



# Monitoring vegetation phenology using an infrared-enabled security camera

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**Monitoring vegetation phenology using an infrared-enabled security camera**

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1 **Abstract**

2           Sensor-based monitoring of vegetation phenology is being widely used to quantify  
3 phenological responses to climate variability and change. Digital repeat photography, in  
4 particular, can characterize the seasonality of canopy greenness. However, these data cannot be  
5 directly compared to satellite vegetation indices (e.g., NDVI, the normalized difference  
6 vegetation index) that require information about vegetation properties at near-infrared (NIR)  
7 wavelengths. Here, we develop a new method, using an inexpensive, NIR-enabled camera  
8 originally designed for security monitoring, to calculate a “camera NDVI” from sequential  
9 visible and visible+NIR photographs. We use a lab experiment for proof-of-concept, and then  
10 test the method using a year of data from an ongoing field campaign in a mixed temperate forest.  
11 Our analysis shows that the seasonal cycle of camera NDVI is almost identical to that of NDVI  
12 measured using narrow-band radiometric instruments, or as observed from space by the MODIS  
13 platform. This camera NDVI thus provides different information about the state of the canopy  
14 than can be obtained using only visible-wavelength imagery. In addition to phenological  
15 monitoring, our method should be useful for a variety of applications, including continuous  
16 monitoring of plant stress and quantifying vegetation responses to manipulative treatments in  
17 large field experiments.

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20 **Keywords:** Digital repeat photography; green chromatic coordinate ( $g_{CC}$ ); near-surface remote  
21 sensing; normalized difference vegetation index (NDVI); phenology; stress monitoring.

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## 1 **Introduction**

2           The phenology of terrestrial vegetation is highly sensitive to climate variability and  
3 change (Rosenzweig et al., 2007; Migliavacca et al., 2012). In the context of climate change,  
4 phenology is important because it mediates many of the feedbacks between terrestrial vegetation  
5 and the climate system (Richardson et al., 2013a). From an ecological perspective, phenology  
6 plays an important role in both competitive interactions and trophic dynamics, as well as in  
7 reproductive biology, primary production, and nutrient cycling (Morissette et al., 2009).

8           Satellite remote sensing can provide global coverage of vegetation phenology, but suffers  
9 from tradeoffs between spatial and temporal resolution (Zhang et al., 2003; White et al., 2009).  
10 Thus, over the last decade, there has been great enthusiasm for increased on-the-ground  
11 monitoring of phenology (Betancourt et al., 2005; Morissette et al., 2009; Polgar and Primack,  
12 2011). The general objective of these efforts is to better understand spatial and temporal  
13 variation in phenology, and how this variability is driven by environmental factors such as  
14 temperature, precipitation, and photoperiod (or insolation). Citizen science networks, such as the  
15 USA National Phenology Network (<http://www.usanpn.org>) and Project Budburst  
16 (<http://budburst.org>), are playing an important role in this monitoring, by engaging large  
17 numbers of motivated volunteers and establishing standardized protocols.

18           Instrument-based approaches (Richardson et al., 2013b) provide a compelling alternative  
19 to observer-based phenology, because of the potential for high frequency, automated data  
20 collection in a manner that is scalable for regional or continental monitoring. In this context,  
21 digital repeat photography (e.g. Richardson et al., 2007, 2009; Sonnentag et al., 2012) is an  
22 attractive option because images can be analyzed either qualitatively or quantitatively, and  
23 analysis can focus on individual organisms or integrate across the field of view to obtain a  
24 community- or canopy-level perspective. Compared to data collected by a human observer,  
25 which tend to focus on discrete phenophases, such as flowering or budburst, the entire seasonal  
26 trajectory of canopy greenness can be characterized from digital camera imagery. Additionally,  
27 the archived images provide a permanent visual record that can be reanalyzed as new tools and  
28 questions are developed. Camera-based monitoring (e.g. the PhenoCam network,  
29 <http://phenocam.sr.unh.edu/>) thus provides data at a spatial scale that is intermediate between  
30 ground observations of individual plants and satellite remote sensing.

1 To date, most camera-based monitoring of vegetation phenology has been conducted  
 2 using standard, consumer-grade digital cameras (e.g. Sonnentag et al., 2012). These typically  
 3 record a three-layer image (red, green and blue: RGB), which is sufficient for the representation  
 4 of colors in the visible spectrum (VIS,  $\lambda = 400\text{-}700$  nm) as perceived by the human eye. For  
 5 quantitative analysis, the average value of each color layer for all pixels within a user-defined  
 6 region of interest (ROI) is extracted from each image to yield a digital number triplet ( $R_{DN}$ ,  $G_{DN}$ ,  
 7  $B_{DN}$ ). Then seasonal variation in the state of the canopy is characterized by the use of several  
 8 color indices, such as the green chromatic coordinate ( $g_{CC}$ , Eq. 1a) and excess green ( $G_{EX}$ , Eq.  
 9 1b) (Sonnentag et al., 2012; Richardson et al., 2013b):

$$10 \quad g_{CC} = G_{DN} / (R_{DN} + G_{DN} + B_{DN}) \quad \text{Eq. 1a}$$

$$11 \quad G_{EX} = 2G_{DN} - (R_{DN} + B_{DN}) \quad \text{Eq. 1b}$$

12 Conversely, satellite remote sensing of vegetation has traditionally used both visible and  
 13 near-infrared (NIR,  $\lambda = 700\text{-}1400$  nm) wavelengths. The reason for this is that healthy vegetation  
 14 can be distinguished from other land cover types by its unique spectral signature, which  
 15 combines low reflectance in the VIS with high reflectance in the NIR. Thus, the camera indices  
 16 presented above, which are based only VIS wavelengths, are not directly comparable to standard  
 17 satellite vegetation indices such as NDVI (Normalized Difference Vegetation Index, Eq. 1c),  
 18 calculated from red band and NIR band reflectances ( $\rho_R$  and  $\rho_{NIR}$ , respectively) (Tucker, 1979).

$$19 \quad NDVI = (\rho_R - \rho_{NIR}) / (\rho_R + \rho_{NIR}) \quad \text{Eq. 1c}$$

20 Intriguingly, the CCD (charge-coupled device) or CMOS (complementary metal-oxide-  
 21 semiconductor) imaging sensors used in most digital cameras are sensitive to wavelengths in the  
 22 NIR portion of the spectrum. An infrared cut filter is typically used to block these wavelengths  
 23 from reaching the imaging sensor, as they are beyond the spectral range to which the human eye  
 24 is sensitive and are thus not necessary for conventional color photography. Customized cameras  
 25 have been used in the past to leverage this NIR sensitivity (Shibayama et al., 2009, 2011;  
 26 Sakamoto et al., 2010, 2012; Nijland et al., 2013). For example, using a two-camera system  
 27 Sakamoto et al. (2012) calculated an NDVI-style index that was more akin to the conventional  
 28 NDVI than either  $g_{CC}$  or  $G_{EX}$ . The two-camera approach allows for simultaneous recording of  
 29 information about the VIS and NIR properties of vegetation, but creates challenges related to  
 30 camera alignment, cross-calibration, and synchronization of image capture. Very recently,  
 31 relatively low-cost NDVI cameras have become available (e.g. MaxMax, Event-38, and Regent

1 brands), but these have not been produced with long-term monitoring in mind, and such cameras  
2 are unable to also produce conventional RGB imagery—that is, infrared wavelengths are  
3 recorded at the expense of information in one of the RGB channels.

