

1      **Solar position confounds the relationship between ecosystem function and vegetation**  
2      **indices derived from solar and photosynthetically active radiation fluxes.**

5      Adrian V. Rocha<sup>1</sup>, Rose Appel<sup>1</sup>, M. Syndonia Bret-Harte<sup>2</sup>, Eugenie Euskirchen<sup>2</sup>, Verity Salmon<sup>3</sup>,  
6      Gus Shaver<sup>4</sup>

9      <sup>1</sup>Department of Biological Sciences and the Environmental Change Initiative, Notre Dame, IN  
10     46556, USA

12     <sup>2</sup>Institute of Arctic Biology, University of Alaska Fairbanks, Fairbanks, AK 99775, USA

14     <sup>3</sup>Environmental Sciences Division and Climate Change Science Institute, Oak Ridge National  
15     Laboratory, Oak Ridge, TN 37831, USA

17     <sup>4</sup>The Ecosystems Center, Marine Biological Laboratory, Woods Hole, MA 02543, USA

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38     Corresponding Author:  
39     Adrian V. Rocha  
40     University of Notre Dame  
41     Department of Biological Sciences and the Environmental Change Initiative  
42     100 Galvin Life Sciences  
43     Notre Dame, IN 46556  
44     Ph: 574-631-9438  
45     Email: arocha1@nd.edu

48 **Abstract:**

49 Vegetation indices derived from solar and photosynthetically active radiation (PAR) sensors (i.e.  
50 radiation derived) have been under-utilized in inferring ecosystem function, despite measurement  
51 capability at hundreds of sites. This under-utilization may be attributed to reported mismatches  
52 among the seasonality of radiation- and satellite-derived vegetation indices and canopy  
53 photosynthesis; herein referred to as measurement biases. Here biases in radiation derived  
54 reflectance and vegetation indices were assessed using a decadal record of satellite and ground  
55 based spectroradiometer data, ecosystem phenology and CO<sub>2</sub> fluxes, and radiation derived  
56 vegetation indices (i.e. the Normalized Difference Vegetation Index [NDVI], the two band  
57 Enhanced Vegetation Index [EVI2]) from a high latitude tundra site (i.e. Inuvik). At Inuvik,  
58 we found poor correspondence between the three types of reflectance and vegetation indices,  
59 especially during the latter part of the growing season. Radiation derived vegetation indices  
60 resulted in incorrect estimates of phenological timing of up to a month and poor relationships  
61 with canopy photosynthesis (i.e. Gross Ecosystem Exchange (GEE)). These mismatches were  
62 attributed to solar position (i.e. solar zenith and azimuth angle) and a method, based on the diel  
63 visible and near-infrared albedo variation, was developed to improve the performance of the  
64 vegetation indices. The ability of radiation derived vegetation indices to infer GEE and  
65 phenological dates drastically improved once radiation derived vegetation indices were corrected  
66 for solar position associated biases at Inuvik. Moreover, radiation derived vegetation indices  
67 became better aligned with MODerate resolution Imaging Spectroradiometer (MODIS) satellite  
68 estimates after solar position associated biases were corrected at Inuvik and at 25 Fluxnet sites  
69 (~90 site years) across North America. Corrections developed here provide a way forward in

70 understanding daily ecosystem function or filling large gaps in eddy covariance data at a  
71 significant number of Fluxnet sites.

72  
73  
74 *Keywords:* Phenology, NDVI, EVI2, Solar Zenith, Gross Ecosystem Exchange, Arctic LTER  
75

## 76 **1.0 Introduction:**

77 Vegetation indices, such as the Normalized Difference Vegetation Index (NDVI), have been  
78 used to infer ecosystem structure and function over the past half century (Rouse 1974). These  
79 indices utilize the low red reflectance -due to chlorophyll absorption-, and the high NIR  
80 reflectance -due to low absorption and high scattering- of green leaves to infer ecosystem  
81 function (e.g. leaf abundance, canopy physiology, and canopy phenology) (Gamon et al. 2010;  
82 Gamon et al. 2006). Historically, these indices were derived from satellite based reflectance;  
83 providing a proxy of ecosystem function at the global scale-albeit at low temporal resolution  
84 (e.g. monthly, bi-monthly). However, these indices also can be derived from commonly used  
85 up- and down-ward facing Photosynthetically Active Radiation (PAR) and solar radiation  
86 sensors (i.e. radiation derived); providing a low cost continuous measure of ecosystem function  
87 even when heavy cloud cover obscures satellite views of the surface (Huemmrich et al. 1999;  
88 Rocha and Shaver 2009; Wilson and Meyers 2007). Although radiation derived vegetation  
89 indices provide a powerful tool for understanding ecosystem function at sub-daily to annual  
90 timescales, a critical assessment of their uncertainties are surprisingly lacking.

91  
92 Despite the wide use of PAR and solar radiation sensors across many eddy covariance sites,  
93 radiation derived vegetation indices have been under-utilized in inferring ecosystem function.  
94 Only a handful of studies have used radiation derived vegetation indices to infer ecosystem

95 function, as compared to the thousands that have used satellite derived vegetation indices  
96 (Jenkins et al. 2007; Wohlfahrt et al. 2010; Wright and Rocha 2018). This imbalance may be  
97 due to the historical precedent of satellite data, or a lack of mechanistic understanding of  
98 measurement uncertainties in radiation derived indices. Radiation derived vegetation indices  
99 differ in magnitude and exhibit less seasonality than those derived from satellite data (Rocha and  
100 Shaver 2009). Jenkins et al. (2007) found that the slope of the relationship between radiation  
101 derived vegetation indices and canopy photosynthesis differed in the early and later part of the  
102 growing season. This contrasts with remote sensing work that models canopy photosynthesis  
103 from satellite derived vegetation indices with a single relationship across the season, and  
104 highlights a significant methodological knowledge gap (Sims et al. 2006; Sims et al. 2011; Xiao  
105 et al. 2005).

106

107 Although various hypotheses have been proposed to resolve the differences in radiation- and  
108 satellite- derived vegetation indices, the mechanisms are still debatable. The lack of  
109 correspondence between radiation- and satellite-derived vegetation indices have often been  
110 attributed to differences in the spatial scale of integration between the two measures or  
111 differences in sensor spectral resolution (Disney et al. 2004; Tittebrand 2009; Wang et al. 2004;  
112 Wang et al. 2012). Ground based radiation derived vegetation indices integrate a smaller area  
113 (i.e. ~100 x 100 m) than satellites such as the MODerate resolution Imaging Spectroradiometer  
114 (MODIS) (i.e. 100-1000 m) (Schmid 1997). Spatial mismatches are less likely to confound  
115 ground radiation- and satellite- derived reflectance and vegetation index comparisons in  
116 homogenous landscapes (Wittich and Kraft 2008). Radiation-derived vegetation indices also are  
117 very broad and integrate spectral information across the visible and infrared wavelengths,

118 whereas satellite derived vegetation indices use more narrow spectral bands that focus on the red  
119 and NIR portions of the electromagnetic spectrum (Wittich and Kraft 2008). This spectral  
120 mismatch is more likely to influence the magnitude- but not the seasonality-of the vegetation  
121 indices. Although both these mechanisms are important at individual sites, they are unlikely to  
122 account for the large magnitude and consistency of radiation- and satellite-derived differences  
123 observed across many sites.

124

125 Sensor measurement biases have been largely overlooked when determining the causal  
126 mechanism behind differences in radiation- and satellite-derived vegetation indices (Balzarolo et  
127 al. 2011; Schaepman-Strub et al. 2006). Satellite sensors measure surface radiance and then  
128 corrects reflectance to minimize solar illumination and sensor view effects using a Bi-Directional  
129 Reflectance Function (BRDF) (Schaepman-Strub et al. 2006). The BRDF corrects for solar  
130 illumination effects from solar position to compare reflectance at the same view angle-typically  
131 defined at nadir. Such corrections are not made for radiation derived vegetation indices  
132 (Balzarolo et al. 2011; Huemmrich et al. 1999; Wilson and Meyers 2007). Although the  
133 radiation sensors are located above the canopy, these sensors integrate radiation from the entire  
134 hemisphere. Despite this hemispherical field of view, shortwave albedo has been shown to be  
135 sensitive to illumination angle (i.e. solar zenith and azimuth angles), which changes over the  
136 course of a day and year (Huemmrich et al. 1999). For example, broadband albedo measured  
137 with pyranometers have been shown to be dependent on solar zenith angle and illumination  
138 intensity for surfaces with high reflectivity such as snow (Carroll and Fitch 1981; Kriebel 1979;  
139 Wang et al. 2005; Wang and Zender 2010; Yang et al. 2008). However, little has been done to

140 understand or correct the impact of illumination angle effects on radiation derived vegetation  
141 indices.

142  
143 Here we assessed the ability of PAR and solar radiation derived reflectance proxies and  
144 vegetation indices to replicate MODIS satellite derived reflectance and vegetation indices; herein  
145 referred to as measurement biases. We also assessed the ability of PAR and solar radiation  
146 derived vegetation indices to infer ecosystem function (i.e. plant phenology and CO<sub>2</sub> fluxes).  
147 We focus on two commonly used vegetation indices: NDVI and EVI2 (Rocha and Shaver 2009).  
148 NDVI has more of a historical precedent in inferring ecosystem function, but EVI2 may provide  
149 a better proxy of ecosystem function due to its insensitivity to non-vegetated background  
150 reflectance (Jiang et al. 2008). Past remote sensing work has demonstrated the impact of solar  
151 position in influencing reflectance and vegetation indices, but lacked biological data to  
152 demonstrate the implications of ignoring such biases for inferring ecosystem function (Bhandari  
153 et al. 2011; Huete 1987; Ma et al. 2019; Middleton 1992). We hypothesized that solar position  
154 will lead to systematic biases in radiation derived vegetation indices that prevent these indices  
155 from correctly inferring vegetation phenology and seasonality in canopy photosynthesis at  
156 Imnaviat. We tested this hypothesis with a decadal record of PAR and solar radiation fluxes,  
157 MODIS, and ground based spectral radiometer measurements at a high latitude tundra site  
158 (Imnaviat), and further corroborated the patterns observed at Imnaviat with a synthesis of  
159 Fluxnet datasets. Imnaviat was chosen because of its landscape homogeneity, its rich long term  
160 ecological dataset (i.e. long term CO<sub>2</sub> fluxes and plant phenology), as well as its high latitude  
161 location with a frequently high solar zenith angle. The attributes of these data provide an ideal  
162 opportunity to determine the major sources of measurement biases leading to the discrepancy

163 between satellite- and radiation-derived vegetation indices, and measures of seasonality in  
164 ecosystem function.

165

166 **2.0 Methods**

167

168 *2.1 Site Description, Instrumentation, and Available Data*

169 This study was conducted on a west-facing hillslope within the Imnaviat Creek watershed on the  
170 North Slope of Alaska, USA (68.61° N; 149.31° W). Vegetation at the site was characteristic of  
171 moist acidic tussock tundra with tussock cottongrass [*Eriophorum vaginatum*], dwarf birch  
172 [*Betula nana*], labrador tea [*Rhododendron tomentosum*], sphagnum moss [*Sphagnum spp.*], and  
173 scattered lichens covering the landscape (Euskirchen et al. 2012). The mean annual temperature  
174 at the site was -7 °C and the mean annual precipitation was 318 mm, with 40% occurring as rain  
175 and 60% as snow. Mean growing season (June-August) temperature was 6 °C, while mean non-  
176 growing season temperature was -11 °C.

177

178 In July of 2008, Imnaviat was instrumented with three (1 upward and two downward) CMP3  
179 pyranometers that measured shortwave solar radiation (SW: units: W m<sup>-2</sup>) [CMP3; Kipp and  
180 Zonen], three PAR sensors that measured Photosynthetically Active Radiation (PAR: units:  
181 μmol m<sup>-2</sup> s<sup>-1</sup>) [LI-190SA; Li-Cor, Lincoln NB], two downward looking surface temperature  
182 radiometers [IRT Infrared Thermometer; Apogee Instruments], a HMP temperature and humidity  
183 sensor [HMP45C-L; Campbell Scientific], and two TCAV soil temperature sensors [TCAV-L;  
184 Campbell Scientific]. Meteorological sensors were mounted at a height of 2.5 meters. Radiation  
185 sensors were well maintained, frequently leveled, and sent for factory calibration every 2-3 years

186 during the measurement period. The radiation tower ran nearly continuously from July 2008-  
187 2018, and was powered by a battery bank connected to two solar panels, which were situated  
188 away from the direct field of view of the sensors.

189

190 The radiation tower was located ~300 m away from three Arctic Observatory Network (AON)  
191 flux towers located along the same west facing hillslope gradient (Euskirchen et al. 2012). The  
192 flux towers measured the Net Ecosystem Exchange of CO<sub>2</sub> (NEE) via the eddy covariance  
193 method, and a suite of meteorological variables including incoming and outgoing PAR and solar  
194 radiation, air temperature, humidity, wind speed, soil moisture, soil temperature, and snow depth  
195 (Baldocchi 2003). We analyzed the mean seasonal cycle of the daily Gross Ecosystem Exchange  
196 (GEE) at the mid-slope Moist Acidic Tundra (MAT) site from 2008-2018 to determine the  
197 relationship between vegetation indices and the seasonality of photosynthesis. The mid-slope  
198 MAT flux tower was chosen because of its similar vegetation composition, slope position, and  
199 NDVI seasonality to the nearby radiation tower [MAT Flux Tower NDVI vs. Imnaviat Radiation  
200 Tower NDVI R<sup>2</sup>: 0.97; Slope: 1.01; Mean Absolute Error (MAE): 0.01]. AON data were  
201 obtained online at <http://aon.iab.uaf.edu>.

202

203 NEE flux partitioning was described in detail in Euskirchen et al. (2012, 2017), and followed  
204 standard Fluxnet protocols for partitioning NEE into canopy photosynthesis (Gross Ecosystem  
205 Exchange: GEE) and ecosystem respiration (ER). Briefly, NEE flux partitioning was  
206 accomplished by fitting a Q10 air temperature response function to well mixed (u-star> 0.10 s m<sup>-1</sup>)  
207 <sup>1)</sup> NEE's that occurred during low light conditions (PAR< 50  $\mu\text{mol m}^{-2} \text{s}^{-1}$ ) (Ueyama et al. 2013;  
208 Euskirchen et al. 2017)). The basal respiration and Q10 parameters of the exponential model

209 were determined through least squares fitting with “low light” NEE and air temperature data  
210 from a 30 day daily moving window. This empirically derived Q10 air temperature response  
211 function was used to estimate half hourly ER. Half hourly GEE was inferred from NEE by  
212 subtracting ER from NEE (GEE=NEE-ER), and temporally scaled up with daily summations.

213

214 *2.2 Ground based Spectral Reflectance Measurements*

215 Ground based reflectance was measured within the footprint of the Imnaviat radiation tower  
216 using three different spectroradiometers over the years. Spectral reflectance was measured with a  
217 Unispec (UniSpec-SC, PP-Systems, Amesbury, MA; Spectral Range: 300-1200 nm at 2 nm  
218 resolution) from 2008-2009, a dual channel Unispec (UniSpec-DC, PP-Systems, Amesbury, MA;  
219 Spectral Range: 300-1200 nm at 2 nm resolution) from 2010-2012, and a FieldSpec 4 (Analytical  
220 Spectral Devices (ASD); Malvern Panalytical Ltd; United Kingdom; Spectral Range: 200-2400  
221 nm at 2 nm resolution) from 2013-2018. Four ~100 m transects separated by ~30 m were  
222 established on the North and South side of the radiation tower forming a 200x120m grid within  
223 the tower footprint. Spectral reflectance was measured during midday hours (11:00 am-2:00 pm  
224 AST) every ~3 meters along each of the four 100 m transects either weekly, bi-monthly, or  
225 monthly during the growing season (June-August) of each year (n=240 scans per sampling date).  
226 A total of 62 sampling campaigns were undertaken from July 2008 to August 2018 with each  
227 campaign taking ~1 hour to accomplish.

228

229 Surface reflectance measurements followed standard procedures described in the  
230 spectroradiometer user manuals. Prior to measurements, each instrument was allowed a 15-20  
231 minute warm up period. A freshly cleaned white Spectralon® diffuse reflectance panel

232 (Labsphere; North Sutton, NH) was used as a reflectance standard to convert spectroradiometer  
233 derived radiance into surface reflectance. Dark current measurements were taken by closing the  
234 detector “door”, which prevented light from hitting the detectors and minimized measurement  
235 artifacts from background electrical instrument noise. Optimal measurement integration times  
236 were dependent on illumination conditions and were automatically determined by each sensor.  
237 White panel, dark current, and optimal measurement integration time measurements were taken  
238 frequently (i.e. every 3-5 minutes depending on sky conditions) to ensure high quality  
239 reflectance data. After each sampling campaign, surface reflectance data were quality checked  
240 for anomalous spectra (i.e. spectra that were  $>3$  standard deviations from the mean) and averaged  
241 across all scans. These spectra were used to calculate NDVI and EVI2 using Equations [2] and  
242 [3] below and spectrally averaged MODIS wavelength definitions for red- (average of 620-670  
243 nm) and NIR- reflectance (average of 841-876 nm) (Schaaf et al. 2002). We also spectrally  
244 averaged all wavelengths to calculate total and visible reflectance to derive a broad band visible,  
245 NIR (using equation 1), NDVI and EVI2 based on ASD spectroradiometer data. ASD averaged  
246 total reflectance was within 10% of the shortwave albedo, while ASD averaged visible  
247 reflectance was within 5% of PAR albedo measured by radiation sensors at Imnaviat.

248

### 249 *2.3 Ground based Phenology*

250 Individual plant species phenologies were measured from 2008-2018 in moist acidic tundra at  
251 the Toolik Lake Arctic Long Term Ecological Research (LTER) station. Toolik field station was  
252 situated  $\sim$ 7 km away and experienced similar weather to Imnaviat. A variety of phenological  
253 events (i.e. first snow free, first visible leaf, first leaf drop, first color change, and last leaf drop)  
254 were measured in several plots around Toolik lake in each year for the dominant MAT species

255 (i.e. *Andromeda polifolia*, *Betula nana*, *Carex bigelowii*, *Cassiope tetragona*, *Empetrum nigrum*,  
256 *Eriophorum vaginatum*, *Ledum palustre*, *Polygonum bistorta*, *Rubus chamaemorus*, *Salix*  
257 *pulchra*, *Vaccinium uliginosum*, *Vaccinium vitis-idaea*). These phenological data were used to  
258 validate satellite- and radiation- derived NDVI and EVI2 estimates of the start-, end-, and length-  
259 of the growing season. The average of the first visible leaf for all species served as a proxy for  
260 the start of the growing season, whereas the maximum last leaf color change served as a proxy  
261 for the end of the growing season.

262

#### 263 *2.4 Radiation derived Vegetation Indices*

264 The radiation tower at Imnaviat measured surface albedo in the visible (400-700 nm) and total  
265 shortwave wavelengths (300-2400 nm) of light. These albedo measures served as a proxy for red  
266 and near infrared reflectance (Rocha and Shaver 2009). Visible ( $\alpha_V$ ) albedo was calculated as  
267 the ratio between reflected ( $r$ ) and incoming ( $i$ ) PAR  $\alpha_V = PAR_r/PAR_i$ , while total albedo ( $\alpha_T$ )  
268 was calculated as the ratio between reflected and incoming shortwave radiation [SW<sub>r</sub> & SW<sub>i</sub>,  
269 respectively]  $\alpha_T = SW_r/SW_i$ .  $\alpha_V$  was used as a proxy for red reflectance, while both  $\alpha_V$  and  $\alpha_T$   
270 were used in Equation 1 as a proxy for NIR reflectance ( $\alpha_N$ ) (Jenkins et al. 2007).

271

$$272 \alpha_N = W * \alpha_T - \alpha_V \quad \text{Equation [1]}$$

273

274 W in Equation 1 equaled 2 for all vegetation types, and represented a weighting term to separate  
275  $\alpha_N$  from  $\alpha_V$  and  $\alpha_T$ . Derivations of red and near infrared reflectance from ground based  
276 radiometers represented broadband definitions of narrowband quantities.  $\alpha_N$  included dynamics  
277 in the near- and short-wave infrared region of the reflectance spectrum, while  $\alpha_V$  included

278 dynamics in the red, blue and green regions of the reflectance spectrum. Other ground  
279 radiometer derivations of  $\alpha_N$  utilize similar assumptions (see Huemmrich et al., 1999 & Wilson  
280 and Meyers, 2007). We used Jenkins et al. (2007) derivation because of its parsimony and its  
281 high correlation with other  $\alpha_N$  derivations (Jenkins vs. Huemmrich  $R^2$  [Mean Absolute Error:  
282 MAE]: 0.91 [0.015]/ MAE Jenkins vs. Wilson & Meyers  $R^2$  [MAE]: 0.99 [0.014]) for the sites  
283 used in this study. We also found that the conclusions from our analyses were independent of the  
284 different formulations of  $\alpha_N$ .

285

286 We focused our analyses on the active growing season during snow-free periods. Data  
287 influenced by snow covered ground were identified with an albedo threshold of  $>0.3$  (i.e.  
288 vegetation albedo  $<0.25$  at all sites) and removed from the half hourly radiation datasets.  
289 Incoming and reflected radiation were averaged over the course of a day (i.e.  $n=48$  for each  
290 value) to minimize diel solar zenith effects (Huemmrich et al. 1999; Rocha and Shaver 2009;  
291 Wilson and Meyers 2007). Sensor drift and snow and dirt accumulation on the sensors were  
292 identified as periods where  $PAR_i/SW_i$  fell beyond or below the mean plus or minus 2 standard  
293 deviations and subsequently removed. The final “cleaned” dataset contained daily ground  
294 radiometer values that were compared with MODIS reflectance and vegetation indices.

295

296 NDVI and EVI2 were calculated from radiation-, spectroradiometer- and MODIS-derived  
297 measures of near infrared ( $\alpha_N$ ) and red reflectance ( $\alpha_R$ ) with Equations [2] and [3] (Jiang et al.  
298 2008).

299

$$NDVI = \frac{\alpha_N - \alpha_R}{\alpha_N + \alpha_R} \quad \text{Equation [2]}$$

301

$$302 \quad EVI2 = 2.5 \frac{\alpha_N - \alpha_R}{\alpha_N + 2.4\alpha_R + 1}$$

**Equation [3]**

303

304 *2.5 Fluxnet Data Synthesis*

305 We conducted a broader survey of ground based radiation derived vegetation indices with  
306 Fluxnet data to determine whether biases observed at the Imnaviait site were consistent across  
307 other sites (Table 1). Data from the Fluxnet network consisted of 25 sites and 90 site years of  
308 half hourly incoming ( $i$ ) and reflected ( $r$ ) PAR and shortwave data (Table 1). 12% of the sites  
309 were from crops, 8% were from deciduous forests, 25% were from evergreen forests, 28% were  
310 from grasslands, 20% were from arctic tundra, and 8% were from a shrub and grassland mix.  
311 Sites had a minimum of two years of data with a maximum of 6 years at 2 sites, and an average  
312 of 3.5 years for the entire dataset. PAR within the 400-700 nm spectral region was measured  
313 with a LI190 quantum sensor (LI-COR Inc., Lincoln, Nebraska) at 85% of the sites, while the  
314 remaining sites used either an Apogee quantum sensor (Apogee Instruments, Logan, Utah) or  
315 BF3 sunshine sensor (Dynamax, Houston Texas). Shortwave radiation (SW) within the 300-  
316 2800 nm spectral region was measured with a CM3 (Kipp & Zonen, Bohemia, NY ) at 90% of  
317 the sites, while the remaining sites used an Apogee pyranometer (Apogee Instruments, Logan,  
318 Utah) or LI200 pyranometer (LI-COR Inc., Lincoln, Nebraska). Data were aligned with MODIS  
319 satellite data (see section 2.7) through 16- day averages that were centered on the MODIS  
320 composite date.

