997). Seasonal temperatures range from average daily minimum temperatures of -6.3°C in December to average daily maximum temperatures of 30.5°C in July (PRISM Climate Group, 2019). Estimates of vegetation cover by species are obtained from 30 long-term monitoring plots established by the NPS-SCPN within the frame. Pinyon-juniper foliar cover in the plots averaged 37% during the 2010–2018 monitoring period, with 75% of the pinyon-juniper basal area contributed by Utah juniper (*Juniperus osteosperma*) and 25% by twoneedle pinyon (*Pinus edulis*), both evergreen woody species. Understory (non-pinyon-juniper) species averaged 8.3% foliar cover and were dominated by nearly equal cover of the perennial

grass blue grama (*Bouteloua gracilis*) and the evergreen shrub Stansbury cliffrose (*Purshia stansburiana*). Other common species in this ecosystem include muttongrass (*Poa fendleriana*), big sagebrush (*Artemisia tridentata*), prickly pear species (*Opuntia* spp.), broom snakeweed (*Gutierrezia sarothrae*), and Fremont's mahonia (*Berberis fremontii*) (Southern Colorado Plateau Network, 2018).

2.2 Phenocam installation and operation

In late August 2017 we installed a 5-megapixel Stardot NetCam IR phenocam in the GCNP-PJ sampling frame (Fig. 2). This camera is the standard model used by the PhenoCam network and provides phenological data consistent with data obtained from spectroradiometers (Petach et al., 2014). The site was chosen to conform to NPS requirements, SCPN ecological priorities, and recommended PhenoCam Network specifications (Richardson et al., 2009; Richardson et al., 2007, https://phenocam.sr.unh.edu/pdf/PhenoCam_Install_Instructions.pdf) for optimal placement: it is within the inference area of the target pinyon-juniper ecosystem monitored by the SCPN (DeCoster et al., 2012), but outside GCNP-designated potential wilderness; has reliable cellular coverage for transmitting image data; is relatively secluded; and has a field of view that includes multiple pinyon and juniper individuals. The camera faces north-northwest and is mounted 2.5 m above the ground surface.

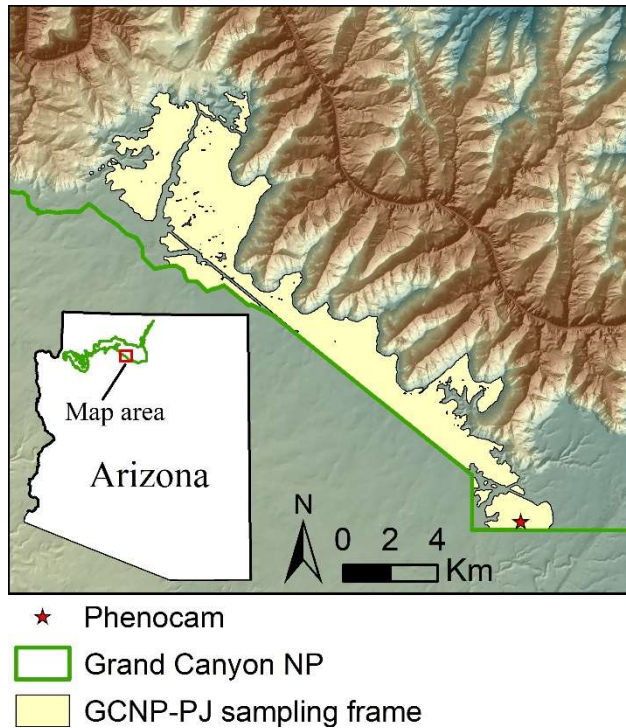


Figure 2. Location of phenocam site (latitude 36.02°, longitude -112.22°, datum: WGS84) within the Southern Colorado Plateau Network pinyon-juniper ecosystem sampling frame at Grand Canyon National Park, Arizona. Basemap derived from the National Elevation Dataset (<https://catalog.data.gov/dataset/usgs-national-elevation-dataset-ned>)

We set the phenocam to record true color (RGB) and NIR photo pairs with a fixed white balance and a resolution of 1296 x 960 pixels every 30 minutes from ~09:15 to ~15:45 local time. Although the exact wavelength specifications for the camera bands are not available, Petach et al (2014) used iterative testing across a range of wavelengths to compare spectroradiometer reflectances to the Stardot NC IR camera digital numbers and found the best correlation for the red band at 575-710 nm and the IR band at 800-815 nm. Date, time, and image exposure are recorded onto each photo image, which is transmitted by cellular connection to the PhenoCam Network public archive (<https://phenocam.sr.unh.edu/webcam/sites/grca1pj/>) (Milliman et al., 2019, Richardson et al., 2018). For nine months of the ~16-month phenocam record, conditions

were unusually warm and dry (see electronic supplement).

2.3 Phenocam image processing

Processing phenocam images broadly consists of (1) downloading images, (2) delineating regions of interest (ROIs), (3) calculating NDVI for each ROI, (4) filtering (e.g. removing cloudy sky values) and (5) grouping (e.g. by time of day) (Fig. 3). Phenocam images for the GCNP-PJ site were retrieved from the PhenoCam Network. We performed ROI delineation, exposure adjustment, and NDVI calculations in the statistical software package R (v3.6.0) (R Core Team, 2019) with the “phenopix” library (Filippa et al., 2016, 2017). Within the camera field of view, we delineated eleven ROIs (Fig. 4). We chose nine species-specific ROIs to monitor the individual green-up and senescence patterns of five woody species common within the GCNP-PJ ecosystem: twoneedle pinyon, Utah juniper, big sagebrush, Stansbury cliffrose, and desert sweet (*Chamaebatiaria millefolium*). All of these species except for the desert sweet are evergreen (USDA-NRCS, 2020). We also created an ROI of sky to allow screening of cloudy and low sun angle images and an ROI comprising the area below the horizon to approximate how ecosystem compositing might affect reflectance values.

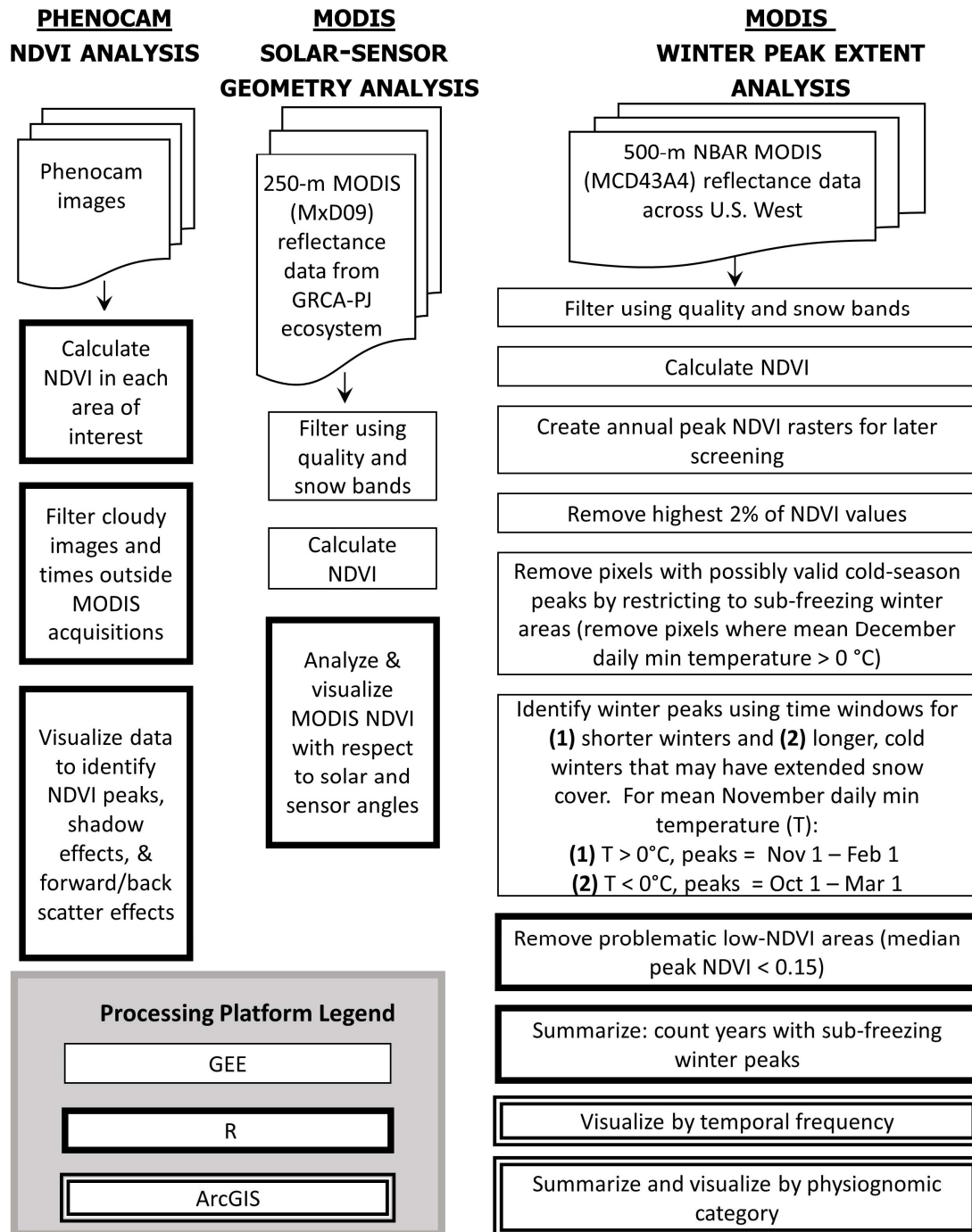


Figure 3. Overview of processing scheme for the analysis of phenocam and MODIS data.

