1   **Title**: Leaf surface water, not plant water stress, drives diurnal variation in tropical forest canopy

2   water content

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Summary:

- Variation in canopy water content (CWC) that can be detected from microwave remote sensing of vegetation optical depth (VOD) has been proposed as an important measure of vegetation water stress. However, the contribution of leaf surface water (LW_s), arising from dew formation and rainfall interception, to CWC is largely unknown, particularly in tropical forests and other high-humidity ecosystems.

- We compared the AMSR-E VOD and CWC predicted by a plant hydro-dynamics model at four tropical sites in Brazil spanning a rainfall gradient. We assessed how LW_s influenced the relationship between VOD and CWC.

- The analysis indicates that while CWC is strongly correlated with VOD (R^2=0.62 across all sites), LW_s accounts for 61-76% of the diurnal variation in CWC despite being less than 10% of CWC. Ignoring LW_s weakens the near-linear relationship between CWC and VOD and reduces the consistency in diurnal variation. The contribution of LW_s to CWC variation, however, decreases at longer, seasonal to interannual, time scales.

- Our results demonstrate that diurnal patterns of dew formation and rainfall interception can be an important driver of diurnal variation in CWC and VOD over tropical ecosystems and therefore should be accounted for when inferring plant diurnal water stress from VOD measurements.

Introduction

Climate change and the accompanying intensification of hydrological cycles are imposing strong and chronic stress on terrestrial ecosystems with higher atmospheric water demand and more frequent drought events (Novick *et al.*, 2016; McDowell *et al.*, 2018). Enhancing our understanding of vegetation water dynamics is therefore critical to predictions of ecosystem sensitivity to global change (Fatichi *et al.*, 2016; Schimel & Schneider, 2019). Recent work has shown that vegetation optical depth (VOD) estimated from microwave remote sensing observations is a reliable proxy for the canopy water content (CWC) and a promising source of data for monitoring and understanding vegetation water dynamics (Konings *et al.*, 2019; Feldman *et al.*, 2020). Changes in VOD can reflect vegetation diurnal water stress patterns (Konings & Gentine, 2017; Li *et al.*, 2017; Anderegg *et al.*, 2018; Zhang *et al.*, 2019), seasonality in plant water potential and leaf area (Guan *et al.*, 2014; Momen *et al.*, 2017), and vegetation biomass changes at longer time scales (Liu *et al.*, 2015; Fan *et al.*, 2019). However, accurate and robust interpretation of VOD variability remains challenging because of the complex physiological and biophysical processes impacting vegetation water dynamics at a wide range of time scales (Grossiord *et al.*, 2017). Variation in VOD can be driven by canopy water interception due to rainfall and dew formation, plant hydraulics, phenology, and structural changes from growth and mortality (Konings *et al.*, 2019). These challenges have hindered direct use of VOD in understanding vegetation water dynamics together with the limited availability of relevant ground measurements of vegetation hydrodynamics.

Spatio-temporal variation in VOD have mostly been linked to changes in leaf and wood internal water content (Jackson & Schmugge, 1991; Cosh *et al.*, 2010; Tian *et al.*, 2016), but theoretically they are also sensitive to surface water arising from dew formation and intercepted rainfall. While a previous study at a temperate agricultural site found relatively little effect of dew on airborne X-band (10.7 GHz) measurements (Du *et al.*, 2012), diurnal changes in leaf surface water were found to modulate tower-based VOD measurements collected at a similar microwave frequency (11.4 GHz) in a tropical canopy in Panama (Schneebeli *et al.*, 2011). This latter study was performed at the scale of a few meters, however, which may show sensitivities not detectable at the ecosystem-scales (Wigneron *et al.*, 2017).

75 At the ecosystem-scale, the contribution of leaf surface water to VOD signals remains largely

76 unknown despite leaf surface water being an important component of the moisture budget,

77 particularly in rainforest ecosystems where significant diurnal and seasonal variation in CWC

78 occurs because of frequent rainfall interception and dew formation (Junqueira Junior *et al.*, 2019;

79 Binks *et al.*, 2020) and where measurements of leaf surface water beyond qualitative leaf

80 wetness data (Binks et al. 2019) do not exist. Therefore, ignoring the contribution of leaf surface

81 water to VOD can lead to overestimation of changes in leaf internal water, which potentially

82 biases the interpretation of VOD data as a measure of vegetation water stress. On the other hand,

83 the ability to separate leaf surface water from canopy water content in VOD data may provide

84 additional information about plant water dynamics. Through its effects on stomatal conductance,

85 leaf surface water influences key aspects of plant metabolism including carbon assimilation

86 (Aparecido *et al.*, 2017; Gerlein-Safdi *et al.*, 2018a,b) and support several important, yet

87 relatively unknown, eco-physiological processes such as leaf foliar water uptake (Eller *et al.*,

88 2013; Binks *et al.*, 2019) and epiphyte water use and survival (Lakatos *et al.*, 2012).

89 Recent advances in mechanistic representation of plant hydrodynamics in terrestrial biosphere

90 models (Mencuccini *et al.*, 2019) provide a new avenue for to interpreting VOD data: these

91 models are now capable of explicit simulation of CWC dynamics from a set of biophysical

92 descriptions and field-based plant functional traits. In turn, VOD data can provide valuable

93 ecosystem scale evaluation data to hydrodynamic models, which are usually benchmarked by

94 individual-level plant hydraulic measurements within forest plots (Xu *et al.*, 2016; Christoffersen

95 *et al.*, 2016; Kennedy *et al.*, 2019; De Kauwe *et al.*, 2020). However, no studies to date have

96 compared simulated CWC from terrestrial biosphere models with satellite VOD data.

97 In this study, we compare terrestrial biosphere model predictions of CWC and satellite VOD, and

98 quantify the contribution of leaf surface water to VOD variation across diurnal to seasonal and

99 inter-annual time scales. Specifically, we hypothesize:

100   (H1) CWC, summed over the representative penetration depth of VOD observations,

101 scales linearly with VOD.

102   (H2) The contribution of leaf surface water to VOD is higher than leaf and wood internal

103 water at diurnal time scale because leaf surface water usually accumulates at night and

104   evaporates during the day while VOD at longer time scales is more likely controlled by changes

105   in plant water stress and canopy biomass.

106   (H3)   The contribution of leaf surface water to VOD is higher at moist sites than at dry

107   sites because there is more rainfall interception and dew formation under humid conditions.

