**Improved modeling of canopy photosynthesis using near-surface remote sensing**

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**Abstract**

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**Introduction**

In deciduous forests, both the amount of foliage, and the physiological activity of that foliage, varies seaonally accoring to environmental conditions, e.g. temperature in winter-dormant temperate and boreal ecosystems, and water availability in Mediterranean and seasonally dry tropical ecosystems (Richardson et al. 2013). This has important implications for .

Modeling analyses show that to replicate the seasonal cycle of canopy photosynthesis, key parameters such as photosynthetic capacity (e.g. Amax or *V*cmax) must be allowed to be time-varying (Wilson et al. 2000, Xu and Baldocchi 2003, Groenendijk et al. 2011).

Leaf traits related to composition (water and nitrogen content, pigmentation), morphology (size, thickness, and tissue density, and consequently LMA or leaf mass to area ratio), optical properties (transmittance and reflectance, in addition to color), as well as both photosynthetic capacity and quantum yield, all covary on seasonal time scales (e.g. Wilson et al. 2000, Morecroft et al. 2003, Keenan et al. 2013).

There is a long history of using leaf-level measurements of spectral reflectance and transmittance to estimate biochemical parameters related to pigmentation (e.g. Gamon and Surfus 1999, Richardson et al. 2001, Sims and Gamon 2002) and photosnthetic efficiency (e.g. the Photochemical Reflectance Index, PRI; Gamon et al. 1992, 1997. Near-surface remote sensing (e.g. Jenkins et al. 2007, Richardson et al. 2007, 2009, Hilker et al 2008, 2011) using broad- and narrow-band radiometric instruments, in addition to imaging sensors (e.g. Richardson et al. 2013) has the potential to provide information about time-varying canopy properties.

Migliavacca et al 2011

Digital repeat photography, as described above, is now being used, to good effect, for phenological monitoring in a diverse array of ecosystems (Richardson et al. 2013). These cameras are reliable, and produce visually appealing images that can be processed to yield ecologically relevant data (Ahrends et al. 2009, Migliavacca et al. 2011, Hufkens et al. 2012). However, a drawback of this approach is that the cameras being used are not ideal if one’s objectives are to understand how the radiometric properties of the canopy, or of individual foliage elements, are changing over time (Keenan et al. 2014). For example, automatic exposure determination, in-camera image processing, and poorly-characterized but overlapping spectral sensitivity of the RGB color channels all complicate the interpretation of the digital number triplets extracted from an ROI. Thus, to provide a the data necessary to improve our understanding of how variation in camera-derived color metrics corresponds to seasonal changes in both structural and physiological attributes of the canopy, we installed a diverse set of radiometric sensors on the Barn Tower, and on the ground in the surrounding forest.

**Data and Methods**

*Study site*

Research was conducted at the Harvard Forest, near the town of Petersham, MA, about 110 km west of Boston. Over the period 2001-2012, the mean annual temperature is 8.3°C and the mean annual precipitation is 1215 mm. In 2012, mean annual temperature was 9.5°C, with marked deviations from the long-term mean in March (4.5°C above mean) and May (2.1°C above mean). At 880 mm, annual precipitation in 2012 was 27% below the long-term mean; compared to the long-term mean, a precipitation deficit of 295 mm had been accumulated by the end of July.

Radiometric measurements were conducted from the 40 m “Barn Tower” (42.5353°N 72.1899°W), while CO2 flux measurements were conducted at the 30 m “EMS (Environmental Monitoring Site) Tower” (42.5378°N 72.1715°W), about 1500 m to the east. The vegetation around the two towers is extremely similar; in both cases, mixed forest stands are dominated by the deciduous species red oak (*Quercus rubra* L., ≈40% of basal area) and red maple (*Acer rubrum* L*.,* ≈20% of basal area), with lesser quantities of other hardwoods (including black oak, *Quercus velutina* Lam., black cherry, *Prunus serotina* Ehrh., and paper birch, *Betula papyrifera* Marsh.), and occasional conifers including white pine (*Pinus strobus* L.), eastern hemlock (*Tsuga canadensis* (L.) Carr.), and red pine (*Pinus resinosa* Ait.).

