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Citation for published version:

Doughty, C, Cheesman, AW, Riutta, T, Thomson, E, Shenkin, A, Nottingham, A, Telford, E, Huaraca Huasco, W, Majalap, N, Teh, YA, Meir, P & Malhi, Y 2021, 'Predicting tropical tree mortality with leaf spectroscopy', *Biotropica*, vol. 53, no. 2, pp. 581-595. <https://doi.org/10.1111/btp.12901>

Digital Object Identifier (DOI):

[10.1111/btp.12901](https://doi.org/10.1111/btp.12901)

Link:

[Link to publication record in Edinburgh Research Explorer](#)

Document Version:

Peer reviewed version

Published In:

Biotropica

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Predicting tropical tree mortality with leaf spectroscopy

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Abstract – Do tropical trees close to death have a distinct change to their leaf spectral signature? Tree mortality rates have been increasing in tropical forests globally, reducing the global carbon sink. Upcoming hyperspectral satellites could be used to predict regions close to experiencing extensive tree mortality during periods of stress, such as drought. Here we show, for a tropical rainforest in Borneo, how imminent tropical tree mortality impacts leaf physiological traits and reflectance. We measured leaf reflectance (400-2500 nm), light saturated photosynthesis (A_{sat}), leaf dark respiration (R_{dark}), leaf mass area (LMA) and % leaf water across five campaigns in a six-month period during which there were two causes of tree mortality: a major natural drought and a co-incident tree stem girdling treatment. We find that prior to mortality, there were significant ($P < 0.05$) leaf spectral changes in the red (650-700 nm), the NIR (1000 -1400 nm) and SWIR bands (2000-2400 nm) and significant reductions in the potential carbon balance of the leaves (increased R_{dark} and reduced A_{sat}). We show that the partial least squares regression technique can predict mortality in tropical trees across different species and functional groups with medium precision but low accuracy (r^2 of 0.65 and RMSE/mean of 0.58). However, most tree death in our study was due to girdling, which is not a natural form of death. More research is needed to determine if this spectroscopy technique can be applied to tropical forests in general.

Keywords – Tropical forests, spectroscopy, girdling, tree mortality, traits, drought, el Niño

45

46 **Introduction**

47 Can future tropical forest tree mortality be predicted with aircraft or satellite remote
48 sensing? This question is of interest because tropical tree mortality is increasing, reducing the
49 global carbon sink (Brienen et al., 2015; Hubau et al., 2020). Increased tree mortality may be
50 driven by recent increases in extreme weather events caused by climate change, including
51 increased drought frequency/severity (Doughty et al., 2015; Rifai et al., 2018, 2019; Rowland et
52 al., 2015) or elevated air temperatures (Clark, 2004; Doughty & Goulden, 2009a). Other causes
53 of mortality include altered disturbance regimes due to land management practices or biological
54 invasions (e.g. grass/fire cycles) and the negative environmental impacts arising from forest
55 degradation (e.g. physical damage to trees from logging or small-scale slash-and-burn
56 agriculture; environmental stress from enhanced edges effects) (Malhi et al., 2014).
57 Experimental drought manipulations in the Amazon (da Costa et al., 2010; Meir et al., 2015;
58 Nepstad et al., 2007) show that larger trees are more susceptible to drought-related mortality for
59 specific high-abundance taxa (Bittencourt et al., 2020).

60 Could changes to leaf properties in these large trees indicate risk of imminent future
61 mortality? Death of these large individuals has the greatest impact on tropical forest vegetation
62 and carbon dynamics (Phillips et al., 2009). “Environmental surveillance” techniques that
63 enable us to identify individuals at risk of mortality or to predict future patterns of senescence
64 would enable us not only to model forest vegetation and carbon dynamics more accurately, but
65 could possibly enable us to manage the spread of forest pathogens and understand environmental
66 stress gradients related to disturbance. Given that these large trees are also the most visible to
67 aircraft and satellites, remote sensing techniques that enable us to identify dying trees hold

68 tremendous potential for detecting and understanding the causes of tree mortality at large spatial
69 scales.

70 Leaf traits, such as leaf chemical composition, photosynthetic capacity or leaf mass per
71 area (LMA), are important indicators of a tree's life history strategy and overall vitality (Poorter
72 et al., 2008; Wright et al., 2004; Wright et al., 2010). Remote sensing of these traits is thus one
73 approach that could enable us to detect individuals or taxa at elevated risk of death from stress.
74 For instance, light-demanding species with rapid growth and high mortality rates are predicted to
75 have lower seed mass, leaf mass per area (LMA), wood density, and tree height (Wright et al.,
76 2010). Variation in LMA in part expresses a trade-off between the energetic cost of leaf
77 construction and the light captured per area that may be reflective of the strategy of the broader
78 tree itself (Díaz et al., 2016; Poorter et al., 2009). Drought tolerance is also reflected in structural
79 traits such as LMA, leaf thickness, leaf toughness and wood density, although further studies are
80 required to better establish the limitations of these metrics and identify other potential indices
81 (Bartlett et al., 2012; Fyllas et al., 2012; Niinemets, 2001; Zanne et al., 2010).

82 Much recent literature has discussed the roles of carbon starvation, hydraulic failure, or a
83 combination of the two on tree death as well as the traits associated with these processes. To
84 predict tree death with remote sensing we must first understand the characteristics that drive tree
85 death. A recent meta-analysis suggests that metrics of hydraulic failure more consistently
86 predicted mortality than carbon starvation as determined by tissue concentrations of non-
87 structural carbohydrates (NSC) (Adams et al., 2017). Another study similarly found hydraulic
88 traits were better at predicting the response of ecosystem fluxes (CO₂ and water vapor) to
89 drought than traits like LMA or wood density (Anderegg et al., 2018). Tree mortality during
90 droughts is highest for species that have a small hydraulic safety margin (the difference between

91 typical minimum xylem water potential experienced and xylem vulnerability to embolism)
92 (Anderegg et al., 2016). Turgor loss point - the leaf water potential that induces wilting - may be
93 a key trait predicting drought tolerance and species distributions relative to water supply
94 (Bartlett et al., 2012). In tropical forests, turgor loss point varied widely across species and was
95 weakly positively correlated with leaf toughness and thickness (Maréchaux et al., 2015). Some
96 literature suggests that both hydraulic failure and carbon depletion are associated with mortality
97 in large part through their effect on leaf water content and turgor (Sapes et al., 2019; Sevanto et
98 al., 2014). Leaf water content can be accurately remotely sensed at the leaf and aircraft scale
99 (Asner et al., 2016; Asner & Martin, 2008).

100 Leaf traits can be sensed remotely by aircraft or from space. Foliar traits such as nitrogen
101 (N) content, chlorophyll content, carotenoids, lignin, cellulose, LMA, soluble carbon, and water
102 can be remotely estimated with leaf spectral reflectance signatures (400-2500nm in 1 nm
103 bandwidths) in many different plants and ecosystems (Ustin et al., 2009), including tropical
104 forests (Asner & Martin, 2008). This is because certain traits are associated with reflectance
105 characteristics within specific spectral regions. For instance, the visible part of the spectrum
106 (400–700 nm) is associated with pigments (mostly chlorophyll), and the near infrared (NIR;
107 700–1,300 nm) is associated with structures such as palisade cell density. LMA and leaf
108 chemistry have been accurately measured and modelled at both the leaf (Asner & Martin, 2008;
109 Curran, 1989; Jacquemoud et al., 2009), canopy and landscape scales (Asner et al., 2016). Other
110 elements not directly expressed in the spectrum, such as phosphorus (P), have been accurately
111 predicted with spectroscopy, possibly through stoichiometric relationships with other chemical
112 species (Ustin et al., 2006, 2009) or correlations with leaf morphological traits via the leaf
113 economics spectrum (Wright et al 2004). Other tropical tree traits not directly associated with

114 leaf spectra, such as photosynthetic capacity (Doughty et al., 2011), and branch wood density,
115 have been predicted with spectroscopy in tropical forests (Doughty et al., 2017). Traits not
116 directly associated with spectral regions can still be predicted through correlations between leaf
117 traits and a tree's life history strategy (Doughty et al., 2017).