108   To evaluate these hypotheses, we compare VOD data derived from X-band (10.7 GHz)

109   measurements by the Advanced Microwave Scanning Radiometer for EOS (AMSR-E) (Du *et al.*,

110   2017b) to predictions of CWC from a terrestrial biosphere model incorporating plant

111   hydrodynamics, at four tropical forest and savannah sites in Brazil across a large rainfall

112   gradient. AMSR-E VOD has relatively long temporal coverage (full annual cycles from 2003 to

113   2010) and local bypassing times at 1:30AM and 1:30PM that can reasonably capture diurnal

114   changes (Konings & Gentine, 2017; Li *et al.*, 2017) in addition to seasonal and inter-annual

115   variation in CWC. The terrestrial biosphere model used in the study is the Ecosystem

116   Demography version 2 (ED2). It is an ideal model platform to evaluate the relationship between

117   canopy water content and leaf surface water with VOD because the model explicitly incorporates

118   plant hydraulics and leaf energy budget (Xu *et al.*, 2016; Longo *et al.*, 2019) enabling it to

119   simulate the dynamics of all of leaf surface water, leaf internal water, and wood internal water,

120   as well as their vertical and horizontal heterogeneity within canopy.

121   **Materials and Methods**

122   *Model description*

123   ED2 (Medvigy *et al.*, 2009) is an individual-based terrestrial biosphere model that represents the

124   dynamics of structurally and functionally-diverse plant canopies. The recent version of the model

125   (ED-2.2, Longo *et al.*, 2019) has explicit representation of the leaf water and energy budget at

126   sub-hourly resolution for each plant cohort, which allows for explicit simulation of leaf surface

127   water following straightforward thermodynamic laws (Gerlein-Safdi *et al.*, 2018b). The model

128   calculates changes of leaf surface water for each plant cohort as the balance of dew formation,

129   evaporation, rainfall interception, and water shedding if total leaf surface water exceeds

130   maximum retention capacity. Detailed description of the water fluxes that contribute to dynamics

131   of leaf surface water in the model can be found in **SI Notes 1**.

132   ED2 is also one of the first models to couple trait-based plant hydraulics with explicit

133   demography-based vegetation dynamics (Xu *et al.*, 2016). The hydraulics-enabled version (ED2-

134   hydro) separates plant internal water pools into leaf and stem water pools at the cohort-level, and

135   estimates sub-hourly water exchanges between these two pools using water potential gradient

136   and cohort-specific stem water conductance following Darcy's law. The integration of plant

137   hydraulics with stomatal conductance and rhizosphere water uptake enables cohort-level

138   simulation of the dynamics of plant internal water content (see **SI Notes 1** for details). ED2-

139   hydro has been calibrated and evaluated in several neotropical forests across a large precipitation

140   gradient (Xu *et al.*, 2016; Powell *et al.*, 2017, 2018).

141   In this study, we used the functionality of ED-2.2-hydro to conduct mechanistic simulations of

142   all major components of vegetation CWC. We updated key plant hydraulic parameters for

143   tropical plant functional types (PFTs) based on a meta-analysis over tropical species

144   (Christoffersen *et al.*, 2016) to incorporate the effects of plant functional diversity. Since vertical

145   structure of vegetation biomass can influence interpretation of VOD data due to the limited

146   penetration depth of microwave signals (Chaparro *et al.*, 2019), we also made several model

147   updates in allometry, trait phenoplasticity, and mortality to improve simulated vegetation

148   structure in tropical forests (details in **SI Notes S1**). The model parameterization used in this

149   study are archived at https://github.com/xiangtaoxu/ED2/tree/VOD.

Model configuration and simulation setup

151   We conducted simulations for two tropical moist forests (Manaus K34 and Reserva Jaru) that

152   both receive more than 2000 mm yr^{-1} mean annual rainfall and two tropical savannah sites

153   (Brasília and Pé-de-Gigante) that both receive less than 1500 mm yr^{-1} mean annual rainfall

154   (**Table 1**). These sites were selected based on the quality of AMSR-E VOD data available for

155   these locations (in particular, minimal contamination from nearby rivers or other large water

156   bodies), and the availability of in-situ meteorological data (Brasília: SONDA-INPE (2020); other

157   sites: de Gonçalves *et al* (2013)).

158   The available site-level meteorological data necessary to drive the biosphere model simulations

159   (incoming shortwave and longwave radiation, temperature, humidity, pressure, precipitation, and

160   wind speed), however, the available does not encompass the full length of AMSR-E VOD time

161   series (2003-2010). We therefore integrated the in-situ meteorological data with climate

162   reanalysis data from Modern-Era Retrospective analysis for Research and Applications, Version

163   2 (MERRA2) (Gelaro *et al.*, 2017). To avoid the known biases in MERRA2 precipitation over

164   tropical regions (Beck *et al.*, 2019), we used precipitation data from Climate Hazards Group

165   InfraRed Precipitation with Station data (CHIRPS) (Funk *et al.*, 2015). To minimize the

166   systematic biases in the reanalysis meteorology relative to local climate, and preserve monthly

167   values, we calculated the difference between the monthly average of the reanalysis data and in-

168   situ data for each variable over the years when in-situ data is available. The dates of the in-situ

169   data range from 1999 to 2012 depending on the site (see **Table 1** for details). We then applied

170   the difference to modify the whole reanalysis time series to get the meteorological forcing (**Fig.**

171   **S1**). The difference for precipitation is in logarithm space so that no rainfall was added to dry

172   days when we applied the difference.

173   Simulations at each site consisted of a 400-year model spin-up to attain steady state vegetation

174   structure and composition followed by a 30-year contemporary simulation (1981 to 2010)

175   encompassing the AMSR-E measurements. For the spin-up simulation, we initialized the model

176   with a small number of seedlings (0.1 individuals per m^2) of all four PFTs and ran the model

177   with a cycling meteorological forcing from 1981 to 2000. Following up the spin-up simulations,

178   we ran the model forced by meteorology from 1981 to 2010. For both sets of simulations, we

179   used a constant rate of 1% of forest area experiencing windthrow disturbance (i.e 0.01 ha ha^{-1} yr^{-}

180   ^{1}) and a constant atmospheric CO_2 at 380 ppm.

181   *VOD retrievals*

182   We used X-band (10.7 GHz) VOD retrieved from observations of the Japanese Aerospace

183   Exploration Agency (JAXA) Advanced Microwave Scanning Radiometer for EOS (AMSR-E)

184   instrument. Specifically, the VOD data were those retrieved by the Land Parameter Data Record

185   (LPDR) version 2 (Du *et al.*, 2017a,b). The LPDR uses a multi-step procedure to disentangle the

186   contributions of VOD, vegetation scattering, soil moisture, temperature, atmospheric humidity,

187   and open water bodies to the observed radiometric brightness temperatures (Jones *et al.*, 2010).

