‘HYPERTEMPORAL’ REMOTE SENSING OF PLANT FUNCTION: A COMPARISON OF PHENOCAM AND GEOSTATIONARY OPERATIONAL ENVIRONMENTAL SATELLITE NDVI DATA PRODUCTS

by

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ABSTRACT

Ongoing climate warming is changing the seasonality of plant canopy function, but common approaches to explore these changes via polar-orbiting satellites often miss rapid canopy transitions due to infrequent observations. I explored the ability of satellites designed for studying weather systems, namely The Geostationary Operational Environmental Satellite (GOES), to track plant canopy status on time scales of minutes. With new capabilities to remotely sense in the infrared, the GOES weather satellites now have the capability to detect photosynthetic activity. Satellite observations of the normalized difference vegetation index (NDVI) are compared against near-surface phenological camera ("PhenoCam") observations from the National Ecological Observation Network (NEON, Inc.) at six sites every 15 minutes for one week in April 2019. Diurnal trends across both observation platforms showed the expected diurnal parabolic structure in NDVI with critical differences in NDVI magnitude between PhenoCams and GOES observations. One tailed T-test results show that there is variability between methods when measuring NDVI, with P-values less than 0.05 in all cases. This was anticipated due to correction factors needed for PhenoCam NDVI observations. However, additional variability can be attributed to other areas such as cloud cover, plant type, and heterogeneity. My proof-of-concept study demonstrates that raw NDVI data from both methods are often comparable, which lends credit to the notion that NDVI can be accurately observed from space at high (up to five minute) temporal resolution. With current research underway on the topics of atmospheric corrections and further surface validation, GOES has the potential to observe land surface attributes at up to 5-minute intervals across entire hemispheres for identifying phenology, disturbance and other vegetation dynamics in real time. With two hypertemporal methods at different spatial scales recently introduced, the research is primed to move towards a real time understanding of plant canopy function across the United States.

BACKGROUND

Plant Phenology

Plant phenology is the study of the seasonal cycle of vegetation structure and function, the role the environment plays in controlling these processes, and increasingly the feedbacks between seasonal vegetation dynamics and the environment itself (Lieth, 1974; Richardson et al., 2012; Hufkens et al., 2012; Richardson et al., 2018). As global temperatures continue to increase, shifts in biological events change accordingly. This can be seen in the early onset of canopy green-up globally (Sherry et al., 2007).

The seasonal cycle of vegetative structure and function is divided into phenophases, periods of time associated with specific plant behaviors that are shifting in response to climate change (Filippa et al., 2016). Plant-canopy phenophases can be broken into leaf emergence, at the start of the growing season (i.e. ‘green up’), peak greenness, and senescence (Filippa et al., 2016). Transitions between phenophases vary in distinction depending on plant type (Lui et al., 2017). For example, grasslands and trees often have differing phenology and tropical evergreen plants tend to have less pronounced phenophase transitions than those in a temperate deciduous forest that experiences all four seasons (Hufkens et al., 2012; Klosterman et al., 2014; Sonnentag et al., 2012; Lui et al., 2017). Transition dates between phenophases are historically the quantitative measure of shifting canopy phenology. However, the accuracy of these dates could be improved through the increased observational capacity of high temporal resolution satellites.

Satellite Remote Sensing

Remote sensing of plant phenology has historically been done via polar-orbiting satellites. There are many instruments with varying spatial and temporal resolutions (Table 1.) The Geostationary Operational Environmental Satellites (GOES) (used in this study) were originally designed to observe weather systems and can collect images every 5 to 15 minutes due to the geosynchronous nature of their orbits. In contrast to polar orbiting satellites that circle the earth and acquire images every one to two days, GOES remains fixed on one portion of Earth's surface and rotates at the speed of the planet's rotation. Due to the enhanced measurement capabilities of the new GOES 16 and GOES 17 satellites, namely new spectral measurements of infrared radiation, it is now possible to use these instruments to address a problem they were not originally designed to solve.

Table 1. Instruments used for plant phenology remote sensing and descriptions of resolution as well as positioning.

Sensor	Temporal Resolution	Spatial Resolution	Position/Orbit
MODIS	1-2 Day	500m	Polar Orbiting
Landsat	16 Day	30m	Polar Orbiting
VIIRS	Daily	500m	Polar Orbiting
SEVRI	15 min	500-3000m	Geosynchronous
GOES	5 min	500-1000m	Geosynchronous
PhenoCam	15 min	Surface Level	Ground Based

Studies of phenology typically utilize the Moderate Resolution Image Spectroradiometer (MODIS) or Landsat (Ganguly et al., 2010; Bradley et al., 2010; Klosterman et al., 2014; Richardson et al., 2017; Yan et al., 2016; Yang et al., 2012).

MODIS and Landsat have spatial resolutions of 500 m and 30 m respectively, typically making them top choices for studies focused on a specific area or ecosystem but lack the temporal resolution of geosynchronous instruments. For example, Lui et al. (2018) comparing multiple satellite remote sensing instruments (including MODIS and Landsat) examined phenology in a mixed grassland with oak trees as compared to an open grassland with no tree cover. Through a higher spatial resolution, they were able to highlight specific areas for a more targeted study, revealing that more homogeneous landscapes have similar plant phenology transition dates over a variety of spatial scales (Lui et al., 2017). Similar studies have been conducted using MODIS that help answer fine spatial scale questions related to crop rotation, plant type, and phenologic transition dates (Xiao et al., 2013; Richardson et al., 2018; Filippa et al., 2018). However, spatially advantageous studies such as these suffer from difficulties in obtaining numerous data due to infrequent overpass times, cloud cover, and atmospheric scattering.

Daily observations often have missing measurements due to cloudiness and other issues central to remote sensing. Although these data gaps can be filled statistically, this practice introduces unwanted uncertainty where actual observation would be preferred. For this reason, geostationary satellites introduce a unique solution. Yan et al. (2016) demonstrated this capability by using the Spinning Enhanced Visible and Infrared Imager (SEVIRI) with a temporal resolution of 15 minutes, and comparing image acquisition to that of MODIS, to increase the number of clear sky data points. They found that a clear image could be produced by SEVIRI at least every three days as compared to sixteen days by MODIS (Yan et al., 2016). With these findings in mind, my study uses GOES, a weather satellite repurposed for analyzing vegetation at 5-minute intervals. The potential of such high temporal resolution brings new insight to the study of canopy phenology, overcoming many of the barriers of polar-orbiting satellites over the entire United States.