118 There is evidence that drought changes tropical forest reflectance at the continental scale,
119 due to changes in leaf traits or increased tree mortality. For instance, Enhanced Vegetation
120 Index (EVI), a greenness index measured with Moderate Resolution Imaging Spectroradiometer
121 (MODIS), increased in the Amazon during the 2005 drought, indicating possible positive
122 impacts of drought on forests due to increased irradiance (Saleska et al., 2007). However, others
123 have challenged the original interpretation of the EVI data (Morton et al., 2014; Samanta et al.,
124 2010), highlighting the challenge of remote sensing at a continental scale. More recently, during
125 a major El Niño drought in Borneo, NDVI initially increased as the drought was strengthening,
126 but decreased at its peak (Nunes et al., 2019). Interpretation of changing NDVI and/or EVI at
127 larger spatial scales is generally complicated in many ecosystems as changes at the leaf level
128 may be compensated for or masked by canopy scale process. For example, leaf senescence and
129 leaf fall may reduce the canopy scale NIR signal. However, remotely sensed LAI signal
130 saturates in tropical forests and LAI variation can be relatively small even following strong
131 climate extremes such as drought. For instance, Meir et al. (2018) found a 12-20% change in
132 LAI during an extreme drought manipulation experiment with a non-droughted natural LAI of
133 $\sim 5.5 \text{ m}^2 \text{ m}^{-2}$, which is within the saturation range. Therefore, changes in tropical forest canopy
134 spectral characteristics at larger spatial scales may be more linked to changes in leaf level
135 spectra, than in other ecosystems with lower LAI (Doughty & Goulden, 2009b; Wu et al., 2018).

136 The 2016 El Niño caused a significant drought in Borneo, both in terms of increased
137 maximum temperatures and reduced precipitation (Figure 1)(Rifai et al., 2019)(Rifai et al.,
138 2018). This El Niño had unusually high temperatures, which have been attributed to climate
139 change (Thirumalai et al., 2017). Recent work in Borneo, near our study site, found the El Niño
140 event was associated with a decrease in chlorophyll and carotenoid concentrations by 35%.
141 They also noted a decrease in NDVI with a change in the shortwave infrared region of leaf
142 spectral signatures (Nunes et al., 2019). The authors hypothesized that trees produced new leaves
143 with higher pigment concentrations at the start of the El Niño event, and then dropped their
144 leaves at its peak.

145 In this study, we focus on tree mortality at a 1 ha long-term study site close to the Nunes
146 et al (2019) study site in Sabah, northern Borneo. We attempt to understand the relationship
147 between leaf traits, spectroscopy and mortality in two different ways: natural death during El
148 Niño and forced mortality induced by girdling. Before, during and after the 2016 El Niño
149 drought (over 5 field campaigns), we measured canopy-top leaf spectra (400-2500 nm), net light
150 saturated photosynthesis, dark respiration and LMA in a representative cross section of the 393
151 monitored trees. We further tried to explore mechanisms of mortality with a girdling campaign
152 (the removal of the phloem in a 10 cm ring around the tree stem) in one half (0.5 ha, 210 stems)
153 of the plot. Here, we test the following hypotheses:

154 *H1 – Leaf traits that are correlated with leaf spectroscopy signals, such as light saturated*
155 *photosynthesis, dark respiration, and LMA, undergo significant change months prior to tree*
156 *mortality.*

157 *H2 - Tropical tree mortality can be predicted with hyperspectral information (400-2500 at 1 nm*
158 *bandwidth leaf reflectance).*

160 **Methods**

161 **Study sites**

162 Our study plots are in Kalabakan Forest Reserve in Sabah, Malaysian Borneo (Tower SAF-05
163 4.716°, 117.609°) within the Stability of Altered Forest Ecosystems (SAFE) Project study site
164 (Ewers et al., 2011; Riutta et al., 2018). A schematic of the study site is shown in figure 1C.
165 Mean annual temperature is approximately 26.7°C and mean annual precipitation is 2,600–
166 2,700 mm with no distinct dry season but, on average, ~12% of months with precipitation below
167 100 mm month⁻¹ (Walsh & Newbery, 1999). The plot has been selectively logged four times
168 since the 1970s, which represents a high logging intensity for this region. The soils are orthic
169 Acrisols or Ultisols on undulating clay soil. The tree basal area is 13.9 m²/ha. Total NPP and
170 autotrophic respiration have been measured at this plot since 2011 and there is an eddy
171 covariance tower nearby (Riutta et al., 2018). The plot is split in half by a small stream. All the
172 trees on one side of the stream were girdled in late January 2016 by removing the phloem tissue
173 in a 10 cm band, as described below (note: the plot was in the process of conversion to oil palm
174 agriculture production). This part of the study site is hereafter referred to as the “girdled plot.”
175 The trees on the other side of the stream were not girdled and represent the treatment control.
176 This part of the study site is hereafter referred to as the “drought plot”. Although all trees
177 experienced drought, the “drought” plot only experienced drought and not the effects of girdling.
178 We collected data during five field campaigns that took place from January to June 2016.
179 Campaigns began on the following days and generally took several days: Campaign 1=21 Jan-
180 16, Campaign 2=10 Feb-16, Campaign 3=01 Mar-16, Campaign 4=29 Mar-16, Campaign 5 08
181 Jun-16. The first field campaign (C1) was conducted before girdling occurred to determine pre-
182 girdling conditions and process rates.

183

184 **Girdling experiment** – In late Jan 2016, after the first field campaign, we further explored the
185 causes of tree mortality by conducting a girdling experiment. Girdling involved removing a 10
186 cm strip of the periderm and phloem in a ring around the tree stem at ~1.2 m height (with
187 exceptions for trees with buttresses, which were girdled above the buttress) above the soil
188 (Figure 1a) in a plot that was scheduled for conversion to a palm oil plantation. This technique
189 prevents carbohydrate transport to the roots but maintains hydraulic connectivity because xylem
190 tissues are not severed. Tree death was determined visually, based on the absence of visible
191 canopy, with regular (average 18-day period) visits to the plots for both the drought and the
192 girdled plots. We give the species measured in both plots in Table 1.

193

194 **Leaf sampling strategy** –In each plot, 20-25 trees were chosen during each campaign, and tree
195 climbers with extendable tree pruners removed one branch per tree that was growing in full
196 sunlight (Asner & Martin, 2008). These branches were quickly recut underwater and taken to
197 the laboratory for further measurements. On each of these branches, five fully expanded non-
198 senescent leaves in randomly selected locations were chosen for measurements of: leaf-gas
199 exchange leaf spectral properties (measured within 1 hour of being cut) and LMA. Leaf area was
200 determined immediately after collection using a digital 476 scanner (Canon LiDE 110). Leaves
201 were then oven dried at 72 °C until constant mass was reached. We subtracted wet weight from
202 dry weight to calculate % leaf water and used dry weight and leaf area in order to calculate
203 LMA.

204

205 **Leaf-level gas exchange** – We used a portable gas exchange system (LI 6400, Li-Cor
206 Biosciences, Lincoln, NE, USA) to measure leaf-level gas exchange. After returning to the
207 laboratory, leaf dark respiration (R_{dark}) was measured by covering branches with an opaque bag
208 for at least 20 minutes prior to measurement at a cuvette temperature of 30° C (Rowland et al.,
209 2017). After this, branches were exposed to sunlight and light-saturated leaf photosynthesis was
210 measured (A_{sat} ; 1200 $\mu\text{mol m}^{-2} \text{s}^{-1}$ PPFD, 400 ppm CO_2 , at 30° C). We chose a light level of
211 1200 $\mu\text{mol m}^{-2} \text{s}^{-1}$ for A_{sat} because we tested photosynthetic capacity and found it generally
212 saturated below light levels of $\sim 1200 \mu\text{mol m}^{-2} \text{s}^{-1}$ PPFD, similar to other tropical studies (Both
213 et al., 2019; Gvozdevaite et al., 2018; Doughty & Goulden, 2009b). We waited for gas exchange
214 values to stabilize before starting a measurement, recorded data every two seconds and averaged
215 the results after eliminating the first 20 measurements. We excluded photosynthesis
216 measurements less than 0 $\mu\text{mol m}^{-2} \text{s}^{-1}$ as this was indicative of a failure to maintain hydraulic
217 connectivity in the sampled branch resulting in stomatal closure. We also excluded dark
218 respiration measurements more negative than -1.5 $\mu\text{mol m}^{-2} \text{s}^{-1}$ as this was considered indicative
219 of a failure to truly represent R_{d} , or in some cases operator error. Most physiological
220 measurements were collected between 07:00 and 14:00 local time and branches were cut from
221 trees between 06:00 and 13:00 local time. An online supplement includes our averaged \pm sd data
222 for each leaf measured for transpiration rate ($\text{mmol H}_2\text{O m}^{-2} \text{s}^{-1}$), vapor pressure deficit based on
223 leaf temperature (kPa), intercellular CO_2 concentration ($\mu\text{mol CO}_2 \text{mol}^{-1}$), conductance to H_2O
224 ($\text{mol H}_2\text{O m}^{-2} \text{s}^{-1}$), and photosynthetic rate ($\mu\text{mol CO}_2 \text{m}^{-2} \text{s}^{-1}$).