4 Here, we show that a commercially-available, network-enabled camera (“webcam”) with  
5 a software-controlled infrared cut filter overcomes the above limitations. With the cut filter in  
6 place, standard 3-layer RGB imagery is recorded; with the filter removed, a monochrome  
7 RGB+NIR image is obtained. We develop a method to compute an NDVI-style vegetation index,  
8 which we call “camera NDVI”, from this imagery. A lab experiment, conducted under controlled  
9 conditions, is used as a proof-of-concept. We then apply the method to a one-year archive of  
10 images from the Harvard Forest to demonstrate the feasibility of employ this method for field  
11 monitoring of vegetation phenology, where day-to-day variation in weather and lighting cause  
12 additional challenges. As a final test, we compare the seasonality of camera NDVI from the  
13 Harvard Forest data with that obtained using co-located narrow-band radiometric instruments  
14 and from satellite sensors. Data from our camera system will be of value for quality assessment  
15 of phenology products derived from satellite imagery (e.g. White et al., 2009).

## 17 **Material and Methods**

### 18 *Camera*

19 We used a NetCam SC IR (StarDot Technologies, Buena Park, CA) camera, featuring a  
20 Micron ½" CMOS active-pixel digital imaging sensor and configured for 1.3 megapixel (1296 x  
21 976) output. The camera was set at manual (fixed) white balance and, unless otherwise noted,  
22 automatic exposure. With a built-in uClinux operating system, the camera operates as a  
23 standalone system with Internet connectivity. Command scripts running on the camera controlled  
24 the infrared cut filter, image capture, and image upload to a remote server via FTP. The  
25 customized scripts used here are available in the “Tools” section of the PhenoCam project page  
26 (<http://phenocam.sr.unh.edu/webcam/tools/>) or from the corresponding author.

### 28 *Proof-of-concept lab experiment*

29 We conducted a lab experiment to evaluate whether camera imagery can be used to  
30 accurately characterize the broadband spectral properties of different materials. We used the  
31 StarDot camera to record sequential color RGB and monochrome RGB+NIR images of materials

1 with a wide range of spectral signatures (Figure 1). Each sample was illuminated from above  
2 with a 50 W Halogen lamp designed for indoor diffuse reflectance measurements (ASD  
3 ProLamp, Analytical Spectral Devices Inc., Boulder, CO). The StarDot camera was mounted on  
4 a tripod to the side of the sample and inclined downward at an angle of about 45°. Each sample  
5 filled approximately one-quarter of the camera's field of view. For quality assurance, we  
6 included a multi-color reference panel in each image, made by painting red, green, blue, white  
7 and grey strips on a flat piece of plastic. We recorded four images of each sample: one image at  
8 fixed exposure (1/300 s) for both color RGB and monochrome RGB+NIR images, and one  
9 image at automatic exposure for both color RGB and monochrome RGB+NIR. Automatic  
10 exposure values were determined by the camera. The mean automatic exposure for the color  
11 RGB images was 1/30 s (minimum 1/120 s), compared with 1/200 s (minimum 1/350 s) for the  
12 monochrome RGB+NIR images. Thus the fixed exposure images were almost always under-  
13 exposed compared to the automatic exposure images.

14 We measured the reflectance spectrum ( $\lambda = 350\text{--}2500$  nm) of each sample using a  
15 spectroradiometer (ASD FieldSpec 3, Analytical Spectral Devices Inc.) connected to a 5 cm (2  
16 inch) three-port integrating sphere (SphereOptics, Concord, NH) and a 10 W hemispheric  
17 collimated light source with a 6 V regulated power supply. White Spectralon discs were used as  
18 reference standards. The sphere featured an 8° near-normal incidence port, such that reflectance  
19 measurements include both diffuse and specular components. We processed the raw data to  
20 reflectances (1 nm increment) using ViewSpecPro software (Analytical Spectral Devices Inc.).  
21 Spectroradiometer NDVI was calculated using red and NIR band reflectances; specific  
22 wavelength ranges are reported below.

23 Most of the samples (42) for this experiment were leaves picked from a selection of trees  
24 and shrubs native to New England, representing a wide range of leaf health and corresponding  
25 colors, from fresh dark green to senesced red to fallen brown leaves (Figure 1). We included  
26 other materials, including asphalt, cardboard, wood, and several paint color chips, for a total of  
27 51 samples.

28

### 29 *Field data*

30 We used field data from an ongoing measurement campaign at the 40 m “Barn Tower”  
31 (42.5353°N 72.1899°W) at the Harvard Forest, near the town of Petersham, MA, 110 km west of

1 Boston. Mixed forest stands surrounding the tower are dominated by the deciduous species red  
2 oak (*Quercus rubra* L., ~40% of basal area) and red maple (*Acer rubrum* L., ~20% of basal  
3 area), with evergreen white pine (*Pinus strobus* L.) the dominant conifer. The MODIS land cover  
4 classification for the tower, and the land immediately surrounding the tower, is deciduous  
5 broadleaf forest.

6 We used imagery (April 1, 2012 through March 30, 2013) from a StarDot camera that is  
7 mounted at the top of the tower. The camera points north and is inclined ~30° below horizontal.  
8 As in the lab experiments, command scripts on the camera trigger the infrared cut filter and  
9 obtain successive (about 30 s apart) color RGB and monochrome RGB+NIR imagery. Automatic  
10 exposure is used for each image. Images are uploaded by FTP to a remote server every 15  
11 minutes between 4 a.m. and 10 p.m.