321

322 *2.6 Testing and Correcting for Solar Position Biases*

323 We corrected solar position biases using diel relationships between solar position and albedo  
324 throughout the season. Diel NIR and visible albedo variability can be more than twice as large  
325 as observed over the course of a season (Huemmrich 1999). These large diel visible and NIR  
326 albedo variations cannot be representing changes in canopy leaf area, that are often related to  
327 vegetation indices, because LAI changes over much longer time scales than a day (i.e. days to  
328 weeks)(Stoy 2013). Rather, this large diel variation arises from the anisotropic properties of  
329 surface reflectance (i.e. the bidirectional reflectance distribution function) and possibly other  
330 sensor issues, such as a sensors' cosine response function (Huete 1987; Middleton 1992; Rahman  
331 et al. 1993).

332

333 Here we used the diel variation in albedo and solar position to empirically derive a correction  
334 factor to apply over the course of the season. We removed vegetation phenology impacts on the  
335 seasonal variability by dividing each daily averaged visible and NIR albedo into each half hourly  
336 visible and NIR albedo value to focus solely on sub-daily variations associated with solar  
337 position (Equation 4). These ratios provided 48 half hourly correction factors for each day and  
338 albedo that can be related to sub-daily solar position changes. When multiplied with each half  
339 hourly NIR or visible albedo, the correction factor scaled these values down to represent a  
340 consistent daily average for all 48 half hourly periods. These constant daily NIR and visible  
341 albedos were consistent with the fact that canopy leaf area does not significantly change on sub-  
342 daily timescales.

343

344

$$\alpha_{Cor} = \frac{Daily\ Value}{Half\ Hourly\ Value} = \frac{\alpha_d}{\alpha_h}$$

**Equation [4]**

345  $\alpha_{Cor}$  was calculated and three dimensional bin averaging on half hourly solar zenith, solar  
 346 azimuth, and  $\alpha_{Cor}$  helped establish the empirical relationship among the three variables. Because  
 347  $\alpha_{Cor}$  was derived across the season and years, we used bin averaging to further smooth the  $\alpha_{Cor}$   
 348 response function in relation to solar zenith and azimuth. We found that twenty-five equal range  
 349 sized bins were sufficient enough to smooth the remaining variability associated with seasonal  
 350 changes in solar zenith and azimuth angle and random noise in the albedo measurements.

351 Machine learning methods with a squared exponential Gaussian process regression model along  
 352 with the binned half hourly  $\alpha_V$  and  $\alpha_N$  were used to derive the empirical correction factor  
 353 equations for each albedo measure (i.e.  $\alpha_V$  and  $\alpha_N$ ) as a function of solar position. Empirical  
 354 correction factors for each day were predicted from the daily averaged solar zenith and azimuth  
 355 angle, and then multiplied by the daily averaged visible and NIR albedo to produce a solar  
 356 position corrected  $\alpha_V$  and  $\alpha_N$ . NDVI and EVI2 were then recalculated using the solar position  
 357 corrected  $\alpha_V$  and  $\alpha_N$  with Equations 2 and 3. Solar position was calculated for each site and half  
 358 hour using the site latitude and longitude and time of year (Myers 2017). Analyses were  
 359 accomplished with Matlab's Regression Learner application (MATLAB 2019b; Mathworks Inc.  
 360 Natick, MA).

361

362 *2.7 MODIS Data*

363 We compared MODIS reflectance and vegetation indices to radiation derived proxies and  
 364 measures. MODIS version 4 data were extracted from a 0.25 km<sup>2</sup> area centered at each tower  
 365 location (<http://daac.ornl.gov>) (ORNL DAAC 2018). For Imnaviat, we used daily Nadir BRDF-

366 Adjusted reflectance (MCD43A4) and extracted data at various spatial scales (i.e. 0.25, 6.25,  
367 20.25, 210.25, and 420.25 km<sup>2</sup>) to determine the impact of spatial aggregation on the comparison  
368 between ground and satellite based data (Shuai et al. 2013). For the Fluxnet Data Synthesis, we  
369 used Nadir-BRDF adjusted 500 m resolution surface reflectance (MODIS NBAR; MCD43A)  
370 from seven spectral bands (Schaaf et al. 2002). We also used the seven MODIS spectral bands  
371 along with empirical equations from Liang (2000) to calculate a total and visible albedo that  
372 were used to derive broadband vegetation indices following Equations 1-3. MCD43A reflectance  
373 was reported every eight days, derived from both Terra and Aqua platforms, and adjusted to  
374 local solar noon with a BRDF calculated over a 16-day interval. Data with >80% of pixels  
375 passing quality control were used in the analyses. Only growing season MODIS data, as defined  
376 by ground based snowless terrestrial albedo values, were used in the analyses.

377

### 378 *2.8 Phenology Model*

379 The start, end, and length of the growing season was determined with a phenology model fit to  
380 the observed seasonal cycle of MODIS- and radiation- derived NDVI and EVI2 in each year at  
381 Imnaviat. The phenology model was a double-logistic function that predicted each vegetation  
382 index based on the day of year (t) (Beck et al. 2006; Fisher et al. 2006; Fisher et al. 2007)  
383 (Equation 5):

384

$$385 v(t) = v_{min} + v_{amp} \left( \frac{1}{1+e^{m_1-n_1t}} - \frac{1}{1+e^{m_2-n_2t}} \right) \quad \text{Equation [5]}$$

386

387 The model was fit by minimizing the sum of squared residuals between model predictions and  
388 observed values. The fitted parameters of the model were  $v_{min}$  and  $v_{amp}$ ,  $m_1$ ,  $n_1$ ,  $m_2$ , and  $n_2$ .  $v_{min}$

389 and  $v_{amp}$  were related to the minimum and amplitude values of the spectral index, respectively.  
390 The parameters in the two exponents determined the seasonality with  $m_1$  and  $n_1$  related to the rate  
391 and timing of green-up, and  $m_2$  and  $n_2$  related to the rate and timing of senescence. The start of  
392 the growing season was given by  $t = m_1/n_1$ , the end of the growing season was given by  $t =$   
393  $m_2/n_2$ , and the length of the growing season was determined by the difference between the start  
394 and end of the growing season.

395

396 *2.9 Statistical Analyses:*

397 Statistical analyses included least squares linear regression to determine the relationship between  
398 two variables, and Mean Absolute Error (MAE) to determine the prediction error of a model or  
399 the error associated with the comparison of a set of similar observations (Ramsey 2013).

400 Statistical significance was determined at the 95% confidence level.

401

### 402 **3. Results**

403

404 *3.1 Assessing Spatial Aggregation Biases*

405 The scale of spatial integration had little impact on the comparison between tower and MODIS  
406 based vegetation indices indicating landscape coherence in phenology within the region  
407 surrounding Imnaviat (Figure 1). Here we minimized spectral definition differences among  
408 sensors by comparing spectroradiometer- and MODIS- derived reflectance's and vegetation  
409 indices. Spectroradiometer derived NDVI explained 70% of the variability in MODIS derived  
410 NDVI, whereas spectroradiometer derived EVI2 explained 60% of the variability in MODIS  
411 derived EVI2. The MAE increased slightly from 6% of NDVI at the ecosystem/watershed level

412 (0-10 km<sup>2</sup>) to 7% of NDVI at the regional scale (>300 km<sup>2</sup>). EVI2 exhibited greater sensitivity  
413 to spatial integration with MAEs increasing from 14% of EVI2 at the ecosystem/watershed scale  
414 to 20% of EVI2 at the regional scale.

415

416 *3.2 MODIS- vs. radiation-derived reflectance and indices comparison*

417 In general, spectroradiometer- and MODIS- derived reflectances and vegetation indices were  
418 more related to each other than those derived from radiation fluxes at Imnaviat (Table 2).  
419 Vegetation indices yielded higher correlations among measurement types than did red and NIR  
420 reflectance. For example, reflectance R<sup>2</sup>'s ranged from 0.17-0.22 for NIR and red reflectance,  
421 while vegetation index R<sup>2</sup>'s ranged from 0.34 to 0.67. Correlations among radiation-,  
422 spectroradiometer-, and MODIS-derived measures were typically higher for EVI2 than for  
423 NDVI. The poor relationships between radiation- and MODIS/spectroradiometer- derived  
424 vegetation indices were largely attributed to differences in seasonality among the  
425 MODIS/spectroradiometer- and radiation- derived measures.

426

427 Seasonality differed among radiation-, spectroradiometer-, and MODIS derived- reflectance and  
428 vegetation indices at Imnaviat (Figure 2). Correspondence among the three measures was  
429 greatest for red reflectance and smallest for NIR, NDVI, and EVI2. Red reflectance  
430 demonstrated similar seasonality among the measures with higher reflectance in the shoulder  
431 seasons and minimum values during the peak of the growing season. In contrast, NIR  
432 reflectance, NDVI, and EVI2 were low at the start of the growing season, reached a maximum  
433 during peak growing season, and then declined to a minimum at the end of the growing season.  
434 All three measures of NIR, NDVI and EVI2 exhibited similar seasonality up until the peak of the

435 growing season, but differed towards the end of the growing season. Radiation-derived NIR  
436 reflectance and vegetation indices were larger than MODIS and spectroradiometer- derived  
437 quantities towards the latter part of the growing season. Consequently, differences between  
438 MODIS and spectroradiometer- and radiation-derived NIR, NDVI, and EVI2 exhibited strong  
439 seasonality with the largest mismatch towards the second half of the growing season.

440

### 441 *3.3 Assessing Sensor Biases*

442 Seasonal differences between MODIS- and radiation- derived indices observed in Figure 2 were  
443 correlated with solar zenith angle at Imnaviat (Figure 3). Larger solar zenith angles produced  
444 larger differences between MODIS- and radiation- derived NIR, NDVI, and EVI2, but had no  
445 impact on differences between MODIS- and radiation- derived red reflectance. Solar zenith  
446 angle explained 41% of the variability in NIR reflectance biases, 28% of the variability in NDVI  
447 biases, and 45% of the variability in EVI2 biases. This represented a bias of 0.004 per 1° change  
448 in zenith angle for NIR reflectance, and a bias of 0.006 per 1° change in zenith angle for NDVI  
449 and EVI2.

450

451 The relationship between measurement bias and solar zenith angle at Imnaviat were consistent  
452 across Fluxnet sites located in vastly different biomes (Figure 4). However, in contrast to the  
453 observed solar zenith dependent measurement biases at the Imnaviat site, there was a statistically  
454 significant measurement bias dependence on solar zenith angle at some of the Fluxnet sites for  
455 red reflectance. For the Fluxnet dataset, MODIS and radiation derived NIR differences positively  
456 scaled with solar zenith angle and all biomes exhibited similar slopes that ranged from 0.002 to  
457 0.003 per 1° change in zenith angle. The solar zenith dependent biases in NIR and red

458 reflectance carried over to NDVI and EVI2, but sometimes canceled each other out. This  
459 cancelling out effect was more predominant for NDVI than for EVI2. For example, NDVI  
460 biases were unrelated to solar zenith angle for evergreens and grass shrublands, whereas solar  
461 zenith angle was correlated with EVI2 biases in all biomes. The bias sensitivity to solar zenith  
462 angle ranged from 0.001 to 0.005- for NDVI, and from 0.003 to 0.005- per 1° change in zenith  
463 angle for EVI2.

464

#### 465 *3.4 Assessing Bandwidth Biases*

466 We used the full range spectroradiometer ASD data (300-2400 nm) to determine whether the  
467 measurement bias dependence on solar position was attributed to broadband versus narrowband  
468 definitions of red and near infrared reflectance used by the radiation sensors (Figure 5).  
469 Correlations between solar zenith angle and the difference between broadband and narrowband  
470 (i.e. Bandwidth Biases) definitions for red (p-value: 0.94), NDVI (p-value: 0.21), and EVI2 (p-  
471 value: 0.06) were not statistically significant. Bandwidth biases were marginally significant and  
472 related to solar zenith angle for NIR (p-value: 0.05), but were opposite in sign to the expected  
473 relationships observed in Figures 3 & 4. Moreover, solar zenith angle only explained 10% of the  
474 variation in bandwidth biases, as opposed to the 67% of the variation in radiation tower and  
475 MODIS differences explained by zenith angle in Figure 3.

476

477 Similar results were found across the Fluxnet sites using MODIS data and differencing broad-  
478 and narrow- band vegetation indices (Figure 1S; Table 1S). Although many relationships were  
479 statistically significant, solar zenith angle only explained <10% of the variation in bandwidth  
480 biases for NDVI, and <11% of the variation in bandwidth biases for EVI2 across all Fluxnets

481 sites on average (Supplementary Figure 1). Moreover, the bandwidth bias sensitivity to solar  
482 zenith angle was sometimes the opposite sign of the expected positive relationships in Figures 3  
483 and 4 and were on average one to two orders of magnitude lower than that observed for tower  
484 and MODIS differences for red, NIR, NDVI, and EVI2 (Supplementary Table 1).

485

486 *3.5 Correcting Solar Position Biases*

487 Diel variability in solar position affected radiation derived visible and NIR albedos that were  
488 used as red and NIR reflectance at Imnaviat (Figure 6). Over the growing season, daily averaged  
489 solar zenith angle changed by 19°, while daily averaged solar azimuth angle changed by 7°  
490 (Figure 6 inset). Visible and NIR albedo were more sensitive to solar zenith- than azimuth-  
491 angles as illustrated by the small scatter in Figure 6. NIR albedo was more sensitive to solar  
492 zenith angle than visible albedo and was almost two times higher than its expected value at an  
493 80° zenith angle. Consequently, the correction factor for NIR albedo declined markedly above  
494 70° from 0.85 to 0.59, whereas the correction factor for visible albedo changed by <1% above  
495 70° solar zenith angle.

496

497 Correcting solar position biases using the machine learning approach described in section 2.6  
498 improved the agreement between MODIS- and radiation- derived red and NIR reflectance,  
499 NDVI, and EVI2 at Imnaviat (Figure 7). After correcting for the dependence of measurement  
500 biases on solar position, MAE decreased and  $R^2$  increased between MODIS- and radiation-  
501 derived reflectance and vegetation indices (Table 3; Figure 7). An exception to this occurred for  
502 MODIS red reflectance, where the  $R^2$  and MAE did not significantly change after correction due

503 to its low sensitivity to solar position. MAE decreased by 40% for NDVI and EVI2, and by 33%  
504 for NIR reflectance after applying the correction factor for seasonal changes in solar position.

505

506 Correcting solar position biases using the machine learning approach also improved the  
507 agreement between MODIS- and radiation-derived NDVI and EVI2 across the Fluxnet sites  
508 (Figure 8). Correcting for measurement biases introduced by solar position reduced the MAE  
509 between MODIS- and radiation- derived NDVI and EVI by 5% to 77%. Grasslands and tundra  
510 experienced the largest decrease in MAE, while crops experienced the smallest decreases in  
511 MAE once the impact of solar position on radiation derived albedo and vegetation indices were  
512 corrected. There was quite a bit of variability in the improved correspondence between MODIS-  
513 and radiation-derived vegetation indices among sites. However, it was difficult, if not  
514 impossible, to attribute this variability to underlying environmental, biophysical or site specific  
515 factors without additional site and sensor specific information. Regardless, correcting biases in  
516 vegetation indices for solar position improved the correspondence between MODIS- and  
517 radiation- derived vegetation indices at 85% of the sites investigated.

518

### 519 *3.6 Implications for Inferring Ecosystem Function with radiation derived NDVI and EVI2*

520 Biases associated with solar position confounded the ecophysiological interpretation of radiation  
521 derived NDVI and EVI2 at Imnaviat (Figure 9). Uncorrected radiation derived vegetation indices  
522 exhibited hysteretic relationships with GEE with different sensitivities-as measured by the slope  
523 of the line- in the first and second half of the growing season. GEE was lower for the same value  
524 of NDVI/EVI2 in the first part of the growing season, and higher for the same value of  
525 NDVI/EVI2 in the second part of the growing season. The relationship between NDVI/EVI2

526 became more linearized with a single relationship throughout the growing season once  
527 vegetation indices were corrected for their solar position dependence (Figure 9 solid line).  
528 Uncorrected NDVI explained 37% of the variability in GEE, whereas solar position corrected  
529 NDVI explained 85% of the variability in GEE. Similar patterns were found for EVI2.  
530 Uncorrected EVI2 explained 37% of the variability in GEE, whereas solar position corrected  
531 EVI2 explained 89% of the variability in GEE.

532

533 Solar position also confounded the determination of the start, end, and length of the growing  
534 season at Imnaviat (Figure 10). On average, correcting radiation derived vegetation indices for  
535 solar position decreased the MAE between leaf level measures of phenology up to ~10 days.  
536 Differences between corrected and uncorrected NDVI/EVI2 derived phenologies were greatest  
537 for the length of the growing season due to compounding errors associated with the start and end  
538 of the growing season estimates. Uncorrected NDVI/EVI2 demonstrated reduced skill at  
539 determining the end of the growing season relative to the start; a finding that is consistent with  
540 trends observed in Figure 2. Solar position corrected radiation derived NDVI/EVI2 performed  
541 similarly to-or in some cases-better than MODIS in predicting the start and end of the growing  
542 season, especially for EVI2. For example, solar position corrected radiation derived EVI2  
543 performed better than MODIS EVI2 in predicting the start and length of the growing season.  
544 When MODIS- and radiation- derived phenological predictions were combined, NDVI  
545 outperformed EVI2 by 5 days for the start of the growing season and 7 days for the length of the  
546 growing season, whereas EVI2 outperformed NDVI by 1 day for the end of the growing season.

547

548 **4.0 Discussion:**

549 Solar position introduced significant bias on PAR and solar radiation derived vegetation indices,  
550 especially during the latter part of the growing season. These errors were largely independent of  
551 broad- to narrow-band definitions (Figures 5 & 1S; Table 1S), and sensor spatial aggregation  
552 errors associated with landscape heterogeneity (Figure 1). The effect of satellite spatial  
553 aggregation errors was minimized by focusing on a relatively homogenous site (i.e. Imnavia),  
554 and were much smaller than that observed for measurement biases [i.e. <0.02 change in  
555 vegetation index MAE from 0-400 km<sup>2</sup> (Figure 1) compared to ~0.05 MAE for tower and  
556 MODIS vegetation comparisons (Table 2)] (Wang et al. 2012). Measurement biases also were  
557 universal and occurred across a wide variety of latitudes, biomes, and sites indicating a persistent  
558 error that cannot be explained by individual site specific conditions (Figures 3,4,7,8). These  
559 measurement biases accounted for some of the limitations and issues highlighted in previous  
560 work with radiation derived vegetation indices (Jenkins et al. 2007; Rocha and Shaver 2009;  
561 Wang et al. 2004; Wittich and Kraft 2008). To our knowledge, this is the first paper, since  
562 Huemmrich et al.'s (1999) seminal work, to develop a methodology using the diel variation in  
563 albedo to correct for these biases and improve the performance of these indices in inferring  
564 ecosystem function.

565

566 Historically, solar position biases on radiation- derived albedo and vegetation indices were  
567 assumed to be negligible over the course of a season, despite known diel variation (Huemmrich  
568 et al. 1999). This incorrect assumption was likely due to data limitations from looking at a single  
569 site over a short time period, the exclusion of solar azimuthal effects, and a lack of multi-sensor  
570 comparisons. Unlike past work, our conclusions were supported by multiple independent  
571 physical and ecological observations. First, solar position corrections improved correspondence

572 between satellite- and radiation- derived vegetation indices at Imnavia and Fluxnet sites (Figures  
573 7 and 8; Table 3). Second, solar position corrections improved the ability of radiation derived  
574 vegetation indices in capturing phenological timing and C fluxes (Figures 9 and 10). It is clear  
575 that our use of combining long time series data obtained from different sensors and scales was  
576 essential in validating and assessing measurement biases in radiation derived vegetation indices.  
577 Our results also demonstrated that, in some cases, solar position associated NIR and visible  
578 biases canceled each other out in the calculation of the vegetation index. This cancelation effect  
579 may explain the discrepancy between this study and past work at single sites that assumed  
580 negligible solar position biases.

581

582 Addressing solar position biases in visible and NIR albedo are important because these biases  
583 resulted in poor relationships with MODIS data and poor inferences of ecosystem function.  
584 Without correcting for solar position, measurement biases reduced the explained variation in  
585 canopy photosynthesis and increased estimation error of the start, end, and length of the growing  
586 season (Figures 9,10). Radiation derived vegetation indices also exhibited less seasonality than  
587 MODIS, which was consistent with previous work with higher than expected NIR and vegetation  
588 indices towards the latter part of the growing season (Rocha and Shaver 2009; Wittich and Kraft  
589 2008). These unique attributes of radiation derived vegetation indices have been previously  
590 reported, but often incorrectly attributed to bandwidth biases rather than solar position ( Rocha  
591 and Shaver 2009; Jenkins et al. 2007; Wang et al. 2004). Broadband derivations of red and NIR  
592 reflectance incorporate dynamics in the shortwave infrared that could potentially confound the  
593 seasonality of the broadband red, NIR, NDVI, and EVI2 measured by PAR and shortwave  
594 radiation sensors. However, bandwidth errors exhibited weak to non-existent relationships with

595 solar position for broadband radiation derived indices across Imnaviat and the Fluxnet sites  
596 (Figures 5 and 1S; Table 1S). On the other hand, measurement bias sensitivity to solar zenith  
597 angle was an order of magnitude larger than that observed for broadband biases across both  
598 Imnaviat and Fluxnet sites (Figures 5; Figure 1S; Table 2S). The improved ability of radiation  
599 derived vegetation indices to replicate MODIS narrowband reflectance and VIs once solar  
600 position correction was applied provides strong evidence to attribute radiation derived biases to  
601 solar position, rather than bandwidth errors (Figures 7,8, 1S).