225 **Leaf spectroscopy** – We randomly selected five leaves within an hour of each branch being cut,
226 and measured hemispherical reflectance near the mid-point between the main vein and the leaf
227 edge (Asner & Martin, 2008). We used an ASD Fieldspec 4 with a fibre optic cable, contact

228 probe and a leaf clip (Analytical Spectral Devices, Boulder, Colorado, USA). The spectrometer
229 records 2175 bands spanning the 325–2500 nm wavelength region. We corrected for small
230 discontinuities between spectral bands (~950 and ~1750 nm), where the instrument transitions
231 from one sensor to another. Measurements were collected with 136-ms integration time per
232 spectrum (Asner & Martin, 2008; Doughty, Asner, et al., 2011). To ensure measurement quality,
233 the spectrometer was calibrated for dark current and stray light, and white-referenced to a
234 calibration panel (Spectralon, Labsphere, Durham, New Hampshire, USA) after each
235 branch(Asner & Martin, 2008; Doughty, Field, et al., 2011). The spectrometer was optimized
236 after every branch so the light levels did not saturate. For each measurement, 25 spectra were
237 averaged together to increase the signal-to-noise ratio of the data.

238

239 **Data analysis** - We used the Partial Least Squares Regression (PLSR) modelling approach to
240 predict leaf traits with spectral information (Geladi & Kowalski, 1986). PLSR incorporates all
241 the spectral information within each leaf reflectance measurement, eventually reducing all
242 spectral data (400-2500 nm) down to a relatively few, uncorrelated latent factors. This approach
243 has been used successfully to predict plant traits across a wide range of ecosystems, including
244 tropical forests (Asner & Martin, 2008; Serbin et al., 2014). We used the PLSregress command
245 in Matlab (Matlab, MathWorks Inc., Natick, MA, USA) to establish predictive models for LMA,
246 Asat, wood density (estimated with tree species and a lookup table (Chave et al., 2009)) and tree
247 mortality (Doughty, Asner, et al., 2011). To avoid over-fitting the number of latent factors we
248 minimized the mean square error with K-fold cross validation (set as an upper bound as 30). To
249 avoid issues of pseudo replication, we emphasize that the unit of analysis in these analyses is the
250 leaf. To create a completely independent testing dataset, we used the above method on 70% of

251 our data to calibrate our model and then the remaining 30% to test the accuracy of our model.
252 We evaluated the accuracy of our modelled estimates using two main metrics: r^2 and root mean
253 square error (RMSE)/mean. We graded our results as high precision and accuracy ($r^2 > 0.70$;
254 %RMSE < 15%), medium precision and accuracy ($r^2 > 0.50$; % RMSE < 30%), low precision
255 and accuracy ($r^2 > 0.50$; % RMSE > 30%). We also calculated NDVI for our five study periods
256 as $NDVI = (NIR-red)/(NIR+red)$ where we use 1000 nm for NIR and 650 nm for red.

257 **Statistical tests** – For our leaf spectral measurements, for each 1 nm bandwidth, we determined
258 statistical significance ($P < 0.05$) between trees within 50 days of mortality and prior to this with a
259 paired t-test (Matlab, Mathworks). To understand significant differences between % water,
260 LMA, R_{dark} , and A_{sat} , we used a t-test. To understand the impact of the girdling between %
261 water, LMA, R_{dark} , and A_{sat} over time, we used a repeated measures ANOVA.

262

263 **Results**

264 The field campaigns overlapped with the 2016 El Niño in Borneo (Figure 1b).
265 Campaign 1 (C1- Jan-21) took place before the period of peak drought and temperature, C3
266 (March -16) was conducted during the peak of the drought and high temperatures, and by C5
267 (June-16) the rains had returned. After C1, all the trees in the girdled plot had their phloem
268 tissue removed in a 10 cm band. Given the downward flux of sugars from the canopy, we might
269 expect an initial build-up of sugars above the girdle followed by eventual tree death as carbon
270 starvation below the girdle impacted tree function, particularly in the roots. Companion papers
271 explore the causes of tree death and the impacts on plant hydraulics and soil respiration.

272 There was little change in leaf reflectance (400-2500 nm) between C1 and C2 (Figure 2)
273 in both the drought and girdled plots. We expected few spectral changes during this short
274 interval between C1 and C2 (Jan-21 to Feb-10) for the natural drought plots, but we were
275 surprised there were also few changes for the girdled plots since these trees experienced a
276 significant trauma. In the later campaigns (C3 to C5 01-Mar to 08-Jun), there were large (~0.03
277 reflectance units) increases in NIR reflectance (750-1500 nm) in both the girdled and natural
278 drought plots (Figure 2 a and b). Reflectance in the visible wavelengths was lower during peak
279 drought (C3) compared to when the rains returned (C4 and C5). The girdled plots showed a
280 consistent increase in visible reflectance. Spectral reflectance increased in the SWIR bands over
281 time during the drought and there were few changes in the girdled plot except for the final
282 campaign where there was a decrease. Figure 2 displays all spectral data taken during each
283 campaign and therefore, changes in spectral properties in the girdled plot might also have
284 resulted from species changes because certain tree species died sooner than others, changing the

285 species composition as the experiment continued. To address this, in figure 5, we compare
286 spectroscopy for only trees that died.

287 Our average A_{sat} values across the campaigns for the girdled plot ($3.7 \mu\text{mol CO}_2 \text{ m}^{-2} \text{ s}^{-1}$)
288 and the drought plot ($4.7 \mu\text{mol CO}_2 \text{ m}^{-2} \text{ s}^{-1}$) were slightly lower, but within 95% confidence
289 intervals of values from a nearby campaign in Borneo (old growth plots - $4.1 \mu\text{mol CO}_2 \text{ m}^{-2} \text{ s}^{-1}$
290 ($2.7\text{--}5.5 = 95\%$ confidence interval) and selectively logged plots - $7.0 \mu\text{mol CO}_2 \text{ m}^{-2} \text{ s}^{-1}$ (5.7--
291 8.4)) (Both et al., 2019). Our average R_{dark} values across the campaigns for the girdled plot (-0.82
292 $\mu\text{mol CO}_2 \text{ m}^{-2} \text{ s}^{-1}$) and the drought plot ($-0.83 \mu\text{mol CO}_2 \text{ m}^{-2} \text{ s}^{-1}$) were likewise slightly less
293 negative than the values from Both et al 2019 of $-1.0 \mu\text{mol CO}_2 \text{ m}^{-2} \text{ s}^{-1}$ (-0.9 to -1.2) for the old
294 growth plots and $-1.3 \mu\text{mol CO}_2 \text{ m}^{-2} \text{ s}^{-1}$ (-1.1 to -1.4) for the selectively logged plots. Light
295 saturated leaf photosynthesis and R_{dark} varied between the wet and dry seasons in both plots over
296 the measurement period (Figure 3). Following the return of the rains, A_{sat} increased in both the
297 drought and girdled plots in C5. Surprisingly, the surviving girdled trees had the highest
298 photosynthetic rates of all the campaigns in C5 despite the damaged phloem. Dark respiration
299 was at its lowest in C3 and 4 during the peak of the drought. In both groups, changes in R_{dark}
300 mirrored those of A_{sat} . The ratio $R_{\text{dark}}/A_{\text{sat}}$ also varied between the wet and dry seasons, with the
301 exception of C4, where the drought plot was less efficient with greater carbon loss per carbon
302 gain. Leaf water content (% leaf water) was also at its lowest in C3 and 4 during the peak of the
303 drought but recovered by C5 (Figure 3e), but we did not find significant effects over time. NDVI
304 was lowest in C3 for both the girdle and drought plots but increased in C4 and C5 (Figure 3f). A
305 repeated measures ANOVA showed no significant differences between A_{sat} , R_{d} , and LMA over
306 time between the girdled and drought plots across the four campaigns (C1 was prior to the girdle)
307 suggesting the girdling had little overall impact of on leaf physiology.