188   Although the Amazon rainforest remains among the most challenging ecosystems for accurate

189   VOD retrieval due to the large heterogeneity in canopy structure and the associated biophysical

190   properties, interpretation of microwave radiometry has proven feasible even in highly complex

191   canopies: for example, Calvet *et al* (1994) used a site-specific model to determine the

192   relationship between Ka-band radiometry and stomatal resistance at Manaus. Nevertheless, the

193   VOD retrievals are expected to be more accurate at the savannah sites than at the densely

194   forested sites.

195   *Model evaluation and comparison with VOD*

196   We first evaluated the terrestrial biosphere model's predictions of vegetation structure and plant

197   hydraulics because both of these characteristics directly affect CWC. We compared the

198   simulated vertical profiles of leaf area index (LAI) with LAI profiles derived from the

199   Geoscience Laser Altimeter System (GLAS) aboard the Ice, Cloud, and the Elevation Satellite

200   (ICESat). GLAS data has previously been shown to capture variation in tropical forest structure

201   (Tang & Dubayah, 2017; Yang *et al.*, 2018). Site-specific average LAI profiles were calculated

202   from GLAS measurements collected between 2003 to 2008 (Zwally *et al.*, 2014) within a 50 km

203   grid box centered around each study site. The LAI profiles were derived from GLAS waveforms

204   using a light-extinction model based on the MacArthur and Horn (1969) approach (Ni-Meister *et*

205   *al.*, 2001; Tang *et al.*, 2014). We extracted simulated average LAI profiles using model outputs

206   from the same period of time for comparison. Both the GLAS and simulated LAI profiles are

207   aggregated to a vertical resolution of 5 meters. LAI can show large seasonal changes especially

208   in the two savannah sites. Therefore, we also compared the average seasonality of total LAI with

209   Moderate Resolution Imaging Spectroradiometer (MODIS) LAI (Didan, 2015).

210   Unlike vegetation structure, there are no high-resolution and long-term measurements of plant

211   hydraulic properties (e.g. leaf water potential) over tropical forests. Limited field measurements

212   suggest leaf water potential for tropical canopy trees normally varies between 0 and -1 MPa

213   within a day at moist sites (Fontes *et al.*, 2018) and can drop below -2 MPa at seasonally dry

214   forest (Wu *et al.*, 2020) and cerrado sites (Bucci *et al.*, 2005). We therefore tested whether the

215   simulated diurnal variation showed a similar range of variation.

216   For leaf surface water, there are no direct measurements on its diurnal and seasonal cycles in the

217   tropics to the best of our knowledge. Limited measurements report predawn values for top

218   canopy leaves ranging from 0.02 to 0.11 kg H_2O m^{-2} leaf in a tropical moist forest at Caxiuanã

219   (personal communication with O. Binks) and from 0.02 to 0.08 kg H_2O m^2 leaf for five species

220   in a tropical moist forest in Costa Rica (Aparecido *et al.*, 2017). Our simulated leaf surface water

221   at predawn (6:00AM) in top canopy leaves showed a consistent range at a similarly wet forest

222   site and predicted top canopy leaves are frequently (>70% of days with leaf surface water

223   exceeding half of the saturated surface water retention) wet at predawn (**Fig. S2**), which is close

224   to a recent report of top canopy leaves being wet for 50-70% of the time at Caxiuanã using leaf

225   wetness sensors (Binks *et al.*, 2020). Altogether, these consistencies suggest the model

226   predictions on leaf surface water dynamics are realistic.

227   Following the model evaluation, we used daily AMSR-E VOD data at both 1:30AM and

228   1:30PM, and extracted the hourly average values of simulated leaf surface water (LW_s), leaf

229   internal water (LW_i), and wood internal water (WW_i), the three components of CWC in ED-2.2-

230   hydro, at the same time of VOD observations. Although the AMSR-E record partially extends to

231   2002 and 2011, we only included 2003-2010 to ensure an equal number of datapoints across

232   seasons. We averaged both VOD and simulated CWC values into bi-weekly values to reduce

233   high-frequency variation and noise in VOD (Konings *et al.*, 2016). In forests, X-band VOD is

234   mostly sensitive to top canopy layers due to its high electromagnetic frequency (Macelloni *et al.*,

235   2001; Guglielmetti *et al.*, 2007). The depth at which significant canopy attenuation occurs,

236   commonly referred to as the penetration depth, depends on both canopy structure and water

237   status, and thus is variable in both space and in time. Spatial and temporal variation in

238   penetration depth is generally not accounted for in retrieval algorithms (Konings *et al.*, 2016; Du

239   *et al.*, 2017b). Recently, Chaparro et al (2019) showed that X-band VOD values saturate when

240   aboveground biomass (AGB) is higher than 1 kgC m^{-2}. Therefore, we chose a conservative

241   average penetration depth by only including LW_s, LW_i, and WW_i for the top 1 kgC m^{-2} of

242   biomass (leaf and wood, which corresponds to 2-10 meters depending on forest biomass vertical

243   profiles) for each forest patch within site-level simulation results (**Fig. S3**) when comparing

244   simulated CWC and AMSR-E VOD. Additionally, we also evaluated how VOD and CWC

245   relationships vary with different assumptions of penetration depth.

246   We conducted analyses using the corresponding VOD data and CWC simulations across diurnal

247   and bi-weekly time scales. First, we extracted the predicted diurnal cycle of LW_s, LW_i, and WW_i

248   to investigate the roles of each water pool in determining CWC dynamics that emerge from ED-

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249   2.2-hydro. Specifically, we derived the contribution of LW_s, LW_i, and WW_i to the variations in

250   total CWC from the model at both diurnal and biweekly time scales by calculating the fractional

251   contributions of each sub-component variance to the total CWC variance. For the diurnal-scale

252   analysis, we calculated the long-term average LW_s, LW_i, and WW_i at both 1:30AM and 1:30PM.

253   Since there are only two observations within each diurnal cycle, we quantified the variance as the

254   value difference between 1:30AM and 1:30PM. For the biweekly-scale analysis, we calculated

255   the variance of the mean of 1:30AM and 1:30PM for each biweekly (14 day) period.