602

603 Here we used a simple machine learning empirically based model based on actual half hourly  
604 data to correct the seasonal biases in visible and NIR albedo. Our empirical model had high  
605 predictive power, explaining 85-95% of solar position biases, followed an expected BRDF  
606 response (i.e. a non-linear positive response with solar zenith angle), and included additional  
607 factors that may be difficult to parameterize in a BRDF model (Figure 6). For example, radiation  
608 sensors may have internal measurement biases due to solar position, known as a sensors cosine  
609 response (Blonquist et al. 2009; Ross and Sulev 2000). A sensor's cosine response describes how  
610 solar radiation is integrated across all solar zenith and azimuthal positions on a Lambertian  
611 receiver. This response differs among sensors and would be subject to measurement drift issues  
612 that would be difficult to quantify without additional information. Differences in a sensor's  
613 cosine response also may explain the differences in the sensitivity of radiation derived  
614 measurements to solar zenith angle among sites (Figures 4,8).

615

616 Quantifying and understanding measurement errors and limitations remains an important process  
617 in the scientific community (Kratzenberg et al. 2006; Richardson et al. 2008; Ross and Sulev

618 2000). This is especially true in ecosystem ecology as new, interdisciplinary, and automated  
619 remote- and near-sensing measurement techniques are being more commonly used.  
620 Understanding error sources and applying the proper corrections will result in improved  
621 understanding or quantification of ecosystem function. For example, the strong relationship  
622 between solar position corrected radiation derived vegetation indices and canopy photosynthesis  
623 demonstrate promise in using these data to fill long gaps in eddy covariance flux data.  
624 Moreover, the high correspondence between solar position corrected radiation- and satellite-  
625 derived vegetation indices indicates that these data can be valuable in gap filling MODIS data  
626 during cloudy periods (Figure 7). However, we caution future users of such data to also consider  
627 other potential important sources of measurement error, such as sensor drift and sensor spectral  
628 sensitivity, that may significantly alter the continuity of high quality radiation based vegetation  
629 indices (Kratzenberg et al. 2006; Ross and Sulev 2000). We encourage future work to  
630 implement, or improve upon, our methodology to gain further understanding the temporal  
631 dynamics of ecosystem C cycling and phenology with vegetation indices derived from solar and  
632 photosynthetically active radiation fluxes.

633

### 634 **Acknowledgements**

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639 trade, product, or firm names is for descriptive purposes only and does not imply endorsement by  
640 the US Government.

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Site Name	Latitude	Years	PFT	PAR Sensor	Pyranometer Sensor
Bondville <sup>1</sup>	40	2004-2007	Crop	Apogee	LI200
ARM SGP <sup>1</sup>	36.5	2004-2009	Crop	LI190	CM3
Sioux Falls <sup>2</sup>	43.2	2007-2009	Crop	NA	NA
UCI 1989 <sup>3</sup>	55.9	2002-2005	Deciduous	LI190	CM3
UCI 1998 <sup>3</sup>	56.5	2002-2005	Deciduous	LI190	CM3
Black Hills <sup>4</sup>	44.2	2004-2008	Evergreen	LI190	CM3
Flagstaff Managed <sup>5</sup>	35.1	2006-2009	Evergreen	BF3/LI190	CM3
UCI 1850 <sup>3</sup>	55.9	2002-2005	Evergreen	LI190	CM3
UCI 1930 <sup>3</sup>	55.9	2002-2005	Evergreen	LI190	CM3
UCI 1964 <sup>3</sup>	55.9	2002-2005	Evergreen	LI190	CM3
UCI 1981 <sup>3</sup>	55.9	2002-2005	Evergreen	LI190	CM3
Brookings <sup>4</sup>	44.3	2004-2010	Grassland	NA	NA
Canaan Valley <sup>4</sup>	39.1	2004-2010	Grassland	Apogee	CM3
Cottonwood <sup>4</sup>	43.9	2006-2009	Grassland	NA	NA
Flagstaff Wildfire <sup>5</sup>	35.4	2005-2009	Grassland	BF3/LI190	CM3
Fort Peck <sup>4</sup>	48.3	2002-2008	Grassland	LI190	Apogee
Goodwin Creek <sup>4</sup>	34.3	2002-2006	Grassland	Apogee	CM3
Kendall <sup>6</sup>	31.7	2004-2009	Grassland	NA	NA
Audubon <sup>4</sup>	31.8	2004-2009	Grassland	LI190	CM3
Ivotuk <sup>7</sup>	68.5	2004-2006	Tundra	LI190	CM3
Imnaviat <sup>8</sup>	68.6	2009-2011	Tundra	LI190	CM3
Unburned <sup>9</sup>	68.9	2008-2011	Tundra	LI190	CM3
Severe <sup>9</sup>	68.9	2008-2011	Tundra	LI190	CM3
Moderate <sup>9</sup>	68.9	2008-2011	Tundra	LI190	CM3
Santa Rita	31.8	2004-2007	Grassland/ Shrub	NA	NA
Mesquite <sup>10</sup>					

646 **Table 1.** Site names, location, years, Plant Functional Type (PFT) and sensors used at each of the  
647 sites used in this study. <sup>1</sup>Hollinger et al. (1994); <sup>2</sup>Verma et al. (2005); <sup>3</sup>Goulden et al. (2011);  
648 <sup>4</sup>Wilson and Myers (2007); <sup>5</sup>Dore et al. (2016); <sup>6</sup>Scott et al. (2010); <sup>7</sup>McEwing et al. (2015);  
649 <sup>8</sup>This study; <sup>9</sup>Rocha and Shaver (2011); <sup>10</sup>Scott et al. (2009)

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	<b>Spectroradiometer v. MODIS <math>R^2</math> [MAE]</b>	<b>Spectroradiometer v. Radiation <math>R^2</math> [MAE]</b>	<b>MODIS v. Radiation <math>R^2</math> [MAE]</b>
Red	0.22 [0.01]	0.21 [0.01]	0.19 [0.01]
NIR	0.17 [0.03]	0.20 [0.03]	0.22 [0.03]
EVI2	0.67 [0.03]	0.42 [0.09]	0.42 [0.05]
NDVI	0.55 [0.05]	0.34 [0.11]	0.34 [0.05]

664 **Table 2.** R-squared and Mean Absolute Error (MAE) of relationships among spectroradiometer-  
665 , MODIS-, uncorrected radiation- derived reflectance and vegetation indices.  
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	<b>MODIS v. U- Radiation <math>R^2</math> [MAE]</b>	<b>MODIS v. C-Radiation <math>R^2</math> [MAE]</b>
Red	0.19 [0.01]	0.19 [0.01]
NIR	0.22 [0.03]	0.47 [0.02]
EVI2	0.42 [0.05]	0.56 [0.03]
NDVI	0.34 [0.05]	0.56 [0.03]

669 **Table 3.** R-squared and Mean Absolute Error (MAE) of relationships among MODIS- ,  
670 uncorrected (U) radiation-, and corrected (C) radiation- derived reflectance and vegetation  
671 indices.  
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687 **Figure 1:** Mean Absolute Error (MAE {unitless VI ratios}: blue circles left y-axis) and r-squared  
688 ( $R^2$  {unitless}: red triangles right y-axis) of the relationship between spectroradiometer- and  
689 MODIS- derived NDVI (top) and EVI2 (bottom) at different MODIS spatial integration scales at  
690 Imnaviat.

691

692 **Figure 2:** Seasonal cycle of spectroradiometer- (black diamonds), radiation- (blue dots), and  
693 MODIS-derived (red dots) red (A) and near-infrared (B) reflectances, and NDVI (C) and EVI2  
694 (D) from quality controlled 2008-2018 Imnaviat data.

695

696 **Figure 3:** Dependence of MODIS- and radiation- derived differences on solar zenith angle for  
697 red reflectance (A), near infrared reflectance (B), NDVI (C), and EVI2 (D) at Imnaviat.  
698 Regression lines indicate significant relationships at the 95% confidence level.

699

700 **Figure 4:** Dependence of MODIS- and radiation- derived differences on solar zenith angle for  
701 red reflectance (A), near infrared reflectance (B), NDVI (C), and EVI2 (D) from Fluxnet sites  
702 across biome types. Lines in panels C and D are only for statistically significant relationships at  
703 the 95% confidence level.

704

705 **Figure 5:** Dependence of ground based spectroradiometer broad- and narrow-band derived  
706 differences (i.e. broadband-narrowband) on solar zenith angle for red reflectance (A), near  
707 infrared reflectance (B), NDVI (C), and EVI2 (D) at Imnaviat. Regression lines indicate  
708 significant relationships at the 95% confidence level.

709

710 **Figure 6:** The correction factor dependence on solar zenith angle for visible (solid dots) and near  
711 infrared (open dots) albedo. The inset plot shows seasonal changes in daily averaged solar zenith  
712 angle (solid line) and daily averaged azimuth angle (dotted line). The grey highlighted area  
713 denotes the growing season period at Imnaviat.

714

715 **Figure 7:** Correspondence between radiation- and MODIS- derived red (A) and near infrared (B)  
716 reflectances, and NDVI (C) and EVI2 (D) at Imnaviat. Grey dots are MODIS and uncorrected  
717 radiation derived reflectance and indices, whereas triangles are MODIS and radiation derived  
718 reflectance and indices that were corrected for solar position biases.

719

720 **Figure 8:** Average percent change in the Mean Absolute Error (MAE) between MODIS satellite-  
721 and radiation-derived NDVI (black bars) and EVI2 (grey bars) relative to the uncorrected values  
722 at the Fluxnet sites. Fluxnet sites were grouped by ecosystem type, and error bars represent  
723 standard errors.

724

725 **Figure 9:** Relationship between Imnaviat Gross Ecosystem Exchange (GEE) and solar position  
726 corrected (open triangles) and uncorrected (grey circles) radiation derived vegetation indices.  
727 NDVI-GEE relationships are in left panel (A), whereas EVI2-GEE are in right panel (B). The  
728 solid line represents the correlation between the solar position corrected vegetation index and  
729 GEE, whereas the dotted line represents the correlation between uncorrected vegetation indices  
730 and GEE. Hatched arrows in left panel represent the hysteresis in the relationship between  
731 uncorrected NDVI and GEE, while numbers represent the day of year of each observation.

732

733 **Figure 10:** Mean Absolute Error (MAE) of the start-(SOS), length-(LOS), and end-(EOS) of the  
734 growing season derived from MODIS- (black bar), uncorrected radiation- (grey), and solar  
735 position corrected radiation- (dark grey) derived NDVI (A) and EVI2 (B) at Imnaviat.

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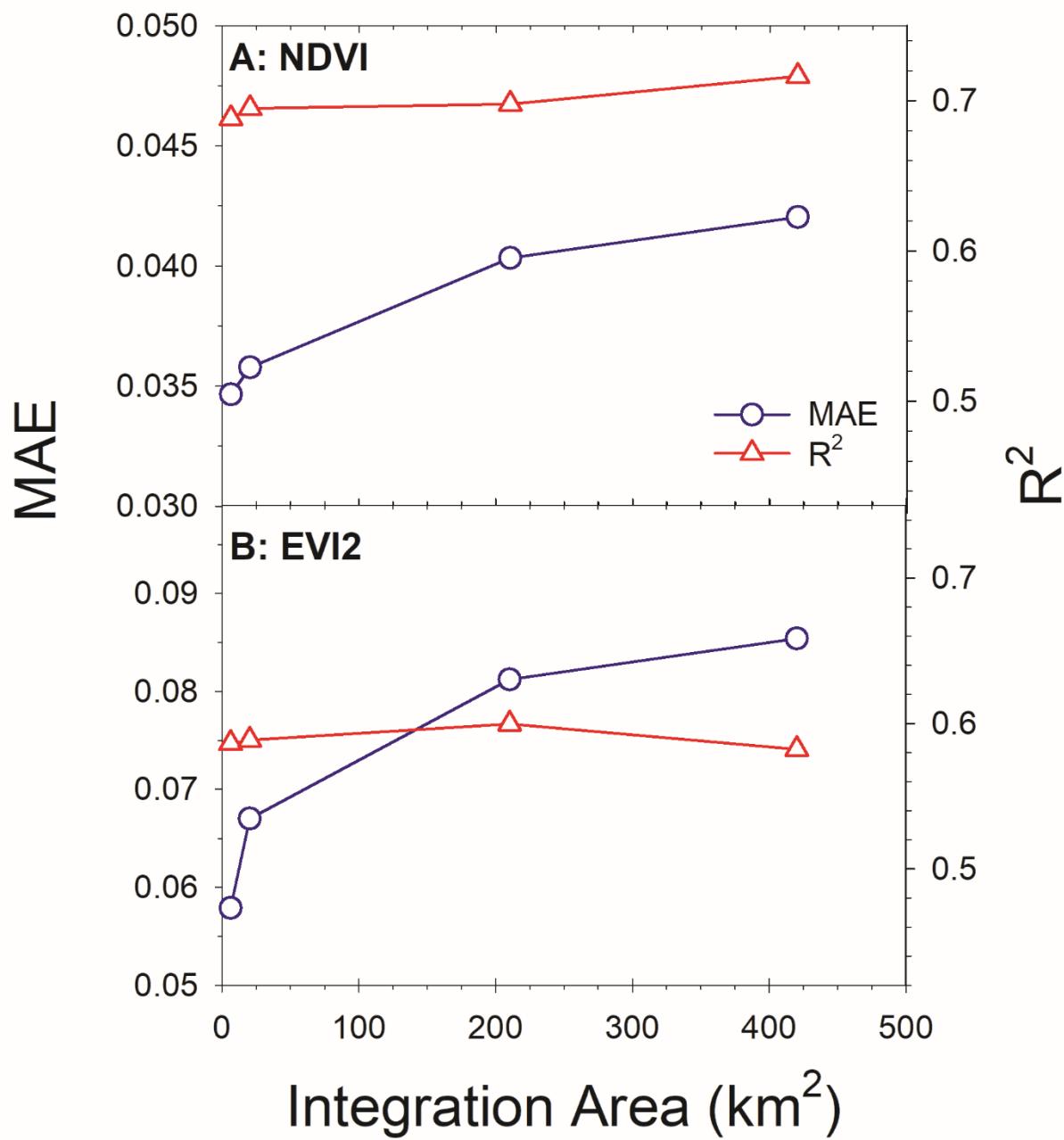
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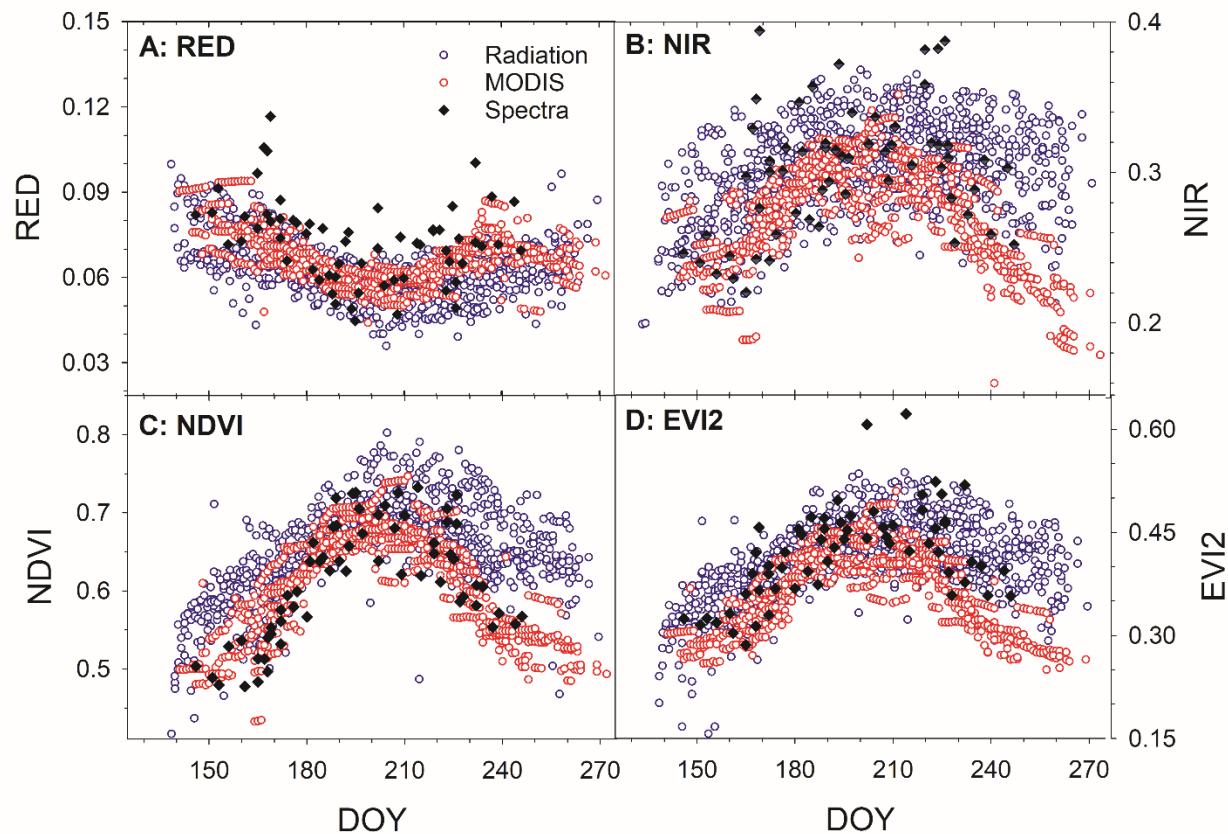
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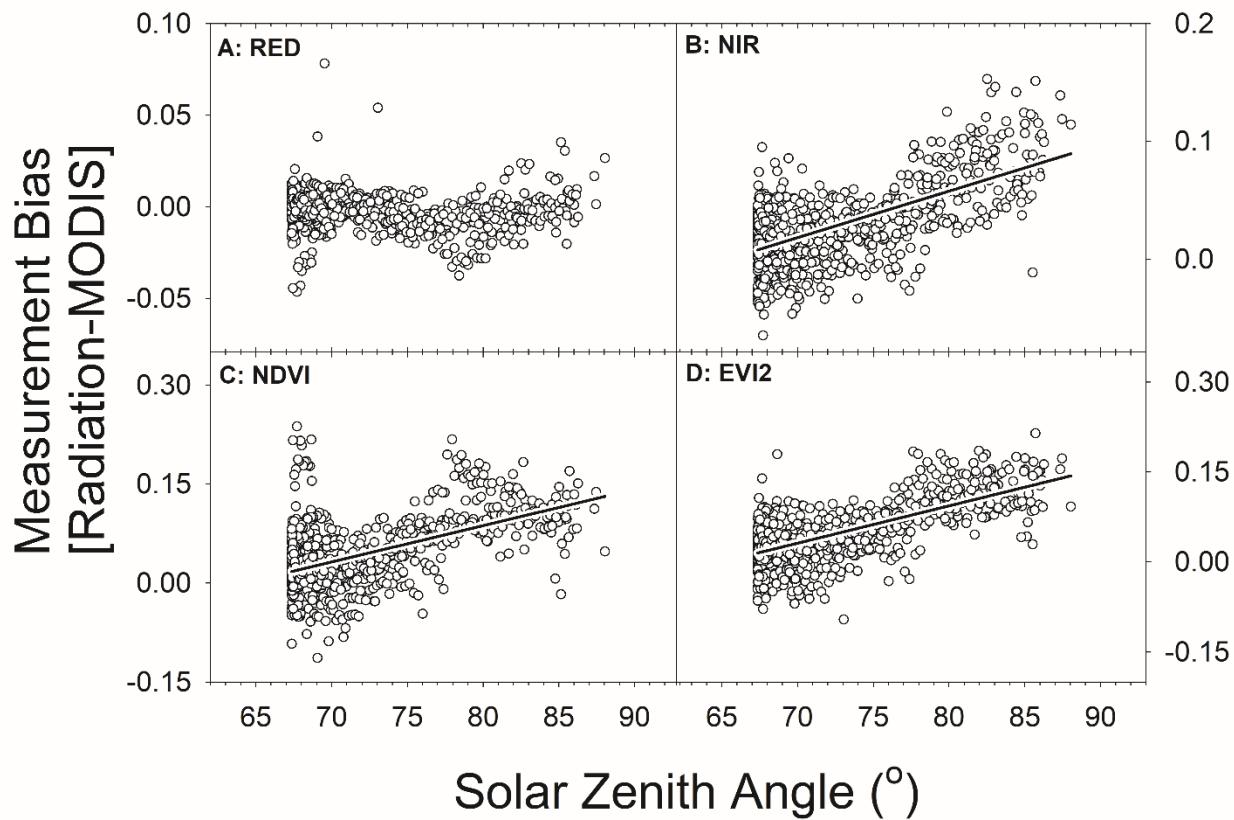
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746 **Figure 1.**  
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**Figure 2.**