308 To understand how the drought and girdling impacted leaf spectral properties in different
309 ways and how these link to functional traits, we binned our results into groups of trees with
310 either high ($>0.5 \text{ g cm}^3$ N= 359 leaves/Campaign) or low wood density ($<0.5 \text{ g cm}^3$ N= 830
311 leaves/Campaign) (Figure 4). During the drought, tree species with lower density showed an
312 increase in leaf reflectance compared to species with higher density wood. For example, during
313 the drought, tree species with lower wood density increased leaf reflectance by ~ 0.05 in the NIR
314 and ~ 0.01 SWIR more than tree species with higher density wood, with fewer significant
315 changes ($P < 0.05$) in the visible bands. In contrast, the high wood density tree species show a
316 stronger reaction to the girdling than the low wood density species, again with large increases in
317 reflectance in the NIR and SWIR bands.

318 We then compared near death leaf reflectance (within 50 days of dying) to leaf
319 reflectance from the same trees, during an earlier period, not near to death (Figure 5). By C5, 38
320 trees or 18% percent of all girdled trees had died. There were large (0.03-0.05 reflectance units)
321 and significant decreases ($P < 0.05$) in leaf reflectance in the visible bands and the red edge as tree
322 death approached. Close to mortality, there were also large (0.02) and significant increases
323 ($P < 0.05$) in leaf reflectance in NIR and SWIR bands. Next, we investigated how drought
324 conditions, caused by the ENSO event, affected leaf spectral properties in trees which died
325 naturally in the non-girdled control plot. In the control plot, only one tree died from drought that
326 was intensively sampled for functional traits. We observed similar significant changes along the
327 same pre-death timeline, in leaf reflectance in this tree as observed in the trees that died
328 following the girdling treatment: reductions in reflectance occurred in the red, the NIR and
329 SWIR bands. However, there was a significant peak in the red edge in the opposite direction

330 compared to the girdling study. The wavelengths that show similarities for both types of death
331 were: red (650-700nm), the NIR (1000 -1400nm) and SWIR bands (2000-2400nm).

332 For both the girdled and non-girdled trees, there were highly significant changes
333 ($P < 0.0001$) to the potential carbon balance ($R_{\text{dark}} / A_{\text{sat}}$ – Figure 6e and f) of the leaves just prior
334 to death (i.e. within 50 days). In both the drought and the girdled plots, there were significant
335 increases in R_{dark} and significant decreases in A_{sat} (Figure 6). This combination of increased
336 respiration and decreased photosynthesis should reduce the carbon available to the tree (again
337 dependent on stomatal conductance changes). There was no significant change in LMA among
338 the girdled trees. In contrast, in the tree that died from drought in the non-girdled plot, the leaves
339 had significantly higher LMA and lower % water near to death. We do not know if this was a
340 result of a changing cohort of leaves present on the sampled branch (i.e. leaves with lower LMA
341 senesced sooner) or if all leaves changed their LMA via altered density prior to death (less likely
342 as structural carbon is fixed).

343 Finally, we used PLSR to predict changes in physiology and time to death with
344 spectroscopy (Figure 7). We used the primary weighting (right side of figure 7) to understand
345 which spectral regions are most important (deviations from 0). Spectroscopy predicted % water
346 and LMA well with an r^2 of 0.72 and 0.74 respectively and RMSE/mean of 0.07 and 0.14
347 (similar to many other studies with high precision and high accuracy (Asner and Martin 2008,
348 Doughty et al 2011) (RMSE = 0.04 and 14.5, RMSE/std = 0.57 and 0.61, # of PLS weights =
349 30)). The primary weighting is in the NIR and SWIR bands which is typical of traits relating to
350 structure. Spectroscopy predicted maximum photosynthetic rate (A_{sat}) with an r^2 of 0.66 and
351 RMSE/mean of 0.69 (medium precision but low accuracy) (RMSE = 3.3, RMSE/std = 0.74, # of
352 PLS weights = 25/30) and wood density with an r^2 of 0.41 and RMSE/mean of 0.24 (low

353 precision but medium accuracy) (RMSE = 0.12, RMSE/std = 0.94, # of PLS weights = 15). The
354 primary weighting of A_{sat} was in the visible bands (likely related to chlorophyll content) and for
355 wood density in NIR and SWIR >1000 nm (likely related to variations in LMA and leaf
356 structure). Finally, we predicted time to death with spectroscopy and the PLSR technique with an
357 r^2 of 0.68 and RMSE/mean of 0.55 (medium precision and low accuracy) (RMSE = 82,
358 RMSE/std = 0.81, # of PLS weights = 30). The primary weighting shows similarity with Figure
359 5 with important spectral regions in the visible (related to photosynthetic characteristics), the
360 NIR (related to structure) and SWIR bands (related to water bands).

361

362

363 **Discussion**

364 **Leaf spectroscopy** - Identification of tropical trees susceptible to mortality through
365 hyperspectral imagery could provide a powerful tool in examining recently reported increases in
366 tree mortality rates across the tropics (Brienen et al., 2015; Hubau et al., 2020). By contributing
367 to “environmental surveillance,” the use of hyperspectral data would have a wide range of
368 applications from the prediction of tree death from heat stress, pests, pathogens or illegal
369 logging. Moreover, this technique could enable us to identify potential tipping points in tropical
370 forests, with wider ramifications for the development of adaptive forest management strategies in
371 the future.

372 Based on these results, future mortality is potentially predictable using hyperspectral data
373 for up to 50 days in advance of tree death (Figure 7). We also observed a tree that died naturally
374 from drought, and saw that there were regions of spectral overlap with the signal from trees
375 killed by girdling in terms of the wavelengths that changed prior to tree death; e.g. red (650-
376 700nm), the NIR (1000 -1400nm) and SWIR bands (2000-2400nm) (blue circles in Figure 5),
377 but it is difficult to draw conclusions from just one tree. Another venue of remotely sensing
378 stress would be through predicting changes in leaf water content which declined in leaves during
379 the drought (drought and gridled trees) and <50 days prior to death (only the drought tree)
380 (Figures 3 and 6), and is highly predictable, with high precision and accuracy (Figure 7). This
381 gives us some confidence that the spectral changes may be general to mortality and not specific
382 to girdling-induced mortality. We demonstrate only changes in leaf reflectance and not overall
383 canopy reflectance. It is important to differentiate between leaf versus canopy reflectance (as
384 seen from aircraft or space) because the latter also incorporates forest structural changes (such as
385 variations in LAI, branch architecture, stem density), which were not measured. Leaf spectral

386 properties strongly influence canopy spectral properties especially in certain wavelengths (Asner
387 and Martin 2008), but changes in other properties, like LAI, would complicate the signal. Leaf-
388 level analyses may also suffer from survivorship bias where the leaves that fare the worst under
389 drought drop first. Large shifts in the spectral regions shown in Fig 5 may be indicative of tree
390 mortality and should be tested with hyperspectral aircraft data in the region for confirmation
391 (Swinfield et al., 2019). A previous study using Hyperion hyperspectral satellite data over an
392 Amazonian drought experiment showed similar declines in magnitude in the NIR and VIS
393 regions as our study (Fig 5) (Asner et al., 2004).

394 Surprisingly, leaf spectral properties did not vary greatly during the period immediately
395 following tree girdling (~1 week). Previous studies have quantified changes in non-
396 photosynthetic vegetation to estimate regional selective logging impacts (Asner et al., 2005).
397 Here we show that significant trauma to the trunk (i.e. the girdling treatment) did not
398 immediately result in changes to leaf spectral properties, but that leaf spectral properties did
399 change significantly within 50 days of tree death. We hypothesize that > 7 days is the time
400 needed to change the biochemistry, physiology and metabolism of leaves to respond to
401 substantive environmental stress because we saw little change between C1 and C2. This
402 indicates that >7 days but <50 are necessary for leaf spectral changes to occur (Figure 5), which
403 could constrain timing for a potential new technique to identify damage to trees from selective
404 logging.

405 Do we succeed in predicting mortality because there are changes in short-term
406 physiological status (e.g. reduced relative % water content in leaves) or because certain trees are
407 just more likely to die than others due to their constitutive traits (e.g. lower LMA linked to a
408 different life history strategy)? In the girdled study, LMA and % water did not change

409 significantly prior to death, but leaf gas exchange metrics did (A_{sat} and R_{dark}), shown in the large
410 and significant changes in the visible and red edge bands (Fig 5). However, the drought-
411 associated tree death event was accompanied by a significant change in LMA and % water
412 content, and the spectral analysis showed a further correlation with significant changes in the
413 NIR and water bands (Fig 5). Therefore, it seems a combination of changes in leaf structure,
414 physiological status and associated reflectance traits combine to enable mortality to be
415 predictable.