Researchers have much to gain from combining sources of remotely sensed phenology to gain a better understanding of their impacts on the larger climate and biological systems. To do this, many recent studies pair satellite remote sensing techniques with near surface webcam data. This information aids in understanding phenology at multiple spatial scales, and helps build knowledge on the corrections needed due to atmospheric scattering, as well as highlighting differences in landscape homogeneity and plant functional type (Richardson et al., 2018).

Near Surface Remote Sensing (PhenoCams)

Recent advances in satellite remote sensing have coincided with techniques that have focused strongly on near surface remote sensing using digital repeat photography (Sonnentag et al., 2012; Hufkens et al., 2012; Keenan et al., 2014; Filippa et al 2016; Filippa et al., 2018; Richardson et al., 2018). Starting in approximately 2000, stationary mounted webcams or "PhenoCams" have created a low-cost solution to collecting high-frequency data on the scale of centimeters to hundreds of meters (Brown et al., 2016). With a typical frequency of one image every 15 minutes, PhenoCams can detect minute changes and effectively capture phenophase transition events from individual plants to ecosystems (Keenan et al., 2014). Early work with PhenoCams has historically focused on the Green Chromatic Coordinate (Gcc), which measures the ratio of image greenness

(G_{DN}) versus image brightness as the sum of red (R_{DN}), green, and blue (B_{DN}) reflectances (Equation 1) (Gillespie et al., 1987; Filippa et al., 2017).

$$G_{cc} = \frac{G_{DN}}{R_{DN} + G_{DN} + B_{DN}} \tag{1}$$

An early goal was the comparison of different plant types at the ecosystem scale, which led to a standardized network of cameras across the United States (PhenoCam Network) (Richardson et al., 2018). This has large implications when considering that both plant type and geographic location have varying degrees of intensity with regards to phenology transitions and growing season length (Ganguley et al., 2010; Hufkens et al., 2012; Sonnentag et al., 2012; Klosterman et al., 2014; Richardson et al., 2018).

Another goal of the near surface PhenoCam remote sensing is to supplement data collected via satellite, where the spatial and temporal scales may be coarse. The establishment of near infrared (NIR) sensing methods for PhenoCams in 2014 was a critical step in comparing near surface to satellite remote sensing (Petach et al., 2014). The first researchers were able to use security camera images in a laboratory to generate data in the form of the normalized difference vegetation index (NDVI), one of the most commonly used indices for calculating the presence of photosynthetically active vegetation (Petach et al., 2014; Filippa et al., 2018) (Equation 2). (Tucker, 1979). PhenoCams do not directly measure radiation in the NIR and therefore it must be estimated from the Digital Number style of measurement. This strategy is discussed in the methods section and an adjusted NDVI calculation is shown in Equation 3.

PhenoCams provide an opportunity to fill gaps left by noisy data as a result of atmospheric scattering and cloud masking.

$$NDVI = \frac{(NIR - R)}{(NIR + R)} \tag{2}$$

$$NDVI_{cam} = \frac{(NIR_{DN} - R_{DN})}{(NIR_{DN} + R_{DN})} \tag{3}$$

Comparison between Satellite and Near Surface Remote Sensing

Efforts to combine satellite (MODIS) and near surface (PhenoCam) remote sensing data have resulted in an increased understanding of plant phenology and the impact to atmospheric and ecosystem interactions (Bradley et al., 2010; Richardson et al., 2018). Richardson et al. (2018) observed four plant types comparing PhenoCam transition dates to MODIS transition dates, including crop, deciduous broadleaf, evergreen needle, and grasslands. The resulting R-squared values of the green-up transition date for these vegetation types were 0.91, 0.83, 0.37 and 0.97, respectively (Richardson et al., 2018). PhenoCams supply information about individual plant types, which becomes more important in relatively heterogeneous landscapes. In addition, the fixed position of PhenoCams with no cloud interference allows for data filling where MODIS may be unable to make observations.

A second recent study incorporating the methods of Petach et al. (2014) compared the NDVI derived from MODIS and PhenoCams at several sites (Filippa et al., 2018).

The study focused not only on comparing NDVI from the two different methods, but also looked at how Gcc compared with camera based NDVI (Filippa et al., 2018). Results showed promise as NDVI from the camera compared well with that of MODIS when a scaling factor was applied. In addition, the authors describe the importance of both NDVI and Gcc and that each has a role to play in studying plant phenology (Filippa et al., 2018).

Geosynchronous satellites have the capability to fill gaps in sampling data left by MODIS and other polar orbiting satellites. Although PhenoCams have high sample frequency, their distribution is limited, whereas GOES samples the entire United States. The number of studies comparing MODIS and near surface remote sensing applications is numerous due to data availability and ease of use. However, a comparison of GOES imagery and near surface remoting sensing could improve the understanding of plant canopy function, when considering the ability of GOES to sample on the scale of minutes and produce consistent data. With GOES 16 and 17 only recently operational over the United States, it is crucial to validate the satellites as a potential source of plant phenology data.

Scope of Study and Goals

My study aims to determine the ability of GOES to identify diurnal plant canopy phenology through high temporal resolution observations. It will also demonstrate the ability of GOES and PhenoCam data to be paired to observe diurnal NDVI patterns at multiple spatial scales. Both GOES and PhenoCams have temporal resolutions on the scale of minutes, but this combination of fine temporal resolution has yet to be compared at different spatial scales, and across different plant functional types, both of which will lead to the contribution of diurnal NDVI observations and understanding to the literature. New methods described in recent articles allow for the comparison of NDVI between the two remote sensing methods, and my study aims to add to those recent contributions, as well as demonstrate their potential. Vegetation type and landscape homogeneity are important factors when considering plant phenology observations and will individually be taken into consideration for the purposes of this study.

This study seeks to address the following:

1. Contribute to the understanding of NDVI comparison between near surface remote sensing (PhenoCams) and satellite radiometric observations (GOES).
2. Proof of concept: The GOES satellite series can be used as a valuable source of information with regards to high temporal resolution vegetation indices.
3. Proof of concept: Valuable information can be gathered from very high (15minute) temporal resolution comparisons between different spatial scales of plant phenology detection.

INTRODUCTION

Ongoing increases in global temperatures are changing the seasonal timing of biological events. Flowers are blooming earlier in the season (Aono & Kazui 2008), seeds are developing earlier – or later – in response to changing temperatures (Sherry et al., 2007), and spring canopy green-up is occurring earlier across much of the globe (Wang et al., 2015). These changes create 'phenological mismatches' between predators and prey (Kudo & Takashi 2013), counter-intuitively place plants at additional risk for cold stress if leaves develop during times when winter storms are likely (Wang et al., 2015), and can feed back to the climate system to further amplify (or dampen) ongoing climate changes (Hogg et al., 2000). Land surface models struggle to correctly simulate the changing patterns of canopy phenology, suggesting that our understanding of the drivers of phenology must improve (Richardson et al., 2012).