We calculated the exposure-adjusted NDVI of each ROI for all photos taken between August 26th, 2017, and December 31st, 2018, following Petach et al. (2014). Exposure adjustment is necessary to obtain corrected brightness levels because the camera adjusts each image's exposure

according to the light levels in the field of view. The exposure printed onto the corner of each image is used to correct the brightness values, as follows:

$$NIR_E = \frac{NIR}{\sqrt{Ex_{NIR}}} \quad (2)$$

$$Red_E = \frac{Red}{\sqrt{Ex_{RGB}}} \quad (3)$$

where NIR_E and Red_E , are exposure-adjusted digital numbers and NIR and Red are raw digital numbers for the near-infrared and red bands, respectively, and Ex_{NIR} and Ex_{RGB} are image exposures for the NIR and true-color images, respectively. These adjusted digital numbers serve as the basis for the camera NDVI calculation:

$$NDVI_C = \frac{NIR_E - Red_E}{NIR_E + Red_E} \quad (4)$$

where $NDVI_C$ is the camera-NDVI, and all other variables follow the designations of equations 2 and 3. This method was described and tested by Petach et al. (2014), who also used a Stardot NetCam IR. They found that the phenocam measurements had a strong linear correlation with spectroradiometer-derived red reflectance ($r = 0.88$), near infrared reflectance ($r = 0.96$) and NDVI ($r = 0.95$). However, the exposure compensation results in negatively shifted NDVI values such that vegetated areas can have NDVI values below zero (Petach et al., 2014). It is possible to calculate corrected NDVI values that fall within the standard range, but that would require either spectroradiometer data or accurate NDVI data from satellites (e.g. Filippa et al., 2018).

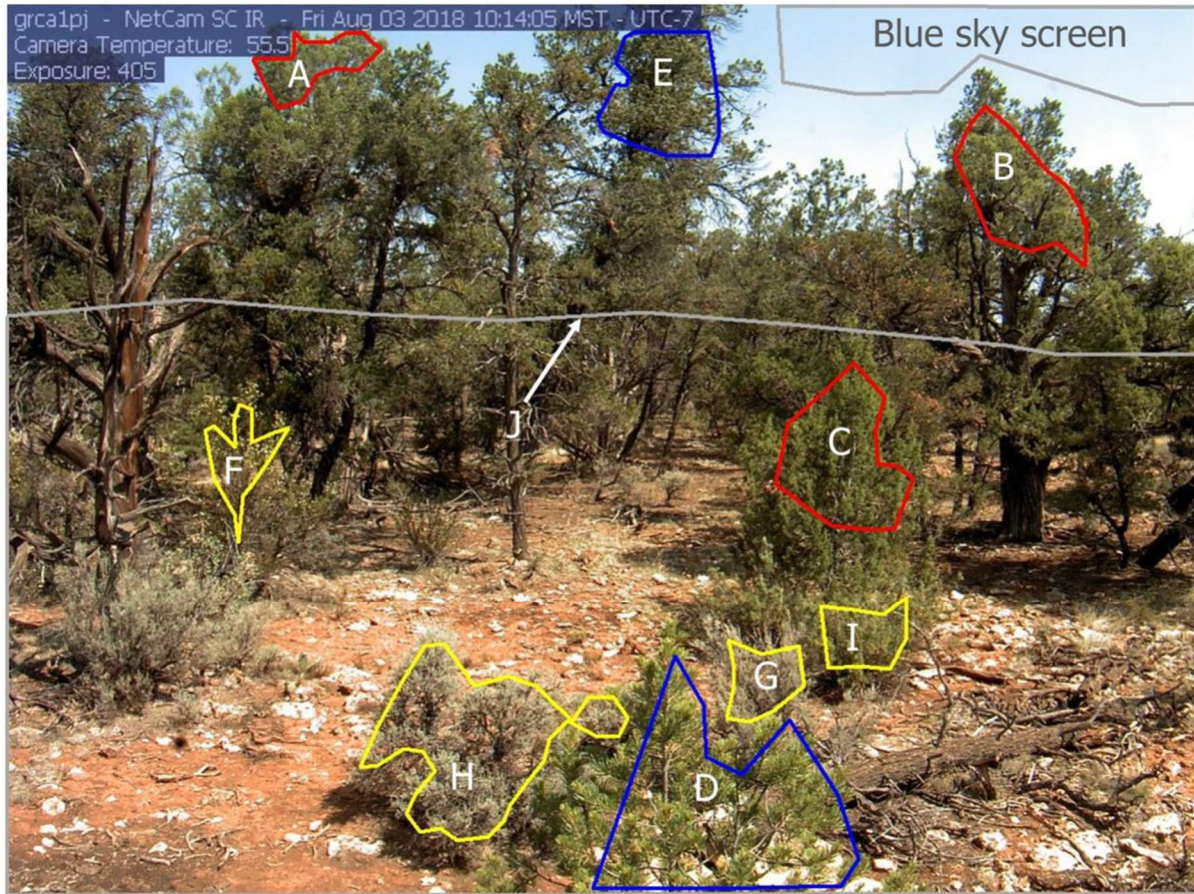


Figure 4. Example phenocam image with outlined species-specific, sky, and composite regions of interest. Labels correspond to NDVI curves in Figure 7; outline colors correspond to juniper (red), pinyon (blue), and other species (yellow). The composite area comprises the field of view beneath the approximate horizon line labelled 'J' (gray).

2.3.1 Linking phenocam data with MODIS conditions

To better compare the phenocam and satellite response patterns, we kept only phenocam photos taken during the approximate time windows of the MODIS satellite overpasses (i.e., 10-11am (Terra) and 1-2pm (Aqua)). We also aligned the phenocam data with clear-sky satellite imagery by applying a conservative screen to the sky ROI to identify and remove photos with cloudy sky conditions (Norris and Walker, 2020). We determined the parameters of the cloudy sky screen by identifying red, green, and blue value limits for several true-color, clear-sky photos

and testing those limits against additional photos. Removing cloudy-sky images also provides cleaner phenological signals (O'Connell and Alber, 2016; Sonnentag et al., 2012), making it easier to identify seasonal peaks in NDVI. In ecosystems with winter snowfall, it may be useful to also screen photos by snow cover. We did not screen for snow because few (<15) photos showed such effects.

2.4 MODIS image processing

2.4.1 Solar-sensor geometry analysis

To explore the relationship between NDVI and solar-sensor geometry, we calculated NDVI from daily 250-m MODIS Aqua and Terra reflectance data (Table 1) for the pixel that contained the phenocam location as well as for all pixels in which $\geq 80\%$ of the pixel area was covered by the GCNP-PJ ecosystem. We used the MxD09GQ MODIS product, which provides atmospherically corrected surface reflectance without Nadir BRDF-adjusted Reflectance (NBAR) corrections and thus maintains information about solar and sensor angles. We used Google Earth Engine (GEE) (Gorelick et al., 2017) to calculate NDVI and to retain only the highest quality, non-snow-affected terrestrial values (state_1km value = 72), following NPS-SCPN protocol (Norris, 2020).

265 Table 1. MODIS products and bands used in solar-sensor geometry and winter peak extent analyses.

Purpose	Aqua product name and identifier	Terra product name and identifier	Band(s) used	Pixel size at nadir
Solar-sensor geometry analysis				
NDVI generation	Surface Reflectance Daily L2G Global 250m MYD09GQ.006	Surface Reflectance Daily L2G Global 250m MOD09GQ.006	Band 1 (Red) Band 2 (Near infrared)	250 m
Quality control screening and solar and sensor angle values	Surface Reflectance Daily L2G Global 1 km and 500 m MYD09GA.006	Surface Reflectance Daily L2G Global 1 km and 500 m MOD09GA.006	State_1km, SensorZenith, SolarZenith, SensorAzimuth, SolarAzimuth	1 km
Winter peak extent analysis				
NDVI generation	Terra and Aqua Nadir BRDF-Adjusted Reflectance Daily L3 Global 500 m MCD43A4.006		Nadir_Reflectance_Band1 Nadir_Reflectance_Band2	500 m
Quality control screening fields	Terra and Aqua Nadir BRDF-Adjusted Reflectance Daily L3 Global 500 m MCD43A4.006 and MCD43A2.006		BRDF_Albedo_Band_Mandatory_Quality_Band, 1-7 (MCD43A4) and Snow_BRDF_Albedo (MCD43A2)	500 m

266 We examined the interactions of several solar-sensor geometry variables with NDVI: solar
 267 azimuth, sensor azimuth, solar zenith, sensor zenith, the angle between the sun and sensor, and
 268 reflectance type (forward/back scatter) (Fig. 5). The angle between the sun and sensor (solar-to-
 269 sensor angle) was calculated as

270
$$SSA = \cos^{-1}((\sin(SnZA) * \sin(SoZA) * \cos(SoAz - SnAz)) + (\cos(SnZA) * \cos(SoZA))) \quad (5)$$

271 with solar-to-sensor angle = **SSA**, sensor zenith angle = **SnZA**, solar zenith angle = **SoZA**, solar
 272 azimuth angle = **SoAz**, and sensor azimuth angle = **SnAz**.