416 It should be noted that prior to this study our plots had been extensively logged (i.e. four
417 times since the 1970's), with 46 to 54 Mg C ha⁻¹ cumulative extracted biomass in the area
418 (Riutta et al., 2018). Logging has been shown with hyperspectral imagery in Borneo to lower
419 canopy foliar nutrient concentrations and to decrease nutrient availability (Swinfield et al.,
420 2019). Our results are therefore biased towards logged/low foliar nutrient forests, although our
421 dataset does include late-successional species as well. However, most forests (72%) in the study
422 region have been selectively logged, and our results should be valid for these forests (Bryan et
423 al., 2013).

424 **Leaf physiology** - Leaf dark respiration, R_{dark} , was at its lowest during the peak of the drought,
425 in campaigns C3 and C4. This stands in contrast to some other tropical rainforest leaf respiration
426 studies during natural and artificial drought that have seen increases in leaf respiration rates
427 (Miranda et al., 2005; Rowland et al., 2015), although recent intensive survey results suggest that
428 the response to experimental drought was taxon-specific rather than observed across a wide
429 range of species (Rowland et al in review). Leaf R_{dark} also did not increase in the leaves of
430 girdled trees despite potential increases in leaf NSC content (as they could not be transported
431 towards the roots following the girdling). Other studies have shown a decrease in overall tree

432 respiration during drought periods as compared to before a drought (Doughty et al., 2015), and
433 this is a similar pattern shown at our plots (Riutta et al 2020).

434 We also observed both increased R_{dark} and decreased A_{sat} 50 days prior to tree death (Fig
435 6), which in combination, are very likely to reduce the carbon available in leaf tissue (although
436 net carbon balance is also dependent on changes in stomatal conductance and light availability).
437 This decreased carbon balance, in turn, could increase the likelihood of carbon starvation
438 (McDowell et al., 2018) and reduce the availability of carbon (or more accurately non-structural
439 carbohydrates) for possible embolism repair in the water conducting xylem tissue (Sala et al.,
440 2012). It is also interesting to note that the highest average photosynthetic capacity (A_{sat}) for the
441 girdled experiment were observed when the rains returned. We speculate that might be due to a
442 growth or sink driven response where, after the return of available water there was increased
443 growth (e.g. leaf flushing, xylem regrowth) to replace senesced tissue. We hypothesize that the
444 increased growth results in a higher carbon sink leading to a higher demand for NSC with a
445 consequent increase in A_{sat} . Overall, this is strong evidence that photosynthesis remains robust
446 to perturbations, and that growth may be maintained preceding a mortality event as the plant
447 attempts to recover damaged xylem capacity (Rowland et al., 2015; Meir et al., 2018).

448 **Conclusion**

449 Our key finding is that remote sensing using spectral imagery shows potential to identify
450 trees at imminent risk of death (approximately 50 days prior) with significant ($P < 0.05$) leaf
451 spectral changes in the red (650-700 nm), the NIR (1000 -1400 nm) and SWIR bands (2000-
452 2400 nm). This technique has widespread relevance and applicability for
453 ecological/management surveillance, prediction of future vegetation and forest carbon dynamics.
454 We suggest aircraft campaigns search for a large shift in visible, red edge, and NIR reflectance

455 and compare this to later observed tree mortality or possibly use past data to “hindcast” this
456 technique for validity. For instance, we hypothesize that comparing hyperspectral aircraft flights
457 before and after the 2016 drought might show large shifts in reflectance properties prior to tree
458 mortality(Davies et al., 2019; Swinfield et al., 2019). This could also be of use for hyperspectral
459 satellites like DESIS to predict changes in long term carbon fluxes associated with tree mortality
460 (Krutz et al., 2019). The large significant changes in leaf reflectance observed here that were
461 shared by both girdling- and drought-killed trees at the same timescale prior to mortality indicate
462 that there could be a spectral indication of tropical tree mortality that has regional or wider
463 application.

464

465

466 **Tables**

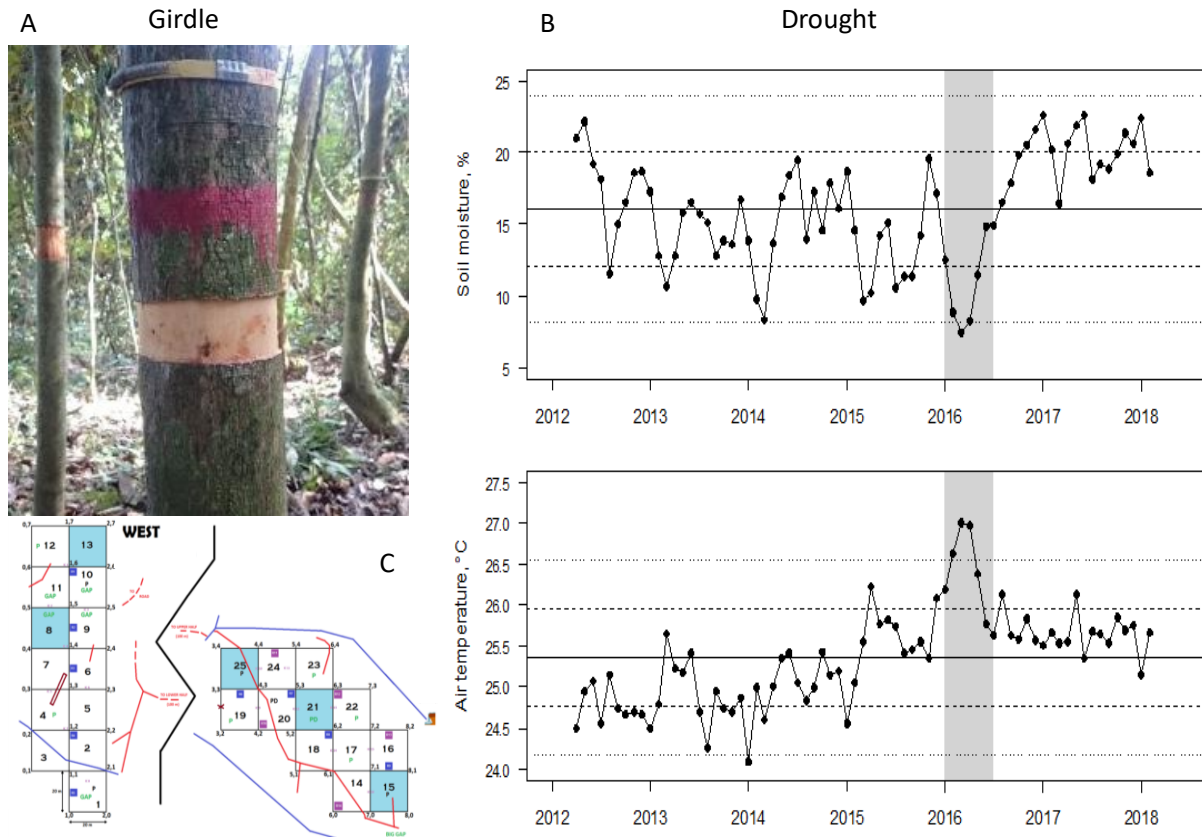
467 **Table 1** – Tree species measured intensively in the drought and girdled plot aligned to show
 468 which species were measured in both plots.

| Girdled Plot | Drought Plot |
|---|--|
| <p><i>Adinandra borneensis</i>, <i>Brownlowia peltata</i>,</p> <p><i>Dryobalanops lanceolate</i>, <i>Duabanga moluccana</i>,</p> <p><i>Hydnocarpus anomalus</i>, <i>Leea aculeate</i>, <i>Lithocarpus blumeanus</i>, <i>Litsea garciae</i>, <i>Lophopetalum sp.</i>, <i>Macaranga hypoleuca</i>, <i>Macaranga pearsonii</i>,</p> <p><i>Neolamarckia cadamba</i>, <i>Nephelium rambutan</i>, <i>Parashorea malaanonan</i>,</p> <p><i>Shorea johorensis</i>, <i>Shorea parvifolia</i>.</p> | <p><i>Adinandra borneensis</i>,</p> <p><i>Cariumna odontophyllum</i>, <i>Diplodiscus paniculatus</i>, <i>Dipterocarpus caudiferus</i>, <i>Dryobalanops lanceolate</i>, <i>Duabanga moluccana</i>, <i>Endospermum peltatum</i>,</p> <p><i>Lithocarpus blumeanus</i>,</p> <p><i>Macaranga pearsonii</i>, <i>Mallotus leucodermis</i>, <i>Nauclea officinalis</i>, <i>Neolamarckia cadamba</i>,</p> <p><i>Parashorea malaanonan</i>, <i>Pleiocarpidia sandakanica</i>, <i>Pterospermum elongatum</i>, <i>Shorea gibbosa</i>, <i>Shorea johorensis</i>,</p> <p><i>Syzygium sp.</i>, <i>Trema orientalis</i></p> |