To achieve these goals, we must also improve our ability to observe phenological changes. Most satellite research on phenology relies on polar-orbiting satellites like MODIS that have single diurnal overpass times, leading to frequent missing measurements due to cloudiness and other common issues in satellite remote sensing (Zhang et al., 2003). These missing observations are often estimated using statistical techniques (Richardson et al., 2012) to create complete time series, which introduces additional uncertainty. A potential solution to this problem arrives from an unexpected source: geostationary satellites that are designed for weather systems (Wheeler & Dietze 2019), specifically the newest versions of the Geostationary Operational Environmental Satellite (GOES) series. GOES-16 and GOES-17 have similar spectral sensitivities as

MODIS and have the potential to measure the land surface every 5 minutes instead of once per day like MODIS-Aqua and MODIS-Terra. The addition of the near infrared (NIR) channel also allows the new GOES satellites to measure photosynthetic activity, previously unachievable in the GOES satellite series. These additions, combined with other global geostationary satellites exhibiting improved spectral sensitivity, indicate that the era of ‘hypertemporal’ land surface remote sensing is just beginning (Miura et al., 2019).

Such advances in satellite remote sensing are occurring alongside a revolution in near-surface observations of canopy phenology. Namely, the ‘PhenoCam’ network of automated cameras take visible and infrared images of plant canopies and submit observations to a central database every half hour to hour at hundreds of sites across the world (Brown et al., 2016), creating a ‘bottom-up’ compliment to ‘top-down’ satellite remote sensing. Phenocams are effective at monitoring rapid vegetation transitions (Browning et al., 2017) but measure small footprints on the order of kilometers at discrete locations and must be connected to satellite measurements for a comprehensive phenology measurement network.

Surface and satellite remote sensing of common observables like the normalized difference vegetation index (NDVI) can now in principle be linked in real time, but the NDVI signal from space remains noisy due to atmospheric scattering, and PhenoCams measure a ‘digital number’ that corresponds to red, blue, green, and infrared reflectance rather than reflectance itself. However, recent advances in both GOES and PhenoCam analytical tools have primed the research for future comparisons. Diurnal curves generated by GOES NDVI observations are being used to fit data sets with high noise due to scattering, and PhenoCam NDVI calculation techniques are being normalized through radiometric comparisons (Wheeler & Dietze, 2019; Petach et al., 2014). To date, GOES and PhenoCams have been compared in eastern U.S. temperate forests (Wheeler & Dietze, 2019) but not in other ecosystems. Here, I compare NDVI observed by GOES and PhenoCams at six sites across the contiguous U.S. that represent a range of ecosystem types.

METHODS

Study Sites

Six study sites were chosen to gain a broad understanding of canopy function with regards to geographic region, vegetation type, and vegetation homogeneity which may impact the ability to scale observations from spatially detailed PhenoCam images (on the order of cm) to GOES pixels (on the order of 1 km) (Table 2). PhenoCam observations come from the National Ecological Observatory Network (NEON) (Figure 1) and Table 2 shows the coordinates for the PhenoCam at each location as well as the primary vegetation and relative homogeneity at each site as identified by NEON metadata.

Bartlett Experimental Forest (44.06, -71.29): The Bartlett Experimental Forest (BART) is located in eastern New Hampshire in NEON region D01 (Northeast). The primary vegetation classification is mixed deciduous forest based on large contributions of both deciduous and evergreen trees in the area (Figure 2a). The dominant tree species are *Fagus grandifolia, Tsuga canadensis,* and *Acer pensylvanicum* (NEON, 2019).

Konza Prairie Biological Station (39.10, -96.56): The Konza Prairie Site (KONZ) is located in northeastern Kansas and is classified as NEON region D06 (Prairie Peninsula). The primary vegetation classification is grassland and the dominant grass species are *Schizachyrium scoparium, Andropogon gerardii*, and *Sorghastrum nutans* (NEON, 2019) (Figure 2b).

Talladega National Forest (32.95, -87.39): The Talladega National Forest (TALL) located in central Alabama is classified as NEON region D08 (Ozarks Complex). The primary vegetation classification is evergreen needleleaf with a secondary classification of mixed forest due to scattered deciduous trees in the area (Figure 2c). The dominant shrub and tree species are *Vaccinium arboreum*, *Pinus palustris*, and *Liquidambar styraciflua*. (NEON, 2019).

LBJ National Grassland (33.40, -97.57): The Lyndon B. Johnson National Grassland (CLBJ) is located in North Central Texas in NEON region D11 (Southern Plains). The primary vegetation classification is deciduous broadleaf within the PhenoCam image, but the area surrounding the PhenoCam is composed of both grassland and forest (Figure 2d). The dominant tree and grass species are *Quercus marilandica*, and *Schizachyrium scoparium* (NEON 2019).

Abby Road, Washington (45.76, -122.33): The Abby Road (ABBY) Tower is located in southwestern Washington and is classified as NEON region D16 (Pacific Northwest). The primary vegetation classification is evergreen needleleaf. The area is mostly homogeneous with little other vegetation in the surrounding areas (Figure 2e).

The dominant shrub and tree species are *Gaultheria shallon, Pseudotsuga menziesii*, and *Corylus cornuta var. californica* (NEON, 2019).

Lower Teakettle California (37.01, -119.01): The Lower Teakettle (TEAK) site is located in Southern California and is classified as NEON region D17 (Pacific Southwest). The primary vegetation classification is evergreen needleleaf, however stem density is low with grass and shrubs interspersed such that it may be argued to share features with savanna ecosystems (Figure 2f).