273 Definitions of forward-scatter and back-scatter condition vary by researcher and by whether the
 274 research is being conducted using ground- or satellite-based measurements (e.g., Fensholt et al.,
 275 2006, Horváth et al., 2014, Kimes, 1983). We differentiate forward scatter and back scatter by

276 whether light reflected from the surface crosses a vertical, north-south plane. MODIS solar and
277 sensor azimuths are reported as angles in either a positive (eastward) or negative (westward)
278 direction. Back scatter occurs when the two azimuths are of the same sign (both eastward or both
279 westward). Forward scatter occurs when the two azimuths are of different signs (one eastward
280 and one westward). This binary definition of forward/back scatter does not adequately address the
281 degree of severity of the forward/back-scatter condition; however, it proves useful when used in
282 combination with other solar-sensor geometry measures.
283

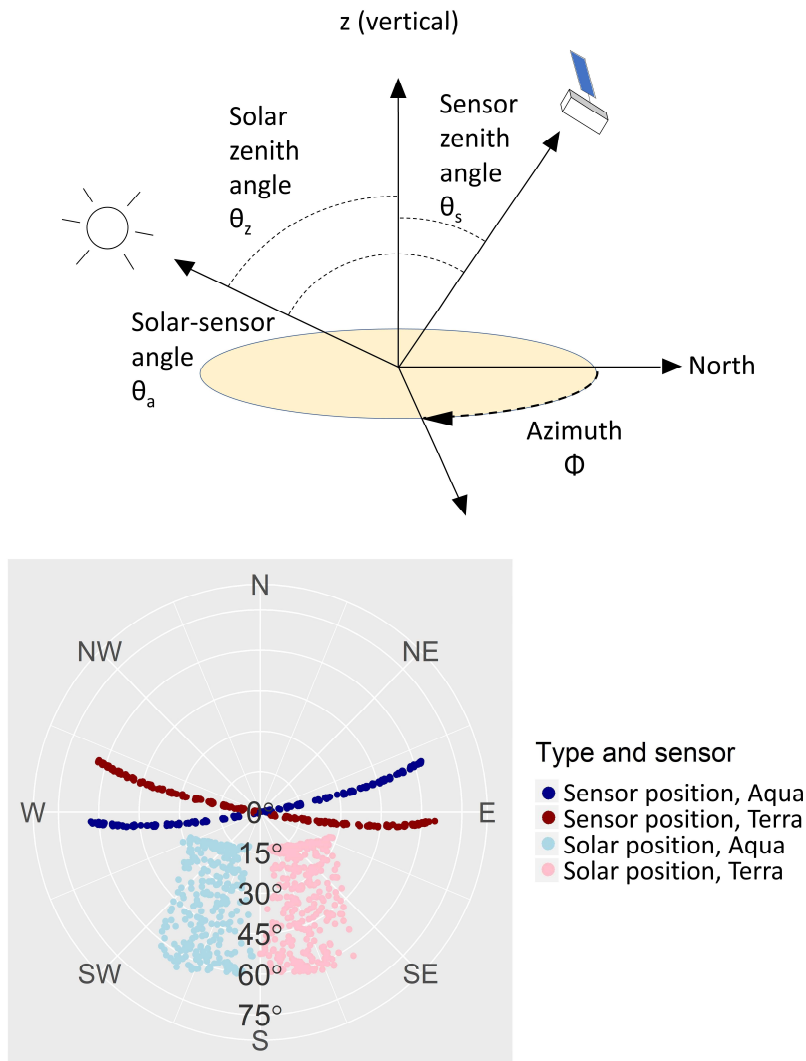


Figure 5. (Top) Diagram of the solar and sensor angles associated with satellite data. The single azimuth angle shown can represent either solar or sensor azimuth. (Bottom) Polar plot showing the range of MODIS solar and sensor azimuth and zenith angles at the GCNP-PJ ecosystem. The plot center represents the 0° zenith position of either the sensor or sun. Concentric circles indicate the degree of off-nadir solar and sensor zenith angle. Cardinal and intercardinal directions on the plot periphery indicate solar and sensor azimuth direction. Points shown are a 500-point random subsample of all high-quality values from 2003-2018.

We examined relationships between NDVI and MODIS solar and sensor geometry at the phenocam location using matrix plots to identify appropriate transformations; we used linear

correlations to identify the strength of the relationships for each variable. We plotted relationships between the time of year, solar zenith angle, and solar-to-sensor angle (Fig. 6).

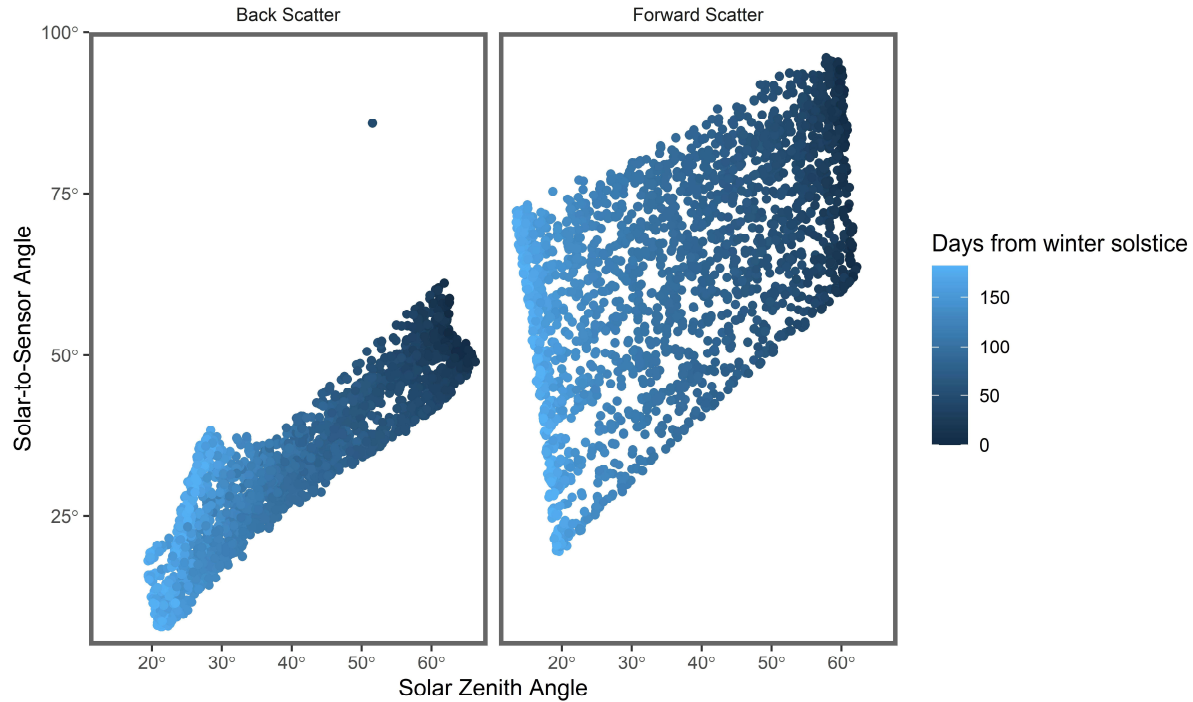


Figure 6. Seasonal relationship of solar-to-sensor angle (MODIS Terra and Aqua) and solar zenith angle for back-scatter and forward-scatter conditions. Outliers in the back-scatter panel appear to be values from the adjacent swath path that are only rarely incorporated into the MxD09GQ product.

After we identified the best NDVI transformation and correlations, we calculated linear models using the transformed NDVI data and plotted model residuals against the remaining solar and sensor azimuths and zeniths to identify any further variables to include in the model. We obtained the most explanatory model results, with evenly distributed residuals, by log-transforming NDVI and using separate models for forward-scatter and back-scatter conditions:

$$\log NDVI_F = a_F(SSA) + b_F \quad (6)$$

and

$$\log NDVI_B = a_B(SSA) + b_B(SnZA) + c_B \quad (7)$$

where $NDVI_F$ and $NDVI_B$ are NDVI from forward-scatter and back-scatter conditions, respectively, SSA is the solar-to-sensor angle, $SnZA$ is the sensor zenith angle, a_F and b_F are constant parameters fitted to the forward-scatter model, and a_B , b_B , and c_B are constant parameters fitted to the back-scatter model.

Residual plots from the final models (equations 6 and 7) showed no apparent patterns with the remaining variables. However, we did not thoroughly explore further possible relationships, because our goal was not to develop the best possible model but to determine the severity of the effect of solar and sensor geometry on NDVI. We tested whether removing the modeled variation would reveal a better picture of the true ecosystem phenology, but plots of model residuals against day-of-year did not show an apparent phenological curve for either the forward-scatter or back-scatter models (see electronic supplement).

To assess the temporal and spatial consistency of the correlations, we used the final model forms to calculate individual models (having a , b , and c parameter values) as well as the associated model r^2 values for each year (2003-2018) for each of 100 pixels (250-m resolution) randomly selected from the GCNP-PJ ecosystem (DeCoster et al., 2012; Norris, 2020). Summarized distributions of the r^2 values are presented in the results.

2.4.2 Winter peak extent analysis

We used the daily combined Aqua-Terra 500-m NBAR dataset (MCD43A4) to map the temporal and spatial extent of winter peaks. The NBAR product adjusts reflectances for anisotropic behavior of surfaces (Schaaf et al., 2002) and was therefore the MODIS option most likely to overcome problems of false winter peaks that might be caused by solar-sensor geometry (Wang et al., 2018). We performed processing in GEE across the western continental United States. We

followed a conservative processing scheme by retaining only pixel values for which all seven quality-control (QC) bands had the highest quality code and for which the snow flag from the associated MCD43A2 dataset indicated no snow. After calculating the NDVI for each pixel, we removed the highest 2% of the aggregate values across the processing extent for each day to screen out potential noise. Because the extensive latitudinal and elevational range of our study area results in different growing season lengths, we created two temporal definitions of winter peaks. The first, “warm area” winter comprised annual NDVI peaks occurring after November 1st and before February 1st ($\text{DOY} \geq 305$ or $\text{DOY} \leq 30$). This threshold could only be used in areas without substantial snow cover and was thus restricted to relatively warm locations where the average November minimum daily temperature was above 0°C . The second, “cold area” winter identified NDVI peaks after October 1st and before March 1st ($\text{DOY} \geq 274$ or $\text{DOY} \leq 60$) and was used in areas where the average November minimum daily temperature was below 0°C .