256   Second, we compared the VOD measurements and CWC and assessed the role of leaf surface

257   water in their relationships. To test our first hypothesis on the scaling between VOD and CWC

258   (H1), we quantified the linear relationship between VOD and CWC using ordinary least squares

259   (OLS) regression for each site and all sites combined. To test our second and third hypothesis on

260   the contribution of leaf surface water to CWC and VOD dynamics and its variation across sites

261   (H2 and H3), we compared VOD and two metrics of CWC: (1) CWC_{int} that only includes the

262   internal water content of leaf and wood; and (2) CWC_{all} that includes both leaf and wood internal

263   water and leaf surface water.

264   Specifically, we assessed the cross-site variation in isohydricity index, a widely-used metric to

265   describe the diurnal behavior of plant water use (Martínez-Vilalta *et al.*, 2014; Konings &

266   Gentine, 2017). This metric (σ) is calculated from the following regression equation:

267    $$X_{1:30PM} = \sigma \times X_{1:30AM} + \Lambda, \qquad \text{(eq 1)}$$

268   where σ is the isohydricity index, Λ is the regression intercept, and X is a state variable

269   describing canopy water status. Low σ implies vegetation is more isohydric because daytime

270   water status is relatively insensitively to nighttime water status due to stomatal control while

271   higher σ implies vegetation is more anisohydric. We calculated σ values for observed VOD,

272   simulated CWC, and leaf water potential to investigate whether and how VOD-based

273   isohydricity (generally assumed to reflect leaf internal water stress) is affected by leaf surface

274   water dynamics.

275   We then contrasted the average seasonality and deseasonalized multi-year variation of VOD and

276   simulated CWC for each study site in terms of (1) absolute values at 1:30AM and (2) relative

277   diurnal range ($100\% - X_{1:30PM} / X_{1:30AM} \times 100\%$). Together with variance decomposition of the

278   simulated CWC, the evaluation of these two metrics enables quantification of the impacts of leaf

279   and wood water content and leaf surface water on VOD.

280   **Results**

281   *Predictions of vegetation structure and plant water potentials*

282   The long-term equilibrium simulations of the terrestrial biosphere model at the four evaluation

283   sites yielded LAI profiles that were generally consistent with GLAS estimates for each site (**Fig.**

284   **1a-d**). Individual-level competition in the model led to a general demographic size structure of a

285   few big trees and many small trees, yielding decreasing leaf area density (LAD) from forest

286   understory to canopy top that largely fall into the uncertainty of lidar-based estimates. At the two

287   forest sites (M34 and RJA), top canopy height reached 35-40 meters while LAD became very

288   small (<0.01 m2/m3) above 20 meters at the two savannah sites (PDG and BSB). However, the

289   model tended to overestimate the total LAI at the sites by 0.3-0.5 $m^2 \ m^{-2}$ (**Fig. 1a-d**), with the

290   excess LAI arising mainly from overestimates of LAD in upper canopy layers. The model

291   simulations also tended to underestimate LAD in the lowest (<5m) canopy layer at the two forest

292   sites.

293   Seasonal changes of predawn leaf water potential govern the seasonal dynamics of canopy leaf

294   phenology the model. As a result, seasonality of total leaf area was minimal at M34 where total

295   rainfall is high and rainfall seasonality is mild. There were slight decreases of LAI at RJA (~0.2

296    $m^2 \ m^{-2}$), and larger (0.5-1 $m^2 \ m^{-2}$) decreases at PDG and BSB toward the end of the dry season

297   (**Fig. 1e-f**). MODIS LAI exhibited qualitatively similar patterns of LAI seasonality between the

298   wet and dry sites. However, at M34, the MODIS LAI estimates exhibit increases in LAI during

299   the wet season, and earlier onset of leaf shedding around the start of dry season at PDG and BSB,

300   compared to the model simulations. Overall, ED-2.2-hydro generated canopy vertical structure

301   and increasing seasonal magnitude in canopy phenology from wet sites to dry sites, which are

302   largely consistent with remote sensing observations.

303   The biosphere model simulations imply significant spatio-temporal variation in leaf water

304   potential (Ψ_{leaf}) across all four sites (**Fig. 2**). For upper canopy leaves, the average maximum

305   Ψ_{leaf} was close to zero for wet sites and for the wet season at dry sites (**Fig. 2e-f**), implying a full

306   recharge of daytime water loss in the model. In the dry season at PDG and BSB, maximum

307   Ψ_{leaf} dropped below -1 MPa, triggering leaf shedding. The daily minimum Ψ_{leaf} of canopy leaves

308   were generally 1-1.5 MPa lower than maximum values depending on moisture supply. These

309   average patterns in leaf hydrodynamics are consistent with observed variation in leaf water

310   potentials over tropical forests (Bucci *et al.*, 2005; Fontes *et al.*, 2018; Wu *et al.*, 2020). Wood

311   water potential at the base of stems (Ψ_{stem}) had similar diurnal cycles and seasonality as Ψ_{leaf}

312   (**Fig. S4**). However, the simulated Ψ_{stem} was always close to zero at M34, the wettest site in our

313   study (**Fig. S4a**), whereas at the two drier sites ψ_{stem} showed reduced diurnal variation during the

314   wet season (**Fig. S4c-d**), but similar seasonal variation as Ψ_{leaf}.

315   While observations of diurnal and seasonal variation in plant water potential were not available,

316   the model's predictions of evapotranspiration (ET) matched observed patterns of ET seasonality

317   that were available from flux tower measurements at M34, RJA, and PDG (**Fig. S5**), providing

318   additional support for the model's ability to capture key characteristics of vegetation

319   hydrodynamics in our study sites.

320   *Spatio-temporal variation in simulated CWC and VOD observations*

321   The model simulations indicate that LW_s dominates the diurnal cycles of CWC, despite being

322   less than 10% of total CWC of upper canopy layers on average (**Fig. 3**). Generally, LW_s

323   accumulated from late afternoon, reached peak values in early morning, then declined to near

324   zero by midday. In contrast, LW_i varied by only 10-15% within a day and WW_i had even smaller

325   diurnal variation (**Fig. 3a-d**). As a result, LW_s showed substantial contribution to CWC diurnal

326   variability (**Fig. 3e-h**), accounting for 76% of CWC differences between 1:30AM and 1:30PM at

327   M34 (wettest site) and 61% at BSB (driest site). LW_i generally accounted for more of the

328   remaining CWC diurnal variances than WW_i. At the biweekly timescale, the contribution of LW_s

329   was considerably lower (18%-36% for RJA, PDG, and BSB), except for M34 where LW_s still

330   drove seasonal and inter-annual variations in the simulated CWC. In addition, at this time scale,

331   WW_i became the dominant driver of CWC variation except for the wettest site (M34). Increasing

332   the penetration depth to $10\,\text{kgC m}^{-2}$ of AGB did not qualitatively change these general cross-site

333 and cross-time-scale patterns; it did however, increase the contribution of wood internal water

334 pools to patterns of diurnal and seasonal patterns of CWC variability (**Fig. S6**).