469

470

471 **Figures**

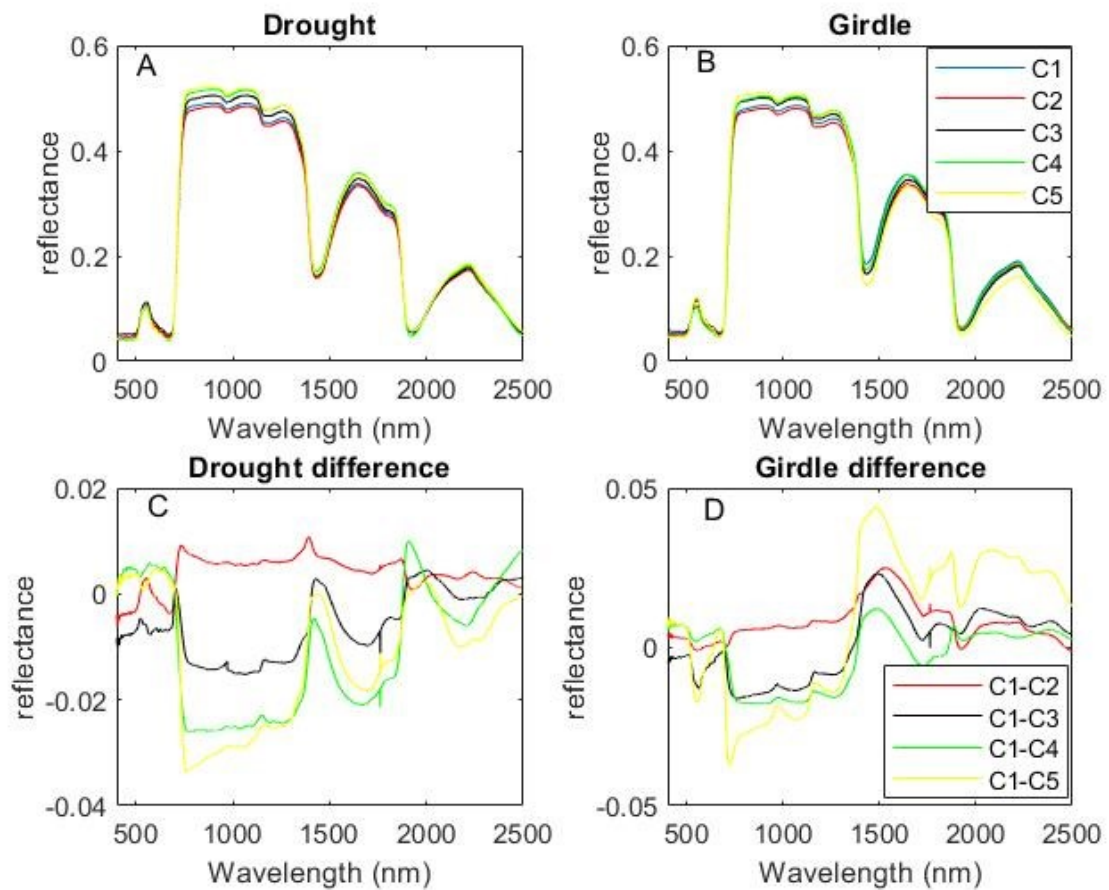


472

473 **Figure 1.** (A) An example tree that was girdled by stripping 10 cm of phloem in a ring around the tree.
474 (B) Monthly volumetric soil moisture content at 20 cm depth (top) and air temperature (bottom) records at
475 the study site. The horizontal continuous line denotes the long-term mean and the dashed lines denote 1
476 and 2 standard deviations. The grey region is the period of our measurements. (C) A schematic of the
477 plot layout with the non-girdled trees in the section labelled West (the other section was girdled). The
478 total area of the plot is 1 ha, with the two sections separated by approximately 200 m. The middle black
479 line represents the river. Each individual square represents a 20 m ×20 m subplot. Red lines are trails
480 and blue lines are small temporary streams.

481

482

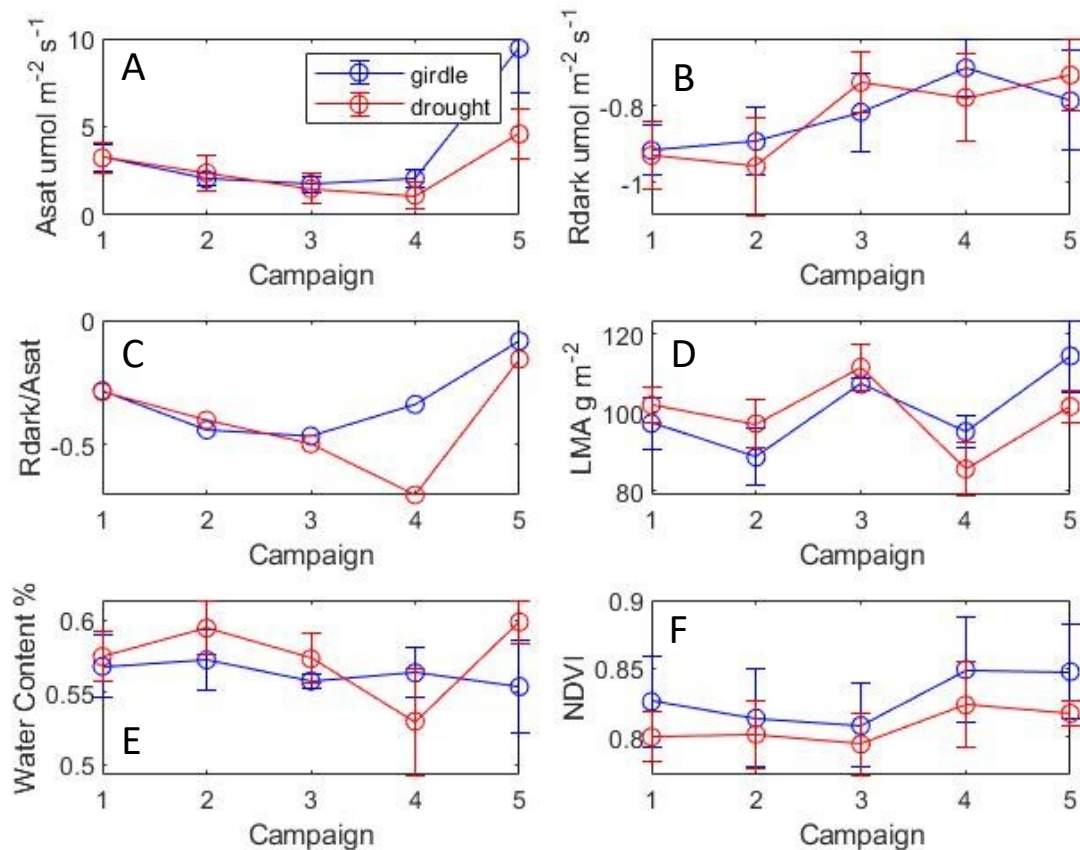


483

484 **Figure 2.** Leaf spectral properties (400-2500nm) for the drought (A) and girdled (B) plots for the 5
 485 campaigns (Jan-June 2015). (bottom) The difference (C1-CX, where X=2-5) in leaf spectral properties
 486 for the drought (C) and the girdled (D) plots. In each campaign, we sampled the same trees unless the
 487 trees died. Reflectance factor is reflected incident light between 0-1.