12 Also mounted atop the same tower is a pair of 4-channel (blue: 470 ± 20 nm, green: 557  
13 ± 25 nm, red: 605 ± 35 nm, NIR: 750 ± 42 nm) narrowband radiometric sensors (Model 1850,  
14 Skye Instruments, Llandrindod Wells, UK). One unit with a cosine diffuser is pointed upwards to  
15 measure incident solar radiation, while the second unit, with a 25° field of view, is pointed in the  
16 same direction as the StarDot camera to measure radiation reflected by the canopy. We log  
17 measurements every 15 seconds and record 30 minute averages on a datalogger (CR1000,  
18 Campbell Scientific, Logan, UT). From these data, we calculated canopy reflectance ( $\rho_i$ ) as in  
19 Eq. 2, where  $Q_i \downarrow$  and  $Q_i \uparrow$  are measurements of the incident and reflected quantum flux,  
20 respectively, for each band  $i$ , and the calibration constant ( $k_i$ ) determined under natural (sunlit)  
21 conditions using a Spectralon panel.

$$22 \quad \rho_i = k_i(Q_i \uparrow / Q_i \downarrow) \quad \text{Eq. 2}$$

23 We calculated two indices from the narrowband radiometric sensors: radiometer NDVI  
24 (Eq. 3a) and radiometer  $g_{CC}$  (Eq. 3b):

$$25 \quad \text{radiometer NDVI} = (\rho_{750} - \rho_{605}) / (\rho_{750} + \rho_{605}) \quad \text{Eq. 3a}$$

$$26 \quad \text{radiometer } g_{CC} = \rho_{557} / (\rho_{605} + \rho_{557} + \rho_{470}) \quad \text{Eq. 3b}$$

27

## 28 *Image processing*

29 Briefly, image analysis for both lab and field data included manual delineation of an  
30 appropriate ROI and extraction of color channel information for that ROI in each image. We also



1 used an optical character recognition algorithm to read the image exposure from the text overlay  
2 at the top of each image.

3 For the lab experiment, the ROI was adjusted for each sample to include as much of the  
4 sample as possible. For the field data, we defined separate deciduous (predominantly red oak and  
5 red maple) and conifer (white pine) ROIs, which were each roughly 440 x 440 pixels in size. The  
6 camera field of view did not change over time, and thus these ROIs were fixed over the period of  
7 analysis.

8 We processed the camera imagery as follows. For each sample, we defined the ROI and  
9 determined the average pixel value (digital number) across the ROI for three channels in the  
10 color RGB images ( $R_{DN}$ ,  $G_{DN}$ ,  $B_{DN}$ ) and one channel in the monochromatic RGB+IR images  
11 ( $Z_{DN}$ ). If both images were taken at the same exposure, then the monochrome RGB+IR images  
12 could be partitioned to a visible component ( $Y_{DN}$ ) plus a NIR component ( $X_{DN}$ ) according to Eq.  
13 4a, with the visible component calculated from the color RGB images as in Eq. 4b (Daniel  
14 Lawton, StarDot Technologies, personal communication). Then the NIR component,  $X_{DN}$ , was  
15 estimated as  $Z_{DN} - Y_{DN}$ .

$$16 \quad Z_{DN} = Y_{DN} + X_{DN} \quad \text{Eq. 4a}$$

$$17 \quad Y_{DN} = 0.30 * R_{DN} + 0.59 * G_{DN} + 0.11 * B_{DN} \quad \text{Eq. 4b}$$

18 However, if the images were taken at different exposures (where  $E_Y$  denotes the exposure  
19 of the color RGB image and  $E_Z$  the exposure of the RGB+IR image), then these exposure  
20 differences had to be accounted for. Exploratory analyses indicated that division through by the  
21 square root of the exposure time offered a straightforward solution (Eq. 5a-d) to exposure  
22 adjustment. Note that camera systems with different gamma values, where  $\gamma$  is the exponent in  
23 the power law relationship between input and output signals of digital imaging systems, may be  
24 different (cf. Sakamoto et al., 2010, 2012). Taking the square root of  $E$  assumes a  $\gamma = 2.0$ , a  
25 reasonable approximation of the actual StarDot value of  $\gamma = 1.7$  (Daniel Lawton, StarDot  
26 Technologies, personal communication). However, our results were essentially the same  
27 regardless of whether we used 2.0 or 1.7.

$$28 \quad Z'_{DN} = Z_{DN} / \sqrt{E_Z} \quad \text{Eq. 5a}$$

$$29 \quad R'_{DN} = R_{DN} / \sqrt{E_Y} \quad \text{Eq. 5b}$$

$$30 \quad Y'_{DN} = Y_{DN} / \sqrt{E_Y} \quad \text{Eq. 5c}$$

$$X'_{DN} = Z'_{DN} - Y'_{DN} \quad \text{Eq. 5d}$$

We calculated camera NDVI as in Eq. 6, in terms of exposure-adjusted digital numbers. For fixed-exposure images, the same calculation was used, ignoring the primes (').

$$\text{Camera NDVI} = (X'_{DN} - R'_{DN}) / (X'_{DN} + R'_{DN}) \quad \text{Eq. 6}$$

For both radiometer and camera data, there was substantial variability in the derived indices at the 30 minute time step, which may be associated with factors such as overall light levels, cloudiness, and illumination geometry (see further analysis in Results). After comparing various averaging, quantile, and filtering methods, we derived daily estimates by calculating the arithmetic mean across all observations where the incident photosynthetic photon flux density (PPFD; measured at the top of the tower using a PQS-1 quantum sensor, Kipp & Zonen, Delft, the Netherlands) was greater than  $200 \mu\text{mol m}^{-2} \text{s}^{-1}$ . This method reduced day-to-day variability in the resulting time series better than the 90<sup>th</sup> percentile approach used by Sonnentag et al. (2012), although an obvious advantage of the latter approach is that it does not require solar radiation data.

Because  $R'_{DN}$  and  $X'_{DN}$  are not direct measurements of reflectance, the magnitude of camera NDVI depends on the spectral distribution of the incident light. Thus, camera NDVI values from the lab experiments are not directly comparable to those from the field experiment, and those from the field experiment are not comparable to either radiometer or satellite NDVI values. To compensate for this, we re-scaled camera NDVI (yielding camera NDVI<sup>R</sup>) by estimating the coefficients of a linear regression between camera NDVI (for the deciduous ROI) and radiometer NDVI, where  $a$  is a slope coefficient,  $b$  is the  $y$ -axis intercept and  $\varepsilon$  is the model residual:

$$\text{radiometer NDVI} = a(\text{camera NDVI}) + b + \varepsilon \quad \text{Eq. 7}$$

## **Results**

### *Lab experiment*

Spectral reflectance signatures differ markedly among the 51 samples scanned by the spectroradiometer (Figure 1). There are pronounced differences in reflectance spectra between green, yellowing, and red leaves, but the non-foliar samples added greatly to the variability among samples across both visible and near-infrared wavelengths. The variation in reflectance

1 across samples is smallest for violet and blue (400-500 nm) wavelengths, and largest for red  
2 (620-700 nm) and near infrared (700-1000 nm) wavelengths.