335 We found a strong linear relationship between VOD and simulated CWC_{all} (top 1 kgC m^{-2} of

336 AGB) with an R^2 of 0.62 (**Fig. 4a**). The relationship remained significant at site-level, but the

337 regression R^2 and slopes varied: simulated CWC_{all} explained less than 20% of variance in VOD

338 at the two moist forest sites M34 and RJA, but accounted for about 50% of variance at the two

339 savannah sites PDG and BSB (**Fig, 4c,d**). At the same time, the sensitivity of VOD to CWC_{all}

340 (indicated by the slope of the VOD regressed against CWC_{all}) increased by approximately 300%

341 from the wettest site (M34; slope = 0.55) to the driest site (BSB; slope = 2.15), whereas the

342 regression slope of data from all sites combined fell in-between these values (slope = 0.86). The

343 relationship between CWC_{int} (CWC excluding leaf surface water) and VOD was weaker (R^2 =

344 0.60 for all data combined) and the site-specific R^2 values declined by 5-10% for M34, BSB, and

345 PDG while RJA showed little change (**Fig. 4b,c**). The site-specific regression slopes of the

346 VOD-CWC_{int} relationship all steepened due to increasing nonlinearity of the relationship while

347 the cross-site variations did not change much (**Fig. 4b**). As a result, the VOD-CWC_{int} regression

348 slope using data from all sites combined (0.96, black line in **Fig. 4**) became lower than site-

349 specific regression slopes (1.2 – 2.8, colored lines in **Fig. 4**). Using a much deeper penetration

350 depth that included the top 10 kgC m^{-2} of AGB yielded similarly high R^2 values (0.61 for both

351 CWC_{all} and CWC_{int}), but the R^2 values were far lower (<10%) for the two moist forest sites, and

352 the cross-site regression slope was much lower than all site-level regression slopes regardless of

353 whether or not LW_s was included (**Fig. S7**). Overall, the model predictions of CWC that includes

354 all forms of canopy water showed robust linear relationships with VOD, but the relationships

355 were stronger at drier sites and across sites along a rainfall gradient.

356 We calculated isohydricity (σ) values from the variability in biweekly VOD estimates and

357 calculated a similar metric from model simulations of bi-weekly variability in CWC_{all}, CWC_{int},

358 and canopy leaf water potential (Ψ). The VOD estimates of isohydricity were comparable to the

359 values estimated by Konings & Gentine, (2017) and Li *et al.*, (2017) from daily VOD

360 observations. As seen in **Fig. 5a-d**, the VOD-based σ was low at the two wet sites (0.44 for M34

361 and 0.59 for RJA respectively) and higher at two dry sites (0.71 for PDG and 0.72 for BSB

362 respectively). The largest difference between VOD-based and model-based isohydricity occurred

363 at M34, where the simulated isohydricity was considerably lower than the VOD-derived estimate

364 (σ =0.18 and 0.44 respectively; see **Fig. 5a,e**). However, the isohydricity values from the model

365 predictions of CWC_{all} and VOD observations were very close at the other three sites (**Fig. 5b-**

366 **d,f-h**) implying that upper canopy CWC_{all} reliably captures the cross-site variations in σ. In

367 contrast, dynamics of CWC_{int} and Ψ implied almost perfect to extreme anisohydric behavior

368 across all sites with σ values very close to or larger than one (**Fig. 5i-p**), highlighting the

369 significant contribution of LW_s to the diurnal variation in simulated CWC, and, by inference, to

370 VOD measures of isohydricity.

371 We also compared the average seasonality of simulated CWC and observed VOD with respect to

372 both their values at 1:30AM and their diurnal ranges (**Fig. 6**). At the two moist forest sites,

373 1:30AM VOD showed seasonal patterns that peaked in the middle of the dry season with a

374 seasonal amplitude of ~10% at M34 and 20% at RJA (black lines in **Fig. 6,** panels **a** and **b,**

375 respectively). Simulated CWC_{all} did not reproduce these patterns, however, showing minimal

376 seasonality at M34 and a small and short decline in late dry season at RJA (green lines in **Fig. 6,**

377 panels **a** and **b,** respectively). At the two savannah sites, 1:30AM VOD showed 20-25% seasonal

378 variations, peaking in the late wet season, and reaching its lowest values in the late dry season

379 (black lines in **Fig. 6,** panels **c** and **d** respectively). The simulated 1:30AM CWC_{all} showed

380 similar seasonal patterns and amplitude (green lines in **Fig. 6c and d** respectively). As a result,

381 the correlation between VOD and simulated CWC_{all} increased from around zero at wet sites to

382 ~0.8 at the dry sites. Interestingly, CWC_{int}, which excludes the highly seasonal (vary by 30%-

383 100%) LW_s that follows the seasonality of rainfall (**Fig. S8a-d**), exhibited a stronger correlation

384 with VOD seasonality particularly at the two wet sites (Pearson's r increased from ~0 to 0.4-0.5),

385 but with a reduction of seasonal amplitude by 5-10% at all sites.

386 The comparison of the seasonality in the diurnal range showed similar patterns with the model-

387 data correlation increasing from wetter sites to drier sites (**Fig. 6e-h**). However, the contribution

388 of LW_s was more prominent at the two drier (savannah sites) despite that diurnal range in LWs

389 increased from 70-80% in wet season to ~100% at all sites (**Fig. S8e-h**): The simulated diurnal

390 range of CWC_{int} peaks in mid to late dry season when daytime atmospheric water demand was

391 high and soil water supply was low but inclusion of LW_s resulted in shifts of the peak to late wet

392 season for CWC_{all}, which is consistent with VOD seasonality and resulted in comparable average

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393 diurnal range values (5-10%) as VOD data. At the two forest sites, the inclusion of LW_s reduced

394 the temporal correlation of the diurnal range between VOD and CWC_{all} at M34 and reversed the

395 correlation at RJA; however, it increased the average diurnal range to be closer with the VOD

396 observations. Because the model-based estimate of wood internal water content is calculated

397 from its value at the base of the stem, which might have smaller diurnal range than branch water

398 pool in nature, we calculated another estimate of WW_i by assuming wood water potential is the

399 same as leaf water potential. This post-hoc correction increased the average diurnal range in

400 CWC for 2-3% but did not change the seasonal patterns and the impact of LW_s (**Fig. S9**).

401 Overall, these results suggest the ED-2.2-hydro did not capture the seasonality in canopy

402 hydrodynamics and phenology at the forest sites, but performed well at the two savannah sites,

403 where consideration of LW_s improved the agreement between simulated CWC and VOD

404 observations.