2.4.3 Exclusion of mild-winter and low-NDVI areas

To focus on ecosystems where winter NDVI peaks would be considered anomalous, we restricted the geographical scope of the study based on thresholds of seasonal temperature and density of vegetation cover. We excluded areas with an average December minimum daily temperature greater than 0°C as derived from 4-km PRISM 30-year monthly climate normals (1981-2010 30-year period, PRISM Climate Group, 2019) using the Norm81m, version M2 dataset provided in GEE. This criterion removed warm desert areas and temperate coastal regions that could theoretically display non-summer peaks in photosynthesis; however, even in these warm-winter areas, the leaf or biomass phenology of most dominant species does not peak in winter (Chiariello, 1989; Halvorson and Patten, 1975; Hufstader, 1978; Yan et al., 2019). We additionally excluded areas with minimal vegetation cover as indicated by low NDVI values. Accurately identifying winter peaks is difficult in low-NDVI systems because of the limited

annual dynamic range in NDVI and low signal-to-noise ratio. The NPS-SCPN LSP protocol development (Norris, 2020) identified consistent, extended periods of missing high-quality data during the growing season in areas with very low peak NDVI. We therefore excluded areas with a median peak NDVI < 0.15 over the study period. We determined the threshold by comparing the spatial distribution of the median peak NDVI to the extent of known problem areas (i.e., areas missing extended periods of high-quality data during the growing season) in several SCPN ecosystems. Annual peak NDVI rasters were calculated in GEE for 2003-2018 using the MODIS MCD43A4 dataset, following the QC screening methods described earlier. Median peak NDVI was calculated from the annual layers using the “raster” package in R (Hijmans, 2019).

2.4.4 Measuring temporal and ecosystem variability in winter peaks

We measured the temporal variability of winter peak occurrence by counting the number of years with winter peaks in the 2003-2018 period. Affected areas were conservatively estimated by retaining only areas with 5 or more years of winter peaks. We identified affected vegetation types by overlaying 30-m LANDFIRE existing vegetation type (EVT) data (LANDFIRE, 2014) on the dataset of pixels with common (≥ 5 years) cold-season peaks. We aggregated (recoded) the EVT classes according to the physiognomy field of the LANDFIRE data (Table 2). Because of the importance of pinyon-juniper ecosystems in the western US, we divided the conifer physiognomy category into pinyon-juniper conifer communities and non-pinyon-juniper conifer vegetation (see electronic supplement for a full crosswalk table). Using the recoded values, we resampled the dataset using a majority rule to the same resolution and registration as the winter peaks dataset (i.e., the projection and resolution of the MCD43A4 product in GEE) in ESRI ArcGIS v. 10.7.1. The resampled raster was then intersected with the winter peaks dataset and displayed in map form. The estimated area of each type was calculated by converting the raster to

a vector format, then projecting to the original Albers equal area projection used by LANDFIRE, but with the central meridian shifted to -110° longitude to better reflect the analysis area.

2.5 Additional sensor analyses

To assess whether winter-peaking patterns are restricted to the two examined MODIS products, we calculated and graphed NDVI time series derived from additional instruments: the 16-day VNP13A1 product from the Visible Infrared Imaging Radiometer Suite (VIIRS) onboard the Suomi National Polar-Orbiting Partnership platform, the European Space Agency's Proba-V mission, Landsat 7, and Sentinel-2. The area of analysis was a 0.02° x 0.02° rectangle centered on the phenocam location for the nominal time span of 2014 to present, depending on sensor availability. Because this portion of the analysis was intended only for visual assessment of annual phenology trends, we followed a minimalist processing scheme in which relevant cloud and cloud shadow masks were applied in GEE (see electronic supplement).

2.6 Data availability

Data and code created as part of these analyses are available as a data release (Norris and Walker, 2020).

3. Results

3.1 Species-specific phenological curves from the phenocam

All nine species-specific ROIs exhibited generally higher NDVI values in the warmer months with peaks during the spring and/or monsoon (late summer/early fall) (Fig. 7). Deviations from this pattern were caused by localized foreground/background shadowing or cloudy skies. The two sagebrush ROIs peaked in late spring, while the pinyon, juniper, and cliffrose ROIs peaked during the monsoon season. The desert sweet ROI peaked during both the spring and monsoon seasons. None of the species-specific annual NDVI profiles exhibited peaks after September 1. We attribute cold-season peaks in the composite NDVI profile to shadowing because they occurred only in the morning, rather than occurring in both morning and afternoon (Fig. 6) as would be expected from a true vegetation response. Those peaks were also consistent with times of sudden NDVI increases due to shadowing in other ROIs. The vegetation monitoring plots (section 2.1) show that the species measured in the ROIs represent ~90% of the vegetation cover in the overall GCNP-PJ ecosystem and provide a robust ground truth to the satellite-derived NDVI signal within this ecosystem.

Intra-seasonal dynamics were also apparent on a species level, as the phenocam captured differentiated responses of individual plants to growing cues or climatic stress. Phenological curves from the species-specific ROIs show that some species responded preferentially to spring moisture, while others responded more strongly to monsoon moisture. Furthermore, several species showed either a small (cliffrose) or substantial (big sagebrush, desert sweet) response to early summer drying that occurs after snowmelt but before the monsoon season.

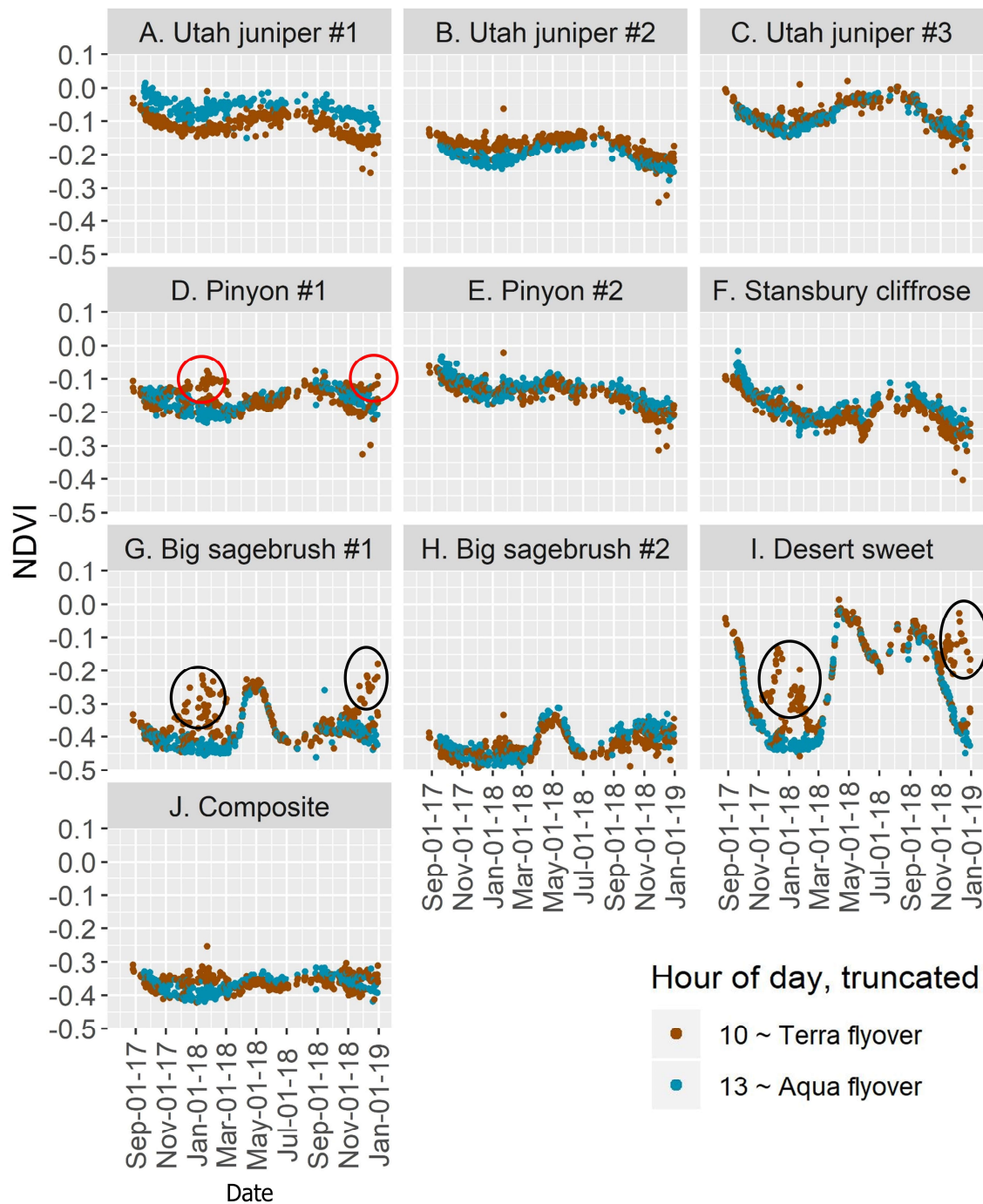


Figure 7. NDVI curves derived from phenocam images for the period of instrument operation (September 2017 - December 2018) for individual regions of interest (ROIs). Letter designations correspond to ROI labels in Figure 4. Data were screened to remove cloudy photos during Aqua and Terra flyover hours. Black ellipses indicate times when the ROI target vegetation was shaded. Red ellipses indicate times

when the background of the ROI was shaded. To improve visibility, the Y axis is restricted and excludes 37 extreme values out of a total of 6698 values. The exposure adjustment method used by the phenopix package produces NDVI values that have a strong linear correlation with spectroradiometer-derived NDVI but are negatively shifted so that vegetated areas often have NDVI values below zero (Petach et al., 2014).