488

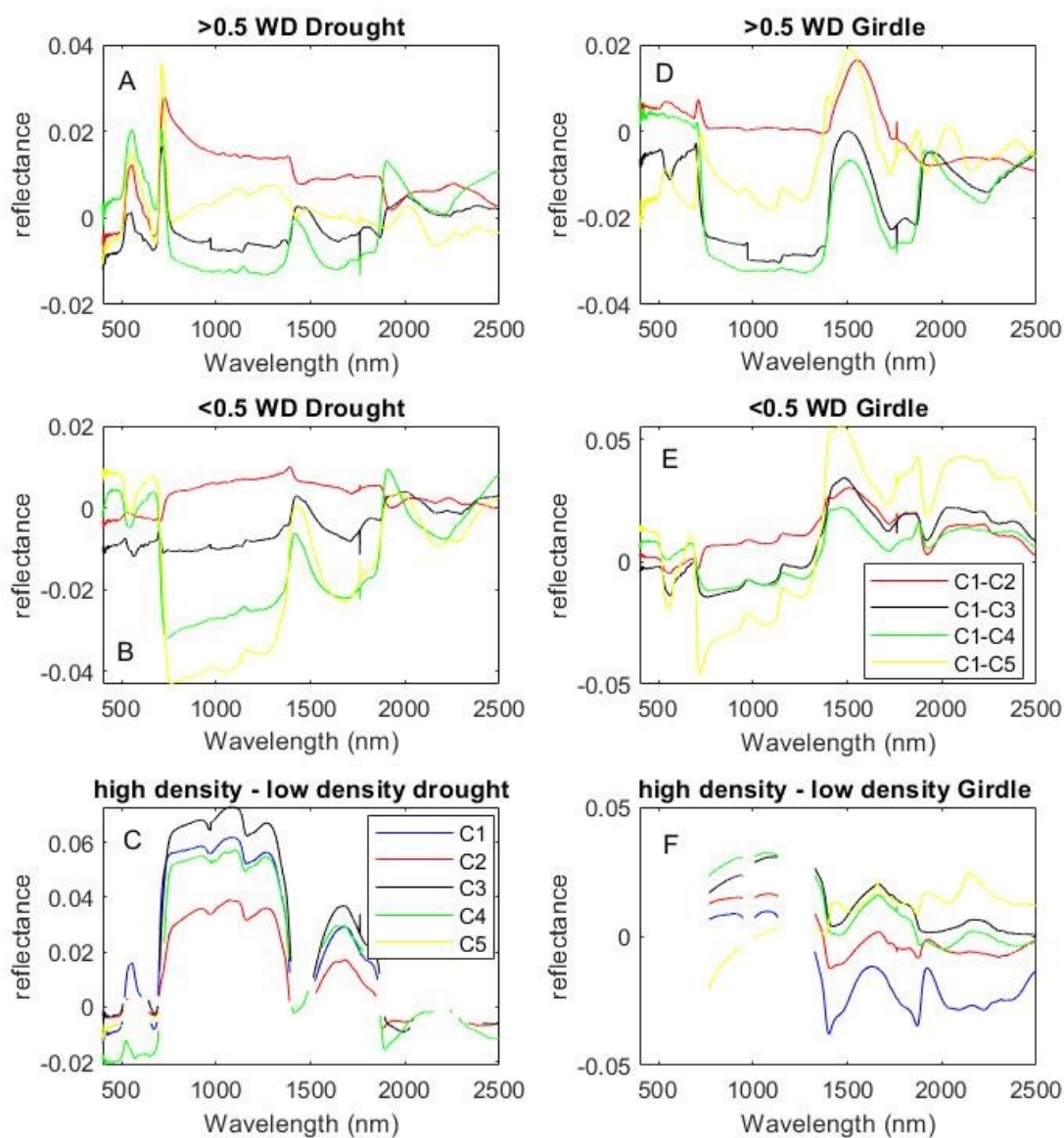
489



491

492 **Figure 3.** Average \pm se (A_{sat}) photosynthetic capacity (A), (R_{dark}) leaf dark respiration (B), A_{sat} / R_{dark} (C)
 493 (LMA) leaf mass area (D), % leaf water (E) and NDVI (F) for the 5 campaigns for the control site (red)
 494 and the girdled site (blue). A_{sat} and R_d were collected at a standard temperature (30°C) during all
 495 campaigns. We subtracted the initial difference ($2 \mu\text{mol m}^{-2} \text{sec}^{-1}$) in the top panel between the average
 496 C1 values to better highlight the impact of the girdling. Peak drought was C3 and the rains returned in
 497 C5.

498



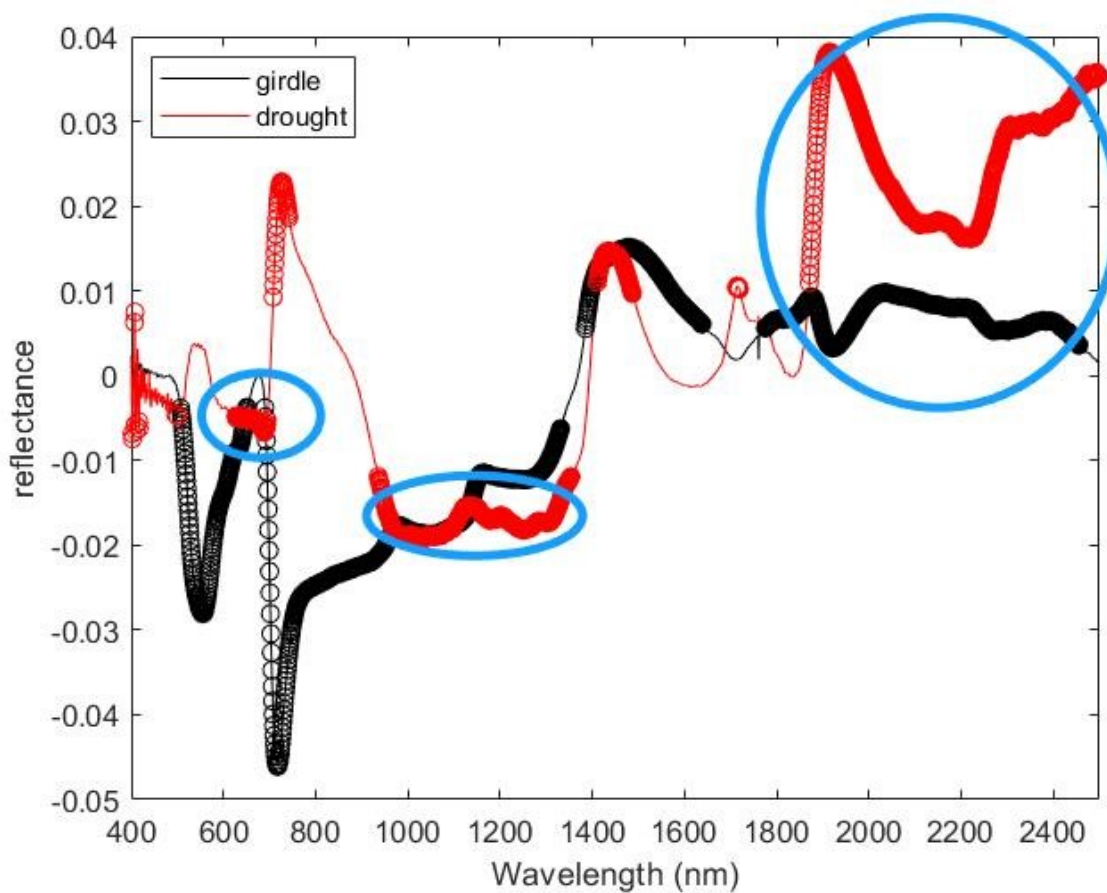
499
 500 **Figure 4.** The change in leaf spectral properties (400-2500 nm) between campaigns comparing drought
 501 plots for species with high wood density (density >0.5 g cm⁻³ - A), low wood density (density <0.5 g cm⁻³,
 502 B), and the difference (C) through the 5 campaigns. The girdled plots for species with high wood density
 503 (density >0.5 g cm⁻³ - D), low wood density (density <0.5 g cm⁻³, E), and the difference (F). For the
 504 difference plots, only significant (P<0.05) spectral regions are shown.