405 At the inter-annual timescale, VOD showed substantial variability relative to its average

406 seasonality in both 1:30AM values and diurnal ranges (**Fig. 7**) due to changes in hydroclimatic

407 conditions. Simulated anomalies of both CWC_{all} and CWC_{int} at 1:30AM were more correlated

408 with anomalies of 1:30AM VOD at the drier sites (significant positive correlation with Pearson's

409 r ranging from 0.36 to 0.53 for PDG and BSB) than at the wet sites (no significant correlations).

410 While including LW_s increased the correlation coefficients by 0.05 to 0.2, it did not change the

411 general cross-site pattern. The simulated diurnal range anomalies in CWC were not correlated

412 with the diurnal range anomalies in VOD at inter-annual time scales no matter whether LW_s was

413 included or not (**Fig. 7e-h**). The simulated diurnal range in CWC generally showed less inter-

414 annual variability with standard deviation of 1.0-1.7% (CWC_{all}) and 0.19-0.37% (CWC_{int}) than

415 the diurnal range in VOD, which had standard deviations ranging from 1.9% to 2.2%. Similar to

416 the seasonal scale analysis, correcting for wood internal water did not change the simulated

417 patterns of inter-annual variations in CWC (**Fig. S10**).

418 **Discussion**

419 *Predicted Canopy Water Content (CWC) and its relationship with Vegetation Optical Depth*

420 *(VOD)*

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421 The increasing use of Vegetation Optical Depth (VOD) to infer large-scale patterns of vegetation

422 water stress builds on the theoretical mechanistic proportionality between VOD and Canopy

423 Water Content (CWC) (Konings *et al.*, 2019). However, quantitative assessments of this

424 relationship have been lacking at the ecosystem scale – the scale at which remote sensing VOD

425 measurements are made (tens of kilometers) – particularly in humid, high-biomass ecosystems

426 such as tropical forests. This is mostly because ground-based measurements of CWC are

427 generally made at the level of leaves or tree branches (Powers & Tiffin, 2010; Chavana-Bryant *et*

428 *al.*, 2016; Martin *et al.*, 2018). Consequently, previous VOD field evaluation studies (Liu *et al.*,

429 2015; Fan *et al.*, 2019; Chaparro *et al.*, 2019) only examined the statistical associations between

430 spatial variation in VOD and above-ground biomass, a quantity that is easier to measure at larger

431 spatial scales via forest inventory and LiDAR measurements.

432 Our study evaluates, for the first time, the VOD-CWC relationship in both the spatial and

433 temporal domains through novel application of a terrestrial biosphere model. Our analyses

434 support the first hypothesis (H1) that VOD scales approximately linearly with CWC across space

435 and time; however, it also reveals important sources of complexity in this relationship: the

436 sensitivity of VOD-CWC relationship (inferred from the slopes of the relationship between

437 terrestrial biosphere model's predictions of CWC and the VOD measurements) varied across

438 sites with different moisture conditions and vegetation structures (**Fig. 4**). While some variation

439 in the slope of VOD-CWC relationship with vegetation type is expected, a three-fold increase in

440 the slope from savannah to forest sites (**Fig. 4d**) is far greater than previously estimated from

441 radiometric experiments in non-forested ecosystems (Van De Griend & Wigneron, 2004) and

442 leads to a relatively sigmoidal or saturating VOD-CWC relationship for cross-site variations.

443 VOD saturation at high aboveground biomass density (Chaparro *et al.*, 2019) should not be the

444 primary factor driving variation in the VOD-CWC slopes because cross-site variation in

445 penetration depth is explicitly considered in our analysis (**Fig. S3**) although our approach might

446 not fully capture small seasonal changes of penetration depth within each site. The larger-than-

447 expected variation in the VOD-CWC slope may reflect deficiencies in the model formulation:

448 most notably, the model's drought-driven phenology scheme generated smaller-than-observed

449 seasonal amplitudes in CWC at the two wet sites, compared to the seasonality in VOD (**Fig. 6**),

450 which may explain the low regression R^2 and slope at M34 and RJA. The cross-site variation in

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451   the slopes of the VOD-CWC relationships could also be due to uncertainty in the VOD

452   retrievals, particularly the uncertainty associated with surface temperature and single-scattering

453   albedo in the densely forested M34 and RJA sites (Du *et al.*, 2017b) or due to multiple scattering

454   (Schwank *et al.*, 2018). Both explanations call for additional calibration of VOD with in-situ

455   measurements of CWC, especially in moist, high-humidity ecosystems such as tropical forests.

456   *The role of leaf surface water (LW$_s$) in CWC and VOD variation across different time scales*

457   Our simulations explicitly consider dew formation, rainfall interception, and the resulting

458   dynamics of LW$_s$. While no direct measurements of canopy LW$_s$ temporal dynamics are

459   available to evaluate the model's predictions, the simulated range of LW$_s$ is consistent with

460   sparse sampling from an Amazon moist forest (**Fig. S2**). In addition, a rare ground-based

461   radiometer study in a Panamanian tropical moist forest (Schneebeli *et al.*, 2011) estimated that

462   whole canopy LW$_s$ could regularly reach 0.17 kgH$_2$O m^{-2} (ground) at pre-dawn from dew

463   formation and intensive rainfall events occasionally increased LW$_s$ to 0.4-1 kgH$_2$O m^{-2}. The

464   model generated comparable average predawn LW$_s$ values of 0.21-0.23 kgH$_2$O m^{-2} at the two

465   tropical forest sites (**Fig. S6**). The simulated average predawn LW$_s$ is close to the observed dew-

466   driven value, but lower than the observed rainfall-driven values likely because reanalysis rainfall

467   underestimates the diurnal cycle (**Fig. S11**).

468   In our model simulations, LW$_s$ accounts for more than 50% of diurnal variation in CWC at all

469   four of the study sites (**Fig. 3**). The large diurnal contribution from the relatively small LW$_s$ pool

470   (< 10% of total CWC) stems from its fast turn-over rate: by midday almost all LW$_s$ accumulated

471   during the night evaporates away (**Fig. 3**). In contrast, simulated LW$_i$ varied by only 10-15%

472   within a day and WW$_i$ by even less. In nature and in the model, this occurs because plant

473   stomatal control constrains daily minimum leaf water potential to be above, or not far below, the

474   leaf turgor loss point (Brodribb & Holbrook, 2003; Fontes *et al.*, 2018), whose corresponding

475   relative water content is approximately 90% for tropical wet forests (Bartlett *et al.*, 2012).