*Baseline phenological monitoring*

To track canopy phenology, we installed a networked digital camera (NetCam SC 5 MP IR, StarDot Technologies, Buena Park CA), on the Barn Tower in the summer of 2011, following methods as described by Richardson et al. (2007) and Sonnentag et al. (2012). This complements a similar camera (StarDot NetCam SC 1.3 MP), which has been collecting canopy imagery from the top of the EMS tower since 2008. Cameras are configured with fixed color balance but automatic exposure determination. Both cameras upload imagery (stored as minimally compressed, 3-layer JPEGs) every 30 minutes to a remote server, with imagery and derived time series of a canopy greenness index displayed in near-real-time on the PhenoCam web page (<http://phenocam.sr.unh.edu>).

To calculate the canopy greenness index, we begin by defining “regions of interest” (ROI) in each image, e.g. separate deciduous and evergreen ROIs. For quantitative analysis, the average value of each color layer (red, green and blue) for all pixels within each ROI is extracted from each image to yield a time series of digital number triplets (*R*DN, *G*DN, *B*DN). Then our canopy greenness index, the green chromatic coordinate (*g*CC,), is calculated from these triplets according to Eq. 1.

Eq. 1



Recently it has been suggested that hue-based color spaces (e.g., HSL: hue, saturation, and lightness; HSV: hue, saturation, and value), may be more effective than the RGB color space for quantifying seasonal variation in canopy color (Saitoh et al. 2012, Mizunuma et al. 2012). Hue (*H*), expressed as an angle (0–360°), defines the overall color, independent of the degree of saturation or brightness, and is calculated from the RGB triplet according to Eq. 2a-c. Note that pure red has a hue of 0°, pure green a hue of 120°, and pure blue a hue of 240°.

*C*max = *max*(*R*DN, *G*DN, *B*DN); *C*min = *min*(*R*DN, *G*DN, *B*DN) Eq. 2a

∆*C* = *C*max – *C*min Eq. 2b

If *G*DN = *C*max then *H* = 60° ((*B*DN – *R*DN)/∆*C*) + 120°

Else if *B*DN = *C*max then *H* = 60° ((*R*DN – *G*DN)/∆*C*) + 240°

Else if *R*DN = *C*max and *G*DN < *B*DN then *H* = 60° ((*G*DN – *B*DN)/∆*C*) + 360°

Else *H* = 60° ((*G*DN – *B*DN)/∆*C*) Eq. 2c

The camera data are supplemented by direct observations of budburst, leaf development, leaf coloration, and leaf fall, made by a single observer at 3–7 day intervals. The observations follow protocols described in Richardson & O’Keefe (2009), and include red oak and red maple trees in the field of view of the Barn Tower camera.

*Radiometric measurements*

To better quantify the seasonal changes in canopy structure and physiological status (e.g. photosynthetic capacity or efficiency), and provide a more rigorous context for interpretation of the camera data, we installed an extensive set of radiometric instruments on the Barn Tower beginning in 2011. A complete list of sensors is given in Table 1; note that these include both broad-band and narrow-band sensors, and sensors with hemispherical, narrow, and multi-angular fields of view.

Following a method developed by Huemmrich et al. (1999), we calculated broadband NDVI using quantum sensor measurements of incoming (*Q*↓) and outgoing (*Q*↑) photosynthetic photon flux density (PPFD, mol m-2 s-1), and pyranometer measurements of incoming (R↓) and outgoing (R↑) shortwave radiation (W m-2). Beginning with the standard equation for NDVI (Eq. 3a), we used *r*vis as an estimate of *r*red (Eq. 3b), and approximated *r*NIR as in Eq. 3c (see Richardson et al. 2013).

Eq. 3a



*r*vis = *Q*↑/*Q*↓ Eq. 3b

Eq. 3c



We used the incoming and outgoing PPFD measurements, as well as measurements of below-canopy transmitted PPFD (*Q*T), to calculate the *APAR* (absorbed photosynthetically active radiation) (Eq. 4a), and *fAPAR*(the absorbed fraction) (Eq. 4b).

 Eq. 4a

Eq. 4b



We used three instruments (the 4-channel, narrow field-of-view Skye sensors; the two-channel hemispherical field-of-view LED sensors; and the hyperspectral, multi-angular AMSPEC II), to make narrowband measurements of canopy reflectance. We estimated narrowband canopy reflectances for each channel of the 4-channel Skye sensors according to Eq. 5a, where *X* is the mV signal from the upward-looking sensor, *Z* is the mV signal from the downward-looking (30° below horizontal) sensor, and  denotes the center wavelength of the channel in question. The channel-specific calibration constant, *k* was determined, with the same viewing geometry, under natural (sunlit) conditions using a 5-inch, 99% reflectance Spectralon (Labsphere, Inc., North Sutton, NH USA) panel. These reflectances were then used to calculate NDVI (as in Eq. 3a, above, using  = 650 nm for red and  = 860 nm for NIR), PRI (Eq. 5b; Gamon et al. 1997), and, similar to camera *g*CC, a Skye *g*CC calculated using reflectances in place of digital numbers (Eq. 5c).