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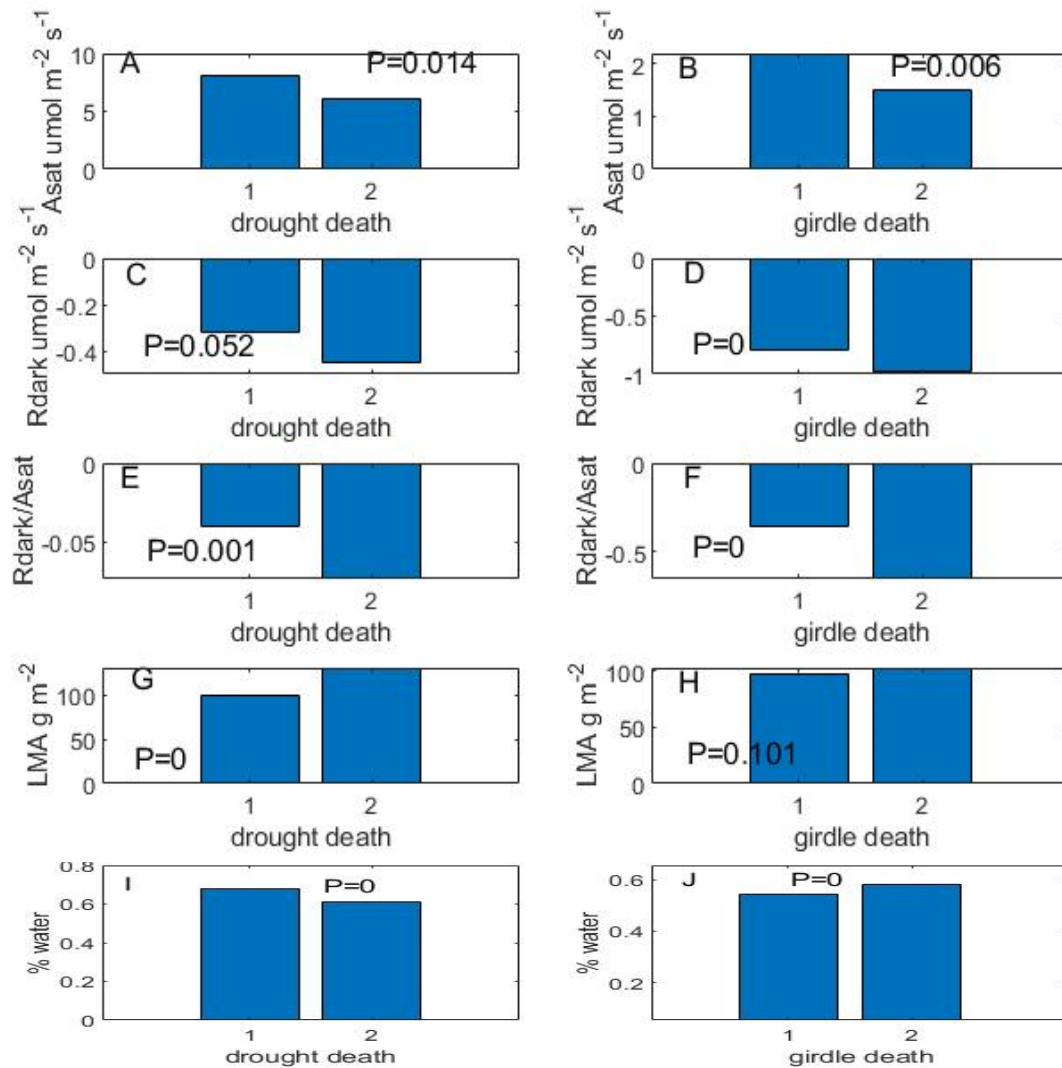


509

510 **Figure 5** –The change (negative is a reduction in reflectance close to death) in leaf spectral
511 properties from healthy leaves (>50 days from death) minus close to death leaves (<50 days from
512 death) on a tree that died of natural drought (red, N=14 leaves) and trees that died during the
513 girdling experiment (black, N=122 leaves). Dots show regions of significant change ($P<0.05$)
514 using a paired t-test. Blue circled areas are key areas of spectral overlap.

515

516

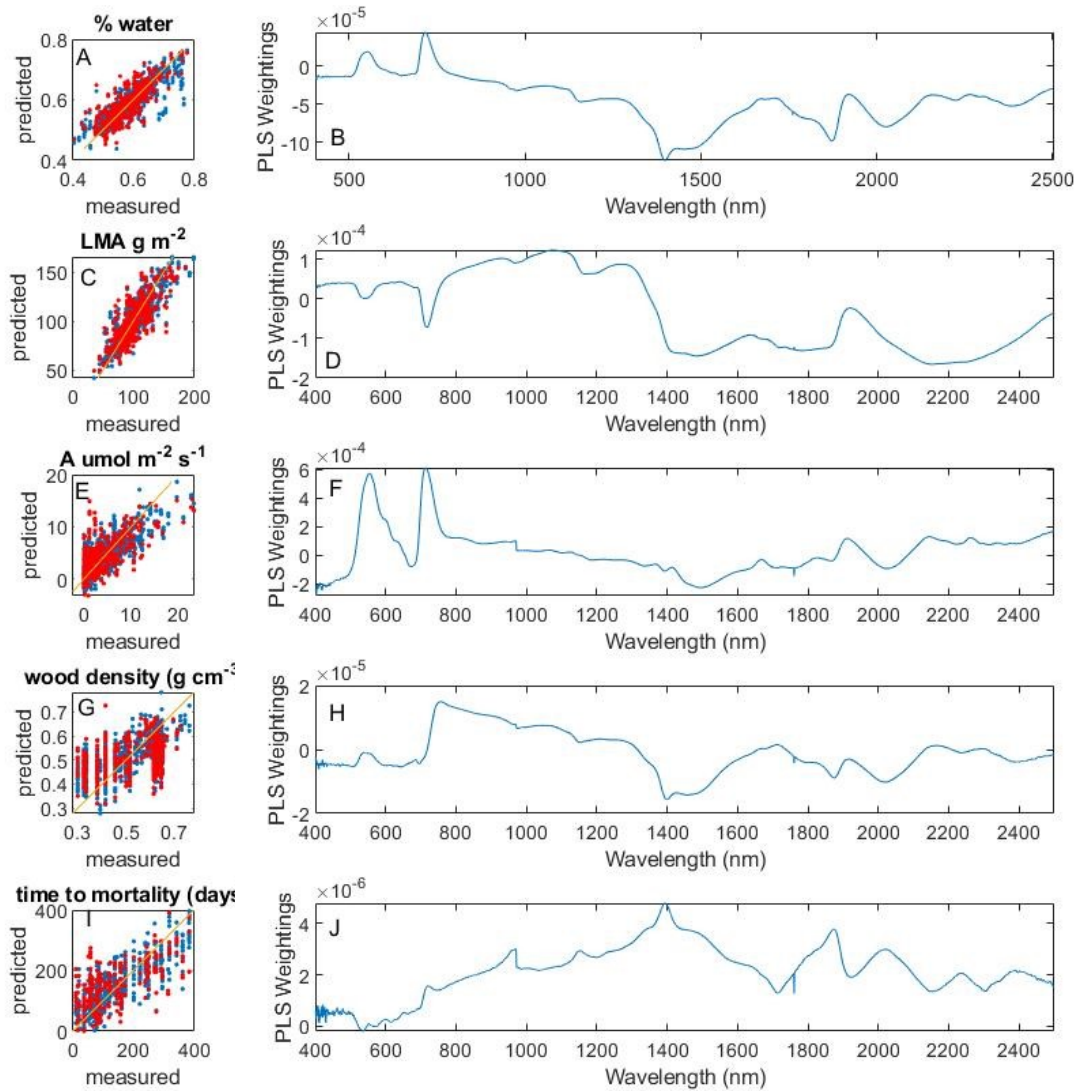


517

518 **Figure 6** – Comparison of the intensively monitored tree that died during the drought (left) and
 519 the girdling experiment (right) for A_{sat} (A,B), R_{dark} (C,D), R_{dark}/A_{sat} (E, F), LMA (G, H) and %
 520 water (I, J) between initial values and values within 50 days of death. The P value listed is the
 521 level of significance to three digits for a student's t-test. P=0 is a P value less than 0.0001.

522

523



524

525 **Figure 7.** On the left is predictive power (measured vs predicted) for the PLSR analysis with the r^2 and
 526 RMSE/mean calculated from the full dataset for various traits including % water (A, $r^2=0.72$, RMSE =
 527 0.07), LMA (C, $r^2=0.74$, RMSE/mean = 0.14), Asat (E, $r^2=0.66$, RMSE/mean = 0.69), wood density (G,
 528 $r^2=0.41$, RMSE/mean = 0.24), and time to tree death (I, $r^2=0.68$, RMSE/mean = 0.55). Red dots are the
 529 data to train the model (70%) and the blue dots are the independent dataset (30%). Sample sizes to train
 530 the models are as follows: % water – N=1035, LMA-N=1028, Asat- N=846, wood density – N= 841, tree
 531 death – N=543. On the right is the primary weighting, which is the PLS weight that explains the most
 532 variance in the data, multiplied by variance explained for % water (B), LMA (D), Asat (F), wood density
 533 (H), and time to tree death (J).

534

535 **Acknowledgements** – We would like to acknowledge Dr. Rob Ewers for his role in setting up
536 the SAFE experiment, Elelia Nahun, Dg Ku Shamirah binti Pg Bakar for their contributions to
537 the field campaign, Unding Jami, Ryan Gray, Rostin Jantan, Suhaini Patik and Rohid Kailoh and
538 the BALI and Lombok project research assistants.

539

540 **Data Availability statement** – The data and code that support the findings of this study are
541 openly available in Data Dryad at <http://doi.org/doi:10.5061/dryad.d51c5b01n>.

542

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