476   Consequently, our results call into question the ability to correctly infer spatial and temporal

477   patterns of plant water stress from diurnal measurements of VOD in humid forest ecosystems

478   such as tropical rainforests, as illustrated in our isohydricity analysis (**Fig. 5**). First, leaf surface

479   water dynamics might contribute most to the VOD-based isohydricity. Second, isohydricity

480   index based on water content is influenced by both leaf internal water stress and the seasonal

481   variation in vegetation structure, and thus can deviate from the isohydricity index based on leaf

482   water potential and converge to one (**Fig. 5i-p**). In addition, if VOD diurnal range reflects diurnal

483   water stress, it should peak in the dry season in tropical forests when plant diurnal water stress is

484   generally the highest -- as shown in both observations (Brodribb & Holbrook, 2004; Fisher *et al.*,

485   2006) and the biosphere model simulations conducted in this study (**Fig. 2**). However, at the two

486   savannah sites, VOD diurnal range peaked in late wet season, which can only be explained by

487   including LW_s (**Fig. 6**). Excluding rainy days (Konings & Gentine, 2017; Li *et al.*, 2017) is

488   likely not enough to eliminate the effects because dew formation can also significantly contribute

489   to LW_s and the simulated importance of LW_s only drops to a low level in months with both low

490   rainfall and humidity (**Fig. S12**). Hence, the influence of LW_s on VOD retrievals may also be

491   important in other humid ecosystems such as those found along the North American Pacific coast

492   (Burgess & Dawson, 2004) and montane forests (Berry *et al.*, 2014).

493   The importance of LW_s decreases, however, at the seasonal and inter-annual time scales (**Fig.**

494   **6&7**), implying that failing to consider LW_s will have less effect in VOD-based inference of

495   canopy phenology (Guan *et al.*, 2014; Wang *et al.*, 2020) and vegetation mortality (Rao *et al.*,

496   2019; Wigneron *et al.*, 2020). Therefore, our results support our second hypothesis (H2) that the

497   contribution of leaf surface water is highest at the diurnal time scale.

498   In contrast, there is only partial support for our third hypothesis (H3) that the contribution of leaf

499   surface water to diurnal VOD dynamics increases as precipitation increases: variance

500   decomposition implies an increasing contribution from LW_s along the gradient from dry to wet

501   sites (**Fig. 3**) and from wet to dry months (**Fig. S12**) is consistent with H3. However, it is

502   difficult to draw strong conclusions regarding H3 given the large uncertainties in VOD retrievals

503   and low level of seasonality in the model simulations compared to the observed seasonality of

504   VOD values and diurnal ranges at the two moist forest sites (**Fig. 6**). In addition, the simulated

505   cross-site variations in LW_s contribution might be biased because ED-2.2-hydro does not

506   represent possible leaf trait adaptation across moisture gradients such as changes in leaf texture

507   and trichome abundance that could regulate leaf surface water retention (Aparecido *et al.*, 2017)

508   and thus influence LW_s dynamics. Further in situ data collection and model improvement and

509   benchmark are necessary to accurately evaluate how LW_s contribution vary across moisture

510   gradients.

Implications for tropical phenology in vegetation models

512   Our model-data analysis also provides a useful evaluation of the plant hydrodynamics and leaf

513   phenology formulations in the ED-2.2-hydro terrestrial biosphere model. As anticipated, there

514   was better agreement between the model predictions and the VOD measurements at the two drier

515   sites where abiotic moisture conditions exhibit large variability that significantly affects canopy

516   water content. However, the predicted seasonal decline of LAI is later than in MODIS LAI

517   estimates (**Fig. 1**), and the relative magnitude of the seasonal decline in CWC was smaller than

518   VOD observations (**Fig. 6**), suggesting that the model's drought-deciduous leaf phenology

519   scheme may not be sufficiently responsive to seasonal water stress. In the current model

520   formulation, leaf-drop is triggered when pre-dawn water potential falls below turgor loss point,

521   whereas drought experiments on tropical seedlings suggest the average of pre-dawn and midday

522   water potential can best predict leaf shedding (Wolfe *et al.*, 2016). Incorporating midday water

523   potential into the drought-deciduous phenology scheme might therefore improve the seasonality

524   at drier savannah sites.

525   Similarly, at the two wet sites, the predicted seasonality in canopy water content was lower than

526   the seasonality in VOD (**Fig. 6**). This may be because the VOD seasonality is partially

527   attributable to unknown retrieval errors caused by seasonally varying properties (e.g. changes in

528   canopy structure) in densely vegetated areas (Konings *et al.*, 2016; Du *et al.*, 2017b). Another

529   possible explanation is that biotic factors, such as leaf ontogeny and phenology can be an

530   important factor influencing seasonal variation in canopy water content under moist conditions.

531   For instance, leaf relative water content can change substantially with leaf age in tropical wet

532   forests (Chavana-Bryant *et al.*, 2016) therefore seasonal changes in leaf demography at tropical

533   moist forests (Wu *et al.*, 2016) may contribute to seasonal variation in CWC and resulting VOD

534   measurements. A simple calculation of CWC changes based on published leaf demography and

535   leaf ontogeny data at Manaus (Chavana-Bryant *et al.*, 2016; Wu *et al.*, 2016) suggests

536   that seasonal variation in leaf age could explain the seasonal amplitude of VOD at M34, albeit

537   with a 1-2 month lag in timing (**Fig. S13**).

Conclusions

Our analyses indicate a large contribution of leaf surface water to diurnal variation in landscape-scale canopy water content (CWC) and AMSR-E Vegetation Optical Depth (VOD) signals over tropical forests. This is important because diurnal variation in VOD has been proposed as a measure of canopy isohydricity, a metric widely used to diagnose the water status of plant canopies. Our analysis shows that leaf surface water also influences seasonal variation in VOD, but to a far lesser extent. In this analysis, we examined VOD measurements from X-band microwave instruments that have relatively low penetration into the dense canopies of tropical forests; however, our findings also apply to VOD measurements from lower (L-band) electromagnetic frequencies (e.g. SMAP and SMOS) because the simulated LW_s contributions remain high even when we evaluated deeper canopy penetration depth (**Fig. S6**). Therefore, future applications of microwave band measurements, as well as and other imaging spectroscopy-based estimates of canopy water content (Asner *et al.*, 2016) should carefully consider the effects of variation in leaf surface water, particularly during moist and humid periods when dew formation and rainfall interception are high. In turn, the sensitivity of VOD to leaf surface water newly identified in this study provides new opportunities to understand leaf surface water dynamics and its impact on plant water use.