3 For the fixed exposure imagery (results not illustrated), digital numbers extracted from  
4 camera imagery for the red channel ( $R_{DN}$ ) are well correlated with mean reflectance over red  
5 wavelengths (620-700 nm) measured with the spectroradiometer ( $r = 0.91$ ). Similarly, digital  
6 numbers for the near infrared ( $X_{DN}$ ) component of the RGB+NIR imagery are well correlated  
7 with mean reflectance over NIR wavelengths (700-1000 nm) measured with the  
8 spectroradiometer ( $r = 0.87$ ). Camera NDVI is well correlated with spectroradiometer NDVI  
9 using these broad bands ( $r = 0.91$ ), or using the spectral range of MODIS bands (band 1 = 620–  
10 670 nm, band 2 = 841–867 nm) ( $r = 0.93$ ).

11 We used an iterative procedure to identify the wavelengths across which reflectance  
12 measured by the spectroradiometer is most highly correlated with  $R_{DN}$  and  $X_{DN}$  from the fixed  
13 exposure imagery. For  $R_{DN}$ , we obtained a correlation of  $r = 0.96$  across the range from 570-660  
14 nm (Figure 2A), whereas for  $X_{DN}$ , we find a correlation of  $r = 0.91$  across the range from 805-  
15 815 nm (Figure 2B). For the fixed exposure imagery, there is an excellent correlation ( $r = 0.99$ )  
16 between camera NDVI and spectroradiometer NDVI calculated using these particular bands  
17 (Figure 2C).

18 We conducted a similar analysis for the automatic exposure imagery. Exposure-adjusted  
19 digital numbers (Eq. 5b, 5d) for each channel are best correlated with mean reflectance,  
20 measured by the spectroradiometer, across an appropriate range of wavelengths (Figure 3). For  
21 example,  $B'_{DN}$  is most strongly correlated with mean reflectance across violet and blue  
22 wavelengths (430-515 nm,  $r = 0.92$ ),  $G'_{DN}$  with green wavelengths (510-570 nm,  $r = 0.94$ ),  $R'_{DN}$   
23 with yellow and red wavelength (575-710 nm,  $r = 0.96$ ; Figure 4A), and  $X'_{DN}$  with near infrared  
24 wavelengths (800-815 nm,  $r = 0.88$ ; Figure 4B). The contour plots in Figure 3 show how the  
25 strength of these correlations tended to fall off rapidly outside the optimal range. For example,  
26  $R'_{DN}$  is not well correlated with wavelengths  $< 575$  nm or  $> 710$  nm, and  $X'_{DN}$  is not well  
27 correlated with wavelengths  $< 700$  nm. For the automatic exposure imagery, camera NDVI is  
28 very well correlated with spectroradiometer NDVI using either the most-highly-correlated bands  
29 identified here (i.e. red 575-710 nm and NIR 800-815 nm;  $r = 0.96$ , Figure 4C), or the standard  
30 MODIS bands ( $r = 0.94$ ).

1 Results from the lab experiment demonstrate the potential of the StarDot camera imagery  
2 for characterizing the spectral properties of diverse materials, particularly in red and near  
3 infrared bands. By processing sequential VIS and VIS+NIR images, we are able to back-  
4 calculate the NIR component. Furthermore, this experiment shows that camera NDVI is strongly  
5 correlated with spectroradiometer NDVI when using either fixed exposure or automatic exposure  
6 imagery. Since field images are recorded with automatic exposures to optimize dynamic range  
7 under varying illumination conditions, our ability to correct for variations in exposure is critical.  
8 These lab results prove that camera NDVI is sensitive to the variation in reflectances of a wide  
9 range of materials and surfaces. This indicates the potential for monitoring canopy phenology in  
10 the field using a similar approach to characterize the seasonal variation in canopy optical  
11 properties, as described in the following section.

12

### 13 *Field measurements*

14 The green chromatic coordinate calculated from the narrowband radiometric sensors,  
15 radiometer  $g_{CC}$  (Figure 5A), exhibits a seasonal pattern that is typical of deciduous forests (e.g.,  
16 Sonnentag et al., 2012; Richardson et al., 2013b). Radiometer  $g_{CC}$  rises rapidly in spring with  
17 budburst (day 115-120) and leaf development to a pronounced spiky peak (day 140; see Keenan  
18 et al., 2014, for discussion), before decreasing gradually over the course of the summer, and then  
19 declining rapidly (day 250) in autumn with leaf coloration and abscission (day 300). For the  
20 deciduous ROI, camera  $g_{CC}$  (Figure 5B) follows essentially the same seasonal pattern, with the  
21 notable exception of a more pronounced dip in greenness around day 290, corresponding to the  
22 peak of autumn colors and a marked increase in canopy redness that is clearly visible in the RGB  
23 camera imagery. The coniferous ROI shows a seasonally varying signal in camera  $g_{CC}$  (Figure  
24 5C), but with substantially smaller amplitude than that for the deciduous ROI, reflecting the  
25 year-round presence of foliage but nevertheless indicating seasonal variation in foliar chlorophyll  
26 concentrations (Richardson et al., 2009). The start of spring green-up also begins about 30 days  
27 earlier, and the end of the autumn decline ends about 60 days later, for the coniferous ROI  
28 compared to the deciduous ROI.

29 By contrast, the seasonal cycle of radiometer NDVI differs from that of radiometer (or  
30 camera)  $g_{CC}$  (Figure 5D). The primary difference is the absence of the spike seen in  $g_{CC}$  around  
31 day 140. A secondary difference is the presence of a broad plateau in radiometer NDVI from

1 about day 130 to day 240. As a result, radiometer NDVI gives a better representation of the  
2 seasonal dynamics of canopy leaf area index (LAI) than does radiometer  $g_{CC}$  (e.g. compare with  
3 Fig. 1 in Richardson et al., 2012). Additionally, the seasonal cycle of radiometer NDVI roughly  
4 parallels (and is comparable in magnitude to) that of MODIS NDVI (Figure 5D). In particular,  
5 the timing of the spring increase and autumn decrease in NDVI is similar in both time series.  
6 However, during the winter months the MODIS data are somewhat noisier than the radiometer  
7 data.