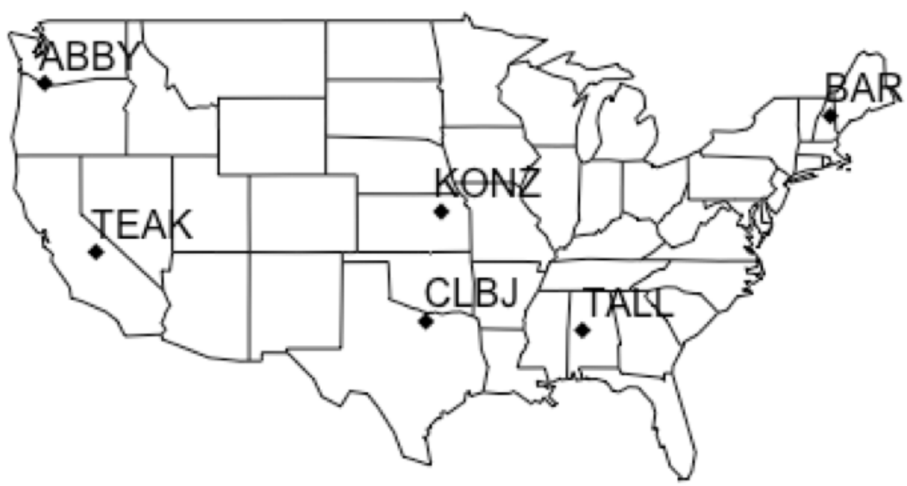
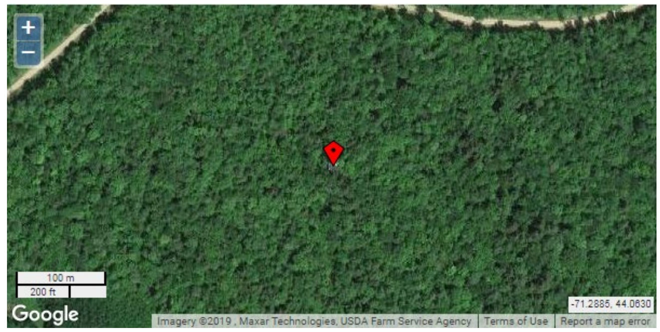


Figure 1: The locations of the PhenoCam observation sites described in Table 2.

Table 2. Study site information based on NEON metadata.

Site Name	Location	Coordinates	Region Description	Primary Plant Type	Relative Homogeneity
BART	Bartlett Experimental Forest	44.0639, -71.2874	Northeast	Mixed forest	Heterogeneous
KONZ	Konza Prairie Biological Station	39.1008, -96.5631	Prairie Peninsula	Grassland	Homogeneous
TALL	Talladega National Forest	32.9505, -87.3933	Ozarks Complex	Evergreen Needleleaf	Homogeneous
CLBJ	LBJ National Grassland	33.4012, -97.5700	Southern Plains	Deciduous Broadleaf	Homogeneous
ABBY	Abby Road	45.7624, -122.3303	Pacific Northwest	Evergreen Needle	Heterogeneous
TEAK	Lower Teakettle	37.0058, -119.0060	Pacific Southwest	Evergreen Needle	Heterogeneous

a) BART



b) KONZ

c) TALL

d) CLBJ

e) ABBY

f) TEAK

Figure 2 Left: Sample PhenoCam image with selected region of interest (ROI) shown with black lines. a: Bartlett Experimental Forest (BART), b: Konza Prairie (KONZ), c: Talladega National Forest (TALL), d: CLBJ National Grassland (LBJ), e: Abby Road (ABBY), f: Teakettle (TEAK). Right: Google Earth imagery of each site with relative scale provided.

PhenoCam Data Acquisition and Processing

Phenocam data were obtained through the National Ecological Observatory Network (NEON) data collection site for the time period ranging from 4/24/2019 0:00 to 4/30/2019 23:45. NEON uses NetCam CS CAM-SEC5IR-B (StarDot Technologies, Buena Park, CA, USA) mounted webcams to obtain images at each of its locations. Cameras are programed to obtain one image every 15 minutes. Two sets of images were obtained, the first was a layering of red, blue, and green (RBG) bands representing the visible light spectrum (VIS), and the other a gray scale image, shows activity level in both visual and IR spectrum levels together (Petach et al., 2014). To obtain NIR digital numbers the true color image is subtracted from the grayscale image, leaving only activity related to NIR. Raw images from each of the six sample sites were downloaded from NEON and saved for processing. The R package “ncdf4” was used to open and extract the raw NEON data from the .nc file type.

The R package *Phenopix* (Filippa et al., 2016) was used to complete the PhenoCam image processing. For each study site, I drew a unique region of interest (ROI) that encompassed a large dominant vegetation sample at the front of the frame (Figure 2). *Phenopix* obtains four Digital Numbers (DN) corresponding to red, green, blue, and NIR bands for each pixel using a combination of the two images. The NIR DN is derived by subtracting the RBG component out of the combined grey scale image as seen in Equation 3d (Petach et al., 2014). A DN is designated for each pixel contained within the ROI and averaged.

The RBG and RBG+NIR images are taken a few seconds apart and with different lenses. The result is varying exposure values that need to be corrected (Petach et al., 2014). The "match exposure" function in *Phenopix* was used to complete this adjustment (Petach et al., 2014). These corrections are described briefly in Equation 3a-3d where *Y* represents R, B, or G, *X* represents NIR, *Z* represents RBG + NIR, *R* is red light, and *E* is exposure (Petach et al., 2014). The corrected DN values for Red and NIR were then used to calculate NDVI as per Equation 2 (Filippa et al., 2016).

$$Z'_{DN} = \frac{Z_{DN}}{\sqrt{E_Z}} \tag{3a}$$

$$R'_{DN} = \frac{R_{DN}}{\sqrt{E_Y}} \tag{3b}$$

$$Y'_{DN} = \frac{Z_{DN}}{\sqrt{E_Z}} \tag{3c}$$

$$X'_{DN} = Z'_{DN} - Y'_{DN} \tag{3d}$$

GOES Data Acquisition and Processing

Satellite data were obtained from the NOAA Geostationary Operational Environmental Satellite (GOES) using the Advanced Baseline Imager (ABI). The image generated from GOES centers on the geographic coordinates of the PhenoCam tower at each of the six sites. The image contains four pixels with a spatial resolution of 1 kilometer each.

The ABI contains 16 observational channels ranging from 0.47 micrometers to 13.3 micrometers. For the purposes of this study Channel 2 (Red) and Channel 3 ("veggie"/NIR) reflectance values were used to calculate NDVI as in Equation 2. The pre-processed reflectance values were averaged across the 4 pixels and were used to calculate the NDVI of the entire area. In addition to the data required to calculate NDVI, GOES data supplied estimated cloud cover to filter data influenced by cloud cover and solar zenith angle to characterize its relationship with NDVI.

Data Analysis

Both PhenoCam and GOES NDVI values were merged into one dataset for comparison. To do so, the temporal resolution of GOES (5 min) needed to match that of the PhenoCam data set (15 min). Every third GOES image was taken from a common starting point in each data set to pair observations. The data set was filtered by PhenoCam exposure values to eliminate irregular and nighttime values. This was done according to methods by Snyder et al. (2019) in which exposure values (EV) greater than 1600 EV, and where RBG was greater than the RBG+NIR, were filtered from the data set.