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**Figure 3.**

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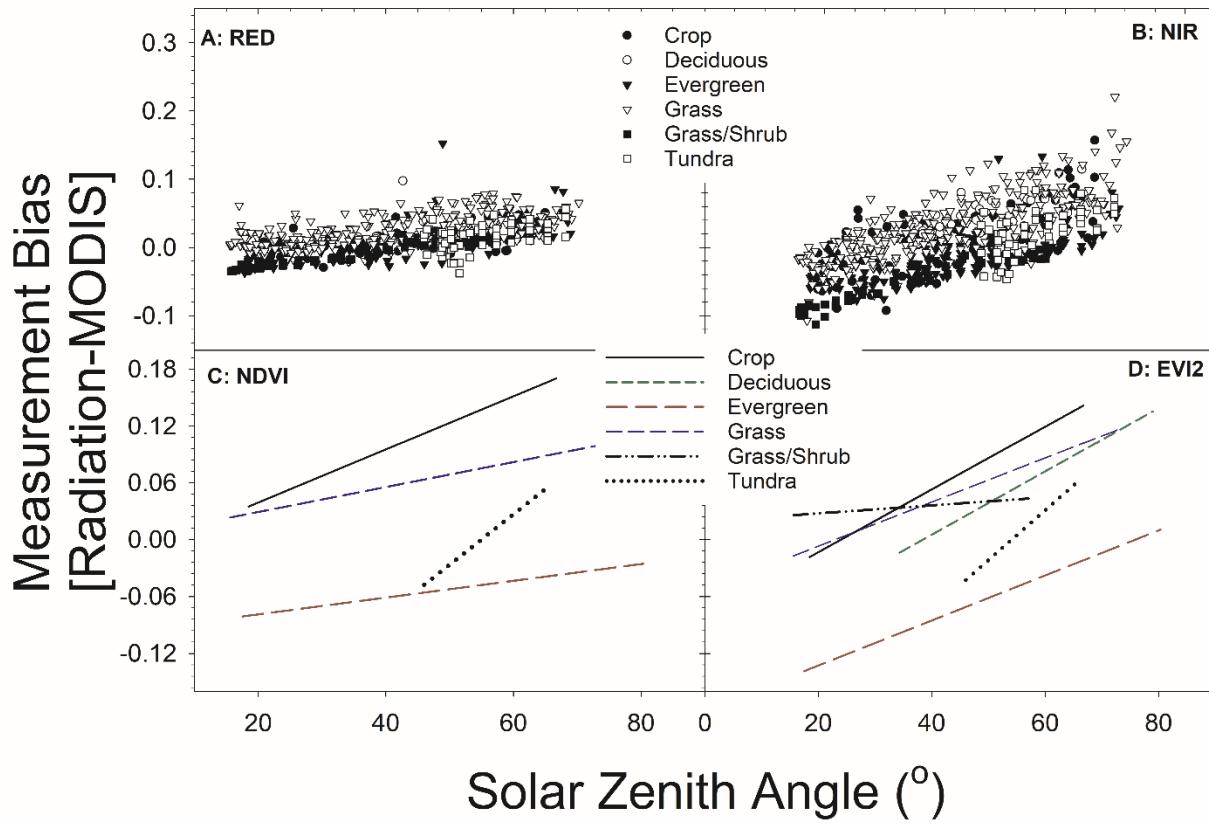
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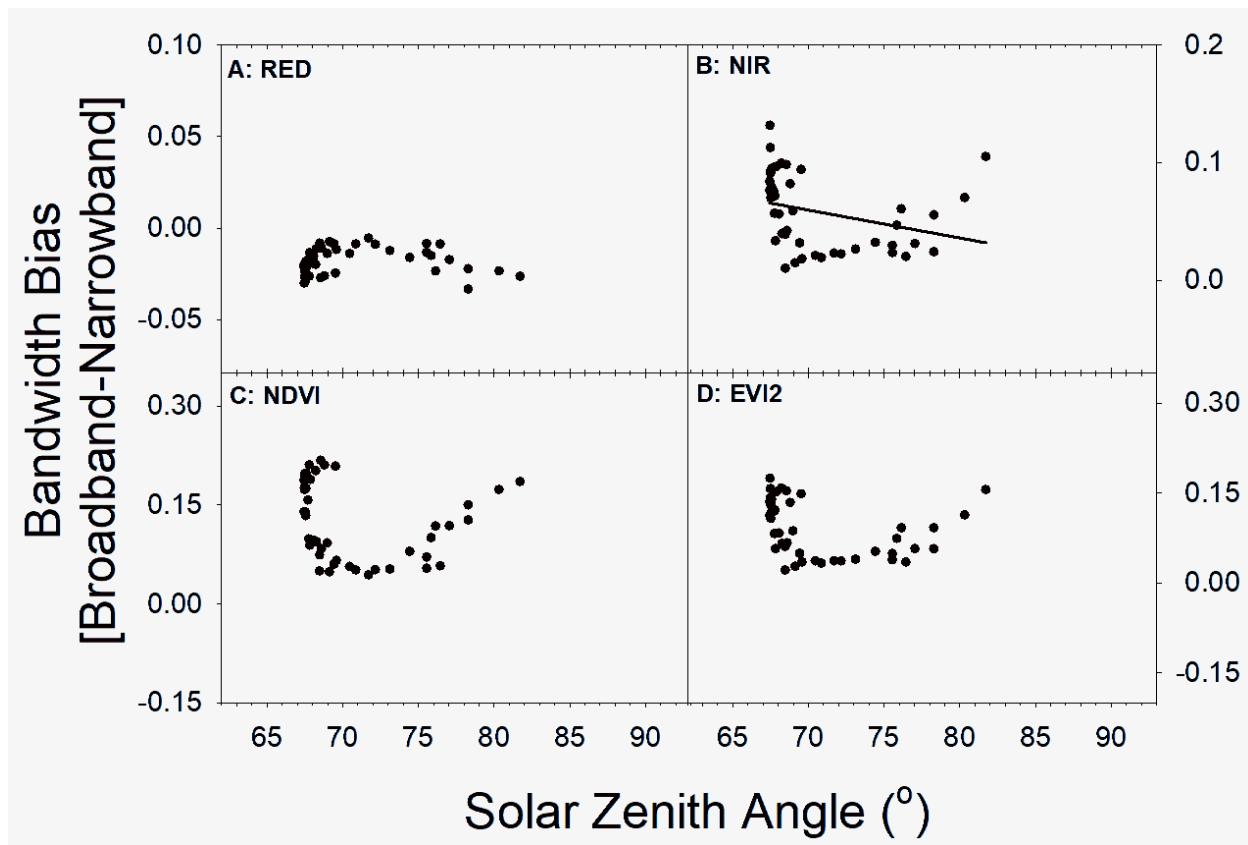
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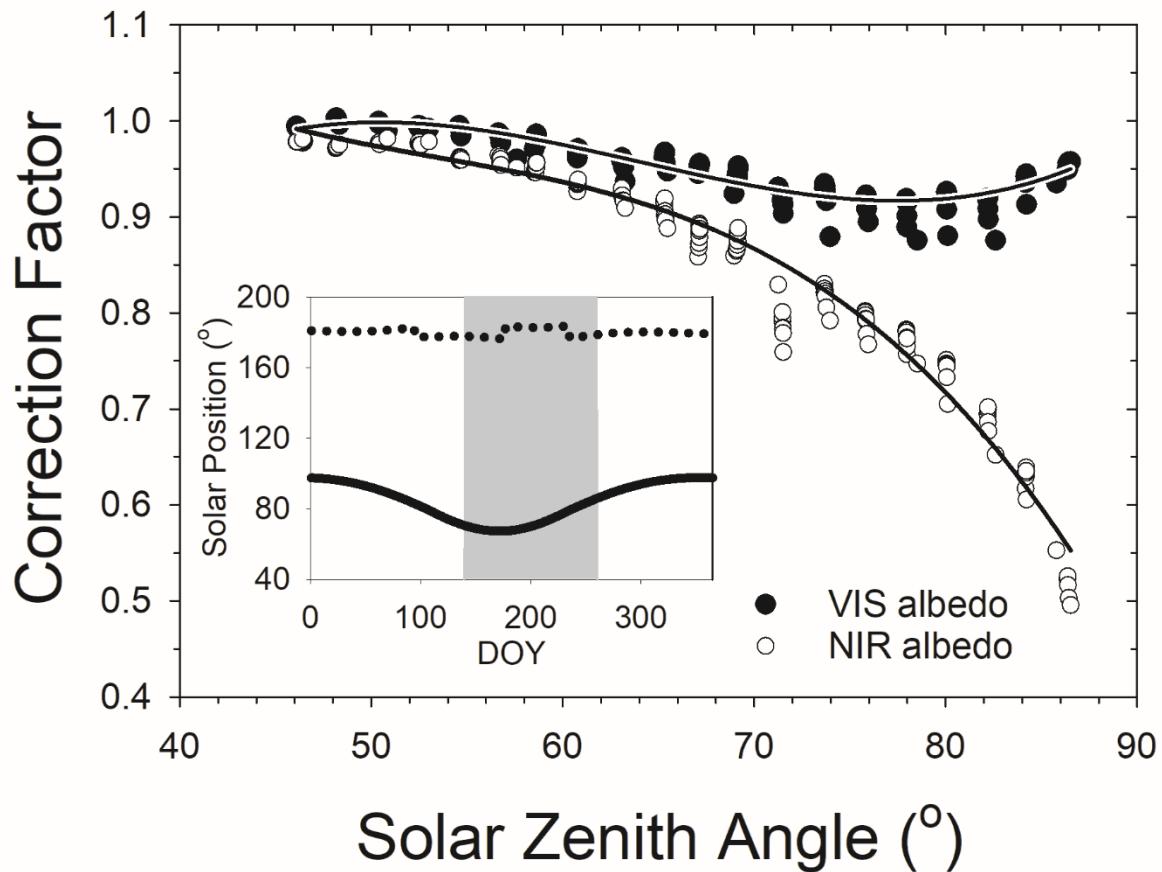
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**Figure 4.**

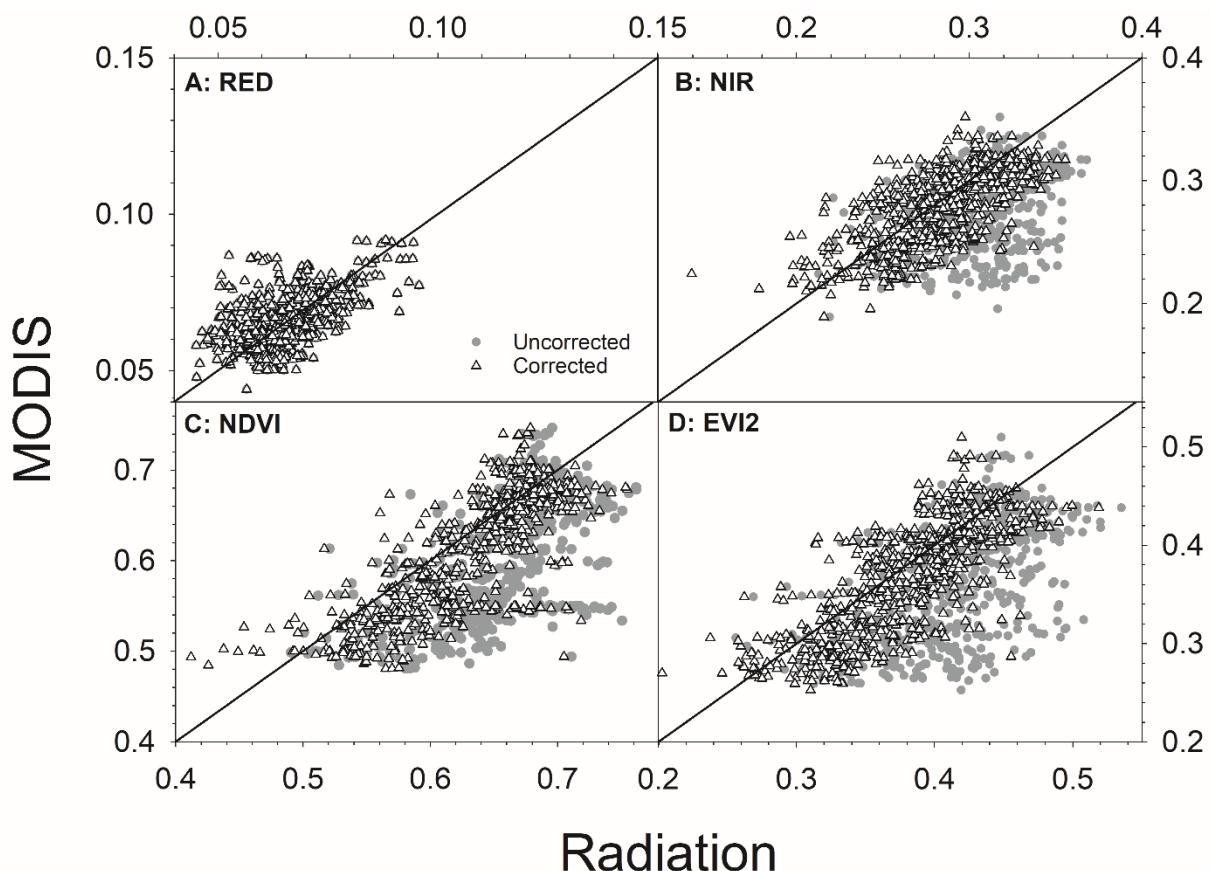
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829 **Figure 5.**  
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838 **Figure 6.**  
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 859 **Figure 7.**  
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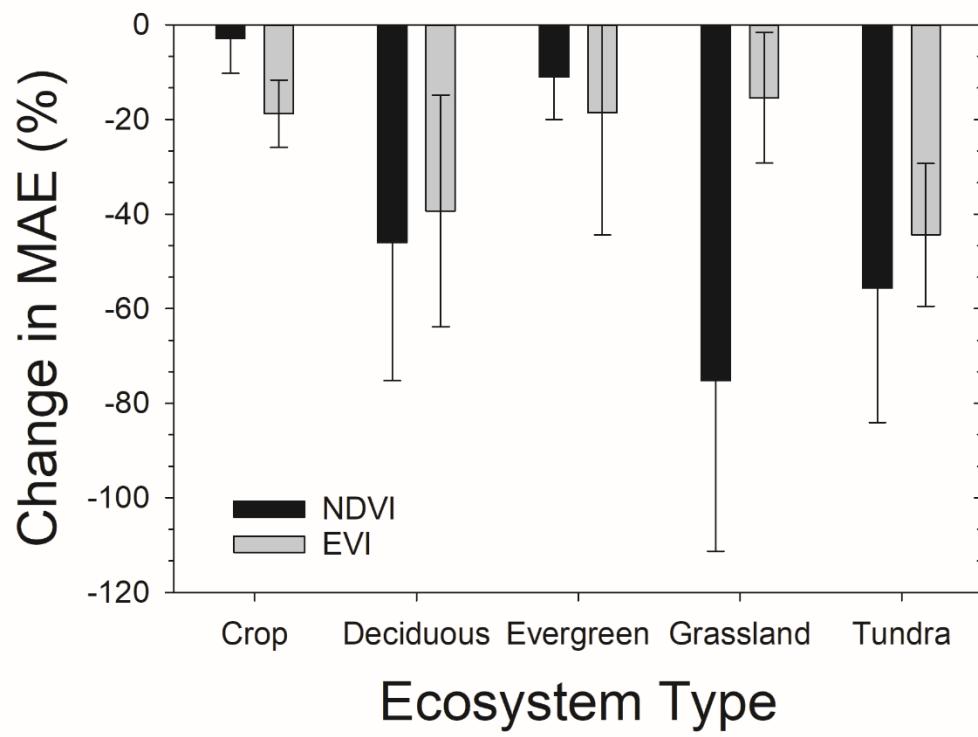
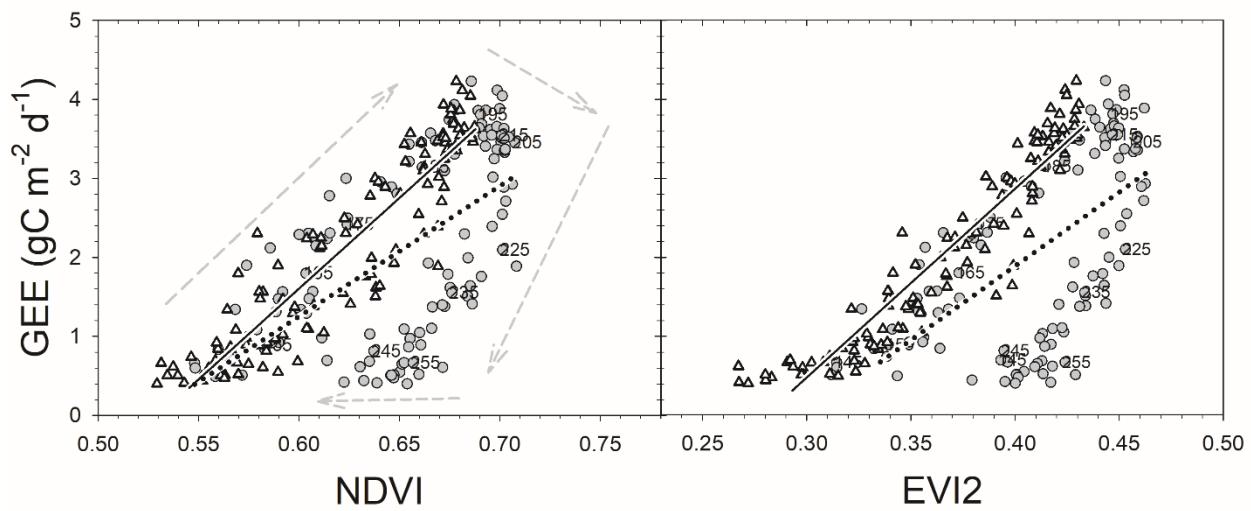
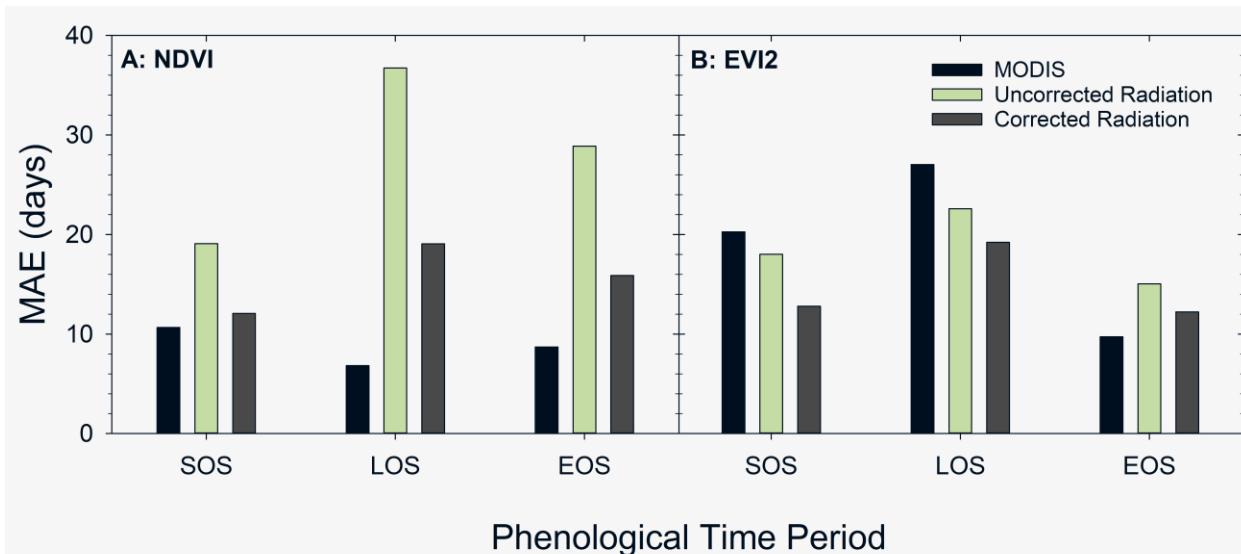


Figure 8.

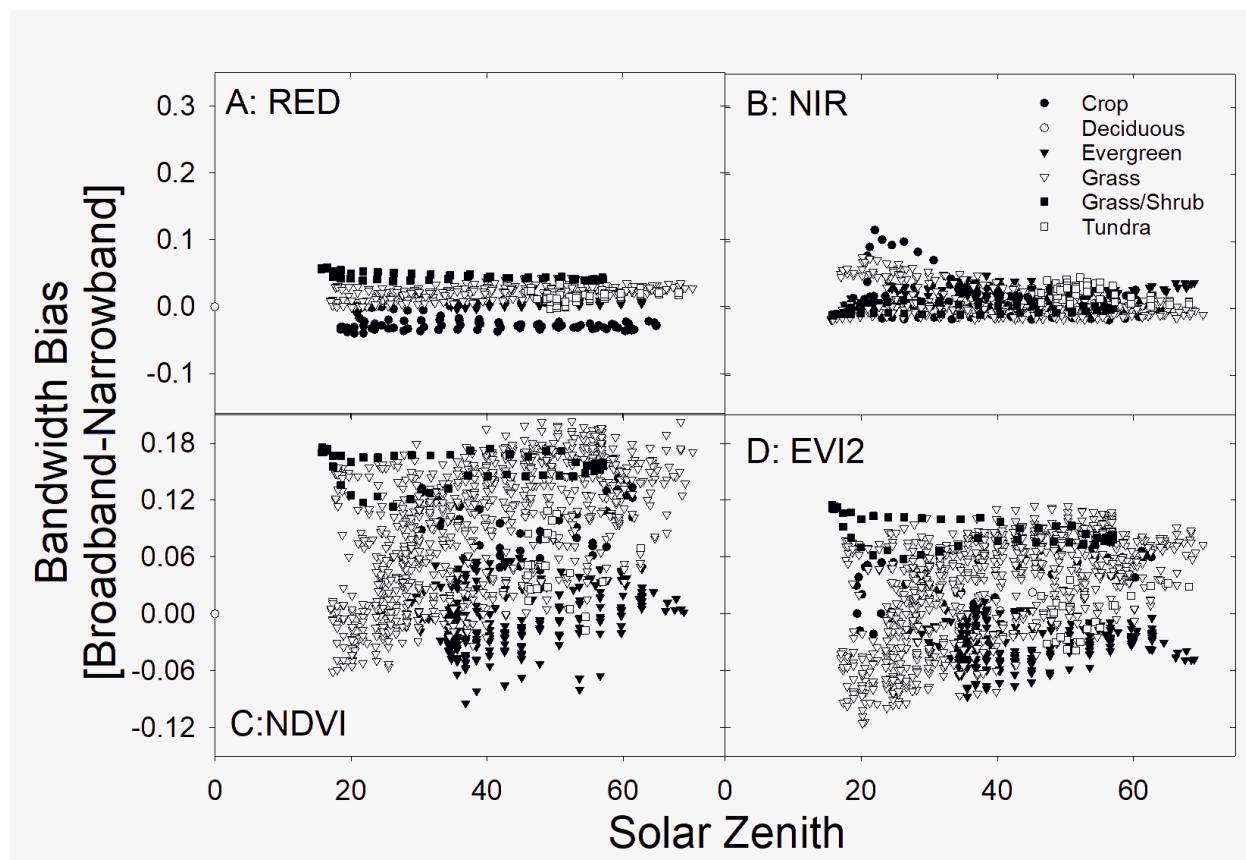


**Figure 9.**



954 **Supplement:**

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957 **Figure 1S:** Dependence of bandwidth biases (broadband-narrowband) derived differences on  
 958 solar zenith angle for red reflectance (A), near infrared reflectance (B), NDVI (C), and EVI2 (D)  
 959 from Fluxnet sites across biome types. Note that the y-axes are scaled to be the same as those  
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977 **Table 1S:** Summary statistics for bandwidth bias correlation with solar zenith angle in Figure  
 978 1S. The number represents the  $R^2$  of the relationship, while the number in [brackets] represents  
 979 the sensitivity to solar zenith angle measured as the slope of the line.

PFT	Red ( $R^2$ [Slope])	NIR ( $R^2$ [Slope])	NDVI ( $R^2$ [Slope])	EVI2 ( $R^2$ [Slope])
<i>Crop</i>	<b>0.06 [-0.0001]</b>	<b>0.09 [-0.0005]</b>	0.01 [0.0002]	<b>0.37 [-0.0007]</b>
<i>Deciduous</i>	<b>0.46 [-0.0003]</b>	<b>0.14 [-0.0006]</b>	0.03 [0.0003]	<b>0.52 [-0.0046]</b>
<i>Evergreen</i>	<b>0.06 [0.0001]</b>	<b>0.12 [0.0003]</b>	<b>0.06 [0.00093]</b>	0.02 [0.0003]
<i>Grass</i>	<b>0.62 [0.0002]</b>	<b>0.11 [-0.0006]</b>	<b>0.06 [0.0009]</b>	<b>0.29 [0.002]</b>
<i>Grass/Shrub</i>	<b>0.10 [0.0001]</b>	<b>0.08 [-0.0005]</b>	0.01 [0.00003]	<b>0.22 [-0.0005]</b>
<i>Tundra</i>	<b>0.16 [0.0005]</b>	<b>0.22 [-0.0008]</b>	0.01 [-0.0001]	<b>0.29 [0.002]</b>

980 \*Numbers in bold represent statistically significant relationships at the 95% Confidence level.