3.2 Solar-sensor geometry controls on MODIS phenology in Grand Canyon pinyon-juniper ecosystem

Examination of MODIS NDVI data in the GCNP-PJ ecosystem shows that over 80% of the annual variability can be explained by a combination of solar-to-sensor angle, forward/back-scatter conditions, and, for back-scatter points, sensor zenith angle (Fig. 8). The forward/back-scatter conditions are evident as separate populations in Figure 8. This distinction demonstrates both the utility of this definition of forward/back-scatter condition and the control of this aspect of solar-sensor geometry on NDVI, since it is not related to other seasonal or environmental variables. As seen in Figure 8, solar-to-sensor angle has a strong relationship with NDVI. Importantly, although we would expect solar-to-sensor angle to be correlated to season, and thus to NDVI, the direction of correlation is the opposite of what would be expected if vegetation were driving NDVI: as solar-to-sensor angle increases (as it more commonly does in winter) NDVI also increases. If NDVI were responding to vegetation we would expect the reverse: as solar-to-sensor angle increases, NDVI decreases. But we have demonstrated that phenocam-derived NDVI in this ecosystem does not increase in the winter. Thus, we believe that the relationship between solar-to-sensor angle and satellite-derived NDVI is driven by optical effects rather than vegetation response. The 2,330-km swath width of the MODIS satellites provides further confirmation of the solar-sensor geometry explanation, because the swath allows for a wide range of solar-to-sensor angles to be present on the same day of year. For example, angles can vary by more than 50 degrees at summer solstice and more than 40 degrees at winter solstice (Fig. 6).

This daily variability allows us to isolate the effect of solar-to-sensor angle on NDVI. The ability of some other climatic or seasonal variable to explain the strong correlations that we observed is limited. As confirmation, the relationship between NDVI and season, measured as day-from-winter solstice, exhibits a significant but much weaker relationship ($r^2 = 0.48$; graph available in electronic supplement). The overall winter-peaking NDVI phenomenon (as opposed to the high daily NDVI variability) would likely be originating in the seasonal driver of solar zenith angle, which drives the seasonal pattern of variability in solar-to-sensor angle.

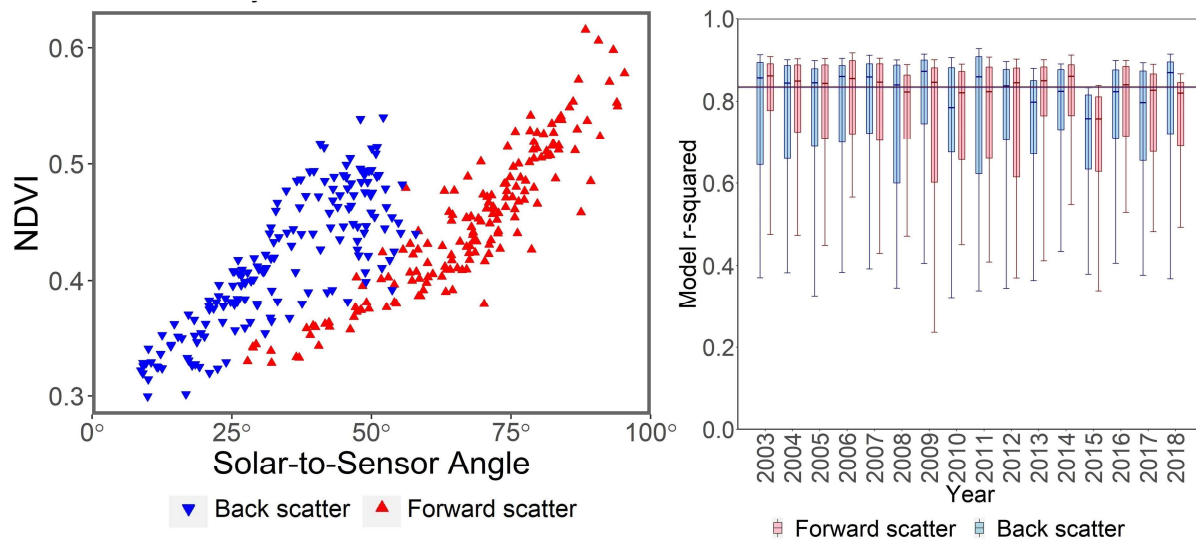
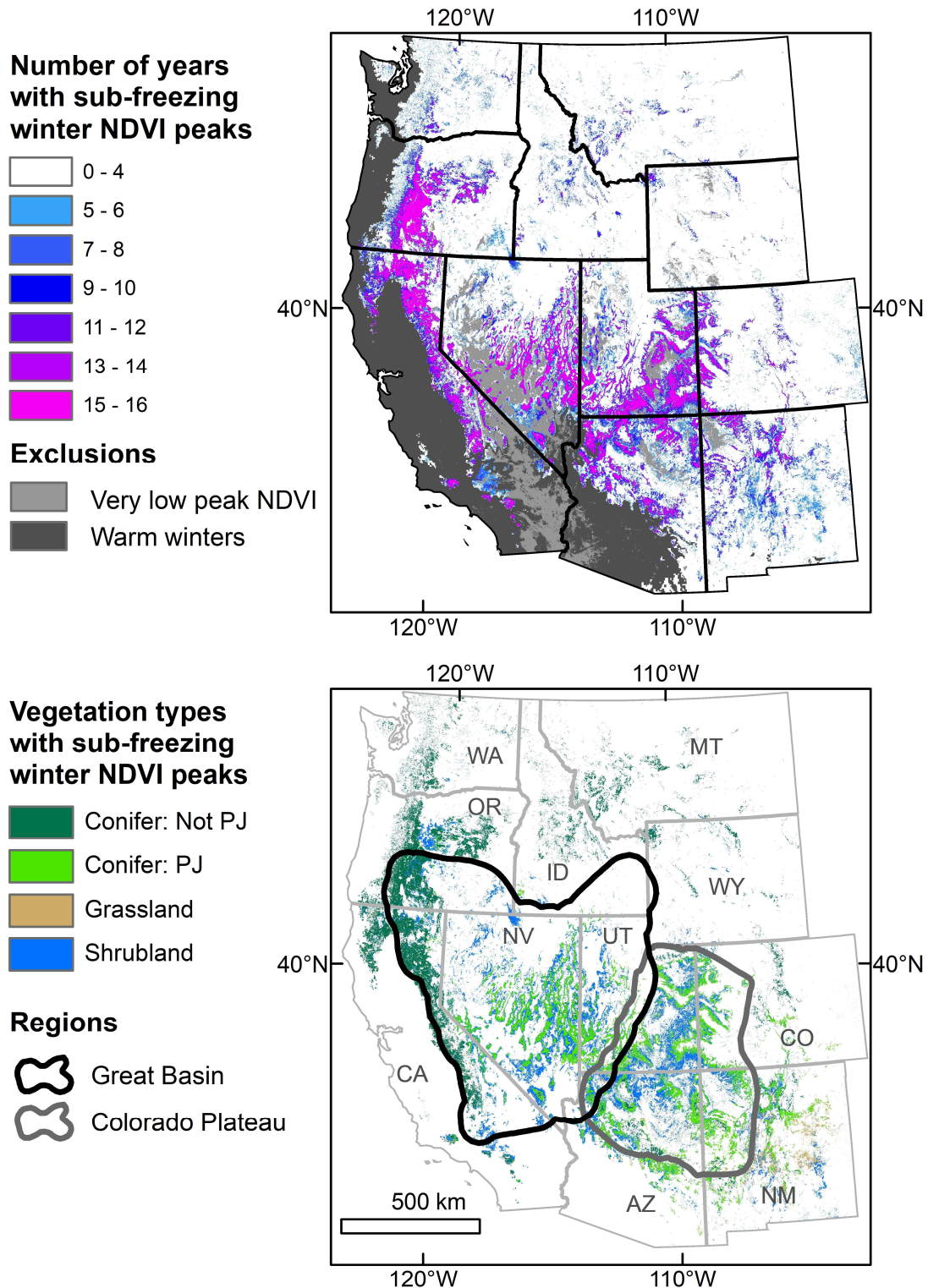


Figure 8. NDVI dependence on solar and sensor geometry demonstrated for both a single pixel/year and for multiple pixels over time. (Left) MODIS NDVI versus solar-to-sensor angle for the Grand Canyon phenocam location in 2018, the year for which there is corresponding phenocam data. (Right) Modeled r^2 values by year for 100 randomly selected MODIS pixels in the SCPN-monitored Grand Canyon pinyon-juniper ecosystem. The model for forward-scatter MODIS-NDVI is $\log(\text{NDVI}) \sim \text{solar-to-sensor angle}$. The model for back-scatter MODIS-NDVI is $\log(\text{NDVI}) \sim \text{solar-to-sensor angle} + \text{sensor zenith angle}$. Boxplots show interquartile ranges; whiskers extend to 10th and 90th percentiles. The horizontal line marking the average median value for forward-scatter r^2 (0.835) is nearly indistinguishable from the back-scatter line (0.833).