The remaining PhenoCam and GOES NDVI values were plotted on time series graphs. Due to differences in scale the data sets were plotted both individually and on the same charts for ease of interpretation. Several basic statistical analyses were used to gain a better understanding of the hypertemporal data sets. This included basic data averaging of daytime values (filtered by methods described above) as well as more specific midday data and cloudless data. A series of one-tailed paired T-tests were also run in R to compare PhenoCam and GOES data.

RESULTS

Time Series Observations

The clearest signals for both the PhenoCam and GOES NDVI data follow a general diurnal pattern, rising in the morning peaking around midday and falling again in the afternoon. The GOES data have a more distinct parabolic diurnal signal than do the data collected from PhenoCam images. The parabolic structure can be measured quantitatively through standard deviation. GOES had a larger standard deviation on average across all study sites at 0.194 while the PhenoCam data had a standard deviation of 0.107. The shape of the PhenoCam diurnal signal is present but shallow (Figure 4). GOES NDVI values are higher than PhenoCam values at each site (average difference = 0.26). This is due in part to the correction requirements of PhenoCam, discussed in the next section. Days with a large amount of noise in both the GOES and PhenoCam data sets are observed to have a large amount of interference from cloud cover. The percentage of cloudy observations at each site are as follows BART 78%, KONZ 68%, TALL 53%, CLBJ, 61%, ABBY 69%, TEAK 86%. A comparison of mean NDVI values from daytime data and clear daytime data are presented in Figure 3. Although the PhenoCam data show only a slight increase in mean NDVI, there is a clear increase in mean NDVI of the GOES data when cloudy observations are removed. Visual time series observations indicate that GOES data at TALL, CLBJ, ABBY, and TEAK had the clearest diurnal signals while BART and KONZ had more noise and apparent interference in the data set (Figure 5). PhenoCam time series observations show signals at

TALL, ABBY, and TEAK were also clear, however BART, KONZ, and CLBJ had less obvious trends (Figure 6).

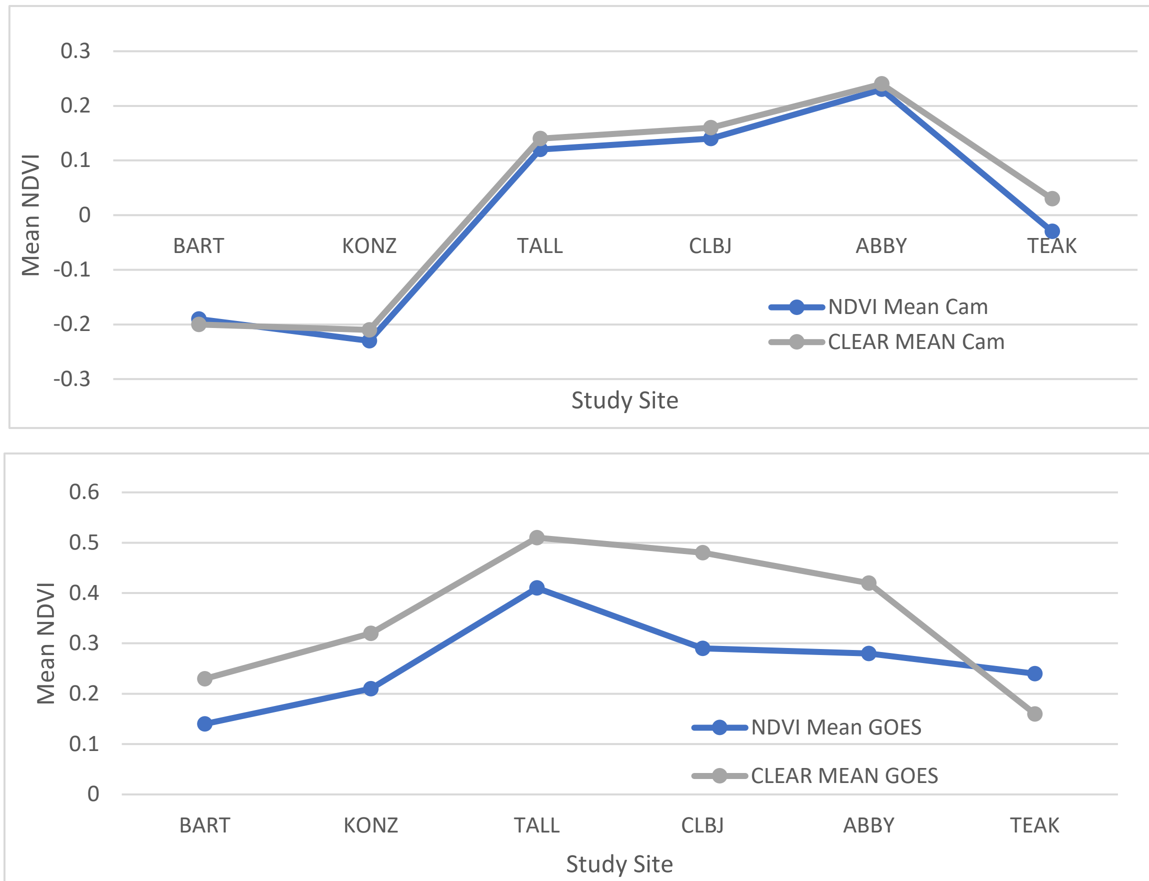


Figure 3 Top: PhenoCam mean NDVI from daytime data (NDVI Mean Cam) and cloudless daytime data (CLEAR MEAN Cam). Bottom: GOES mean NDVI from daytime data (NDVI Mean GOES) and cloudless daytime data (CLEAR MEAN GOES).

Table 3. Results of upper one-tailed paired T-tests comparing GOES and PhenoCam time series for several filtered data sets at all sites

T tests	T-value	df	P-value	mean of diff
BART Total	31.175	362	2.20E-16	0.331
BART Midday	21.684	118	2.20E-16	0.38
BART Clear	14.476	79	2.20E-16	0.426
KONZ Total	38.03	349	2.20E-16	0.432
KONZ Midday	25.523	116	2.20E-16	0.499
KONZ Clear	25.231	112	2.20E-16	0.532
TALL Total	19.324	345	2.20E-16	0.29
TALL Midday	19.876	113	2.20E-16	0.381
TALL Clear	16.097	162	2.20E-16	0.365
CLBJ Total	10.108	343	2.20E-16	0.149
CLBJ Midday	9.3479	116	4.01E-16	0.22
CLBJ Clear	12.958	134	2.20E-16	0.311
ABBY Total	2.4894	100	7.00E-03	0.0466
ABBY Midday	7.5542	30	1.01E-08	0.186
ABBY Clear	5.5797	30	2.27E-06	0.183
TEAK Total	26.783	352	2.20E-16	0.275
TEAK Midday	25.797	117	2.20E-16	0.382
TEAK Clear	3.92	50	1.34E-04	0.122