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1      **Solar position confounds the relationship between ecosystem function and vegetation**  
2      **indices derived from solar and photosynthetically active radiation fluxes.**

5      Adrian V. Rocha<sup>1</sup>, Rose Appel<sup>1</sup>, M. Syndonia Bret-Harte<sup>2</sup>, Eugenie Euskirchen<sup>2</sup>, Verity Salmon<sup>3</sup>,  
6      Gaius Shaver<sup>4</sup>

9      <sup>1</sup>Department of Biological Sciences and the Environmental Change Initiative, Notre Dame, IN  
10     46556, USA

12     <sup>2</sup>Institute of Arctic Biology, University of Alaska Fairbanks, Fairbanks, AK 99775, USA

14     <sup>3</sup>Environmental Sciences Division and Climate Change Science Institute, Oak Ridge National  
15     Laboratory, Oak Ridge, TN 37831, USA

17     <sup>4</sup>The Ecosystems Center, Marine Biological Laboratory, Woods Hole, MA 02543, USA

25     *Submitted to: Agricultural and Forest Meteorology*

38     Corresponding Author:  
39     Adrian V. Rocha  
40     University of Notre Dame  
41     Department of Biological Sciences and the Environmental Change Initiative  
42     100 Galvin Life Sciences  
43     Notre Dame, IN 46556  
44     Ph: 574-631-9438  
45     Email: arocha1@nd.edu

48 **Abstract:**

49 Vegetation indices derived from solar and photosynthetically active radiation (PAR) sensors (i.e.  
50 radiation derived) have been under-utilized in inferring ecosystem function, despite measurement  
51 capability at hundreds of sites. This under-utilization may be attributed to reported mismatches  
52 among the seasonality of radiation- and satellite-derived vegetation indices and canopy  
53 photosynthesis; herein referred to as measurement biases. Here biases in radiation derived  
54 reflectance and vegetation indices were assessed using a decadal record of satellite and ground  
55 based spectroradiometer data, ecosystem phenology and CO<sub>2</sub> fluxes, and radiation derived  
56 vegetation indices (i.e. the Normalized Difference Vegetation Index [NDVI], the two band  
57 Enhanced Vegetation Index [EVI2]) from a high latitude tundra site (i.e. Inuvik). At Inuvik,  
58 we found poor correspondence between the three types of reflectance and vegetation indices,  
59 especially during the latter part of the growing season. Radiation derived vegetation indices  
60 resulted in incorrect estimates of phenological timing of up to a month and poor relationships  
61 with canopy photosynthesis (i.e. Gross Ecosystem Exchange (GEE)). These mismatches were  
62 attributed to solar position (i.e. solar zenith and azimuth angle) and a method, based on the diel  
63 visible and near-infrared albedo variation, was developed to improve the performance of the  
64 vegetation indices. The ability of radiation derived vegetation indices to infer GEE and  
65 phenological dates drastically improved once radiation derived vegetation indices were corrected  
66 for solar position associated biases at Inuvik. Moreover, radiation derived vegetation indices  
67 became better aligned with MODerate resolution Imaging Spectroradiometer (MODIS) satellite  
68 estimates after solar position associated biases were corrected at Inuvik and at 25 Fluxnet sites  
69 (~90 site years) across North America. Corrections developed here provide a way forward in

70 understanding daily ecosystem function or filling large gaps in eddy covariance data at a  
71 significant number of Fluxnet sites.

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74 *Keywords:* Phenology, NDVI, EVI2, Solar Zenith, Gross Ecosystem Exchange, Arctic LTER  
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## 76 **1.0 Introduction:**

77 Vegetation indices, such as the Normalized Difference Vegetation Index (NDVI), have been  
78 used to infer ecosystem structure and function over the past half century (Rouse 1974). These  
79 indices utilize the low red reflectance -due to chlorophyll absorption-, and the high NIR  
80 reflectance -due to low absorption and high scattering- of green leaves to infer ecosystem  
81 function (e.g. leaf abundance, canopy physiology, and canopy phenology) (Gamon et al. 2010;  
82 Gamon et al. 2006). Historically, these indices were derived from satellite based reflectance;  
83 providing a proxy of ecosystem function at the global scale-albeit at low temporal resolution  
84 (e.g. monthly, bi-monthly). However, these indices also can be derived from commonly used  
85 up- and down-ward facing Photosynthetically Active Radiation (PAR) and solar radiation  
86 sensors (i.e. radiation derived); providing a low cost continuous measure of ecosystem function  
87 even when heavy cloud cover obscures satellite views of the surface (Huemmrich et al. 1999;  
88 Rocha and Shaver 2009; Wilson and Meyers 2007). Although radiation derived vegetation  
89 indices provide a powerful tool for understanding ecosystem function at sub-daily to annual  
90 timescales, a critical assessment of their uncertainties are surprisingly lacking.

91  
92 Despite the wide use of PAR and solar radiation sensors across many eddy covariance sites,  
93 radiation derived vegetation indices have been under-utilized in inferring ecosystem function.  
94 Only a handful of studies have used radiation derived vegetation indices to infer ecosystem

95 function, as compared to the thousands that have used satellite derived vegetation indices  
96 (Jenkins et al. 2007; Wohlfahrt et al. 2010; Wright and Rocha 2018). This imbalance may be  
97 due to the historical precedent of satellite data, or a lack of mechanistic understanding of  
98 measurement uncertainties in radiation derived indices. Radiation derived vegetation indices  
99 differ in magnitude and exhibit less seasonality than those derived from satellite data (Rocha and  
100 Shaver 2009). Jenkins et al. (2007) found that the slope of the relationship between radiation  
101 derived vegetation indices and canopy photosynthesis differed in the early and later part of the  
102 growing season. This contrasts with remote sensing work that models canopy photosynthesis  
103 from satellite derived vegetation indices with a single relationship across the season, and  
104 highlights a significant methodological knowledge gap (Sims et al. 2006; Sims et al. 2011; Xiao  
105 et al. 2005).

106

107 Although various hypotheses have been proposed to resolve the differences in radiation- and  
108 satellite- derived vegetation indices, the mechanisms are still debatable. The lack of  
109 correspondence between radiation- and satellite-derived vegetation indices have often been  
110 attributed to differences in the spatial scale of integration between the two measures or  
111 differences in sensor spectral resolution (Disney et al. 2004; Tittebrand 2009; Wang et al. 2004;  
112 Wang et al. 2012). Ground based radiation derived vegetation indices integrate a smaller area  
113 (i.e. ~100 x 100 m) than satellites such as the MODerate resolution Imaging Spectroradiometer  
114 (MODIS) (i.e. 100-1000 m) (Schmid 1997). Spatial mismatches are less likely to confound  
115 ground radiation- and satellite- derived reflectance and vegetation index comparisons in  
116 homogenous landscapes (Wittich and Kraft 2008). Radiation-derived vegetation indices also are  
117 very broad and integrate spectral information across the visible and infrared wavelengths,

118 whereas satellite derived vegetation indices use more narrow spectral bands that focus on the red  
119 and NIR portions of the electromagnetic spectrum (Wittich and Kraft 2008). This spectral  
120 mismatch is more likely to influence the magnitude- but not the seasonality-of the vegetation  
121 indices (Elvidge and Chen 1995; Zhao et al. 2007). Although both these mechanisms are  
122 important at individual sites, they are unlikely to account for the inconsistency of radiation- and  
123 satellite-derived seasonality differences observed across many sites.

124

125 Sensor measurement biases have been largely overlooked when determining the causal  
126 mechanism behind differences in radiation- and satellite-derived vegetation indices (Balzarolo et  
127 al. 2011; Schaepman-Strub et al. 2006). Satellite sensors measure surface radiance, which are  
128 ultimately converted into a corrected surface reflectance that minimizes solar illumination and  
129 sensor view effects using a Bi-Directional Reflectance Function (BRDF) (Schaepman-Strub et al.  
130 2006). The BRDF corrects for solar illumination effects from solar position to compare  
131 reflectance at the same view angle-typically defined at nadir. Such corrections are not made for  
132 radiation derived vegetation indices (Balzarolo et al. 2011; Huemmrich et al. 1999; Wilson and  
133 Meyers 2007). Although the radiation sensors are located above the canopy, these sensors  
134 integrate radiation from the entire hemisphere. Despite this hemispherical field of view,  
135 shortwave albedo has been shown to be sensitive to illumination angle (i.e. solar zenith and  
136 azimuth angles), which changes over the course of a day and year (Huemmrich et al. 1999). For  
137 example, broadband albedo measured with pyranometers have been shown to be dependent on  
138 solar zenith angle and illumination intensity for surfaces with high reflectivity such as snow  
139 (Carroll and Fitch 1981; Kriebel 1979; Wang et al. 2005; Wang and Zender 2010; Yang et al.

140 2008). However, little has been done to understand or correct the impact of illumination angle  
141 effects on radiation derived vegetation indices.

142

143 Here we assessed the ability of PAR and solar radiation derived reflectance proxies and  
144 vegetation indices to replicate MODIS satellite derived reflectance and vegetation indices; herein  
145 referred to as measurement biases. We also assessed the ability of PAR and solar radiation  
146 derived vegetation indices to infer ecosystem function (i.e. plant phenology and CO<sub>2</sub> fluxes).  
147 We focus on two commonly used vegetation indices: NDVI and EVI2 (Rocha and Shaver 2009).  
148 NDVI has more of a historical precedent in inferring ecosystem function, but EVI2 may provide  
149 a better proxy of ecosystem function due to its insensitivity to non-vegetated background  
150 reflectance (Jiang et al. 2008). Past remote sensing work has demonstrated the impact of solar  
151 position in influencing reflectance and vegetation indices, but lacked biological data to  
152 demonstrate the implications of ignoring such biases for inferring ecosystem function (Bhandari  
153 et al. 2011; Huete 1987; Ma et al. 2019; Middleton 1992). We hypothesized that solar position  
154 will lead to systematic biases in radiation derived vegetation indices that prevent these indices  
155 from correctly inferring vegetation phenology and seasonality in canopy photosynthesis at  
156 Imnaviat. We tested this hypothesis with a decadal record of PAR and solar radiation fluxes,  
157 MODIS, and ground based spectral radiometer measurements at a high latitude tundra site  
158 (Imnaviat), and further corroborated the patterns observed at Imnaviat with a synthesis of  
159 Fluxnet datasets. Imnaviat was chosen because of its landscape homogeneity, its rich long term  
160 ecological dataset (i.e. long term CO<sub>2</sub> fluxes and plant phenology), as well as its high latitude  
161 location with a frequently high solar zenith angle. The attributes of these data provide an ideal  
162 opportunity to determine the major sources of measurement biases leading to the discrepancy

163 between satellite- and radiation-derived vegetation indices, and measures of seasonality in  
164 ecosystem function.

165

166 **2.0 Methods**

167

168 *2.1 Site Description, Instrumentation, and Available Data*

169 This study was conducted on a west-facing hillslope within the Imnaviat Creek watershed on the  
170 North Slope of Alaska, USA (68.61° N; 149.31° W). Vegetation at the site was characteristic of  
171 moist acidic tussock tundra with tussock cottongrass [*Eriophorum vaginatum*], dwarf birch  
172 [*Betula nana*], labrador tea [*Rhododendron tomentosum*], sphagnum moss [*Sphagnum spp.*], and  
173 scattered lichens covering the landscape (Euskirchen et al. 2012). The mean annual temperature  
174 at the site was -7 °C and the mean annual precipitation was 318 mm, with 40% occurring as rain  
175 and 60% as snow. Mean growing season (June-August) temperature was 6 °C, while mean non-  
176 growing season temperature was -11 °C.

177

178 In July of 2008, Imnaviat was instrumented with three (1 upward and two downward) CMP3  
179 pyranometers that measured shortwave solar radiation (SW: units: W m<sup>-2</sup>) [CMP3; Kipp and  
180 Zonen], three PAR sensors that measured Photosynthetically Active Radiation (PAR: units:  
181 μmol m<sup>-2</sup> s<sup>-1</sup>) [LI-190SA; Li-Cor, Lincoln NB], two downward looking surface temperature  
182 radiometers [IRT Infrared Thermometer; Apogee Instruments], a HMP temperature and humidity  
183 sensor [HMP45C-L; Campbell Scientific], and two TCAV soil temperature sensors [TCAV-L;  
184 Campbell Scientific]. Meteorological sensors were mounted at a height of 2.5 meters. Radiation  
185 sensors were well maintained, frequently leveled, and sent for factory calibration every 2-3 years

186 during the measurement period. The radiation tower ran nearly continuously from July 2008-  
187 2018, and was powered by a battery bank connected to two solar panels, which were situated  
188 away from the direct field of view of the sensors.

189

190 The radiation tower was located ~300 m away from three Arctic Observatory Network (AON)  
191 flux towers located along the same west facing hillslope gradient (Euskirchen et al. 2012). The  
192 flux towers measured the Net Ecosystem Exchange of CO<sub>2</sub> (NEE) via the eddy covariance  
193 method, and a suite of meteorological variables including incoming and outgoing PAR and solar  
194 radiation, air temperature, humidity, wind speed, soil moisture, soil temperature, and snow depth  
195 (Baldocchi 2003). We analyzed the mean seasonal cycle of the daily Gross Ecosystem Exchange  
196 (GEE) at the mid-slope Moist Acidic Tundra (MAT) site from 2008-2018 to determine the  
197 relationship between vegetation indices and the seasonality of photosynthesis. The mid-slope  
198 MAT flux tower was chosen because of its similar vegetation composition, slope position, and  
199 NDVI seasonality to the nearby radiation tower [MAT Flux Tower NDVI vs. Imnaviat Radiation  
200 Tower NDVI R<sup>2</sup>: 0.97; Slope: 1.01; Mean Absolute Error (MAE): 0.01]. AON data were  
201 obtained online at <http://aon.iab.uaf.edu>.

202

203 NEE flux partitioning was described in detail in Euskirchen et al. (2012, 2017), and followed  
204 standard Fluxnet protocols for partitioning NEE into canopy photosynthesis (Gross Ecosystem  
205 Exchange: GEE) and ecosystem respiration (ER). Briefly, NEE flux partitioning was  
206 accomplished by fitting a Q10 air temperature response function to well mixed (u-star> 0.10 s m<sup>-1</sup>)  
207 <sup>1)</sup> NEE's that occurred during low light conditions (PAR< 50  $\mu\text{mol m}^{-2} \text{s}^{-1}$ ) (Ueyama et al. 2013;  
208 Euskirchen et al. 2017)). The basal respiration and Q10 parameters of the exponential model

209 were determined through least squares fitting with “low light” NEE and air temperature data  
210 from a 30 day daily moving window. This empirically derived Q10 air temperature response  
211 function was used to estimate half hourly ER. Half hourly GEE was inferred from NEE by  
212 subtracting ER from NEE (GEE=NEE-ER), and temporally scaled up with daily summations.

213

214 *2.2 Ground based Spectral Reflectance Measurements*

215 Ground based reflectance was measured within the footprint of the Imnaviat radiation tower  
216 using three different spectroradiometers over the years. Spectral reflectance was measured with a  
217 Unispec (UniSpec-SC, PP-Systems, Amesbury, MA; Spectral Range: 300-1200 nm at 2 nm  
218 resolution) from 2008-2009, a dual channel Unispec (UniSpec-DC, PP-Systems, Amesbury, MA;  
219 Spectral Range: 300-1200 nm at 2 nm resolution) from 2010-2012, and a FieldSpec 4 (Analytical  
220 Spectral Devices (ASD); Malvern Panalytical Ltd; United Kingdom; Spectral Range: 200-2400  
221 nm at 2 nm resolution) from 2013-2018. Four ~100 m transects separated by ~30 m were  
222 established on the North and South side of the radiation tower forming a 200x120m grid within  
223 the tower footprint. Spectral reflectance was measured during midday hours (11:00 am-2:00 pm  
224 AST) every ~3 meters along each of the four 100 m transects either weekly, bi-monthly, or  
225 monthly during the growing season (June-August) of each year (n=240 scans per sampling date).  
226 A total of 62 sampling campaigns were undertaken from July 2008 to August 2018 with each  
227 campaign taking ~1 hour to accomplish.

228

229 Surface reflectance measurements followed standard procedures described in the  
230 spectroradiometer user manuals. Prior to measurements, each instrument was allowed a 15-20  
231 minute warm up period. A freshly cleaned white Spectralon® diffuse reflectance panel

232 (Labsphere; North Sutton, NH) was used as a reflectance standard to convert spectroradiometer  
233 derived radiance into surface reflectance. Dark current measurements were taken by closing the  
234 detector “door”, which prevented light from hitting the detectors and minimized measurement  
235 artifacts from background electrical instrument noise. Optimal measurement integration times  
236 were dependent on illumination conditions and were automatically determined by each sensor.  
237 White panel, dark current, and optimal measurement integration time measurements were taken  
238 frequently (i.e. every 3-5 minutes depending on sky conditions) to ensure high quality  
239 reflectance data. After each sampling campaign, surface reflectance data were quality checked  
240 for anomalous spectra (i.e. spectra that were  $>3$  standard deviations from the mean) and averaged  
241 across all scans. These spectra were used to calculate NDVI and EVI2 using Equations [2] and  
242 [3] below and spectrally averaged MODIS wavelength and sensor response definitions for red-  
243 (MODIS spectral response weighted average of 620-670 nm) and NIR- reflectance (MODIS  
244 spectral response weighted average of 841-876 nm) (Xiong et al. 2006; Schaaf et al. 2002). We  
245 also spectrally averaged all wavelengths to calculate total and visible reflectance to derive a  
246 broad band visible, NIR (using equation 1), NDVI and EVI2 based on ASD spectroradiometer  
247 data. ASD averaged total reflectance was within 10% of the shortwave albedo, while ASD  
248 averaged visible reflectance was within 5% of PAR albedo measured by radiation sensors at  
249 Imnaviat.

250

### 251 *2.3 Ground based Phenology*

252 Individual plant species phenologies were measured from 2008-2018 in moist acidic tundra at  
253 the Toolik Lake Arctic Long Term Ecological Research (LTER) station. Toolik field station was  
254 situated  $\sim$ 7 km away and experienced similar weather to Imnaviat. A variety of phenological

255 events (i.e. first snow free, first visible leaf, first leaf drop, first color change, and last leaf drop)  
256 were measured in several plots around Toolik lake in each year for the dominant MAT species  
257 (i.e. *Andromeda polifolia*, *Betula nana*, *Carex bigelowii*, *Cassiope tetragona*, *Empetrum nigrum*,  
258 *Eriophorum vaginatum*, *Ledum palustre*, *Polygonum bistorta*, *Rubus chamaemorus*, *Salix*  
259 *pulchra*, *Vaccinium uliginosum*, *Vaccinium vitis-idaea*). These phenological data were used to  
260 validate satellite- and radiation- derived NDVI and EVI2 estimates of the start-, end-, and length-  
261 of the growing season. The average of the first visible leaf for all species served as a proxy for  
262 the start of the growing season, whereas the maximum last leaf color change served as a proxy  
263 for the end of the growing season.

264

#### 265 *2.4 Radiation derived Vegetation Indices*

266 The radiation tower at Imnaviaat measured surface albedo in the visible (400-700 nm) and total  
267 shortwave wavelengths (300-2400 nm) of light. These albedo measures served as a proxy for red  
268 and near infrared reflectance (Rocha and Shaver 2009). Visible ( $\alpha_V$ ) albedo was calculated as  
269 the ratio between reflected ( $r$ ) and incoming ( $i$ ) PAR  $\alpha_V = PAR_r/PAR_i$ , while total albedo ( $\alpha_T$ )  
270 was calculated as the ratio between reflected and incoming shortwave radiation [ $SW_r$  &  $SW_i$ ,  
271 respectively]  $\alpha_T = SW_r/SW_i$ .  $\alpha_V$  was used as a proxy for red reflectance, while both  $\alpha_V$  and  $\alpha_T$   
272 were used in Equation 1 as a proxy for NIR reflectance ( $\alpha_N$ ) (Jenkins et al. 2007).

273

$$274 \alpha_N = W * \alpha_T - \alpha_V \quad \text{Equation [1]}$$

275

276 W in Equation 1 equaled 2 for all vegetation types, and represented a weighting term to separate  
277  $\alpha_N$  from  $\alpha_V$  and  $\alpha_T$ . Derivations of red and near infrared reflectance from ground based

278 radiometers represented broadband definitions of narrowband quantities.  $\alpha_N$  included dynamics  
279 in the near- and short-wave infrared region of the reflectance spectrum, while  $\alpha_V$  included  
280 dynamics in the red, blue and green regions of the reflectance spectrum. Other ground  
281 radiometer derivations of  $\alpha_N$  utilize similar assumptions (see Huemmrich et al., 1999 & Wilson  
282 and Meyers, 2007). We used Jenkins et al. (2007) derivation because of its parsimony and its  
283 high correlation with other  $\alpha_N$  derivations (Jenkins vs. Huemmrich  $R^2$  [Mean Absolute Error:  
284 MAE]: 0.91 [0.015]/ MAE Jenkins vs. Wilson & Meyers  $R^2$  [MAE]: 0.99 [0.014]) for the sites  
285 used in this study. We also found that the conclusions from our analyses were independent of the  
286 different formulations of  $\alpha_N$ .

287

288 We focused our analyses on the active growing season during snow-free periods. Data  
289 influenced by snow covered ground were identified with an albedo threshold of  $>0.3$  (i.e.  
290 vegetation albedo  $<0.25$  at all sites) and removed from the half hourly radiation datasets.  
291 Incoming and reflected radiation were averaged over the course of a day (i.e.  $n=48$  for each  
292 value) to minimize diel solar zenith effects (Huemmrich et al. 1999; Rocha and Shaver 2009;  
293 Wilson and Meyers 2007). Sensor drift and snow and dirt accumulation on the sensors were  
294 identified as periods where  $PAR_i/SW_i$  fell beyond or below the mean plus or minus 2 standard  
295 deviations and subsequently removed. The final “cleaned” dataset contained daily ground  
296 radiometer values that were compared with MODIS reflectance and vegetation indices.

297

298 NDVI and EVI2 were calculated from radiation-, spectroradiometer- and MODIS-derived  
299 measures of near infrared ( $\alpha_N$ ) and red reflectance ( $\alpha_R$ ) with Equations [2] and [3] (Jiang et al.  
300 2008).

301

$$302 \quad NDVI = \frac{\alpha_N - \alpha_R}{\alpha_N + \alpha_R}$$

**Equation [2]**

303

$$304 \quad EVI2 = 2.5 \frac{\alpha_N - \alpha_R}{\alpha_N + 2.4\alpha_R + 1}$$

**Equation [3]**

305

306 *2.5 Fluxnet Data Synthesis*

307 We conducted a broader survey of ground based radiation derived vegetation indices with  
 308 Fluxnet data to determine whether biases observed at the Imnaviait site were consistent across  
 309 other sites (Table 1). Data from the Fluxnet network consisted of 25 sites and 90 site years of  
 310 half hourly incoming (<sub>i</sub>) and reflected (<sub>r</sub>) PAR and shortwave data (Table 1). 12% of the sites  
 311 were from crops, 8% were from deciduous forests, 25% were from evergreen forests, 28% were  
 312 from grasslands, 20% were from arctic tundra, and 8% were from a shrub and grassland mix.  
 313 Sites had a minimum of two years of data with a maximum of 6 years at 2 sites, and an average  
 314 of 3.5 years for the entire dataset. PAR within the 400-700 nm spectral region was measured  
 315 with a LI190 quantum sensor (LI-COR Inc., Lincoln, Nebraska) at 85% of the sites, while the  
 316 remaining sites used either an Apogee quantum sensor (Apogee Instruments, Logan, Utah) or  
 317 BF3 sunshine sensor (Dynamax, Houston Texas). Shortwave radiation (SW) within the 300-  
 318 2800 nm spectral region was measured with a CM3 (Kipp & Zonen, Bohemia, NY ) at 90% of  
 319 the sites, while the remaining sites used an Apogee pyranometer (Apogee Instruments, Logan,  
 320 Utah) or LI200 pyranometer (LI-COR Inc., Lincoln, Nebraska). Data were aligned with MODIS  
 321 satellite data (see section 2.7) through 16- day averages that were centered on the MODIS  
 322 composite date.