The strong dependence of NDVI on solar-sensor geometry was investigated through time across the GCNP-PJ ecosystem: the median ecosystem model r^2 value was calculated for each year ($n = 100$ points). Median values were used to mitigate against both quantified and unquantified estimates of error in mapping the GCNP-PJ ecosystem. GCNP-PJ ecosystem boundaries were derived from SSURGO soils map geodatabases (Soil Survey Staff, 2010), which estimated that the target ecological site associated with the pinyon juniper ecosystem had 75% cover within that map unit (DeCoster et al., 2012). The average r^2 of the annual medians was 0.835 (forward scatter) and 0.833 (back scatter). Thus, slightly more than 83% of the within-year NDVI variability in the GCNP-PJ ecosystem can be explained by solar and sensor geometry. In particular, solar-to-sensor angle exercised a strong positive control on NDVI, and solar-to-sensor angle generally increases with increased solar zenith angles in the winter (Fig. 6). Thus, the general increase in solar-to-sensor angle in winter provides the best explanation for the satellite-based winter peaks in the GCNP-PJ ecosystem although the solar-to-sensor angle effect may encompass effects from one or more seasonally correlated variables like solar zenith angle (Fig. 6).

3.3 Geographic and biological distribution of cold-season peaks

Both consistent and occasional winter peaks in NDVI are widespread in ecosystems of the western United States, even when calculated on the basis of the MODIS product that specifically adjusts for view-angle differences (MCD43A4). Consistent winter peaks (i.e., ≥ 14 years out of 16) are concentrated in the conifer forests and woodlands of California and Oregon, and in the pinyon-juniper woodlands of the Great Basin—centered on Nevada—and the Colorado Plateau (Fig. 9). Smaller areas of shrublands, particularly on the Colorado Plateau, also have consistent winter peaks. Common cold-season peaks (i.e., ≥ 5 years out of 16) occur in shrublands of the Great Basin, on the Colorado Plateau, and across New Mexico.



484 Figure 9. Temporal and ecosystem distribution of winter NDVI peaks in the western continental US, 2003
 485 to 2018, derived from MODIS MCD43A4 product. (Top) Number of years with winter peaks in areas that
 486 meet defined thresholds for biomass (median annual peak NDVI ≥ 0.15) and temperature (mean

487 December minimum daily temperature $\leq 0^{\circ}\text{C}$). (Bottom) Predominant LANDFIRE Existing Vegetation
488 Type physiognomy (i.e., mode of each 500-m MODIS pixel) in areas with ≥ 5 years of winter peaks.
489 Present in lesser proportions but not identified on the map for legibility reasons are conifer-hardwood,
490 exotics, riparian, and sparsely vegetated physiognomic categories as well as non-natural/non-terrestrial
491 ecosystem categories (Table 2 “Excluded” class). State abbreviations are AZ (Arizona), CA (California),
492 CO (Colorado), ID (Idaho), MT (Montana), NV (Nevada), NM (New Mexico), OR (Oregon), WA
493 (Washington), and WY (Wyoming).

494 The results of analyzing winter-peak occurrence by vegetation physiognomy are not uniform
495 across coniferous forests. Although many conifer forests display winter peaks, some closed-
496 canopy conifer forests (e.g. the North Rim of Grand Canyon NP) do not. Open-canopy conifer
497 woodlands like pinyon-juniper are consistently affected, in spite of the potential for interspersed
498 deciduous grasses and shrubs to overwhelm the winter-peak signal with higher spring-summer
499 pulses of greenness.

Table 2. Aggregated vegetation physiognomy categories derived from the LANDFIRE Existing Vegetation Type dataset and area within each category affected by common winter peaks.

Category	Area with ≥ 5 years of winter peaks, millions of hectares	Area as percent of total category area within the western US	LANDFIRE Physiognomy Value
Conifer-Hardwood	0.26	10.1%	Conifer-Hardwood
Conifer: not PJ	13.22	21.8%	Conifer
Conifer: PJ	12.12	66.1%	Conifer
Exotic	0.96	8.8%	Exotic Herbaceous
			Exotic Tree-Shrub
Grassland	1.97	4.7%	Grassland
Hardwood	0.24	4.9%	Hardwood
Riparian	0.55	11.2%	Riparian
Shrubland	15.74	14.7%	Shrubland
Sparsely vegetated	1.30	15.7%	Sparsely Vegetated
Exclude	2.99	6.2%	Agricultural
			Barren
			Developed
			Developed-High Intensity
			Developed-Low Intensity
			Developed-Medium Intensity
			Developed-Roads
			Nodata
			Open Water
			Quarries-Strip Mines-Gravel Pits
			Snow-Ice

3.4 Additional sensor analyses

NDVI series from VIIRS, Proba-V, Landsat 7, and Sentinel-2 data collected around the phenocam location also display winter peaking patterns (Fig. 10). Some of these time series are relatively noisy because they could not easily be processed to an equivalent quality level as the MODIS data. In particular, the VIIRS, Proba-V, and Sentinel-2 data were not screened to remove snow-affected values, which typically cause sharp drops in NDVI (Jönsson et al., 2010). The

509 vegetation in the sample area is dominated by evergreen pinyon and juniper, which compose >
510 80% of the vegetation cover in the GCNP-PJ ecosystem (Southern Colorado Plateau Network,
511 2018). Thus, it is reasonable to ignore the ecologically improbable sudden and extreme changes
512 in NDVI in these graphs and focus on the relatively consistent phenological curves. Although a
513 shorter time period is available for the more highly corrected Sentinel-2 Level-2A data, the
514 derived profile follows the same winter peaking pattern as the Sentinel-2 Level-1C data.
515 The observation of winter-peaking NDVI from other satellite platforms is further extended by
516 Kaufmann et al. (2000). They investigated the effect on AVHRR-derived NDVI of solar zenith
517 angle, which is broadly correlated with the solar-sensor angle variable that we use (Fig. 6).
518 Across the 13 global biomes examined, they found evidence of a statistically significant effect of
519 solar zenith angle in 4 biomes: wooded grassland/shrub, closed bushlands, open shrublands and
520 bushes, all of which they note as having a relatively sparse canopy (Kaufmann et al., 2000).
521 These biomes and the association with sparse canopy are consistent with the results we find in the
522 western continental United States.

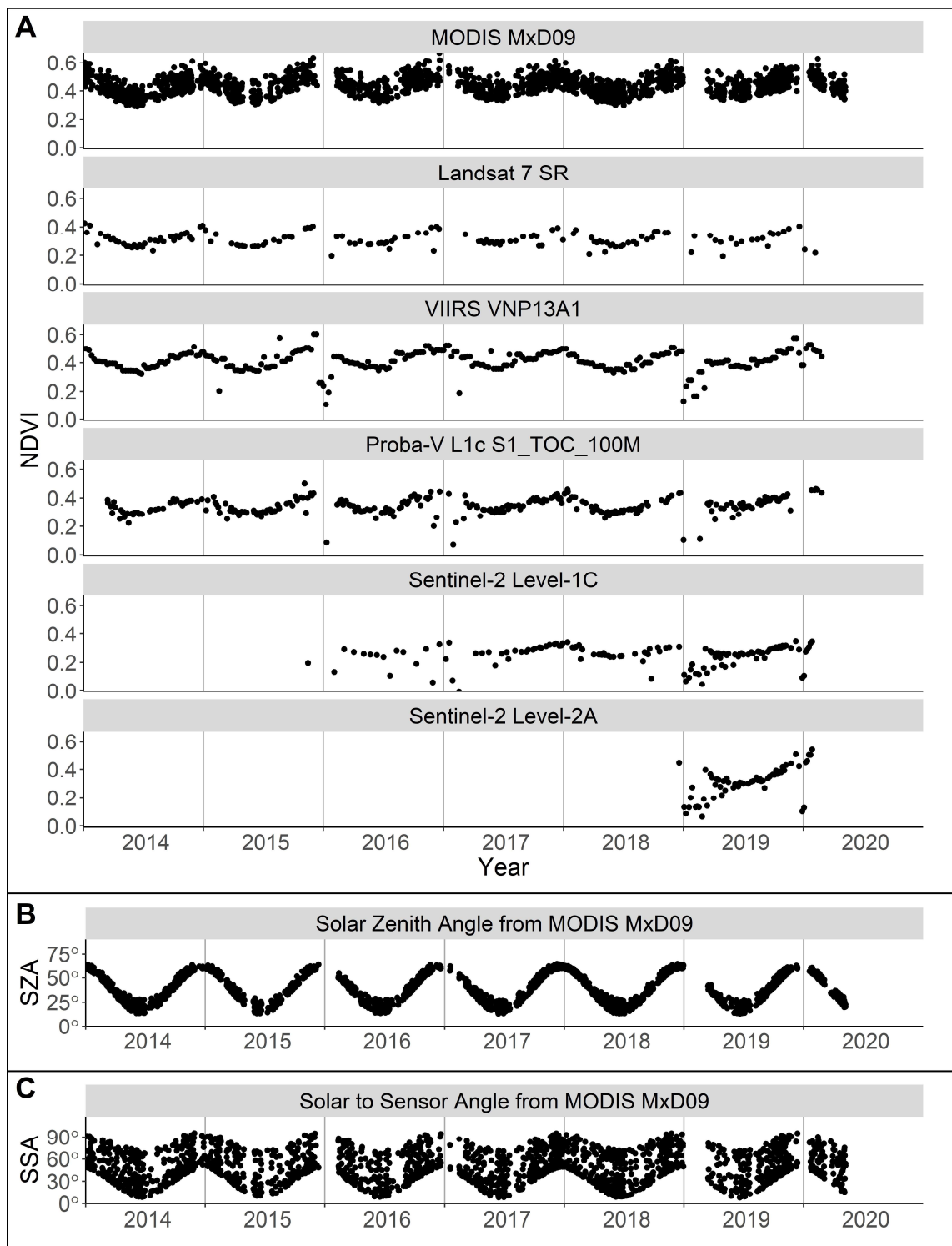


Figure 10. Comparison of satellite-based datasets centered on the Grand Canyon phenocam location. A) NDVI time series from the MODIS MxD09 product compared to NDVI time series of five products derived from other commonly used satellite sensors: Landsat 7 surface reflectance data (Landsat 7 SR), Visible

Infrared Imaging Radiometer Suite (VIIRS) VNP13A1 data, Proba-Vegetation (V) L1c data, Sentinel-2 top-of-atmosphere data (Sentinel-2 Level-1C), and Sentinel-2 bottom-of-atmosphere data (Sentinel-2 Level-2A). Vertical lines mark boundaries between calendar years. Given that the vegetation in this ecosystem is >80% evergreen, abrupt NDVI changes can be ignored, and the underlying winter-peaking pattern across the products is clear. B) Patterns of solar zenith angle from the MODIS satellite show its potential as a seasonal driver. C) Patterns of solar-to-sensor angle show both the seasonal effects caused by solar zenith angle as well as high day-to-day variability caused by the wide swath of the MODIS satellite.