Statistical Analysis

One tailed paired T-tests were run on each site for datasets including the total data set generated as per methods described above, as well as Midday (10am-2pm) and Clear (no cloud cover) data sets (Table 3). With very low P-values (all $P < 0.05$), it is clear that the GOES and PhenoCam data sets have a large amount of shared variability between them. This was anticipated due to the observed PhenoCam NDVI challenges discussed by Petach et al, (2014). However, there valuable information can still be obtained by comparing T-values from the three data sets described above for each method. An example of such a comparison is demonstrated by the cloudless data sets relatively low T values as compared to the total daytime values when averaged across all study sites (21.3 and 13.0 respectively). This shows that cloud cover impacts the variability between methods. However, even when only clear observations are included there is a large amount of variability still to be explained.

The major plant functional groups observed in this study (from NEON metadata) are mixed , deciduous broadleaf, evergreen needle, and grassland. In the GOES data set, the evergreen needle sites at ABBY and TEAK (and TALL to a lesser degree) had time series charts most representing a parabolic structure. The deciduous broadleaf and grassland sites (CLBJ and KONZ respectively) also had relatively clear signals. The mixed plant type (BART) had a very scattered signal with little to know diurnal pattern visible (Figure 4). When comparing variability between methods through T-tests no pattern emerged with respect to plant type (Table 3) (Figure 4). The noteworthy exception being the relatively poor performance of the grassland (KONZ). T-values at

KONZ were the highest in all data sets including daytime total, midday, and cloudless with T-values of 38.03, 25.52 and 25.23 respectively (Table 3).

There is a large range of homogeneity between sites qualitatively observed through Google satellite imagery provided via the PhenoCam network (Figure 2). KONZ, TALL, and CLBJ are relatively homogeneous, while BART, ABBY, and TEAK are observed to have relatively heterogeneous landscapes with regards to the primary vegetation type. Both ABBY and TEAK have visible patches of understory (grass and shrubs) between the evergreen needle primary vegetation. At BART there is a mix of two tree types that can be readily seen in the PhenoCam images in Figure 2. The T-test analysis showed that heterogeneous sites (BART, ABBY, and TEAK) counterintuitively outperformed homogeneous sites (KONZ, TALL, and CLBJ) when comparing clear observations, with T values of 18.1 and 8.0 respectively when averaged across sites (Table 3). No quantitative ranking system of homogeneity was used in this study and therefore regressions were not included.

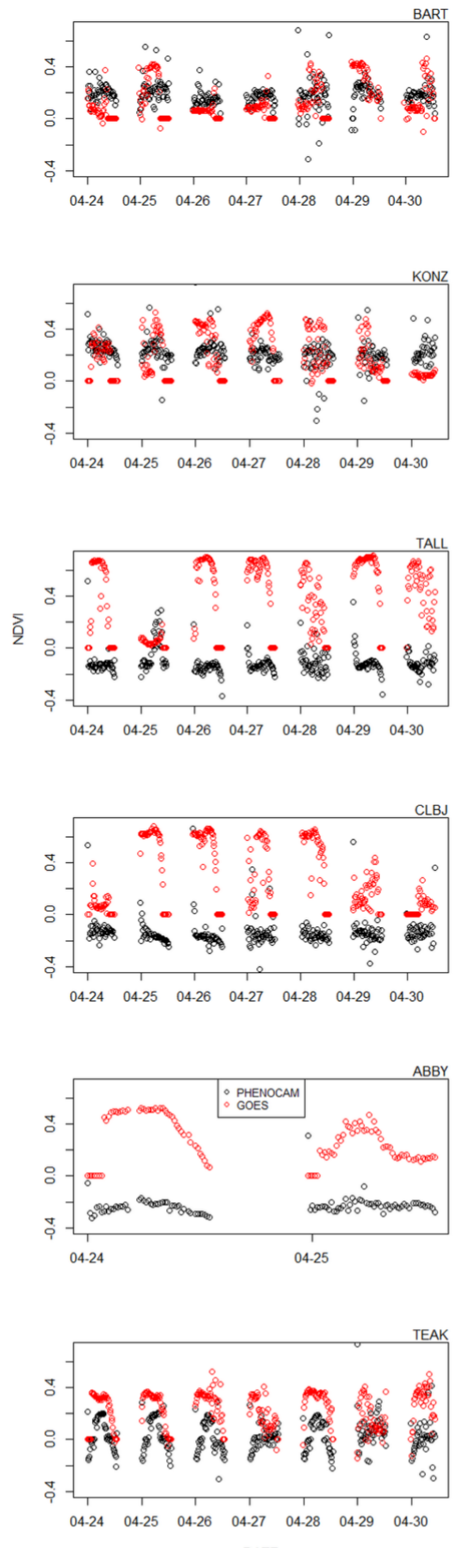


Figure 4: NDVI derived from 15 min observations via PhenoCam and GOES at six sites for the week of April 24, 2019.

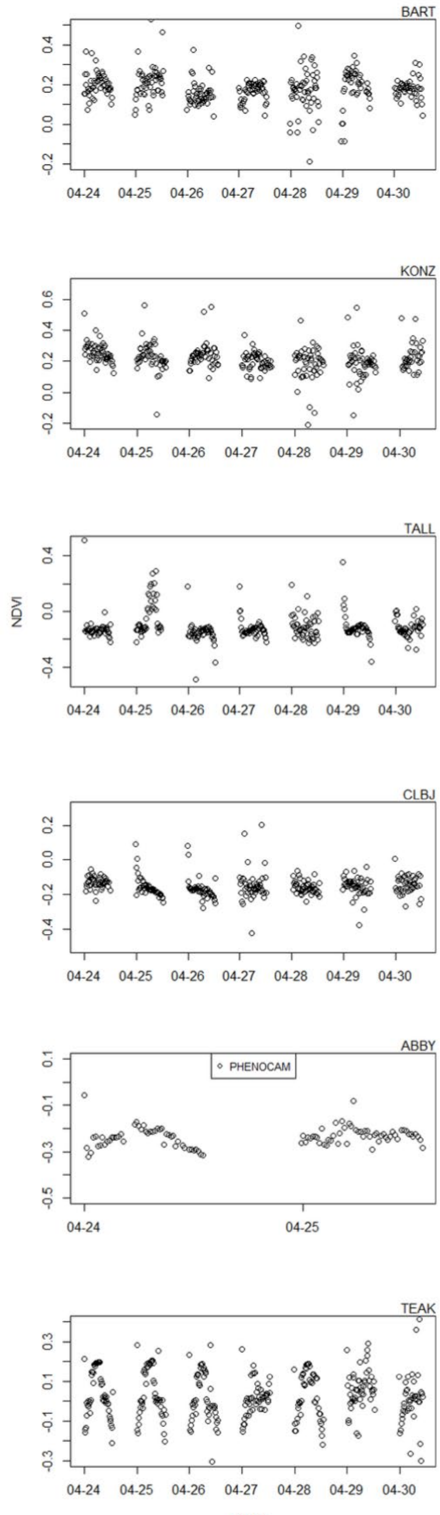


Figure 5: NDVI derived from 15 min PhenoCam observations at six sites for the week of April 24, 2019.