323

324 *2.6 Testing and Correcting for Solar Position Biases*

325 We corrected solar position biases using diel relationships between solar position and albedo  
326 throughout the season. Diel NIR and visible albedo variability can be more than twice as large  
327 as observed over the course of a season (Huemmrich 1999). These large diel visible and NIR  
328 albedo variations cannot be representing changes in canopy leaf area, that are often related to  
329 vegetation indices, because LAI changes over much longer time scales than a day (i.e. days to  
330 weeks)(Stoy 2013). Rather, this large diel variation arises from the anisotropic properties of  
331 surface reflectance (i.e. the bidirectional reflectance distribution function) and possibly other  
332 sensor issues, such as a sensors' cosine response function (Huete 1987; Middleton 1992; Rahman  
333 et al. 1993).

334

335 Here we used the diel variation in albedo and solar position to empirically derive a correction  
336 factor to apply over the course of the season. Solar position was calculated for each site and half  
337 hour using the site latitude and longitude and time of year (Myers 2017). We removed divided  
338 each daily averaged visible and NIR albedo into each half hourly visible and NIR albedo value to  
339 remove vegetation phenology effects and focus solely on sub-daily variations associated with  
340 solar position (Equation 4).

341

$$\alpha_{cor} = \frac{\text{Daily "unbiased" Value}}{\text{Half Hourly "biased" Value}} = \frac{\alpha_d}{\alpha_h} \quad \text{Equation [4]}$$

342 Here, given the large sub-daily variation in solar position, we assumed that the half hourly NIR  
343 and visible albedos were more “biased” in response to solar position than the daily averaged  
344 values (i.e. “unbiased”). Hence,  $\alpha_{\text{Cor}}$  represented a correction factor that could be used to remove  
345 the solar position bias from the albedo measurements. For each day, we calculated 48 half  
346 hourly  $\alpha_{\text{Cor}}$  ratios, which could be used to create a temporally consistent albedo value throughout  
347 the day through multiplication (i.e. Half Hourly biased \*Daily average unbiased/ Half Hourly  
348 biased = Daily averaged unbiased). This sub-daily consistency of NIR and visible albedos were  
349 more aligned with the fact that LAI changes occur over longer time scales than a day. By  
350 understanding the dependence of  $\alpha_{\text{Cor}}$  on solar position, we could remove any measurement bias  
351 introduced by seasonal changes in solar zenith and azimuth. If radiation derived albedos were  
352 not dependent on solar position, then  $\alpha_{\text{Cor}}$  would equal one across different solar azimuth and  
353 zenith angles. If radiation derived albedos were dependent on solar position, then  $\alpha_{\text{Cor}}$  would  
354 significantly differ from 1 and scale with solar azimuth and zenith angles.

355

356 Here we used the solar position dependence of  $\alpha_{\text{Cor}}$  at the half hourly time scale to reduce any  
357 solar position biases observed across the season. Half hourly  $\alpha_{\text{Cor}}$  was empirically related to half  
358 hourly solar-zenith and -azimuth angles through a machine learning squared exponential  
359 Gaussian process regression model. This half hourly statistical model was used to predict  $\alpha_{\text{Cor}}$   
360 across the season using daily averaged solar zenith and azimuth angles as dependent variables.  
361 Regression model predicted daily  $\alpha_{\text{Cor}}$  was multiplied by the daily averaged visible and NIR  
362 albedos to produce solar position (i.e. “biased free”) corrected  $\alpha_V$  and  $\alpha_N$ . Solar position  
363 corrected  $\alpha_V$  and  $\alpha_N$  were then used to recalculate NDVI and EVI2 using Equations 2 and 3.

364 Analyses were accomplished with Matlab's Regression Learner application (MATLAB 2019b;  
365 Mathworks Inc. Natick, MA).

366

367 *2.7 MODIS Data*

368 We compared MODIS reflectance and vegetation indices to radiation derived proxies and  
369 measures. For the Fluxnet data synthesis, MODIS Nadir-BRDF adjusted 500 m resolution  
370 collection 4 surface reflectance data (MODIS NBAR; MCD43A) were extracted from a 2.5 x 2.5  
371 km<sup>2</sup> area centered at each tower location in 2012 (<http://daac.ornl.gov>) (Schaaf et al. 2002;  
372 ORNL DAAC 2018). We also used the equations from Liang (2000) to calculate a total and  
373 visible albedo from the seven MODIS spectral bands. These MODIS derived total and visible  
374 albedos were used to derive broadband vegetation indices following Equations 1-3. For  
375 Imnaviat, we used collection 6 version 1 daily Nadir BRDF-Adjusted reflectance (MCD43A4)  
376 and extracted data at various spatial scales (i.e. 0.25, 6.25, 20.25, 210.25, and 420.25 km<sup>2</sup>) to  
377 determine the impact of spatial aggregation on the comparison between ground and satellite  
378 based data (Shuai et al. 2013). Data with >80% of pixels passing quality control were used in the  
379 analyses. Only growing season MODIS data, as defined by ground based snowless terrestrial  
380 albedo values greater than 0.25, were used in the analyses.

381

382 *2.8 Phenology Model*

383 The start, end, and length of the growing season was determined with a phenology model fit to  
384 the observed seasonal cycle of MODIS- and radiation- derived NDVI and EVI2 in each year at  
385 Imnaviat. The phenology model was a double-logistic function that predicted each vegetation

386 index based on the day of year (t) (Beck et al. 2006; Fisher et al. 2006; Fisher et al. 2007)

387 (Equation 5):

388

$$389 \quad v(t) = v_{min} + v_{amp} \left( \frac{1}{1+e^{m_1-n_1t}} - \frac{1}{1+e^{m_2-n_2t}} \right) \quad \text{Equation [5]}$$

390

391 The model was fit by minimizing the sum of squared residuals between model predictions and  
392 observed values. The fitted parameters of the model were  $v_{min}$  and  $v_{amp}$ ,  $m_1$ ,  $n_1$ ,  $m_2$ , and  $n_2$ .  $v_{min}$   
393 and  $v_{amp}$  were related to the minimum and amplitude values of the spectral index, respectively.

394 The parameters in the two exponents determined the seasonality with  $m_1$  and  $n_1$  related to the rate  
395 and timing of green-up, and  $m_2$  and  $n_2$  related to the rate and timing of senescence. The start of  
396 the growing season was given by  $t = m_1/n_1$ , the end of the growing season was given by  $t =$   
397  $m_2/n_2$ , and the length of the growing season was determined by the difference between the start  
398 and end of the growing season.

399

400 *2.9 Statistical Analyses:*

401 Statistical analyses included least squares linear regression to determine the relationship between  
402 two variables, and Mean Absolute Error (MAE) to determine the prediction error of a model or  
403 the error associated with the comparison of a set of similar observations (Ramsey 2013).

404 Statistical significance was determined at the 95% confidence level.

405

### 406 **3. Results**

407

408 *3.1 Assessing Spatial Aggregation Biases*

409 The scale of spatial integration had little impact on the comparison between tower and MODIS  
410 based vegetation indices indicating landscape coherence in phenology within the region  
411 surrounding Imnaviat (Figure 1). Here we minimized spectral definition differences among  
412 sensors by comparing spectroradiometer- and MODIS- derived reflectance's and vegetation  
413 indices. Spectroradiometer derived NDVI explained 70% of the variability in MODIS derived  
414 NDVI, whereas spectroradiometer derived EVI2 explained 60% of the variability in MODIS  
415 derived EVI2. The MAE increased slightly from 6% of NDVI at the ecosystem/watershed level  
416 (0-10 km<sup>2</sup>) to 7% of NDVI at the regional scale (>300 km<sup>2</sup>). EVI2 exhibited greater sensitivity  
417 to spatial integration with MAEs increasing from 14% of EVI2 at the ecosystem/watershed scale  
418 to 20% of EVI2 at the regional scale.

419

420 *3.2 MODIS- vs. radiation-derived reflectance and indices comparison*

421 In general, spectroradiometer- and MODIS- derived reflectances and vegetation indices were  
422 more related to each other than those derived from radiation fluxes at Imnaviat (Table 2).  
423 Vegetation indices yielded higher correlations among measurement types than did red and NIR  
424 reflectance. For example, reflectance R<sup>2</sup>'s ranged from 0.17-0.22 for NIR and red reflectance,  
425 while vegetation index R<sup>2</sup>'s ranged from 0.34 to 0.67. Correlations among radiation-,  
426 spectroradiometer-, and MODIS-derived measures were typically higher for EVI2 than for  
427 NDVI. The poor relationships between radiation- and MODIS/spectroradiometer- derived  
428 vegetation indices were largely attributed to differences in seasonality among the  
429 MODIS/spectroradiometer- and radiation- derived measures.

430

431 Seasonality differed among radiation-, spectroradiometer-, and MODIS derived- reflectance and  
432 vegetation indices at Imnaviat (Figure 2). Correspondence among the three measures was  
433 greatest for red reflectance and smallest for NIR, NDVI, and EVI2. Red reflectance  
434 demonstrated similar seasonality among the measures with higher reflectance in the shoulder  
435 seasons and minimum values during the peak of the growing season. In contrast, NIR  
436 reflectance, NDVI, and EVI2 were low at the start of the growing season, reached a maximum  
437 during peak growing season, and then declined to a minimum at the end of the growing season.  
438 All three measures of NIR, NDVI and EVI2 exhibited similar seasonality up until the peak of the  
439 growing season, but differed towards the end of the growing season. Radiation-derived NIR  
440 reflectance and vegetation indices were larger than MODIS and spectroradiometer- derived  
441 quantities towards the latter part of the growing season. Consequently, differences between  
442 MODIS and spectroradiometer- and radiation-derived NIR, NDVI, and EVI2 exhibited strong  
443 seasonality with the largest mismatch towards the second half of the growing season.

444

### 445 *3.3 Assessing Sensor Biases*

446 Seasonal differences between MODIS- and radiation- derived indices observed in Figure 2 were  
447 correlated with solar zenith angle at Imnaviat (Figure 3). Larger solar zenith angles produced  
448 larger differences between MODIS- and radiation- derived NIR, NDVI, and EVI2, but had no  
449 impact on differences between MODIS- and radiation- derived red reflectance. Solar zenith  
450 angle explained 41% of the variability in NIR reflectance biases, 28% of the variability in NDVI  
451 biases, and 45% of the variability in EVI2 biases. This represented a bias of 0.004 per 1° change  
452 in zenith angle for NIR reflectance, and a bias of 0.006 per 1° change in zenith angle for NDVI  
453 and EVI2.

454

455 The relationship between measurement bias and solar zenith angle at Imnaviat were consistent  
456 across Fluxnet sites located in vastly different biomes (Figure 4). However, in contrast to the  
457 observed solar zenith dependent measurement biases at the Imnaviat site, there was a statistically  
458 significant measurement bias dependence on solar zenith angle at some of the Fluxnet sites for  
459 red reflectance. For the Fluxnet dataset, MODIS and radiation derived NIR differences positively  
460 scaled with solar zenith angle and all biomes exhibited similar slopes that ranged from 0.002 to  
461 0.003 per 1° change in zenith angle. The solar zenith dependent biases in NIR and red  
462 reflectance carried over to NDVI and EVI2, but sometimes canceled each other out. This  
463 cancelling out effect was more predominant for NDVI than for EVI2. For example, NDVI  
464 biases were unrelated to solar zenith angle for evergreens and grass shrublands, whereas solar  
465 zenith angle was correlated with EVI2 biases in all biomes. The bias sensitivity to solar zenith  
466 angle ranged from 0.001 to 0.005- for NDVI, and from 0.003 to 0.005- per 1° change in zenith  
467 angle for EVI2.

468

#### 469 *3.4 Assessing Bandwidth Biases*

470 We used the full range spectroradiometer ASD data (300-2400 nm) to determine whether the  
471 measurement bias dependence on solar position was attributed to broadband versus narrowband  
472 definitions of red and near infrared reflectance used by the radiation sensors (Figure 5).  
473 Correlations between solar zenith angle and the difference between broadband and narrowband  
474 (i.e. Bandwidth Biases) definitions for red (p-value: 0.94), NDVI (p-value: 0.21), and EVI2 (p-  
475 value: 0.06) were not statistically significant. Bandwidth biases were marginally significant and  
476 related to solar zenith angle for NIR (p-value: 0.04), but were opposite in sign to the expected

477 relationships observed in Figures 3 & 4. Moreover, solar zenith angle only explained 10% of the  
478 variation in bandwidth biases, as opposed to the 67% of the variation in radiation tower and  
479 MODIS differences explained by zenith angle in Figure 3.

480

481 Similar results were found across the Fluxnet sites using MODIS data and differencing broad-  
482 and narrow- band vegetation indices (Figure 1S; Table 1S). Although many relationships were  
483 statistically significant, solar zenith angle only explained <10% of the variation in bandwidth  
484 biases for NDVI, and <11% of the variation in bandwidth biases for EVI2 across all Fluxnets  
485 sites on average (Supplementary Figure 1). Moreover, the bandwidth bias sensitivity to solar  
486 zenith angle was sometimes the opposite sign of the expected positive relationships in Figures 3  
487 and 4 and were on average one to two orders of magnitude lower than that observed for tower  
488 and MODIS differences for red, NIR, NDVI, and EVI2 (Supplementary Table 1).

489

### 490 *3.5 Correcting Solar Position Biases*

491 Diel variability in solar position affected radiation derived visible and NIR albedos that were  
492 used as red and NIR reflectance at Imnaviat (Figure 6). Over the growing season, daily averaged  
493 solar zenith angle changed by 19°, while daily averaged solar azimuth angle changed by 7°  
494 (Figure 6 inset). Visible and NIR albedo were more sensitive to solar zenith- than azimuth-  
495 angles as illustrated by the small scatter in Figure 6. NIR albedo was more sensitive to solar  
496 zenith angle than visible albedo and was almost two times higher than its expected value at an  
497 80° zenith angle. Consequently, the correction factor for NIR albedo declined markedly above  
498 70° from 0.85 to 0.59, whereas the correction factor for visible albedo changed by <1% above  
499 70° solar zenith angle.

500

501 Correcting solar position biases using the machine learning approach described in section 2.6  
502 improved the agreement between MODIS- and radiation- derived red and NIR reflectance,  
503 NDVI, and EVI2 at Imnaviat (Figure 7). After correcting for the dependence of measurement  
504 biases on solar position, MAE decreased and  $R^2$  increased between MODIS- and radiation-  
505 derived reflectance and vegetation indices (Table 3; Figure 7). An exception to this occurred for  
506 MODIS red reflectance, where the  $R^2$  and MAE did not significantly change after correction due  
507 to its low sensitivity to solar position. MAE decreased by 40% for NDVI and EVI2, and by 33%  
508 for NIR reflectance after applying the correction factor for seasonal changes in solar position.

509

510 Correcting solar position biases using the machine learning approach also improved the  
511 agreement between MODIS- and radiation-derived NDVI and EVI2 across the Fluxnet sites  
512 (Figure 8). Correcting for measurement biases introduced by solar position reduced the MAE  
513 between MODIS- and radiation- derived NDVI and EVI by 5% to 77%. Grasslands and tundra  
514 experienced the largest decrease in MAE, while crops experienced the smallest decreases in  
515 MAE once the impact of solar position on radiation derived albedo and vegetation indices were  
516 corrected. There was quite a bit of variability in the improved correspondence between MODIS-  
517 and radiation-derived vegetation indices among sites. However, it was difficult, if not  
518 impossible, to attribute this variability to underlying environmental, biophysical or site specific  
519 factors without additional site and sensor specific information. Regardless, correcting biases in  
520 vegetation indices for solar position improved the correspondence between MODIS- and  
521 radiation- derived vegetation indices at 85% of the sites investigated.

522

523 *3.6 Implications for Inferring Ecosystem Function with radiation derived NDVI and EVI2*

524 Biases associated with solar position confounded the ecophysiological interpretation of radiation

525 derived NDVI and EVI2 at Imnaviat (Figure 9). Uncorrected radiation derived vegetation indices

526 exhibited hysteretic relationships with GEE with different sensitivities-as measured by the slope

527 of the line- in the first and second half of the growing season. GEE was lower for the same value

528 of NDVI/EVI2 in the first part of the growing season, and higher for the same value of

529 NDVI/EVI2 in the second part of the growing season. The relationship between NDVI/EVI2

530 became more linearized with a single relationship throughout the growing season once

531 vegetation indices were corrected for their solar position dependence (Figure 9 solid line).

532 Uncorrected NDVI explained 37% of the variability in GEE, whereas solar position corrected

533 NDVI explained 85% of the variability in GEE. Similar patterns were found for EVI2.

534 Uncorrected EVI2 explained 37% of the variability in GEE, whereas solar position corrected

535 EVI2 explained 89% of the variability in GEE.

536

537 Solar position also confounded the determination of the start, end, and length of the growing

538 season at Imnaviat (Figure 10). On average, correcting radiation derived vegetation indices for

539 solar position decreased the MAE between leaf level measures of phenology up to ~10 days.

540 Differences between corrected and uncorrected NDVI/EVI2 derived phenologies were greatest

541 for the length of the growing season due to compounding errors associated with the start and end

542 of the growing season estimates. Uncorrected NDVI/EVI2 demonstrated reduced skill at

543 determining the end of the growing season relative to the start; a finding that is consistent with

544 trends observed in Figure 2. Solar position corrected radiation derived NDVI/EVI2 performed

545 similarly to-or in some cases-better than MODIS in predicting the start and end of the growing

546 season, especially for EVI2. For example, solar position corrected radiation derived EVI2  
547 performed better than MODIS EVI2 in predicting the start and length of the growing season.  
548 When MODIS- and radiation- derived phenological predictions were combined, NDVI  
549 outperformed EVI2 by 5 days for the start of the growing season and 7 days for the length of the  
550 growing season, whereas EVI2 outperformed NDVI by 1 day for the end of the growing season.

551

## 552 **4.0 Discussion:**

553 Solar position introduced significant bias on PAR and solar radiation derived vegetation indices,  
554 especially during the latter part of the growing season. These errors were largely independent of  
555 broad- to narrow-band definitions (Figures 5 & 1S; Table 1S), and sensor spatial aggregation  
556 errors associated with landscape heterogeneity (Figure 1). The effect of satellite spatial  
557 aggregation errors was minimized by focusing on a relatively homogenous site (i.e. Innnaviat),  
558 and were much smaller than that observed for measurement biases [i.e. <0.02 change in  
559 vegetation index MAE from 0-400 km<sup>2</sup> (Figure 1) compared to ~0.05 MAE for tower and  
560 MODIS vegetation comparisons (Table 2)] (Wang et al. 2012). Measurement biases also were  
561 universal and occurred across a wide variety of latitudes, biomes, and sites indicating a persistent  
562 error that cannot be explained by individual site specific conditions (Figures 3,4,7,8). These  
563 measurement biases accounted for some of the limitations and issues highlighted in previous  
564 work with radiation derived vegetation indices (Jenkins et al. 2007; Rocha and Shaver 2009;  
565 Wang et al. 2004; Wittich and Kraft 2008). To our knowledge, this is the first paper, since  
566 Huemmrich et al.'s (1999) seminal work, to develop a methodology using the diel variation in  
567 albedo to correct for these biases and improve the performance of these indices in inferring  
568 ecosystem function.

569

570 Historically, solar position biases on radiation- derived albedo and vegetation indices were  
571 assumed to be negligible over the course of a season, despite known diel variation (Huemmrich  
572 et al. 1999). This incorrect assumption was likely due to data limitations from looking at a single  
573 site over a short time period, the exclusion of solar azimuthal effects, and a lack of multi-sensor  
574 comparisons. Unlike past work, our conclusions were supported by multiple independent  
575 physical and ecological observations. First, solar position corrections improved correspondence  
576 between satellite- and radiation- derived vegetation indices at Imnaviat and Fluxnet sites (Figures  
577 7 and 8; Table 3). Second, solar position corrections improved the ability of radiation derived  
578 vegetation indices in capturing phenological timing and C fluxes (Figures 9 and 10). It is clear  
579 that our use of combining long time series data obtained from different sensors and scales was  
580 essential in validating and assessing measurement biases in radiation derived vegetation indices.  
581 Our results also demonstrated that, in some cases, solar position associated NIR and visible  
582 biases canceled each other out in the calculation of the vegetation index. This cancelation effect  
583 may explain the discrepancy between this study and past work at single sites that assumed  
584 negligible solar position biases.

585

586 Addressing solar position biases in visible and NIR albedo are important because these biases  
587 resulted in poor relationships with MODIS data and poor inferences of ecosystem function.  
588 Without correcting for solar position, measurement biases reduced the explained variation in  
589 canopy photosynthesis and increased estimation error of the start, end, and length of the growing  
590 season (Figures 9,10). Radiation derived vegetation indices also exhibited less seasonality than  
591 MODIS, which was consistent with previous work with higher than expected NIR and vegetation

592 indices towards the latter part of the growing season (Rocha and Shaver 2009; Wittich and Kraft  
593 2008). These unique attributes of radiation derived vegetation indices have been previously  
594 reported, but often incorrectly attributed to bandwidth biases rather than solar position ( Rocha  
595 and Shaver 2009; Jenkins et al. 2007; Wang et al. 2004). Broadband derivations of red and NIR  
596 reflectance incorporate dynamics in the shortwave infrared that could potentially confound the  
597 seasonality of the broadband red, NIR, NDVI, and EVI2 measured by PAR and shortwave  
598 radiation sensors. However, bandwidth errors exhibited weak to non-existent relationships with  
599 solar position for broadband radiation derived indices across Imnaviat and the Fluxnet sites  
600 (Figures 5 and 1S; Table 1S). On the other hand, measurement bias sensitivity to solar zenith  
601 angle was an order of magnitude larger than that observed for broadband biases across both  
602 Imnaviat and Fluxnet sites (Figures 5; Figure 1S; Table 2S). The improved ability of radiation  
603 derived vegetation indices to replicate MODIS narrowband reflectance and VIs once solar  
604 position correction was applied provides strong evidence to attribute radiation derived biases to  
605 solar position, rather than bandwidth errors (Figures 7,8, 1S).