Eq. 5a



Eq. 5b



Eq. 5c



The custom-built LED sensors use light emitting diodes, in reverse, to measure the flux of solar radiation across relatively narrow wavebands, as described by Ryu et al. (2010). Our sensor, with red- and NIR-sensitive LEDs, was constructed expressly to permit the calculation of NDVI. The instrument’s sensors were cross-calibrated using data, collected over the course of a day, from a spectrometer (Jaz Spectrometer, Ocean Optics Inc., Dunedin, FL) with all sensors mounted in the upwards position, measuring incident solar radiation. NDVI was calculated as in Eq. 3a.

The AMSPEC II, which is described in detail by Hilker et al. (2010), recorded measurements (as digital numbers) of incident and reflected solar radiation (154 wavebands spanning 400-900 nm) at different zenith angles (X-Y in Z° increments) and azimuth angles (X-Y in Z° increments) every half hour. These were converted to reflectances using a method similar to that for the Skye sensors (Eq. 5a), and then the reflectances used to calculate NDVI (Eq. 3a), a Chlorophyll normalized difference index (Chl NDI, using *r*750 for *r*NIR, and *r*705 for *r*red; Richardson et al. 2002), and PRI (Eq. 5b), as above. Here we focus on data from a zenith angle of X and azimuth angle of Y, corresponding most directly to the field of view from the Skye sensors. We also used the multi-angular data to estimate BRDF-corrected (bidirectional reflectance distribution function) canopy reflectances as described by Hilker et al. (2010).

A custom StarDot NetCam SC, which lacked a Bayer filter and thus produced monochrome (single-layer) images, was paired with a motorized filter wheel (FW102C, ThorLabs Inc., Newtown, NJ) fitted with two broad (visible and NIR) bandpass filters, and four narrow (20 nm width) bandpass filters (see Table X). Filters were chosen so that we could calculate (using average pixel values, as digital numbers rather than true reflectances) broad- and narrow-band NDVI (Eq. 3a), PRI (Eq. 5b), and *g*CC (Eq. 1). The filter wheel was positioned immediately in front of the camera’s lens. A serial connection between the camera and the filter wheel allowed a script running on the camera to automatically step through each of the filters, and record a sequence of six photographs, over a two-minute period every 30 minutes. The exposure was set automatically at *e* for the visible bandpass filter, and then set at 8*e* for the narrow-bandpass filters, and *e*/2 for the NIR bandpass filter (the shorter exposure for NIR vs. visible was chosen because of the high reflectance of green vegetation in NIR wavelengths). Images were processed in a manner similar to the normal (three-layer RGB) camera imagery, as described above.

We used 30-minute imagery from an upward-looking, non-fisheye, digital camera (IP7160, Vivotek, New Taipei City, Taiwan) to estimate canopy leaf area index (LAI) using the digital cover photography (DCP) method as described by McFarlane et al. (2007). We refer to this as LAIDCP. The camera was located about 30 m north of the Barn tower.

We also measured air temperature and relative humidity (HMP 35c, Vaisala Oyj, Helsinki, Finland), and the direct beam () and diffuse () components of incident PPFD (BF-5, Delta-T Devices, Cambridge, UK), and we used the outgoing longwave radiation flux measured by the pyrgeometer on the net radiometer (CNR-4, Kipp & Zonen, Delft, the Netherlands) to estimate the effective canopy temperature, assuming that the surface behaves like a perfect blackbody.



*CO2 flux measurements*

The net ecosystem exchange, NEE (mol m-2 s-1), of CO2 between the forest and the atmosphere was measured using the eddy covariance method, following established procedures (including quality control, flux corrections and data editing) described by Wofsy et al. (1993), Barford et al. (2001), and Urbanski et al. (2007).

Fluxes were computed at a 60 minute time step, and because our modeling focus is on photosynthesis, we use only daytime data, which we define as periods during which the solar zenith angle is ≤ 85° (i.e. a solar elevation of at least 5°). We limit our analysis to days 90 to 320, which roughly corresponds to the growing season, plus a month on either end. NEE data coverage over this period is approximately 75%. There were two major gaps in the data, the first a two-week gap in early April, before the start of the growing season, and the second a 10-day gap in early August, prior to the start of autumn senescence. As described below, our modeling analysis is based on the hourly NEE data, rather than daily integrals, and thus it was not necessary to empirically fill missing data points. We note that our sign convention follows the standard micrometeorological approach: a negative NEE flux is a flux into the system, i.e. net CO2 uptake.