4. Discussion

4.1 Overview

In this study we evaluated the validity of winter-peaking phenology extracted from satellite-derived NDVI time series in a pinyon-juniper ecosystem in the western US. The independent perspectives of our dual ground-based and satellite-derived approach allow us to reject the premise that vegetation growth underlies the cold-season rise in NDVI. Instead, the phenomenon can be attributed to solar-sensor geometry effects that overwhelm the comparatively muted growth dynamics of the pinyon-juniper canopy to create an artificial signal of maximum photosynthetic activity during winter months. This specious indication of cold-season greenness in the MODIS-derived record is displayed across the western continental US in ecosystems broadly characterized by dominant evergreen species, sparse canopy coverage, and vertical vegetation structure.

4.2 Nature of solar-sensor geometry effect

We were able to explain more than 80% of the intra-annual NDVI variability in the GCNP-PJ using these solar-sensor geometry variables: solar-to-sensor angle, sensor zenith angle, and forward/back-scatter condition. Increases in solar-to-sensor angle and sensor zenith angle both result in increased NDVI values, and increases in solar-to-sensor angle are correlated with winter solstice timing; thus, these variables alone can explain the winter peaking pattern in the GCNP-

PJ. Forward and back-scatter condition, as defined by this study, significantly affects NDVI but is not itself dependent on seasonality.

The most likely mechanism by which solar-to-sensor angle and sensor zenith angle alter NDVI is through the increased visibility of shadows that occurs during winter in vegetation types that have complex vertical structure, such as woodlands or sparse forests. Ranson and Daughtry (1987) used manually spaced balsam firs mounted on a turntable to demonstrate how the presence of shadows raised sensor-detected NDVI. The same study also demonstrated that shadowed area increases both with increasing solar zenith angle and with sparse canopy density. As discussed in the introduction, other factors likely contribute to the solar-to-sensor angle effects; however, the prevalence of the winter-peaking signal in sparse-canopied ecosystems across the western continental US suggests that shadows are the most important driver. Our ground-based phenocam data also showed that shadows cause artificial increases in NDVI in species-specific ROIs and in the composite ROI.

Thus, we postulate that four environmental factors are necessary to delay the timing of NDVI peaks:

- 1) low annual true greenness variation, such as that found in evergreen conifer systems and dryland vegetation systems, which allows for the dominance of solar-sensor geometry effects
- 2) vertical and relatively sparse vegetation canopy structure, which results in a high amount of shadowing visible to airborne sensors
- 3) sun angle that creates substantial shadows; i.e., large solar zenith angle

- 4) large solar-to-sensor angle, which increases shadow visibility and is more prevalent during times of large solar zenith angle

The substantial solar-to-sensor angle is necessary because even at solar angles that cause shadowing (i.e., sun closer to the horizon), a sensor in alignment with the sun (solar-to-sensor angle ≈ 0) will detect minimal shadows.

4.3 Phenocam analysis

Phenocam data were instrumental for resolving the question of whether pinyon-juniper ecosystem components exhibit measurable growth during cold, late-season conditions. Time series of NDVI values extracted from the GCNP-PJ phenocam imagery show that the dominant woody species in the sampling frame maintain a non-winter peaking phenology. The sporadic appearance of late-season increases in NDVI within certain ROIs can be attributed to shadowing effects rather than plant growth. The documentation of peak NDVI during spring or summer months is consistent with the results of Snyder et al. (2016) and Snyder et al. (2019), who describe late-summer peaks in pinyon-juniper vegetation imaged by a phenocam. The warm-season timing of peak growth recorded at the GCNP-PJ phenocam is also consistent with general expectations of vegetation dormancy and/or reduced photosynthetic activity under winter conditions at higher elevations or northern mid-to-high latitudes (Berry and Bjorkman, 1980; Monson et al., 2005; Öquist, 1983; Zhang et al., 2006). Even in areas of the western continental US with mild winters, most species display non-winter greenness peaks (Chiariello, 1989; Halvorson and Patten, 1975; Hufstader, 1978; Yan et al., 2019). The ability of the phenocam to detect dissimilar responses to moisture inputs from individual species ROIs in this study supports our confidence that true cold-season growth would have been recorded had it been present. Further support is the fact that no winter peaks were recorded despite the favorable conditions for winter photosynthetic activity; for an

extended period (October 2017 - June 2018) during phenocam data acquisition, weather patterns were unusually warm and dry, which might have been expected to prolong the growing season.

4.3.1 Forward and back scatter effects

In the GCNP-PJ ecosystem, forward/back-scatter viewing conditions have a significant effect on both MODIS-derived and phenocam NDVI. In the MODIS-derived time series, slightly more than 83% of within-year NDVI variability in the GCNP-PJ ecosystem can be explained by solar and sensor geometry. For a given solar-to-sensor angle, the back-scatter NDVI values are higher than the forward-scatter NDVI; however, forward-scatter NDVI values are higher overall because of their association with higher solar-to-sensor angles (Fig. 8). The pattern of higher NDVI in the forward-scatter direction is consistent with most reported studies that have investigated the effects of forward/back scatter on recorded NDVI from vegetated surfaces (e.g. Huete et al., 1992; Kimes, 1983; Ranson et al., 1986; Sims et al., 2011). Our study was not designed to parse the individual mechanisms behind forward/back-scatter differences; however, at least two factors that may account for our results have been previously described. Kimes (1983) found stronger visible light reflectance in the back-scatter direction from soils, while infrared light had very weak overall soil reflectance; thus, the difference between back scatter and forward scatter was less pronounced. In the same study, Kimes observed that sparse canopies had stronger visible reflectance in the back-scatter direction, while infrared reflectances were less affected by direction of scatter. Both the soil and canopy differences in visible light reflectance would have the effect of decreasing NDVI in the back-scatter direction and are consistent with our results in the GCNP-PJ ecosystem. These effects are not the only possible factors driving forward/back-scatter differences; Huete et al. (1992) describe the larger group of 'angular reflectance properties' that a BRDF-correction should theoretically encompass. The MxD09GQ data we used for geometry analyses employed BRDF (<https://lpdaac.usgs.gov/products/mod09gqv006/>)

adjustments to assign snow, cloud, and cloud shadow flags, but the reflectances themselves were not BRDF-adjusted. The combined MODIS product (MCD43A4) is BRDF-adjusted to estimate nadir reflectance and may remove the forward/back-scatter effects. In further confirmation of the forward/back-scatter effect, the phenocam ROIs showed an increase in forward-scatter NDVI, but only for the juniper ROI and not for the Stansbury cliffrose ROI. It could be useful to know what other species or growth forms show this distinct response to forward/back-scatter conditions because of its apparent effects on the more widely used satellite-based NDVI in this pinyon-juniper ecosystem, and perhaps other ecosystems.

4.4 Distribution of winter peaks in the western US

We identified winter NDVI peaks in an array of ecosystems across the continental US West. Although our phenocam data are limited to a pinyon-juniper ecosystem, phenological literature demonstrates that true winter growth peaks are unlikely across our cold-winter analysis area. Winter dormancy has been well established for the most common pine, fir, and spruce species in the western United States (Bowling et al., 2018, Harrington et al., 2010, Harrington and Gould, 2015, Royce and Barbour, 2001) although some species are able to grow, albeit at much lower rates, during the winter (Franklin and Waring, 1980, Law et al., 2000). Among dominant shrubs in the western United States, non-winter vegetation peaks have been demonstrated for big sagebrush (*Artemisia tridentata*) in Nevada (Everett et al., 1980) and Oregon (Barker and McKell, 1986), and creosote bush (*Larrea tridentata*) in Nevada (Ackerman et al., 1980), as well as for many other common shrubland and grassland species (Ackerman et al., 1980, Fernandez and Caldwell, 1975). These results are consistent with the strong limitations on plant growth imposed by freezing temperatures (Berry and Bjorkman, 1980). Thus, it is reasonable to extrapolate from those results to conclude that solar-sensor geometry effects, rather than true

vegetation growth, are also the most likely cause of winter peaks detected in other conifer and shrub ecosystems in the western continental United States.

The vegetative characteristics of the similarly affected conifer ecosystems generally fit the profile of low annual greenness variation, pronounced vertical structure, and sparse canopy density. By mapping the locations of common winter peaks, we show the minimum spatial extent of this phenomenon and identify ecosystems for which NDVI-derived phenometrics are an inappropriate tool. The mapped area likely underestimates the full extent of the impact, because we focus on pixels where the effect is strong enough to shift the annual NDVI peak to the winter season more than 25% of the time (≥ 5 years out of 16). In other ecosystems or years, a warm-season NDVI peak may be high enough to outweigh the solar-sensor geometry impact. We also do not map the extent of this effect in warm winter areas, even though we know from phenocam data that in some of these locations (Yan et al., 2019) the true vegetation phenology does not peak in the winter. Furthermore, many of the warm, dry ecosystems likely have low overall NDVI amplitude and vertical vegetation structure, which would be expected to result in the same shift of apparent NDVI peaks to winter.