606

607 Here we used a simple machine learning empirically based model based on actual half hourly  
608 data to correct the seasonal biases in visible and NIR albedo. Our empirical model had high  
609 predictive power, explaining 85-95% of solar position biases, followed an expected BRDF  
610 response (i.e. a non-linear positive response with solar zenith angle), and included additional  
611 factors that may be difficult to parameterize in a BRDF model (Figure 6). For example, radiation  
612 sensors may have internal measurement biases due to solar position, known as a sensors cosine  
613 response (Blonquist et al. 2009; Ross and Sulev 2000). A sensor's cosine response describes how  
614 solar radiation is integrated across all solar zenith and azimuthal positions on a Lambertian

615 receiver. This response differs among sensors and would be subject to measurement drift issues  
616 that would be difficult to quantify without additional information. Differences in a sensor's  
617 cosine response also may explain the differences in the sensitivity of radiation derived  
618 measurements to solar zenith angle among sites (Figures 4,8).

619

620 Quantifying and understanding measurement errors and limitations remains an important process  
621 in the scientific community (Kratzenberg et al. 2006; Richardson et al. 2008; Ross and Sulev  
622 2000). This is especially true in ecosystem ecology as new, interdisciplinary, and automated  
623 remote- and near-sensing measurement techniques are being more commonly used.

624 Understanding error sources and applying the proper corrections will result in improved  
625 understanding or quantification of ecosystem function. For example, the strong relationship  
626 between solar position corrected radiation derived vegetation indices and canopy photosynthesis  
627 demonstrate promise in using these data to fill long gaps in eddy covariance flux data.

628 Moreover, the high correspondence between solar position corrected radiation- and satellite-  
629 derived vegetation indices indicates that these data can be valuable in gap filling MODIS data  
630 during cloudy periods (Figure 7). However, we caution future users of such data to also consider  
631 other potential important sources of measurement error, such as sensor drift and sensor spectral  
632 sensitivity, that may significantly alter the continuity of high quality radiation based vegetation  
633 indices (Kratzenberg et al. 2006; Ross and Sulev 2000). We encourage future work to  
634 implement, or improve upon, our methodology to gain further understanding the temporal  
635 dynamics of ecosystem C cycling and phenology with vegetation indices derived from solar and  
636 photosynthetically active radiation fluxes.

637

638 **Acknowledgements**

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643 trade, product, or firm names is for descriptive purposes only and does not imply endorsement by  
644 the US Government.

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Site Name	Latitude	Years	PFT	PAR Sensor	Pyranometer Sensor
Bondville <sup>1</sup>	40	2004-2007	Crop	Apogee	LI200
ARM SGP <sup>1</sup>	36.5	2004-2009	Crop	LI190	CM3
Sioux Falls <sup>2</sup>	43.2	2007-2009	Crop	NA	NA
UCI 1989 <sup>3</sup>	55.9	2002-2005	Deciduous	LI190	CM3
UCI 1998 <sup>3</sup>	56.5	2002-2005	Deciduous	LI190	CM3
Black Hills <sup>4</sup>	44.2	2004-2008	Evergreen	LI190	CM3
Flagstaff Managed <sup>5</sup>	35.1	2006-2009	Evergreen	BF3/LI190	CM3
UCI 1850 <sup>3</sup>	55.9	2002-2005	Evergreen	LI190	CM3
UCI 1930 <sup>3</sup>	55.9	2002-2005	Evergreen	LI190	CM3
UCI 1964 <sup>3</sup>	55.9	2002-2005	Evergreen	LI190	CM3
UCI 1981 <sup>3</sup>	55.9	2002-2005	Evergreen	LI190	CM3
Brookings <sup>4</sup>	44.3	2004-2010	Grassland	NA	NA
Canaan Valley <sup>4</sup>	39.1	2004-2010	Grassland	Apogee	CM3
Cottonwood <sup>4</sup>	43.9	2006-2009	Grassland	NA	NA
Flagstaff Wildfire <sup>5</sup>	35.4	2005-2009	Grassland	BF3/LI190	CM3
Fort Peck <sup>4</sup>	48.3	2002-2008	Grassland	LI190	Apogee
Goodwin Creek <sup>4</sup>	34.3	2002-2006	Grassland	Apogee	CM3
Kendall <sup>6</sup>	31.7	2004-2009	Grassland	NA	NA
Audubon <sup>4</sup>	31.8	2004-2009	Grassland	LI190	CM3
Ivotuk <sup>7</sup>	68.5	2004-2006	Tundra	LI190	CM3
Imnaviat <sup>8</sup>	68.6	2009-2011	Tundra	LI190	CM3
Unburned <sup>9</sup>	68.9	2008-2011	Tundra	LI190	CM3
Severe <sup>9</sup>	68.9	2008-2011	Tundra	LI190	CM3
Moderate <sup>9</sup>	68.9	2008-2011	Tundra	LI190	CM3
Santa Rita	31.8	2004-2007	Grassland/	NA	NA
Mesquite <sup>10</sup>			Shrub		

650 **Table 1.** Site names, location, years, Plant Functional Type (PFT) and sensors used at each of the  
 651 sites used in this study. <sup>1</sup>Hollinger et al. (1994); <sup>2</sup>Verma et al. (2005); <sup>3</sup>Goulden et al. (2011);  
 652 <sup>4</sup>Wilson and Myers (2007); <sup>5</sup>Dore et al. (2016); <sup>6</sup>Scott et al. (2010); <sup>7</sup>McEwing et al. (2015);  
 653 <sup>8</sup>This study; <sup>9</sup>Rocha and Shaver (2011); <sup>10</sup>Scott et al. (2009)

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	<b>Spectroradiometer v. MODIS</b> <i>R</i> <sup>2</sup> [MAE]	<b>Spectroradiometer v. Radiation</b> <i>R</i> <sup>2</sup> [MAE]	<b>MODIS v. Radiation</b> <i>R</i> <sup>2</sup> [MAE]
Red	0.22 [0.01]	0.21 [0.01]	0.19 [0.01]
NIR	0.17 [0.03]	0.20 [0.03]	0.22 [0.03]
EVI2	0.67 [0.03]	0.42 [0.09]	0.42 [0.05]
NDVI	0.55 [0.05]	0.34 [0.11]	0.34 [0.05]

668 **Table 2.** R-squared and Mean Absolute Error (MAE) of relationships among spectroradiometer-  
 669 , MODIS-, uncorrected radiation- derived reflectance and vegetation indices.

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	<b>MODIS v. U- Radiation</b> <i>R</i> <sup>2</sup> [MAE]	<b>MODIS v. C-Radiation</b> <i>R</i> <sup>2</sup> [MAE]
Red	0.19 [0.01]	0.19 [0.01]
NIR	0.22 [0.03]	0.47 [0.02]
EVI2	0.42 [0.05]	0.56 [0.03]
NDVI	0.34 [0.05]	0.56 [0.03]

673 **Table 3.** R-squared and Mean Absolute Error (MAE) of relationships among MODIS- ,  
 674 uncorrected (U) radiation-, and corrected (C) radiation- derived reflectance and vegetation  
 675 indices.

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691 **Figure 1:** Mean Absolute Error (MAE {unitless VI ratios}: blue circles left y-axis) and r-squared  
692 ( $R^2$  {unitless}: red triangles right y-axis) of the relationship between spectroradiometer- and  
693 MODIS- derived NDVI (top) and EVI2 (bottom) at different MODIS spatial integration scales at  
694 Imnaviat.

695

696 **Figure 2:** Seasonal cycle of spectroradiometer- (black diamonds), radiation- (blue dots), and  
697 MODIS-derived (red dots) red (A) and near-infrared (B) reflectances, and NDVI (C) and EVI2  
698 (D) from quality controlled 2008-2018 Imnaviat data.

699

700 **Figure 3:** Dependence of MODIS- and radiation- derived differences on solar zenith angle for  
701 red reflectance (A), near infrared reflectance (B), NDVI (C), and EVI2 (D) at Imnaviat.  
702 Regression lines indicate significant relationships at the 95% confidence level.

703

704 **Figure 4:** Dependence of MODIS- and radiation- derived differences on solar zenith angle for  
705 red reflectance (A), near infrared reflectance (B), NDVI (C), and EVI2 (D) from Fluxnet sites  
706 across biome types. Lines in panels C and D are only for statistically significant relationships at  
707 the 95% confidence level.

708

709 **Figure 5:** Dependence of ground based spectroradiometer broad- and narrow-band derived  
710 differences (i.e. broadband-narrowband) on solar zenith angle for red reflectance (A), near  
711 infrared reflectance (B), NDVI (C), and EVI2 (D) at Imnavia. Regression lines indicate  
712 significant relationships at the 95% confidence level.

713

714 **Figure 6:** The correction factor dependence on solar zenith angle for visible (solid dots) and near  
715 infrared (open dots) albedo. The inset plot shows seasonal changes in daily averaged solar zenith  
716 angle (solid line) and daily averaged azimuth angle (dotted line). The grey highlighted area  
717 denotes the growing season period at Imnavia.

718

719 **Figure 7:** Correspondence between radiation- and MODIS- derived red (A) and near infrared (B)  
720 reflectances, and NDVI (C) and EVI2 (D) at Imnavia. Grey dots are MODIS and uncorrected  
721 radiation derived reflectance and indices, whereas triangles are MODIS and radiation derived  
722 reflectance and indices that were corrected for solar position biases.

723

724 **Figure 8:** Average percent change in the Mean Absolute Error (MAE) between MODIS satellite-  
725 and radiation-derived NDVI (black bars) and EVI2 (grey bars) relative to the uncorrected values

726 at the Fluxnet sites. Fluxnet sites were grouped by ecosystem type, and error bars represent  
727 standard errors.

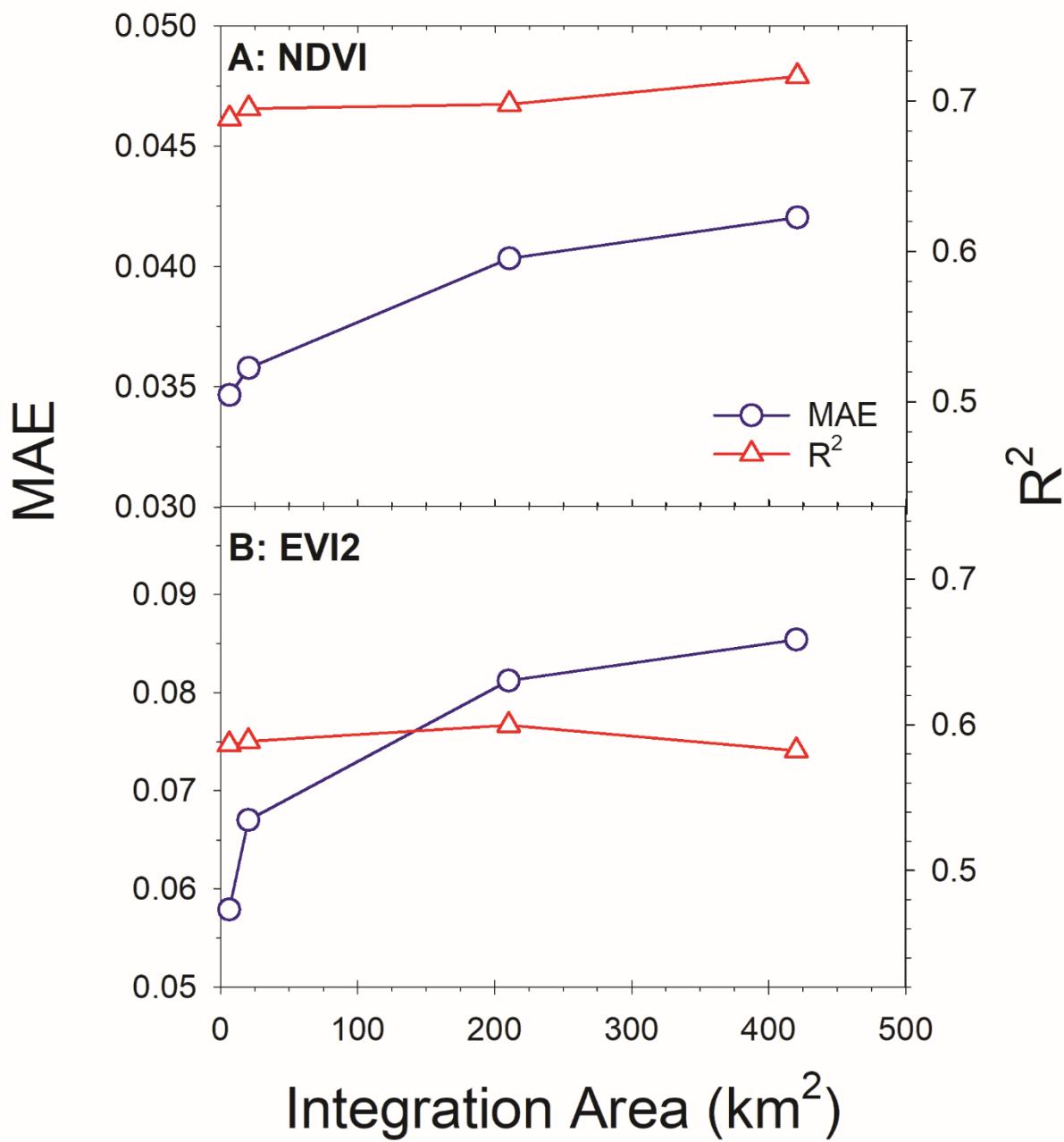
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729 **Figure 9:** Relationship between Imnaviat Gross Ecosystem Exchange (GEE) and solar position  
730 corrected (open triangles) and uncorrected (grey circles) radiation derived vegetation indices.  
731 NDVI-GEE relationships are in left panel (A), whereas EVI2-GEE are in right panel (B). The  
732 solid line represents the correlation between the solar position corrected vegetation index and  
733 GEE, whereas the dotted line represents the correlation between uncorrected vegetation indices  
734 and GEE. Hatched arrows in left panel represent the hysteresis in the relationship between  
735 uncorrected NDVI and GEE, while numbers represent the day of year of each observation.

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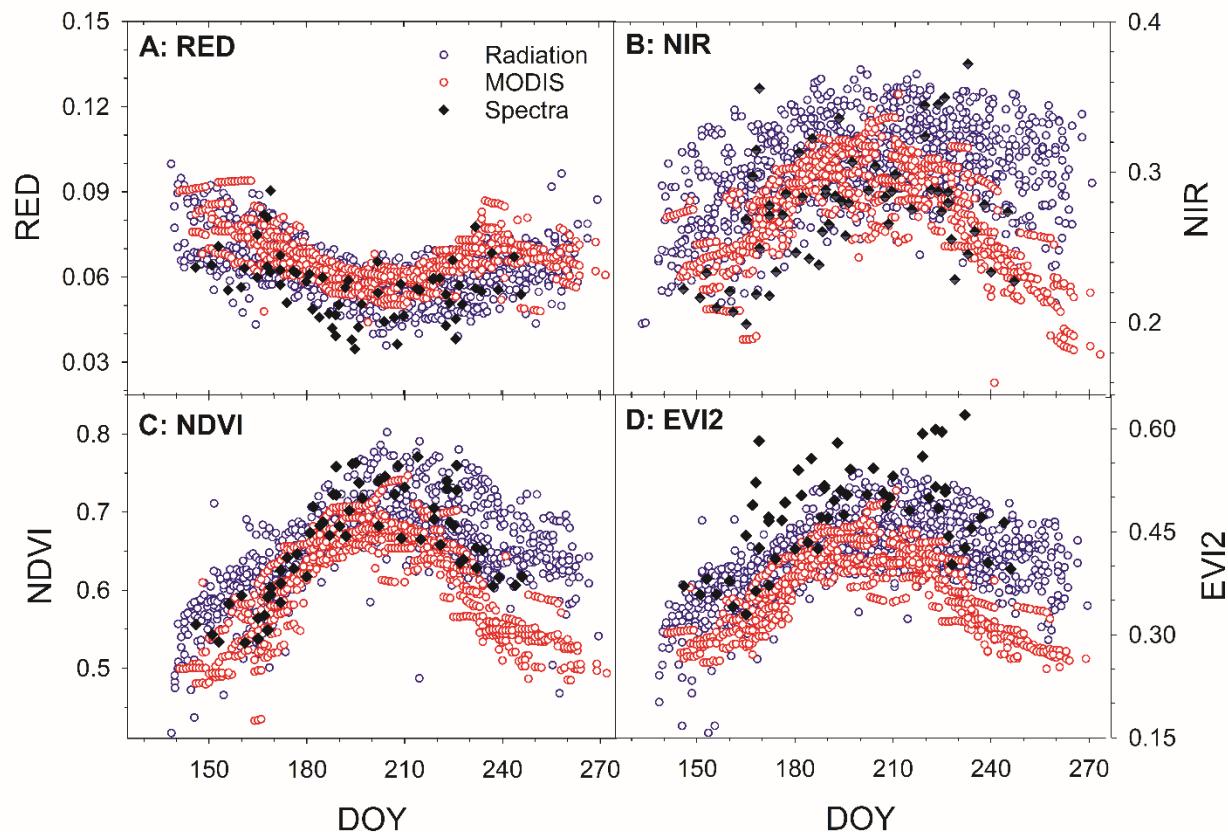
737 **Figure 10:** Mean Absolute Error (MAE) of the start-(SOS), length-(LOS), and end-(EOS) of the  
738 growing season derived from MODIS- (black bar), uncorrected radiation- (grey), and solar  
739 position corrected radiation- (dark grey) derived NDVI (A) and EVI2 (B) at Imnaviat.

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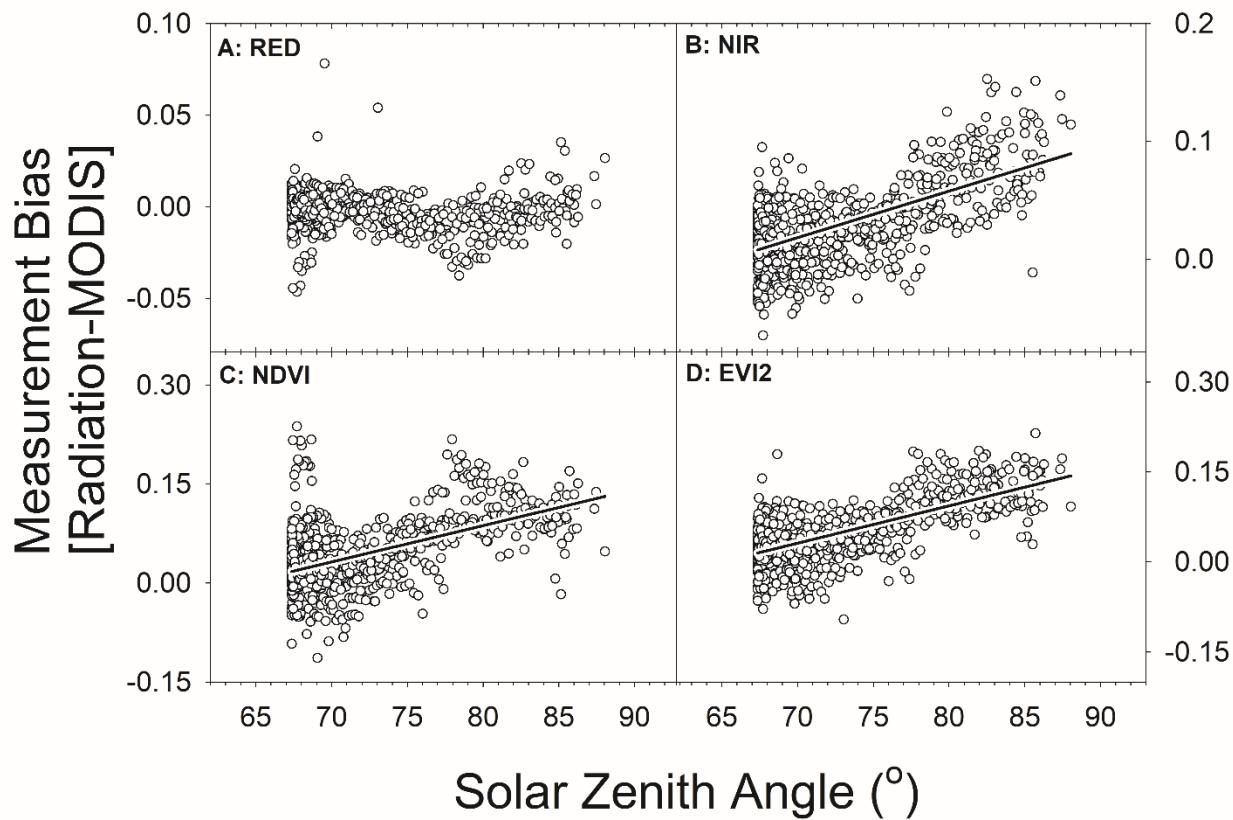
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763 **Figure 2.**