LAI was also measured approximately monthly across a network of 34 plots in the dominant footprint of the EMS tower. The measurements were completed at dawn and dusk using standard instrumentation based on gap fraction theory (LAI-2000, LiCor Biosciences, Lincoln NE). Five measurements were made at each plot (one in the center and four more at points 2 meters away from the center, in each of the cardinal directions), and averaged. The outer ring of the sensor was excluded from all calculations. We refer to the LAI measured in this manner as LAI2000.

*Modeling canopy photosynthesis*

Here we compare a variety of different models for canopy photosynthesis, and evaluate the information contributed to each by constraining the parameter associated with photosynthetic capacity using the radiometric and color indices described above.

A light response curve based on Michaelis-Menten kinetics (Eq. 6a) provides a simple, empirical approximation of the sensitivity of gross photosynthesis (*P*g) to incident solar radiation. This method has been widely applied at the canopy level in analyses of eddy covariance CO2 flux data (e.g. Wofsy et al. 1993). In this formulation, *Asat* is the hypothetical light-saturated rate of photosynthesis (which may or may not be achieved under naturally occurring light levels), and *Km* is the half-saturation constant.

Eq. 6



This model can potentially be improved upon by considering the limitation of photosynthesis by factors such as leaf temperature and vapor pressure deficit (*VPD*). Scaling factors for canopy temperature (*Tc,* in °C) and VPD (*edef,* in kPa), as in Eq. 7a (**1 and **2 are the temperature minimum and temperature optimum, at which = 0 and = 1, respectively) and 7b (**1 and **2 are coefficients that characterize the sensitivity of to VPD), respectively, reduce the potential rate of photosynthesis to an effective rate (*P*g′) that is realized under sub-optimal environmental conditions (Eq. 7c).



Eq. 7a



Eq. 7b



Eq. 7c



These models do not explicitly account for leaf area, and its seasonal variation, which influences how much of the incident solar radiation can be absorbed and used to drive photosynthesis. The simplest way to achieve this is to scale the effective photosynthesis from Eq. 7c linearly with *f*APAR, as in Eq. 8.

Eq. 8



Gu et al. (2002), Jenkins et al. (2007), and others have highlighted the importance of distinguishing between direct beam and diffuse solar radiation in models of canopy photosynthesis, because the light use efficiency of canopy photosynthesis is considerably higher for diffuse radiation than it is for direct beam radiation at the same quantum flux. The reason for this effect is that there is a more even distribution of light across all leaves in the canopy when the diffuse fraction is high compared to when the direct beam fraction is low. Starting with a rearranged version of Eq. 6, where ** is the initial slope of the light response function and ** is interpreted as a linearity coefficient but is also equivalent to *Asat* (Eq. 9a), Gu et al. (2002) developed a simple model that features separate ** and ** parameters for direct beam (*dir*, *dir*) and diffuse (*dif*, *dif*) radiation, and the effective values of ** and **depend on the relative direct beam and diffuse fluxes (and ). The resulting model for is given in Eq. 9b, and substituting for *P*g in Eqs. 7 and 8 yields two additional models, and .



Eq. 9a



Eq. 9b



As an alternative to these single-layer “big leaf” representations of the canopy, Norman’s (1980, 1982) sun-shade model explicitly accounts for radiative transfer through the canopy, which depends on the solar elevation, **, and total leaf area, *F.* Assuming a spherical leaf angle distribution, and following the implementation of this model by Hollinger and Richardson (2005), the amount of sun-lit leaf area, *Fsun*, is given by Eq. 10a, while the amount of shaded leaf area, *Fshade*, is given by Eq. 10b.

Eq. 10a



*Fshade* = *F* – *Fsun* Eq. 10b

The quantum flux incident on the shaded leaf area (Eq. 11a) is a function of the diffuse flux,, accounting for extinction through the canopy, and a scattering component, *C*. The scattering component is itself a function (Eq. 11b) of a scattering coefficient, *k*, the direct beam flux, , total leaf area, *F*, and solar elevation, **. Note that scattering is predicted to increase when the solar elevation is low. The scattering coefficient, *k*, is a function of the average leaf absorbance across visible wavelengths, *A*, which we take to be 0.85, yielding *k* = 0.10 (Eq. 11c). The total quantum flux incident on the sun-lit leaf area has both a direct beam component (a function of the mean leaf-sun angle, *a*, which is 60° for the spherical leaf angle distribution, and the solar elevation), and a diffuse component.