8         There is a strong linear relationship ( $R^2 = 0.89$ ) between radiometer NDVI and camera  
9 NDVI for the deciduous ROI. The best-fit linear scaling coefficients (Eq. 7) are  $a = 0.53 \pm 0.02$   
10 SE and  $b = 0.84 \pm 0.01$ , with  $\sigma(\epsilon) = 0.041$ . Henceforth, we focus on the rescaled time series,  
11 camera NDVI<sup>R</sup>, for which the seasonal cycle is much more similar in shape to that of radiometer  
12 NDVI than camera  $g_{CC}$ . For example, the relative rate of increase in both radiometer NDVI and  
13 camera NDVI<sup>R</sup> for the deciduous region of interest in spring is more gradual than the  
14 corresponding rate of increase in radiometer or camera  $g_{CC}$ , and conspicuously absent in the  
15 camera NDVI<sup>R</sup> data for the deciduous region of interest is the  $g_{CC}$  spike that occurs around day  
16 140. For the coniferous region of interest, camera  $g_{CC}$  shows a seasonal pattern that is less  
17 pronounced than that for the deciduous region of interest. However, there is no clear seasonal  
18 cycle in the camera NDVI<sup>R</sup> data for the coniferous region of interest. Together, these results  
19 suggest that camera NDVI is capturing different aspects of seasonal canopy dynamics than  
20 indices, such as  $g_{CC}$ , that are based only on visible wavelengths (cf. Nijland et al. 2013). The use  
21 of both  $g_{CC}$  and camera NDVI together give more information than can be obtained from either  
22 index on its own. The advantage of  $g_{CC}$  is that it is sensitive to leaf color, which is related to  
23 pigmentation (Keenan et al. 2014), while camera NDVI is a better proxy for LAI.

24

#### 25 *Non-phenological sources of variability in camera NDVI*

26         Even with averaging of 30-minute data to a daily product, the signal-to-noise ratio of  
27 camera NDVI<sup>R</sup> is somewhat higher than that of camera  $g_{CC}$  (day-to-day variability being equal to  
28 about 8% of the seasonal amplitude for camera NDVI<sup>R</sup>, compared with 5% for camera  $g_{CC}$ ;  
29 compare Figures 5B and 5E), and indeed also higher than that of radiometer NDVI (compare  
30 figures 5E and 5D). Of course, some of the variation in both camera NDVI and radiometer NDVI  
31 can potentially be attributed to sky condition, shadow fraction, and illumination geometry, all of

1 which can change over the course of the day or between one day and the next. And, some of this  
2 variability is undoubtedly the result of the brief (30 s) lag between the VIS and VIS+NIR  
3 imagery, which is unavoidable as the camera needs some time to adjust after the cut filter has  
4 been triggered on or off.

5 We further investigate some of the factors associated with variability in camera NDVI<sup>R</sup>  
6 using the 30-minute data, focusing on the period from day 160 to day 200, when camera NDVI<sup>R</sup>  
7 for the deciduous region of interest is essentially stable at its maximum summertime value.  
8 During this period, camera NDVI<sup>R</sup> at the 30-minute time step (1 SD = 0.13) was 10 times more  
9 variable than at the daily time step (1 SD = 0.01). Much of the variability in the 30-minute data  
10 results from imagery captured under low-to-intermediate light levels (1 SD = 0.17 for PPFD <  
11 500  $\mu\text{mol m}^{-2} \text{s}^{-1}$ ; 1 SD = 0.06 for PPFD  $\geq$  500  $\mu\text{mol m}^{-2} \text{s}^{-1}$ ). At both dawn and dusk, camera  
12 NDVI<sup>R</sup> is considerably lower, and markedly more variable, than at mid-day, indicating both a  
13 systematic bias and a lower signal-to-noise ratio under low-light conditions. However, excluding  
14 periods with PPFD < 200  $\mu\text{mol m}^{-2} \text{s}^{-1}$ , the diurnal pattern (data from 6 a.m. to 6 p.m.) in camera  
15 NDVI<sup>R</sup> is negligible: a polynomial function of time of day accounts for no more than 2% of the  
16 total variance in camera NDVI<sup>R</sup>. This suggests that illumination geometry has only a minimal  
17 effect on camera NDVI<sup>R</sup>. Similarly, although camera NDVI<sup>R</sup> is highly variable when the ratio of  
18 diffuse/total PPFD is  $\geq$  0.90, the noisy observations are all associated with PPFD < 500  $\mu\text{mol m}^{-2}$   
19  $\text{s}^{-1}$ .

20 A final—and important, because it can not be entirely eliminated by filtering for lower-  
21 light conditions—source of variation in camera NDVI<sup>R</sup> is the ratio of the exposure times for the  
22 RGB and RGB+NIR imagery, i.e.  $E_{\text{ratio}} = E_Y/E_Z$ . A second-order polynomial of  $E_{\text{ratio}}$  explains  
23 73% of the variation in 30-minute camera NDVI<sup>R</sup>, with both low (< 2) and high (>5) values of  
24  $E_{\text{ratio}}$  contributing to this pattern. Filtering for periods with PPFD  $\geq$  500  $\mu\text{mol m}^{-2} \text{s}^{-1}$  eliminates  
25 most instances of low  $E_{\text{ratio}}$ . High values of  $E_{\text{ratio}}$  are most often associated with anomalously long  
26 RGB exposures (high  $E_Y$ ). The RGB images associated with these long exposures are  
27 characterized by an anomalously bluish cast. We are unable to identify the specific lighting  
28 conditions (total PPFD, PPFD variance, direct PPFD, diffuse PPFD, or the direct/total PPFD  
29 ratio) that cause this effect. However, even considering only data acquired with  $2 < E_{\text{ratio}} < 5$ ,  
30  $E_{\text{ratio}}$  still accounts for 40% of the variation in camera NDVI<sup>R</sup> between day 160 and day 200.  
31 Using a fixed exposure setting (with potentially different values of  $E_Y$  and  $E_Z$ ), and limiting the

1 analysis to high-light, mid-day conditions, it should be possible to eliminate this source of  
2 variability in camera NDVI<sup>R</sup>.