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785 **Figure 3.**

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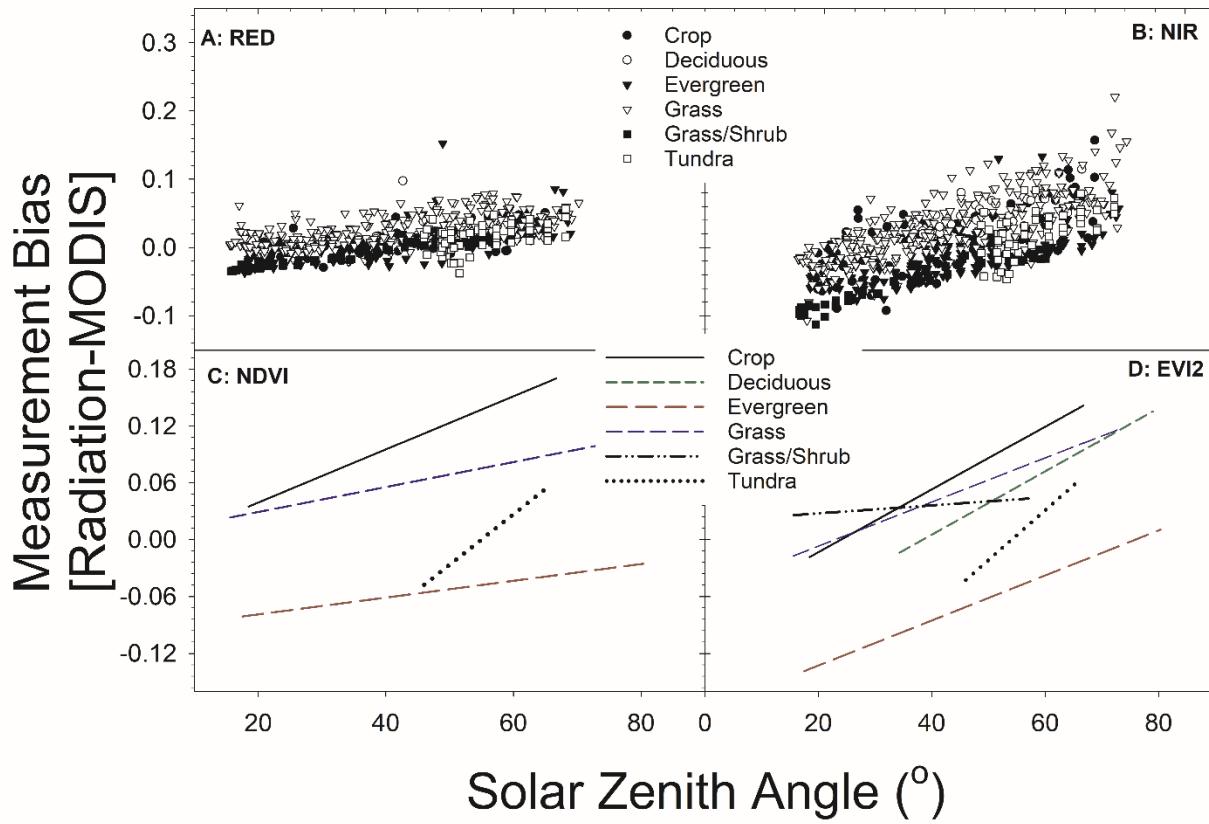
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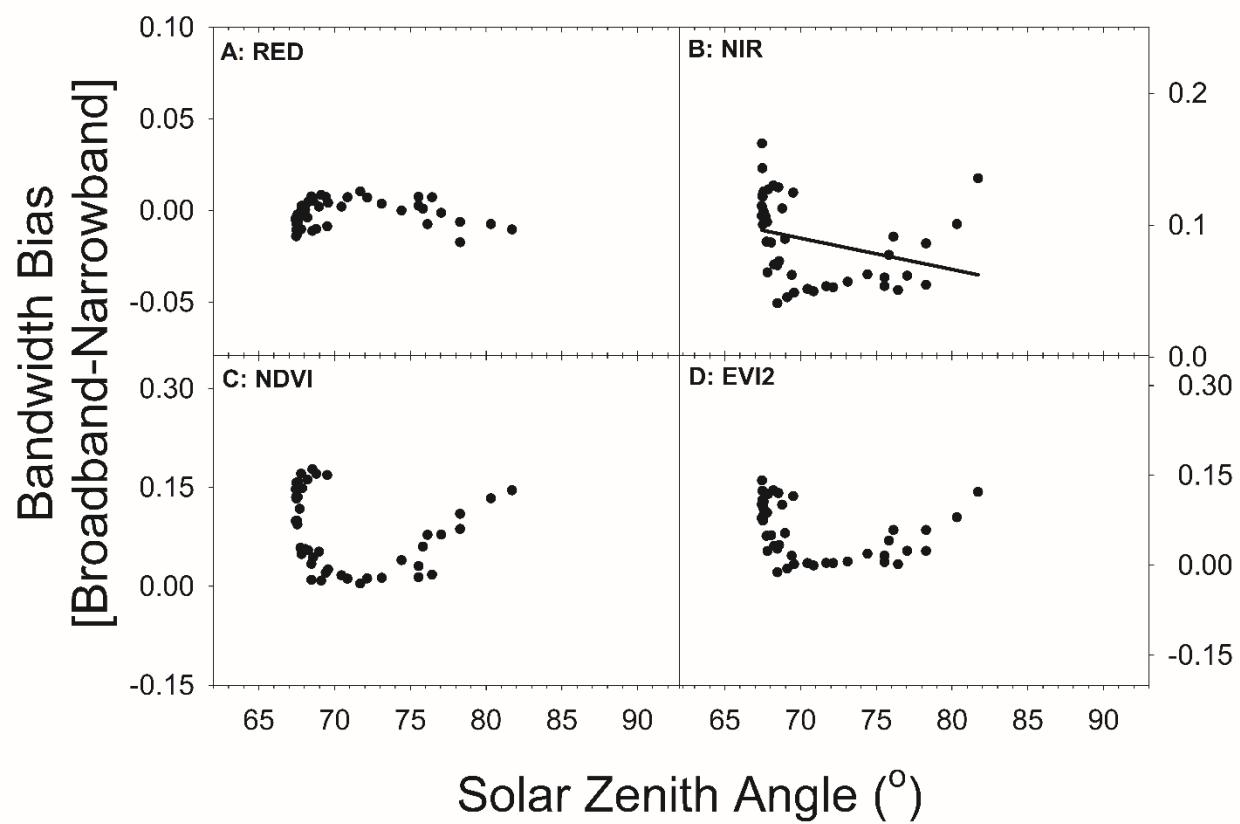


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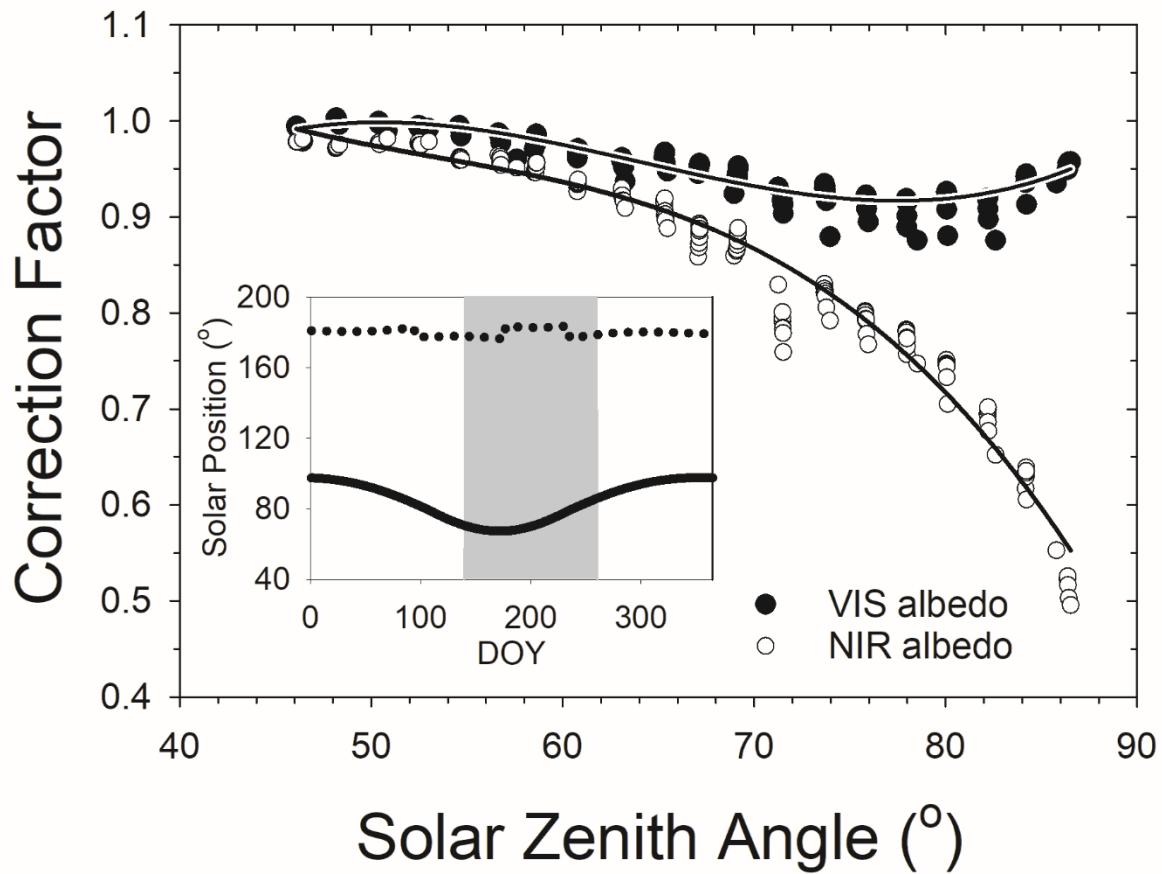
**Figure 4.**

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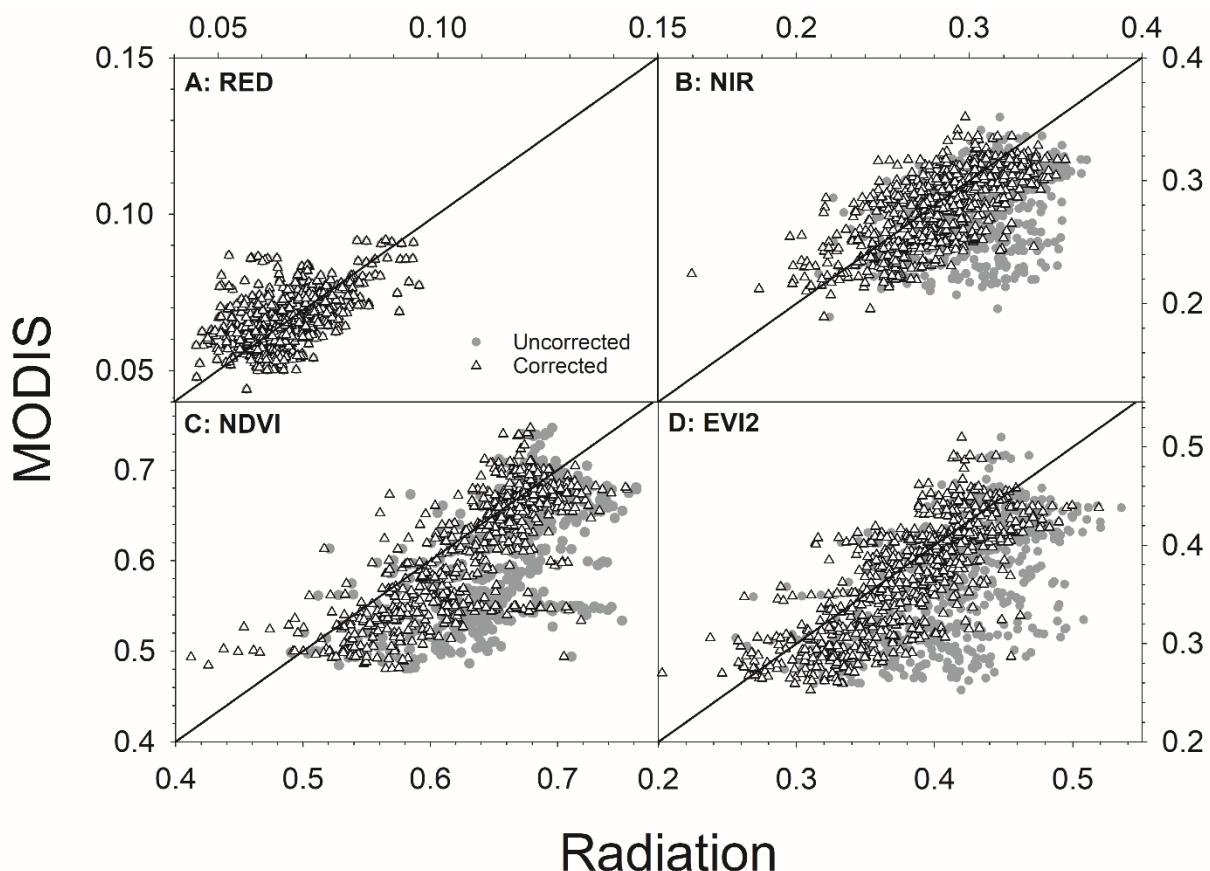
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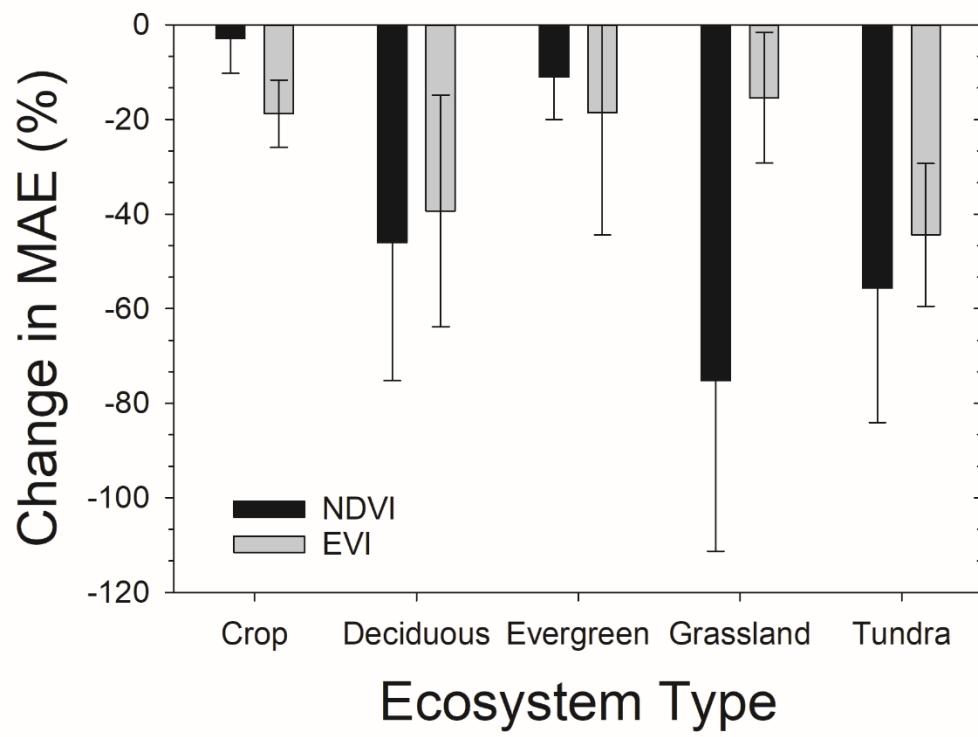
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836 **Figure 5.**  
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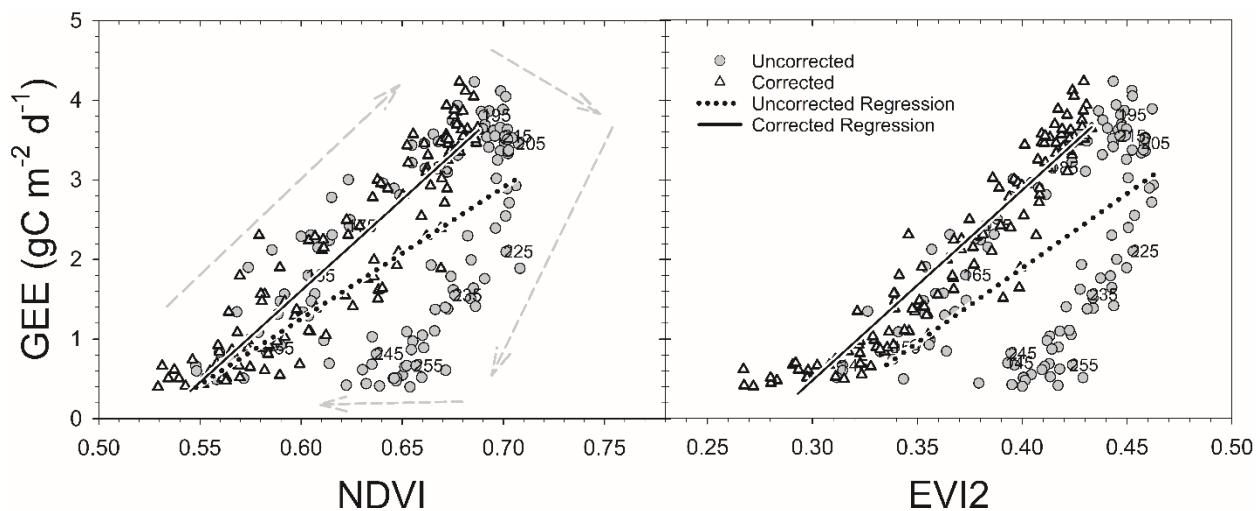
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845 **Figure 6.**  
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 866 **Figure 7.**  
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884 **Figure 8.**  
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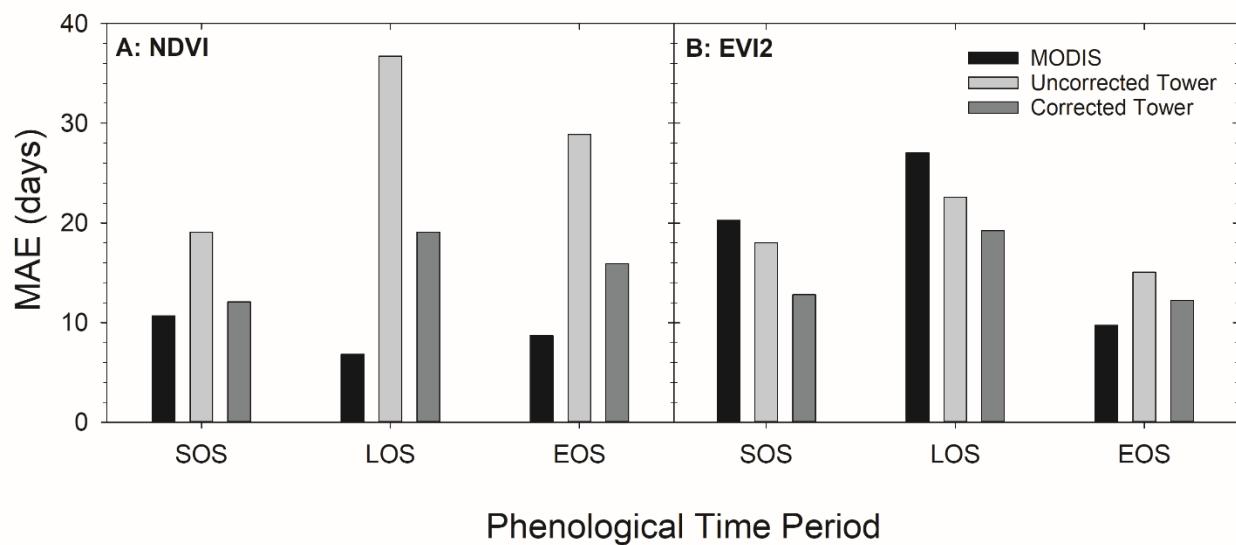


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**Figure 9.**

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**Figure 10.**

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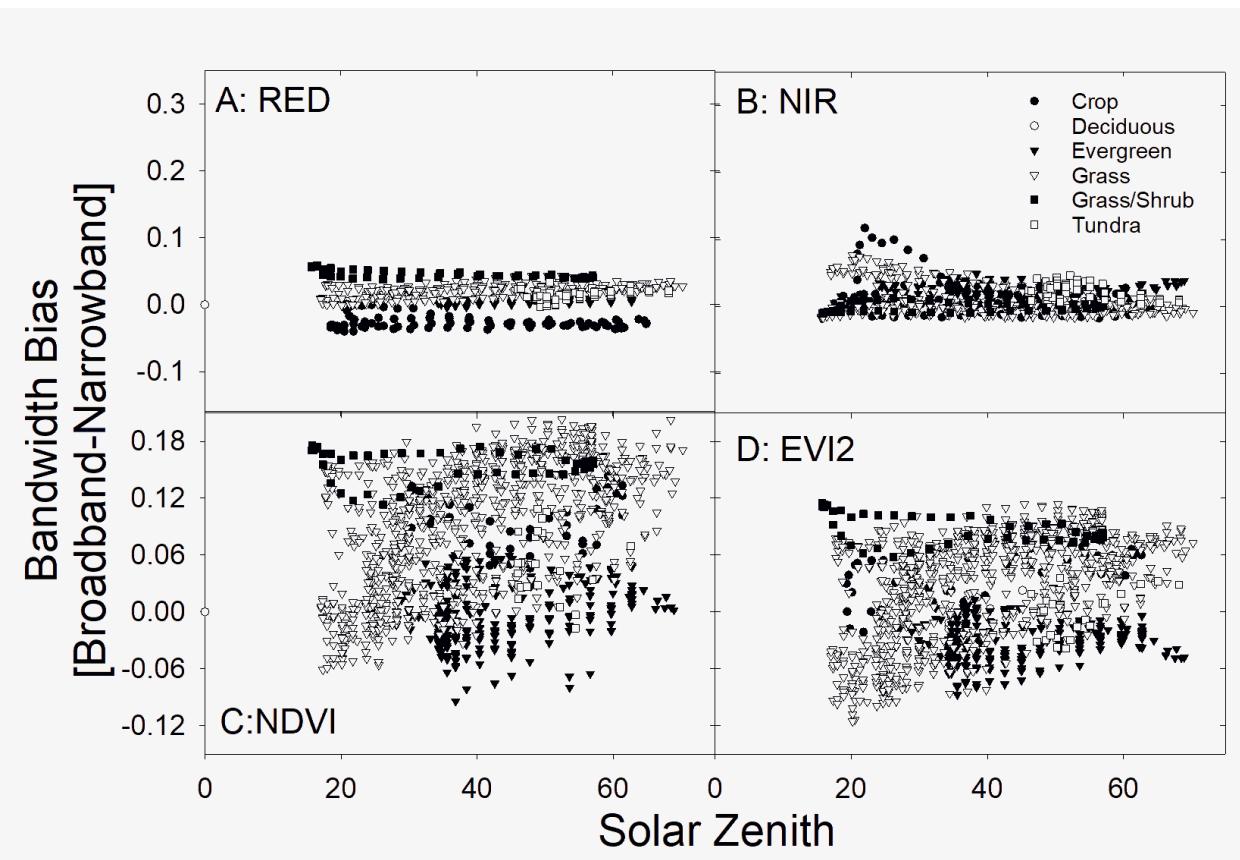
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**Supplement:**

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965 **Figure 1S:** Dependence of bandwidth biases (broadband-narrowband) derived differences on  
966 solar zenith angle for red reflectance (A), near infrared reflectance (B), NDVI (C), and EVI2 (D)  
967 from Fluxnet sites across biome types. Note that the y-axes are scaled to be the same as those  
968 observed in Figure 4.

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985 **Table 1S:** Summary statistics for bandwidth bias correlation with solar zenith angle in Figure  
986 1S. The number represents the  $R^2$  of the relationship, while the number in [brackets] represents  
987 the sensitivity to solar zenith angle measured as the slope of the line.

PFT	Red (R <sup>2</sup> [Slope])	NIR (R <sup>2</sup> [Slope])	NDVI (R <sup>2</sup> [Slope])	EVI2 (R <sup>2</sup> [Slope])
<i>Crop</i>	<b>0.06 [-0.0001]</b>	<b>0.09 [-0.0005]</b>	0.01 [0.0002]	<b>0.37 [-0.0007]</b>
<i>Deciduous</i>	<b>0.46 [-0.0003]</b>	<b>0.14 [-0.0006]</b>	0.03 [0.0003]	<b>0.52 [-0.0046]</b>
<i>Evergreen</i>	<b>0.06 [0.0001]</b>	<b>0.12 [0.0003]</b>	<b>0.06 [0.00093]</b>	0.02 [0.0003]
<i>Grass</i>	<b>0.62 [0.0002]</b>	<b>0.11 [-0.0006]</b>	<b>0.06 [0.0009]</b>	<b>0.29 [0.002]</b>
<i>Grass/Shrub</i>	<b>0.10 [0.0001]</b>	<b>0.08 [-0.0005]</b>	0.01 [0.0003]	<b>0.22 [-0.0005]</b>
<i>Tundra</i>	<b>0.16 [0.0005]</b>	<b>0.22 [-0.0008]</b>	0.01 [-0.0001]	<b>0.29 [0.002]</b>

988 \*Numbers in bold represent statistically significant relationships at the 95% Confidence level.

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