Eq. 11a



Eq. 11b



Eq. 11c



Eq. 11d



Then, for both sunlit and shaded leaves (Eq. 12a, b), we scaled up a Michaelis-Menten model (Eq. 6), with leaf-level (rather than canopy-level) parameters, to yield the total canopy photosynthesis, *Ptotal* (Eq. 12c). Note that unlike Hollinger and Richardson (2005), we allow for the *A* and *K* parameters to be different for sunlit and shaded leaves.

Eq. 12a



Eq. 12b



*Ptotal* = *Psun* + *Pshade* Eq. 12c

This gives us a total of 7 different models for canopy photosynthesis (*P*g, ,, , , , and *Ptotal*). The objective of the modeling work was to evaluate the degree to which the various radiometric and color indices, as described above, can provide any information about the seasonal trajectory of the parameter denoting photosynthetic capacity in these models. The null hypothesis is that once the seasonality of LAI and the various environmental driers (solar radiation, VPD, and canopy temperature) are accounted for, photosynthetic capacity can be treated as a constant. Thus for each model, we compare two versions: one where *Asat* is treated as a constant, and one where *Asat* is allowed to be time-varying as a linear function of a radiometric or color index.



Note that we measured NEE but model canopy photosynthesis; thus, there is a missing ecosystem respiration term (*Re*) that must be accounted for as well, as in Eq. 13a. The negative sign on *P* indicates C uptake and reflects the sign convention described above, whereas the positive sign on *Re* indicates C release from the ecosystem to the atmosphere. We use a standard *Q*10 model for Re (Eq. 13a), where *Q*10 is the temperature sensitivity of respiration to a 10°C change in temperature and *Rref* is the respiration at 10°C.

NEE = –*P + Re* Eq. 13a

Eq. 13b



Model parameterization was conducted in SAS (version 9.2, SAS Institute, Cary NC USA) using PROC NLIN. We conducted a grid search for preliminary exploration of parameter space, and then used the Gauss-Newton method to identify the optimal parameter set. Richardson et al. (2006) derived CO2 flux measurement uncertainty estimates for this site, which we use here to obtain maximum-likelihood model parameter estimates, based on a weighted least squares cost function following Hollinger and Richardson (2005). In this approach, data in which we have higher confidence are accorded greater weight than those in which we have lower confidence.

Our analysis presented is based on data from 2012, which was the first complete seasonal cycle, from dormancy through canopy development, senescence, and back to dormancy, with overlapping camera and radiometric data, and CO2 flux measurements.

**Results**

*Effects of illumination geometry*

To investigate effects of illumination geometry on the various radiometric and color indices, we examined relationships between index values (measured every 30 minutes) and solar zenith angle for the period between day 190 and day 200. This time frame was chosen because by this point the canopy was more or less fully developed, and most indices had essentially reached a stable mid-summer plateau (see below). We found that certain measurements were more sensitive to illumination geometry than others. Measurements could thus be divided into three classes. In the first group were those measurements that were essentially insensitive to zenith angle. These include Skye NDVI, LED NDVI, and AMSPEC PRI, for which zenith angle explained <10% of the variation in index value.

In the second group were those measurements that were more variable at certain zenith angles. For example, LAIDCP was highly variable at low zenith angles (1 s.d. = 0.7 m2 m-2 for SZA < 45°), but well constrained (1 s.d. = 0.1 m2 m-2 for SZA ≥ 45°) at high zenith angles. This is attributed to sun flecks and lens flare, which typically occurred only when the sun was high in the sky. Conversely, other measurements were more variable at high zenith angles. For example, all indices calculated from the multi-channel Skye sensors tended to be substantially more variable at SZA ≥ 70°. This appears to be the result of high SZA corresponding to low levels of incident solar radiation (*R*↓), when there are simply not enough photons reflected from the canopy and passing through the instrument’s narrow bandpass filter to achieve an acceptable signal-to-noise ratio.