#### 4 **Discussion**

5 We have proposed a method by which an off-the-shelf networked digital camera,  
6 originally marketed for security monitoring applications, can be repurposed and used to obtain  
7 information about the spectral properties of vegetation in both visible and NIR wavelengths, and  
8 thus to calculate NDVI-style indices (cf. Nijland et al. 2013, who found that imagery from a  
9 filtered, infrared-sensitive camera was of no more value than conventional RGB imagery for  
10 tracking plant phenology and health). The lab experiment described here is used as a proof-of-  
11 concept (Figs. 2, 4), and shows that not only can we back out the IR component from the  
12 RGB+NIR imagery, but also that our method for exposure-correction of auto-exposed imagery is  
13 effective. The field data, on the other hand, show how this method can be applied for long term  
14 monitoring of vegetation phenology in real-world conditions with varying solar illumination and  
15 weather conditions. Specifically, we show good agreement between data obtained using the  
16 camera NDVI method and the seasonal trajectory of NDVI measured using radiometric sensors  
17 (Fig. 5). This approach is highly economical: the camera used here retails for about US\$1200,  
18 which is a fraction of the cost of a pair (upward- and downward-looking) of multi-channel  
19 radiometric sensors. While we did not rely on a reference panel for standardization, inclusion of  
20 a grey Spectralon (or other diffuse reflector) panel within the field of view of the camera would  
21 potentially be of value for normalization under changing illumination conditions (e.g. cloudy vs.  
22 sunny days); however, the results shown here suggest that even without this kind of calibration  
23 standard, it is possible to obtain high-quality data on the seasonal variation in canopy NDVI.  
24 Although our field experiment was conducted in a mixed forest ecosystem, there is no reason to  
25 believe that this method would not be applicable in other vegetation types, especially those with  
26 a strong seasonal cycle such as crops or grasslands. The signal-to-noise ratio may, however, be  
27 inadequate for tracking the seasonality of evergreen vegetation with a high LAI. This method is  
28 currently implemented at more than 40 core sites within the PhenoCam network  
29 (<http://phenocam.sr.unh.edu>), and future analysis of those data will confirm the viability of this  
30 approach.

1 Networked cameras are well suited to field monitoring applications because with Internet  
2 connectivity (using cell phone modems, this is now possible even at remote field sites) images  
3 can be archived to an off-site server, and camera functionality can be monitored remotely.  
4 Furthermore, since this eliminates the need for manually swapping out memory cards, the  
5 potential for shifts in camera alignment are minimized, making it is easier to maintain a constant  
6 field of view. This facilitates image processing and improves data quality.

7 We acknowledge that cameras with red and NIR sensitivity, primarily designed for  
8 precision agriculture applications, have been developed and are commercially available (e.g. the  
9 Agricultural Digital Camera by Tetracam, Inc., Chatsworth, CA, which retails for US\$4800).  
10 These have been used for ecological studies (e.g. Steltzer and Welker, 2006; Higgins et al.,  
11 2011), but we are not aware of this type of camera being installed in the field for continuous,  
12 long-term monitoring applications. Conventional digital cameras have also been customized and  
13 used for similar work, but these have typically made use of two-camera systems, with one  
14 camera filtered for visible wavelengths and the other for near infrared wavelengths (e.g.  
15 Shibayama et al., 2009, 2011; Sakamoto et al., 2010, 2012; see also Nijland et al., 2013). What is  
16 unique about the present approach is that by controlling the camera's infrared cut filter we  
17 instead obtained sequential images from a single sensor, rather than simultaneous images from  
18 two sensors. Not only does the single-camera approach reduce costs, it also eliminates issues  
19 related to parallax, sensor calibration, and image alignment. Our method could, in principle, be  
20 used with other camera systems although the linear scaling coefficients ( $a$ ,  $b$ ) reported here are  
21 probably specific to the StarDot NetCam SC IR.

22 Compared to other low-cost, sensor-based methods for monitoring seasonal changes in  
23 the spectral properties of vegetation (e.g. radiometric instruments based on photodiodes, Garrity  
24 et al., 2010, or light emitting diodes, Ryu et al., 2010), a clear advantage of the camera approach  
25 is that it yields high-resolution images. This enables tracking the phenology of different  
26 organisms or groups of organisms by breaking the image into different regions of interest—e.g.,  
27 deciduous and coniferous trees (e.g. Fig. 5E,F). False-color images similar to those traditionally  
28 generated from satellite imagery can also be generated using near infrared, red, and green bands  
29 (i.e. XRG rather than RGB), as shown in Figure 6. Thus, the camera effectively becomes a four-  
30 channel imaging sensor. We acknowledge that higher-quality spectral image data could,  
31 potentially, be obtained from existing, commercially available multichannel or hyper-spectral



1 cameras, e.g. Surface Optics SOC-710 or TetraCam MCA. However, for budget-limited  
2 observational and experimental studies, the system proposed here may represent an acceptable  
3 compromise, given its substantially lower cost and proven performance.

4 Our camera NDVI approach is conceptually similar to that used to obtain broadband  
5 NDVI from readily available radiometric measurements of incident and canopy-reflected visible  
6 (PPFD) and total shortwave radiation (Huemmrich et al., 1999; Wang et al., 2004; Jenkins et al.,  
7 2007; see review in Richardson et al., 2013b). The similarity of camera NDVI to radiometer  
8 NDVI, and the dissimilarity between camera NDVI and camera  $g_{CC}$ , highlights the potential for  
9 camera NDVI to provide different information about the state of the canopy than can be obtained  
10 using only visible-wavelength (RGB) imagery. Furthermore, indices such as EVI (the enhanced  
11 vegetation index, which also uses blue channel information) can be calculated from the camera  
12 imagery in a similar manner. The resulting data should therefore be of great value for “apples-to-  
13 apples” evaluation of landscape phenology products derived from satellite remote sensing, as  
14 suitable data for this kind of analysis are currently lacking (cf. Hufkens et al., 2012; note that  
15 landscape heterogeneity and the mismatch between the camera field of view and the satellite  
16 pixel to which it is being compared remain outstanding challenges). More generally, camera  
17 NDVI could be used for continuous monitoring of plant stress in greenhouse or nursery  
18 applications, or even quantifying responses to experimental manipulations in large field  
19 experiments (e.g. nutrient additions, elevated CO<sub>2</sub>, rainfall exclusion, etc.).