4.5 Advances made by this study

The effects of solar-sensor geometry on measured reflectances from vegetated surfaces have been exhaustively analyzed in preceding decades. Our study adds to the body of knowledge by reporting on two relatively overlooked aspects. The first is that solar-sensor geometry can shift the apparent timing of annual NDVI peak in certain ecosystems by seasonally biasing the magnitude of NDVI. This effect occurs even in the MODIS BRDF-adjusted dataset (MCD43A4). The second is the spatial extent of the impact. Although other studies have reported the phenomenon of winter-peaking Landsat- and MODIS-derived NDVI in coniferous environments,

we believe ours is the first to map the prevalence of such signals within vegetation physiognomic categories on a broad geographical basis.

There are comparatively few ecosystem-wide overviews of the severity and spatial extent of solar-sensor geometry interactions. Notable exceptions are Morton et al. (2014), who attributed the presumed seasonal green-up in the Amazon Basin to an artifact of solar-sensor geometry changes, and Fensholt et al. (2010), who identified ecosystems along a transect in West Africa that were more vulnerable to sensor angle effects. We posit several factors that contribute to the lack of more widespread recognition of the severity of solar-sensor geometry effects, which likely affect more aspects of land surface phenology research than problematic winter peaks:

- 1) *Most phenological work is conducted in deciduous environments.* Many relationships between NDVI and vegetation response have been established in ecosystems with pronounced phenological signals. As others have documented (Cai et al., 2017; White et al., 2009), many aspects of land surface phenology are not suited to the convenience of a single processing approach and require more nuanced and careful analyses.
- 2) *Inadequate snow screening.* Snow contamination dramatically decreases NDVI and can create an apparent winter low in NDVI when not adequately removed (Cai et al. (2017); Jönsson et al. (2010), Karlsen et al. (2009), and Walther et al., 2016); this effect has been documented in conifer ecosystems of the southwestern United States (Norris, 2020).
- 3) *Smoothing NDVI time series data.* Fitting a curve to NDVI time series, particularly when combined with inadequate snow screening, can mask increases in the early winter months.
- 4) *Temporal compositing.* Retrieving the highest constrained NDVI on a defined temporal basis (e.g. 16-day composites) reduces the user's ability to identify

ecologically improbable shifts, such as those due to snow contamination, and obscures the visual effect of increasing NDVI in the fall-early winter months (Norris, 2020)

- 5) *Lack of awareness*. The growing recognition of phenology as an ecologically relevant tool and the concurrent availability of satellite data and processing tools have enabled the ready application of phenometrics for operational or research purposes. Interpreting pre-calculated or derived phenometrics without awareness of issues specific to environmental factors or vegetation indices can lead to erroneous conclusions about ecosystem dynamics.

4.6 Possible solutions

Land surface phenology is a critical tool for understanding ecosystem response to interannual climate variability and rising temperatures, but meaningful metrics can only be derived from time series that faithfully represent ground-level vegetation dynamics. Three possible approaches for reducing the influence of solar-sensor geometry on the vegetation signal are:

- 1) **Restrict analyses to consistent solar zenith angle and solar-to-sensor angle**. The best approximation of NDVI unbiased by solar-sensor geometry might come from combining the smallest solar-to-sensor angle values with nearest-to-nadir solar zenith angles, such as those occurring at the summer solstice. However, even those cannot be stated as the most accurate with certainty. Regardless, the goal in most phenological studies is not to obtain the single most accurate NDVI for a year, but to detect change through the year, as well as changes from year-to-year in the timing of events such as the start of the growing season. Therefore, it could be more appropriate to choose a consistent moderate solar-to-sensor angle combined with a consistent solar zenith angle that occurs at multiple times of year by using the overpasses of both satellites. This forced combination is far from ideal.

2) **Find an alternative vegetation index.** Other vegetation indices might provide suitable replacements, and candidates include over 15 established indices identified by Wu (2014). However, other vegetation indices also have known limitations, including greater sensitivity of SAVI and EVI to topographic variation (Moreira et al., 2016), which is common in the western continental United States, and reduced sensitivity of EVI to subtle changes in vegetation productivity (Gao et al., 2000) such as those that would be expected in dryland and evergreen systems.

3) **Unmix/remove the effect of solar-to-sensor angle in the data.** This approach might allow better identification of ecosystems that we hypothesize are also affected by solar-to-sensor angle, but for which the impact is not so severe as to change the timing of the annual peak. Data products that include estimates of canopy height and density are available, such as MODIS MOD44B (Dimiceli et al., 2015), LiDAR-based GLAS (Healey et al., 2015) and LANDFIRE (LANDFIRE, 2014). These products could be used to model effects related to shadowing. Geometric-optical or 3D models may also be helpful in clarifying the shadowing dynamics.

4.7 Future research

The data from the GCNP-PJ phenocam and other phenocams in the southwestern United States are valuable in at least four ways:

1) Use of species-specific ROIs provides useful ground truth information to corroborate satellite-based phenological signals and to link those signals to ground-based responses. In this study the GCNP phenocam identified a disconnect between actual vegetation phenology and satellite-derived phenology. We expect that normally a phenocam could provide a useful link to identify which species are most important in driving satellite-based phenological signals. For NPS-SCPN

monitoring we have the final link provided by many ground-based monitoring plots that provide robust estimates of species cover across an ecosystem.

2) Due to the problems we have identified in using satellite-based NDVI, phenocam data are especially valuable because they provide one of the only reliable methods available for monitoring phenology in many western ecosystems.

3) We anticipate that the information from this and other phenocams can be used in the future to demonstrate whether alternative satellite-based measures of phenology are recording vegetation response and can therefore replace NDVI in measuring land surface phenology.

4) The phenological curve data provided by phenocams are locally valuable to ecologists and resource managers. The GCNP-PJ ecosystem, like many across the southwestern United States, is projected to have earlier, drier springs in the future as well as longer periods of extreme dryness each year before the arrival of summer monsoon moisture (Andrews et al., 2019a, b, c, d, e, f, g, h, i). The phenocam data help identify the responses of individual species to the timing and amount of moisture as well as their sensitivity to the length and severity of the early-summer dry period, both of which may be important in predicting their future success.

We foresee multiple avenues of research that would build on the conclusions of this study. It would be useful to broaden the temporal and spatial scope of the investigation to place the late-peaking behavior documented here in the context of climatic and environmental variability. The continued collection of data from the phenocam used in this study will be invaluable for exploration of phenological behavior. Similarly, incorporating observational data from other phenocams would expand the applicability of this effort. The PhenoCam Network currently numbers more than 500 sites, which provide a ready source of data to explore species or

vegetation structure controls on forward/back-scatter effects. In addition to the raw images, phenometric data are also published for phenocam images (Seyednasrollah et al., 2019). It would be useful to examine more years of data and data from other pinyon-juniper ecosystem locations to establish the consistency of species phenological patterns across years and ecosystems, and therefore, how useful the phenological patterns are for understanding ecosystem drivers and predicting responses.

5. Conclusions

Solar-sensor geometry severely affects phenological measurements derived from satellite-derived NDVI for many ecosystems in the western continental United States. The increase in solar zenith angle and solar-to-sensor angle in winter months contributes to the greater shading of the landscape; shading is known to increase recorded NDVI and is a likely mechanism for the winter NDVI peaks. The defining biophysical characteristics of ecosystems most vulnerable to false increases in winter NDVI are (1) relatively low annual variations in greenness due to the dominance of evergreen species and/or low biomass, and (2) vertical structure and spatial arrangements that lead to increased shadowing under oblique solar angles. Our maps of ecosystems that most consistently display winter peaks include large areas of pinyon-juniper woodland, shrublands, and other open-canopy coniferous forests and woodlands. Given the nature of the solar-sensor geometry relationship, we expect that there are other western continental US ecosystems that experience substantial effects on NDVI that do not result in a shift in peak NDVI timing. We also expect impacts in locations that we excluded from our analysis (i.e., warm-winter areas in the western continental United States) as well as in ecosystems across the globe that have similar vegetative characteristics. The winter-peaking problem identified here is already interfering with our ability to correctly use land surface

phenology to anticipate natural resource management needs. In 2019, SCPN published reports for multiple ecosystems that project how climate change will alter seasonal availability of soil moisture between the present and the year 2100 (Andrews et al., 2019a, b, c, d, e, f, g, h, i). These reports include analyses of correlations between ecosystem productivity as estimated by NDVI and current patterns of seasonal soil moisture, which would allow us to predict which vegetation communities may be most vulnerable to climate change. The correlations of productivity to seasonal soil moisture were key to assessing seasonal dependence on soil moisture; however, the correlations in the pinyon-juniper ecosystems were not valid because of the winter peaking problem, and the reports for pinyon-juniper ecosystems will not be published until those analyses are removed. It is likely that many more analyses are being similarly affected by this problem.

Acknowledgements

We thank the staff of the PhenoCam Network (<https://phenocam.sr.unh.edu/webcam/>) for promoting the phenocam data-sharing concept and providing technical assistance in phenocam installation, maintenance, and data archiving. Ronda Newton and other Grand Canyon National Park staff assisted with logistics and permitting. Jon Mason and John Vogel assisted with phenocam installation. The manuscript was improved by comments and suggestions from Bijan Seyednasrollah, Jean Palumbo, Kristin Straka, and three anonymous reviewers. Funding: This work was supported by the National Park Service Inventory and Monitoring Program, Southern Colorado Plateau Network; the U.S. Geological Survey Climate Research and Development Program; and the U.S. Geological Survey Mendenhall Postdoctoral Program. Any use of trade, firm, or product names is for descriptive purposes only and does not imply endorsement by the U.S. Government.

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