Finally, in the third group were those measurements that showed a clear dependence on illumination geometry. For example, camera GCC (R2 = 0.48), AMSPEC GCC (R2 = 0.68), and the the BRDF-corrected AMSPEC PRI (R2 = 0.41) all declined linearly with increasing zenith angle. However, even in the worst of these cases, we estimate that changes in zenith angle account for only a relatively small proportion (always less than 20%, and in most cases less than 5%) of the total variance in measured index values over the course of the whole year. The reason for this is that the total variance between day 190 and day 200 generally tended to be relatively small when compared to the total variance over the course of the whole year, which was dominated by the (much larger) seasonal cycle.

*Filtering and time averaging*

For each index, we converted the 30-minute measurements to three-day values after first empirically comparing different filtering criteria (based on *Q*↓, , diffuse fraction, time of day, and solar zenith angle), and different averaging procedures (mean, median, 10th, 25th, 75th and 90th quantile). We identified the combination of filtering and averaging that minimized the short-term variability in the resulting time series, as quantified by the residual variance relative to a smoothing spline fit to the data. We found that for most indices, taking the mean of all data points measured under high light (*Q*↓ ≥ 1000 mol m-2 s-1) was the most effective approach. For LAIDCP, we restricted our analysis to high zenith angles (SZA > 60°) or when the diffuse fraction was high (/*Q*↓ > 0.90), to minimize sunflecks and lens flare. For *f*APAR, we restricted our analysis to zenith angles between 52° and 62°, approximately corresponding to the “magic angle” of 57° where all leaf angle distribution (*G*) functions converge to 0.5.

The resulting

Seasonal Patterns

Confidence by looking at diffuse only days.

Inversion

**Acknowledgments**

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**Table 1.** Radiometric and imaging sensors installed at the Harvard Forest “Barn Tower”.

|  |  |  |
| --- | --- | --- |
| **Radiometric Instrument** | **Measurement** | **Location** |
| Kipp & Zonen CNR4 (4 channel net radiometer), Delft, the Netherlands | Incoming SW (300-2800 nm; W m-2)  Outgoing SW (“)  Incoming LW (4500-42000 nm; W m-2)  Outgoing LW (“) | Top of tower (40 m)  “  “  “ |
| Kipp & Zonen PQS1 (quantum sensor), Delft, the Netherlands | Incoming PPFD (400-700 nm, mol m-2 s-1)  Outgoing PPFD (“)  Below-canopy PPFD (“) | Top of tower (40 m)  “  1.5 m above ground level (x4 loc.) |
| Delta-T BF-5 (sunshine sensor), Cambridge, UK | Incoming direct PPFD (400-700 nm, mol m-2 s-1)  Incoming diffuse PPFD (“) | Top of tower (30 m) |
| Skye 1850 (4 channel radiometric sensor), Llandrindod Wells, UK | Incoming and reflected (blue: 470 ± 20 nm, green: 557 ± 25 nm, red: 605 ± 35 nm, NIR: 750 ± 42 nm; mV and reflectance) | Top of tower (40 m) |
| Skye 1850 (4 channel radiometric sensor), Llandrindod Wells, UK | Incoming and reflected (green 1: 530 ± 11 nm, green 2: 570 ± 10 nm, red: 650 ± 55 nm, NIR: 860 ± 60 nm; mV and reflectance) | Top of tower (40 m) |
| Ryu LED (2 channel sensor), custom built: see Ryu et al. (2010) | Incoming and reflected, red and NIR bands (red: 646±56 nm, NIR: 843±72 nm; mV and reflectance) | Top of tower (40 m) |
| AMSPEC II (automated multiangular radiometer; incorporates a Unispec DC spectrodatiometer, PP Systems Inc., Amesbury, MA), custom built: see Hilker et al. 2010 | Incident and reflected 400-900 nm (154 wavelengths, ≈3.25 nm increment; digital numbers and reflectance) | Top of tower (40 m) |
| StarDot NetCam SC 5 MP IR networked camera (color webcam), Buena Park, CA | Canopy imagery, 1.3 MP (red, green and blue channels; digital numbers) | Top of tower (35 m) |
| StarDot NetCam 6-Channel networked camera (monochrome webcam with 6-filter wheel), Buena Park, CA | Canopy imagery, 1.3 MP (broadband visible: ≤ 700 nm, broadband NIR: ≥ 700 nm, blue: 470 ± 10 nm, green 1: 530 ± 10 nm, green 2: 570 ± 10 nm, red: 610 ± 10 nm; digital numbers) | Top of tower (35 m) |
| Vivotek IP7160 networked camera (color webcam), New Taipei City, Taiwan | Upward-looking canopy imagery, 2 MP (red, green and blue channels; digital numbers) | 1 m above ground level |