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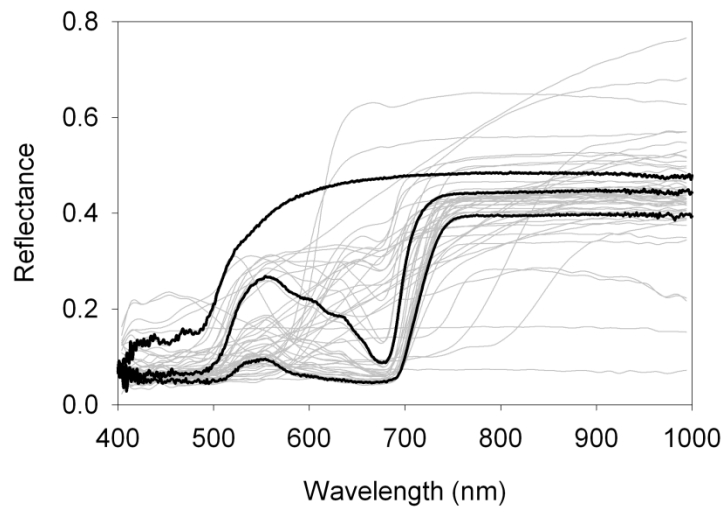
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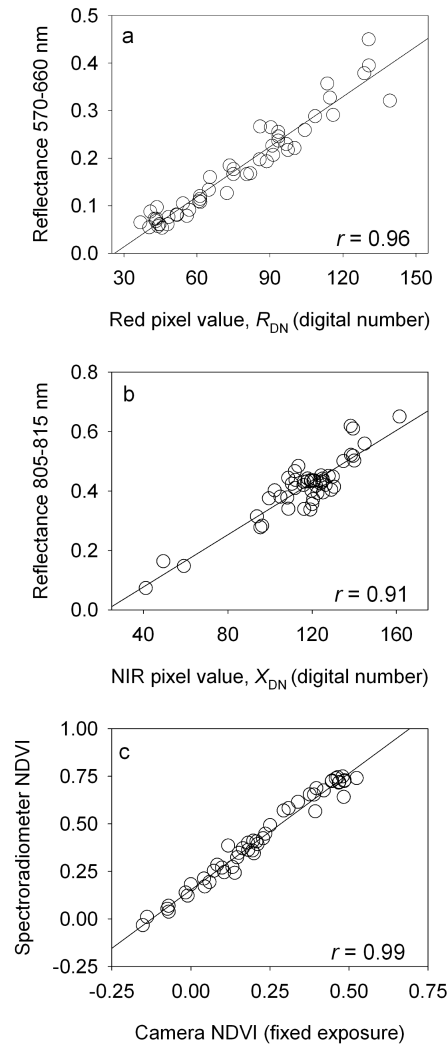
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1 **Figure 1.** Reflectance spectra of the 51 samples (thin grey lines) used in the laboratory  
2 experiment. The heavier black lines indicate representative spectra from a healthy green leaf  
3 (bottom), a yellowing leaf (middle), and a red (top) leaf.



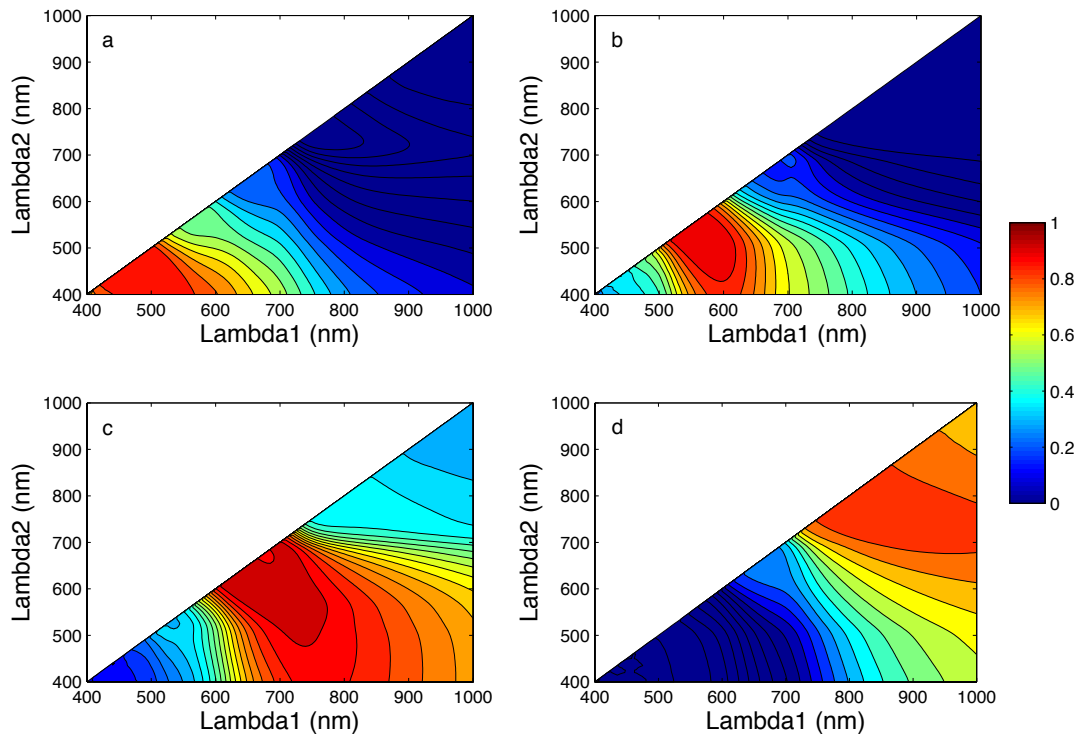
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1 **Figure 2.** Correlation of digital number (color bands extracted from fixed-exposure camera  
2 imagery) and mean reflectance (measured with a spectroradiometer) for  $n = 51$  samples in  
3 laboratory experiment. (a) mean reflectance from 570-660 nm vs. digital number of camera red  
4 channel; (b) mean reflectance from 805-815 nm vs. digital number of NIR component of camera  
5 RGB+NIR imagery; (c) spectroradiometer NDVI vs. camera NDVI calculated using  $R_{DN}$  and  
6  $X_{DN}$ .  
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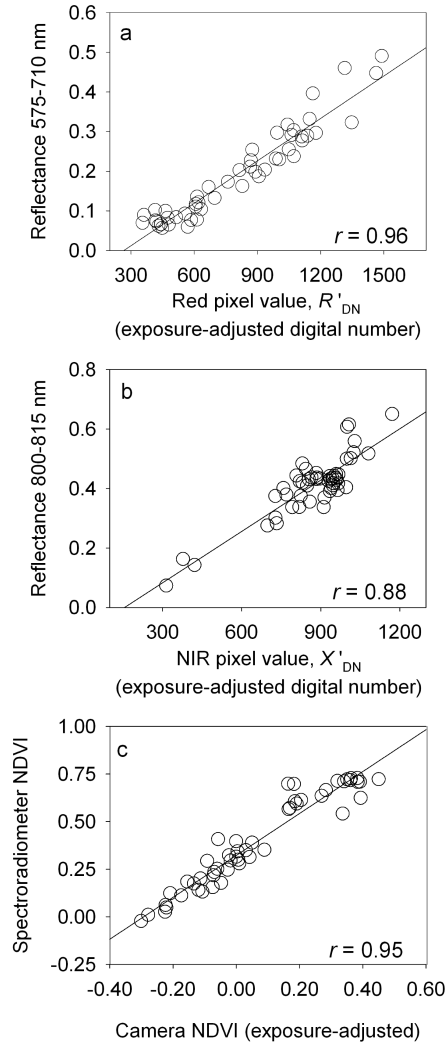
1 **Figure 3.** Contour plot showing linear correlation (Pearson's  $r$ ) of pixel values (digital numbers)  
2 of individual color bands, from digital camera imagery, with mean spectral reflectance over the  
3 region from  $\lambda_1$  ( $x$  axis) to  $\lambda_2$  ( $y$  axis) nm, as measured on a spectroradiometer. (a) Camera blue  
4 channel; (b) camera green channel; (c) camera red channel; (d) NIR component of RGB+NIR  
5 imagery.