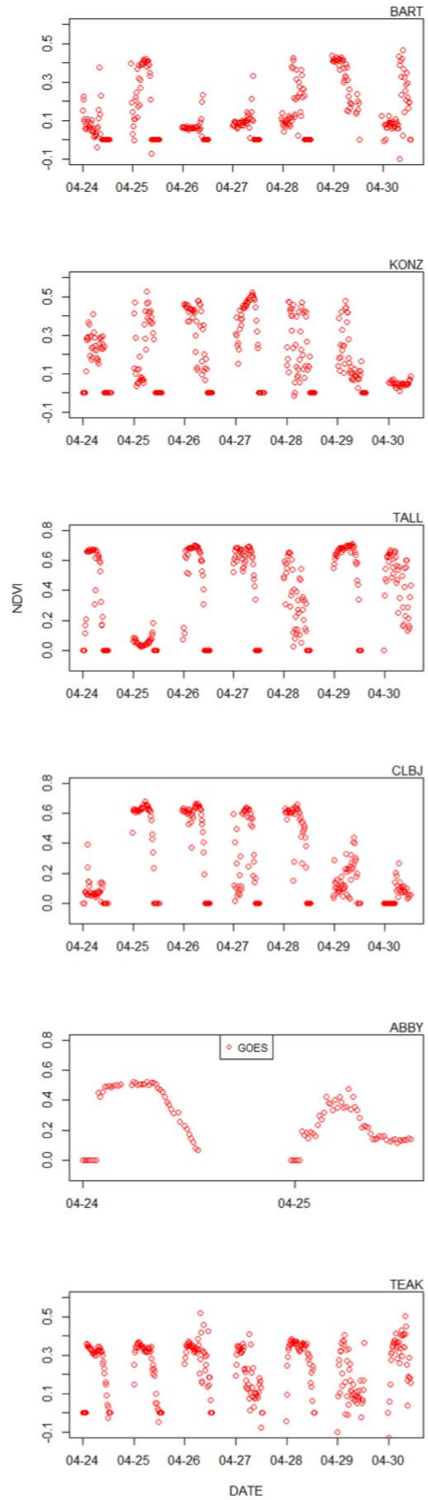


Figure 6: NDVI derived from 15 min GOES observations at six sites for the week of April 24, 2019.

DISCUSSION & LIMITATIONS

Time Series Observations

At all study locations, the observed NDVI obtained from GOES is consistently higher than the NDVI achieved from PhenoCams, even in cases where diurnal signals appear to align. The low bias of PhenoCam NDVI as compared to NDVI sensed by radiometers has been documented (Petach et al. 2014). The lower NDVI values recorded by PhenoCams arises from the collection method of which obtains a DN rather than a true reflectance value for each channel as are obtained by the radiometer aboard GOES (Petach et al., 2014; Snyder et al., 2019). Despite this difference, the NDVI obtained at high temporal resolution from both instruments align well, especially under optimal (cloud-free) sky conditions.

The one-tailed paired T-tests demonstrate the impact of cloud cover and midday observations on the two observation methods. When averaging across sites, the average T-value is highest for the complete daytime data, and lowest when comparing data from cloud free observations (21.3 and 13.0 respectively). This implies that a large portion of the differing NDVI values between PhenoCam and GOES is caused by noise from cloud cover. The remaining variability can likely be attributed to a consistent low bias in the PhenoCam data due to the methods of NDVI calculation. The impact of cloud cover on all sites is further demonstrated by a regression analysis comparing the percentage of cloudy observations to the difference in T values between the total daytime data and cloud free data at each site (Figure 7, R^2=0.59). These analyses demonstrate the need for additional data filtering due to atmospheric noise.

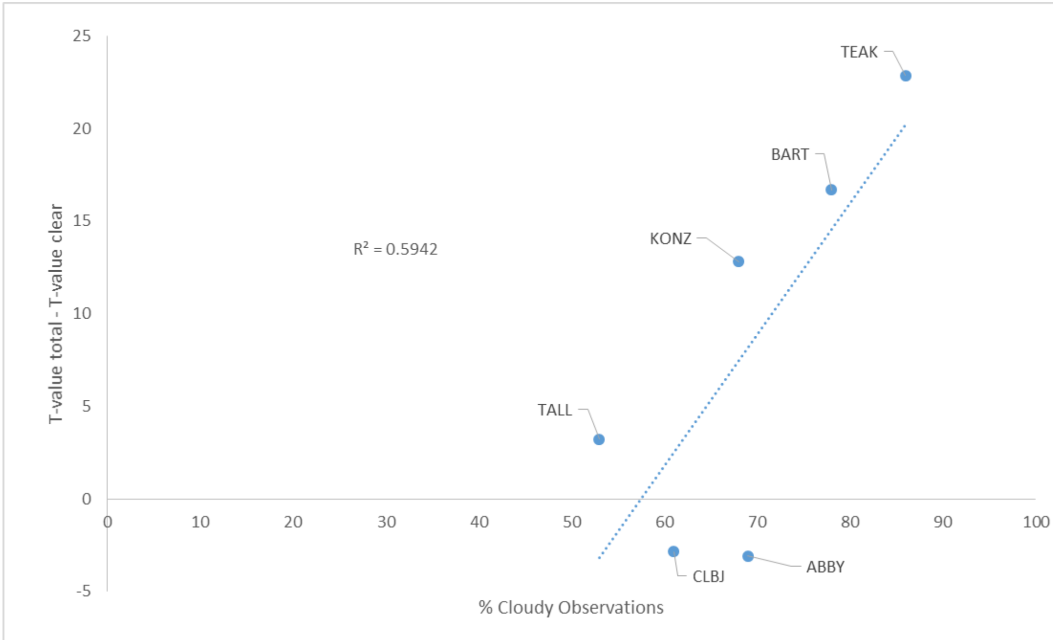


Figure 7. Regression comparing the difference in total and clear T values to the cloudy observation percentage at each of the six study locations