Our analyses also highlight the value of explicitly representing plant hydrodynamics in terrestrial biosphere model formulations. The consistency between VOD and model predicted CWC across diurnal, seasonal, and inter-annual timescales at the two tropical savannah sites suggests that the current model structure is able to capture important processes governing plant hydrodynamics; however, capturing diurnal and seasonal patterns of VOD in wet tropical forests is likely to require consideration of phenological processes affecting canopy water content, such as seasonal leaf demography and ontogeny.

Author Contributions

X.X., P.M., A.K., and S.S. designed the research. M.L. and X.X. processed the meteorology and flux tower data. A.K. and A.F. processed AMSR-E VOD data. L.X. and S.S. provided GLAS

566   Lidar LAI. D.W. provided the MODIS data. J.W. provided the in-situ leaf trait and demography

567   data. X.X. performed model simulation, conducted analyses, and drafted the manuscript. All

568   authors contributed to writing of the manuscript.

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Tables and Figure Legends

817 **Table 1** Description of climate and soil conditions used for ED-2.2-hydro simulations at the four

818 study sites.

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Site name	Location (lon, lat)	MAT (ºC)	MAP (mm)	Soil Texture (% of sand and clay)*	Temporal coverage of *in situ* meteorology
Manaus K34 **(M34)**	-60.21,-2.61	25.7	2673	0.2,0.68	1999-2006
Reserva Jaru **(RJA)**	-61.93,-10.08	25.0	2069	0.8,0.1	1999-2002
Pé-de-Gigante **(PDG)**	-47.65,-21.62	22.8	1453	0.85,0.03	2001-2003
Brasília **(BSB)**	-47.71,-15.60	21.7	1344	0.13,0.53	2010-2012

820 *We used the best estimates of soil texture following previous ED2 simulations (Longo, 2014;

821 Restrepo-Coupe *et al.*, 2017) and we used the same soil depth of 10 meters.

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Figure 1 Evaluation of vegetation structure in ED-2.2-hydro across four study sites along a rainfall gradient. (**a-d**) The average profile of leaf area index (LAI) within forest canopy from GLAS lidar inversion (red) and model simulations (black). The x-axis represents leaf area density (LAD) for each 5 meter band from 0m to 50m above ground while the y-axis represents height of each band. Inset plots within each panel compare the total LAI from model and GLAS data. (**e-h**) Seasonality of monthly average canopy total LAI from model simulation (black) and MODIS observations (blue). Grey bars denote the average monthly rainfall in millimeters. Each column displays results for a study site with site acronym and mean annual rainfall at the top of each column.

Figure 2 Simulated leaf hydrodynamics in ED-2.2-hydro. (a-d) vertical distribution of daily maximum (blue) and minimum (red) leaf water potential. We averaged cohort-level leaf water potential for every 5 meter height bands, using cohort leaf area index as weighting factors. (e-h) seasonality of average daily maximum and minimum leaf water potential for upper canopy leaves. We define upper canopy as the top 1kgC m^{-2} biomass.

Figure 3 Contribution of leaf surface water to canopy water content in model simulations. (**a-d**) Average diurnal cycles of CWC partitioned into wood internal water (WW_i, brown), leaf internal water (LW_i, green), and leaf surface water (LW_s, blue) for our four study sites. The vertical dashed lines represent the local bypassing time of AMSR-E VOD measurements (1:30AM and 1:30PM). (**e-h**) Variance decomposition of CWC temporal variations into the three sub-components at both the diurnal scale (black bars) and biweekly scale (red bars). We only used the simulated CWC at the same time as AMSR-E VOD measurements (dashed lines in panels a-d) for this analysis.

Figure 4 Relationship between VOD and (**a**) simulated CWC_{all} (including LW_s) and (**b**) CWC_{int} (excluding LW_s). Each dot represents bi-weekly average of 1:30AM or 1:30PM values, with the colors indicating the different study sites, M34 (brown), RJA (red), PDG (purple), and BSB (blue). Solid black lines represent ordinary least square linear regression between VOD and CWC using all data combined while solid color lines represent regressions for each site. Regression R^2 (**c**) and slopes (**d**) are also shown for each site and all sites combined. We only include CWC dynamics from the top 1kgC m^{-2} biomass in the simulations.

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Figure 5 Isohydricity index (σ) from VOD (**a-d**), CWC$_{all}$ (**e-h**, including LW$_s$), CWC$_{int}$ (**i-l**, excluding LW$_s$), and Ψ (**m-p**, leaf water potential in MPa). Each column represents results from one study site. Each dot represents a biweekly average of VOD, CWC$_{all}$, CWC$_{int}$ or Ψ. CWC and Ψ values represent water contents and average leaf water potential of the upper canopy layers (top 1 kgC m^{-2}). Red lines represent linear regression results with σ values shown on top of each panel. All regressions are significant.

Figure 6 Comparison of average seasonality between VOD and simulated CWC across four study sites. (**a-d**) seasonality of 1:30AM VOD (black), CWC$_{all}$ (green), and CWC$_{int}$ (purple). To facilitate comparison, we normalized the seasonality by dividing the maximum seasonal values for each variable. (**e-h**) similar to **a-d** but for diurnal ranges calculated as $(1 - X_{1:30PM} / X_{1:30AM}) \times$ 100%. We calculated Pearson's r between the average seasonality in VOD and the simulated CWC (with and without LW$_s$) and showed the correlation coefficients using the same color as the different CWC lines. Significant correlation ($p < 0.05$) was marked with *. In all panels, we only included water from the top 1 kgC m^{-2} biomass within the canopy and gray bars represent average monthly rainfall.

Figure 7 Comparison of interannual -year variability between VOD and simulated CWC after removing average seasonality across four study sites. (**a-d**) variability of 1:30AM VOD (black), CWC$_{all}$ (green), and CWC$_{int}$ (purple). We normalized the time series by dividing the maximum as in Figure 6. (**e-h**) similar to **a-d** but for diurnal ranges calculated as $(1 - X_{1:30PM} / X_{1:30AM}) \times$ 100%. We calculated Pearson's r between the average seasonality in VOD and the simulated CWC (with and without LW$_s$) and showed the correlation coefficients using the same color as the different CWC lines. Significant correlation ($p < 0.05$) was marked with *. In all panels, we only included water from the top 1 kgC m^{-2} biomass. Due to high-frequency variation in the simulated CWC, we averaged the biweekly data into bimonthly values to facilitate comparison.