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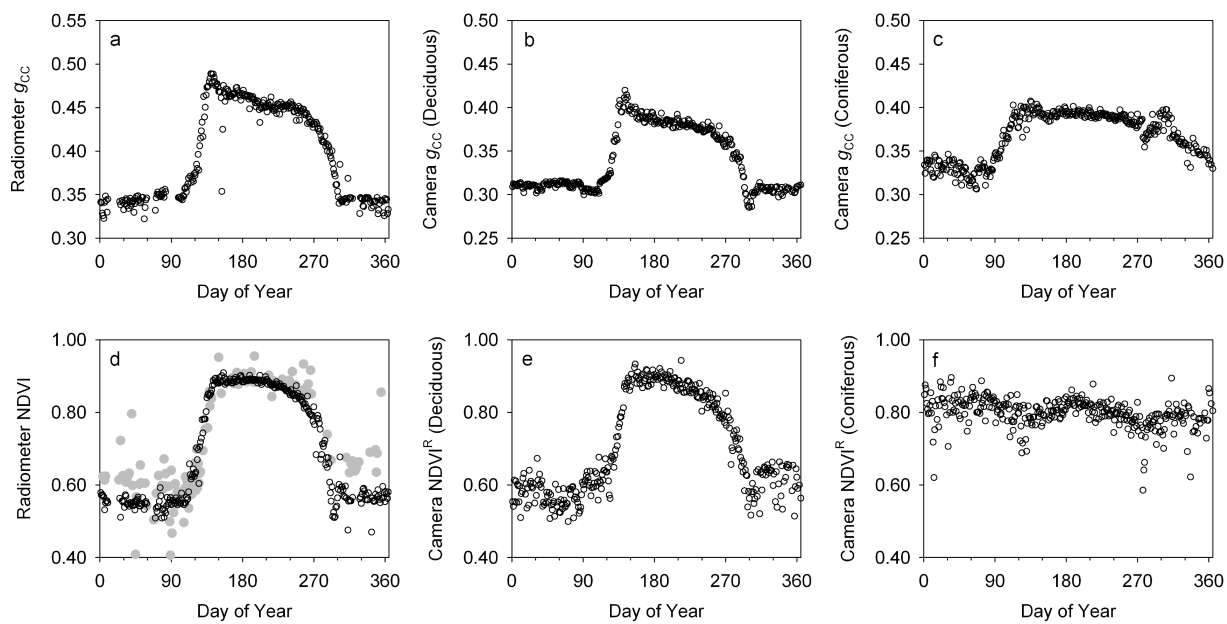


1 **Figure 4.** Correlation of exposure-adjusted digital number (color bands extracted from auto-  
 2 exposure camera imagery) and mean reflectance (measured with a spectroradiometer) for  $n = 51$   
 3 samples in laboratory experiment. (a) mean reflectance from 575-710 nm vs. exposure-adjusted  
 4 digital number of camera red channel ( $R'_{DN}$ ); (b) mean reflectance from 800-815 nm vs.  
 5 exposure-adjusted digital number of NIR component of camera RGB+NIR imagery ( $X'_{DN}$ ); (c)  
 6 spectroradiometer NDVI vs. camera NDVI calculated using  $R'_{DN}$  and  $X'_{DN}$  vs. spectroradiometer  
 7 NDVI.



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1 **Figure 5.** Time series of daily means (calculated for  $PPFD \geq 200 \mu\text{mol m}^{-2} \text{s}^{-1}$ ) of vegetation  
 2 indices calculated from radiometric instruments (a, d) and digital camera imagery, analyzed  
 3 separately for deciduous (b, e) and coniferous (c, f) regions of interest, from instruments  
 4 mounted on the Harvard Forest Barn Tower. In (d), the gray filled circles are the mean value of  
 5 MODIS NDVI from a 3x3 window centered on the tower pixel.  $g_{CC}$  is the green chromatic  
 6 coordinate, NDVI is the normalized difference vegetation index.

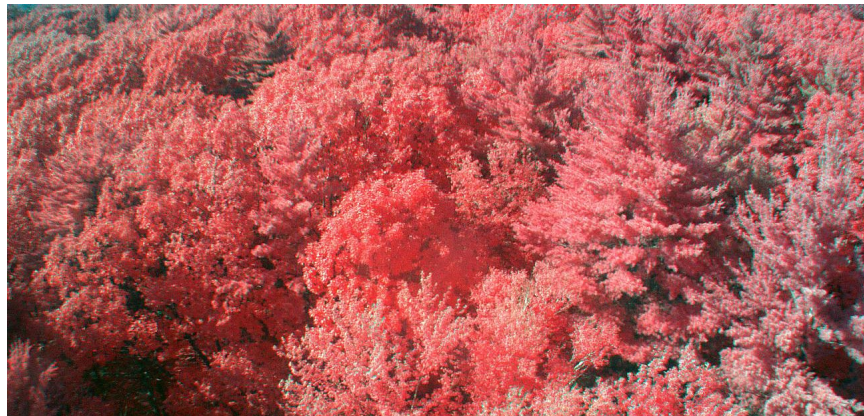


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1 **Figure 6.** Winter (February 1, top) and summer (July 6, bottom) false-color images (XRG)  
2 obtained from an infrared-enabled security camera mounted on the Harvard Forest Barn Tower.  
3 The near infrared component (X) is mapped to the red (R) channel, the red channel is mapped to  
4 the green (G) channel, and the green channel is mapped to the blue channel. Both images were  
5 taken from the top of the tower at 4 PM local standard time. The evergreen trees that are clearly  
6 visible in the top image are white pine (*Pinus strobus*).  
7



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