With full operation of GOES 16 and 17 occurring only within the last two years, early information about the ability to track NDVI becomes incredibly important. Not only the advent of the images themselves but the introduction of the NIR band to the list of available channels has allowed for these calculations (Wheeler & Dietze, 2019). Wheeler and Dietze (2019) observed some of the first diurnal patterns in NDVI captured by the GOES satellites, and the time series plots observed in this study appear to follow suit. Low noise days observed by Wheeler and Dietze (2019) are those that tightly fit to a parabolic shape with little error, as seen early in the week at TEAK and during the two days of data collected at ABBY (Figures 4 & 5). High noise days are those with a large amount of scatter such as are seen at BART and KONZ (Figures 4 &5). Wheeler and Dietze (2019) propose methods for fitting high noise days to the known parabolic structure of diurnal observations and could vastly improve the data collection for NDVI from the GOES products, and the visual results of the time series presented in this study further support this need.

The time series plots generated in this study demonstrate that similar diurnal patterns are observed at different spatial scales. This observation follows the results of other studies that have observed agreement between methods when comparing modeled daily values over seasonal time scales (Filippa et al., 2018; Snyder et al., 2019). In this study, observations remain largely qualitative but seek to show the potential of comparing methods at this scale. The Lower Teakettle site had visibly the most agreement between methods and shows the possibility for future research to focus on deriving these clear signals from both GOES and PhenoCams.

Plant Type and Heterogeneity Comparison

Results showed that only the grassland plant type had a notable difference in variability between PhenoCam and GOES methods. With little improvement between midday and cloudless values, a homogeneous landscape, and a relatively low cloud observation percentage (68%), the plant type is one factor that could be responsible for this variability. The KONZ site was still very early in the growing season with little to no green color in the images. Due to the nature of PhenoCam observations, this could be a contributing factor to the large variability. More research will be needed comparing the two methods at grasslands to ensure that the capability seen in the forest plant types is matched.

Perhaps more noteworthy than the plant type was plant greenness as mentioned above. The PhenoCam images that appeared most green tend to have the lowest T-values. Due to the late April sample date, the BART and KONZ sites had very high T-values likely due to the lack of spring color in the area. Though the TEAK site had high T-values, the very low value in the cloudless data set implies that this difference was not due to any lack of green color (as the site contains evergreen needle trees) but rather due to a large portion of cloudy observations at that site (86%).

For plant type, the GOES observations were able to obtain at least one very clear diurnal signal in each week for each plant type. This implies that the GOES satellites are capable of documenting NDVI change over the course of a single day regardless of plant type. This is encouraging for the use of GOES as a source of plant functional data and should be noted separately from the comparison to PhenoCam measurements.

Compared with cloud cover, heterogeneity appears to have played less of a role in the variability between NDVI measuring methods. However, it was unexpected for heterogeneous sites to outperform homogeneous sites in this analysis. As described in the results, the heterogeneous sites had lower overall T values in the cloudless data sets than did the homogeneous sites. This is counterintuitive, due to the difference in spatial scales GEOS will have much more anticipated variability in NDVI at heterogeneous sites. It should be noted that sample size for this comparison is relatively low and more research will be needed to determine the true role of heterogeneity on method comparison.

Through the results of this analysis, however, it may play less of a role than previously anticipated.

Study Limitations

As a proof-of-concept study, there are several limitations to the processes described in this article. The most important of these likely being the one-week timeframe in which the data were obtained. Longer GOES time series are being requested from NASA and the Cooperative Institute for Meteorological Satellite Studies at the University of Wisconsin – Madison. Ideally at least one full growing season would be captured in a study such as this to obtain transition dates based on the annual curve of NDVI. For the purposes of this article however, one week of data is sufficient to show diurnal patterns across multiple spatial scales can be obtained and analyzed.

Another limiting factor is the lack of correction in the data sets obtained. Several tools have recently been shown to improve data sets from both GOES and PhenoCam NDVI. Petach et al. (2014) demonstrates the ability to correct for the low bias in PhenoCam NDVI calculation methods as opposed to direct radiometric measurement. GOES improvements were demonstrated by Wheeler & Dietze (2019). They showed the potential for fitting missing data points to a known parabolic curve indicating diurnal NDVI.

CONCLUSIONS & FUTURE CONSIDERATIONS

Though the results of this study are largely qualitative in nature, the concepts demonstrated through visual time series generation can help guide future research. Several studies have already shown that identifying changes in plant-canopy phenology season to season is vital to our understanding of the biological and climate systems (Richardson et al., 2018). By comparing two methods at such fine temporal resolution, changes on the magnitude of hours could be identified. This advent could aid research of biological systems, urban planning, climate change, agriculture and others.

It is now possible to observe NDVI using both near surface PhenoCams and the newly launched GOES satellite series. Due to the difference in NIR detection between the two methods, the PhenoCam values are biased slightly low (Petach et al., 2014). My study demonstrates agreement in diurnal signal between the two high temporal resolution remote sensing techniques, implying that comparing the two methods would be an excellent source of information to improve upon the PhenoCam NDVI correction factors. These improvements could span several plant types and heterogeneities as demonstrated in just the small sample provided in this study.

GOES will likely gain popularity for studies involving NDVI with the new NIR capabilities. My study supports the work of others in observing a clear parabolic diurnal pattern achieved from the high temporal resolution of observation (Wheeler & Dietze 2019). The geosynchronous orbit allows for these high frequency observations increasing the amount of high-quality data achieved with limited cloud cover and interference. Even with such frequent data points, the need to correct for noise within diurnal observations is clear. Tools are currently in development that aim to fit diurnal data to parabolic curves correcting for noise and filling data points to limit error (Wheeler and Dienske 2019). Such tools will lead to complete data sets with a larger quantity of data points than have been seen in the past using polar orbiting satellites.

With tools in place to correct both PhenoCam and GOES data, the comparison of the two will be incredibly valuable. This study demonstrates the capacity of diurnal patterns to show agreement, but it also shows the ability of one method to supplement where the other falls short. Examples of gaps identified in this study include the heterogeneity of GOES pixels resulting in an NDVI biased low, and the early season photosynthetic activity being detected via GOES but with limited green light to be detected by PhenoCam. This is not the first study to identify the benefits of comparing multiple spatial scales to gain a more complete understanding of plant phenology, however, for the first time that valuable information can be observed in near real time.

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