

Predicting tropical tree mortality with leaf spectroscopy

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

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48 **Introduction**

49 Can future tropical forest tree mortality be predicted with aircraft or satellite remote
50 sensing? This question is of interest because tropical tree mortality is increasing, reducing the
51 global carbon sink (Hubau et al., 2020)(Brienen et al., 2015). Increased tree mortality may be
52 driven by recent increases in extreme weather events caused by climate change, including
53 increased drought frequency/severity (Rifai et al., 2019)(Rifai et al., 2018)(Rowland et al.,
54 2015)(Doughty et al., 2015) or elevated air temperatures (Clark, 2004; Doughty & Goulden,
55 2009a). Other causes of mortality include altered disturbance regimes due to land management
56 practices or biological invasions (e.g. grass/fire cycles) and the negative environmental impacts
57 arising from forest degradation (e.g. physical damage to trees from logging or small-scale slash-
58 and-burn agriculture; environmental stress from enhanced edges effects) (Malhi et al., 2014).
59 Experimental drought manipulations in the Amazon (Meir et al., 2015)(da Costa et al., 2010;
60 Nepstad et al., 2007) show that larger trees, especially for specific high-abundance taxa
61 (Bittencourt et al., 2020), are more susceptible to mortality. Could changes to leaf properties in
62 these large trees indicate risk of imminent future mortality? Death of these large individuals has
63 the greatest impact on tropical forest vegetation and carbon dynamics (Phillips et al., 2009).
64 “Environmental surveillance” techniques that enable us to identify individuals at risk of death or
65 to predict future patterns of senescence would enable us not only to more accurately model forest
66 vegetation and carbon dynamics, but could possibly enable us to manage the spread of forest
67 pathogens and understand environmental stress gradients related to disturbance. Given that these
68 large trees are also the most visible to aircraft and satellites, remote sensing techniques that
69 enable us to identify dying trees hold tremendous potential for detecting and understanding the
70 causes of tree mortality at large spatial scales.

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

83 Is tree death caused by carbon starvation, hydraulic failure, or a combination of the two
84 and what traits are associated with this? To predict tree death with remote sensing we must
85 understand the characteristics that drive tree death. A recent meta-analysis suggests that metrics
86 of hydraulic failure more consistently predicted mortality than carbon starvation as determined
87 by tissue concentrations of NSC (Adams et al., 2017). Another study found hydraulic traits were
88 better at predicting the response of ecosystem fluxes (CO₂ and water vapor) to drought than traits

89 like LMA or wood density (Anderegg et al., 2018). Tree mortality during droughts is highest for
90 species that have a small hydraulic safety margin (the difference between typical minimum
91 xylem water potential experienced and xylem vulnerability to embolism) (Anderegg et al., 2016).
92 Turgor loss point - the leaf water potential that induces wilting - may be a key trait predicting
93 drought tolerance and species distributions relative to water supply (Bartlett et al., 2012). In
94 tropical forests, there are species-specific changes to turgor loss point at the leaf level
95 (Maréchaux et al., 2015) and xylem pressure at 50% conductivity (xylem-P₅₀), leaf turgor loss
96 point (*TLP*) and cellular osmotic potential (π_o) all occurred at significantly higher water
97 potentials for the drought-intolerant PFT compared to the drought-tolerant PFT (Powell et al.,
98 2017).

99 Leaf traits can be sensed remotely by aircraft or from space. Foliar traits such as nitrogen
100 (N), chlorophyll content, carotenoids, lignin, cellulose, LMA, soluble carbon, and water can be
101 remotely estimated with leaf spectral reflectance signatures in many different plants and
102 ecosystems (Ustin et al., 2009), including tropical forests (Asner & Martin, 2008). This is
103 because certain traits are associated with reflectance characteristics within specific spectral
104 regions. For instance, the visible part of the spectrum (400–700 nm) is associated with leaf N
105 concentration, and the shortwave infrared (SWIR; 700–1,300 nm) is associated with structures
106 such as palisade cell density. LMA and leaf chemistry have been accurately measured and
107 modelled at both the leaf (one nm bandwidth) (Asner & Martin, 2008; Curran, 1989;
108 Jacquemoud et al., 2009), canopy and landscape scales (at 10 nm bandwidth) (Asner et al.,
109 2016). Other elements not directly expressed in the spectrum, such as phosphorus (P), have been
110 accurately predicted with spectroscopy, possibly through a stoichiometric relationships with
111 other chemical species (Ustin et al., 2006, 2009) or correlations with leaf morphological traits via
112 the leaf economics spectrum (Wright et al 2004). Other tropical tree traits not directly associated
113 with leaf spectra, such as leaf age (Chavana-Bryant et al., 2017), photosynthetic capacity
114 (Doughty et al., 2011), and branch wood density, have been predicted with spectroscopy in
115 tropical forests (Doughty et al., 2017). Predicted traits not directly associated with spectral
116 regions are likely correlations between leaf traits and a tree's life history strategy (Doughty et al.,
117 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, EVI, a greenness index, as
120 measured with Moderate Resolution Imaging Spectroradiometer (MODIS) increased in the
121 Amazon during the 2005 drought (Saleska et al., 2007). However, others have challenged the
122 original interpretation of the EVI data (Morton et al., 2014; Samanta et al., 2010), highlighting
123 the challenge of remote sensing at a continental scale. More recently, during a major El Niño
124 drought in Borneo, NDVI initially increased as the drought was strengthening, but decreased at
125 its peak (Nunes et al., 2019). Interpretation of changing NDVI and/or EVI, at a larger spatial
126 scales is generally complicated in many ecosystems as changes at the leaf level may be
127 compensated for or masked by branch level process, for example leaf senescence and drop may
128 reduce the canopy scale NIR signal. However, remotely sensed LAI signal saturates in tropical
129 forests and LAI variation can be relatively small even following strong climate extremes such as
130 drought. For instance, Meir et al. 2018 found a 12-20% change in LAI during an extreme

131 drought manipulation experiment with a $\sim 5.5 \text{ m}^2 \text{ m}^{-2}$ LAI which is within the saturation range.
132 Therefore, changes in tropical forest canopy spectral characteristics at larger spatial scales may
133 be more linked to changes changes in leaf level spectra, than in other ecosystems (Doughty &
134 Goulden, 2009b; Wu et al., 2018).

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

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

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

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

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158

159 **Methods**

160 **Study sites**

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

181

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

191

192 **Leaf sampling strategy** –In each plot, 20-25 trees were chosen during each campaign, and tree
193 climbers with extendable tree pruners removed one branch per tree that was growing in full
194 sunlight. These branches were quickly recut underwater and returned to a central lab building
195 for further measurements. On each of these branches, five fully expanded non-senescent leaves
196 in randomly selected locations were chosen for measurements of: leaf-gas exchange (respiration
197 and photosynthesis), and dark respiration, leaf spectral properties (measured within 1 hour of
198 being cut) and LMA. Leaf area was determined immediately after collection using a digital 476
199 scanner (Canon LiDE 110) and then oven dried at 72 °C until constant mass was reached.

200

201 **Leaf-level gas exchange** – We used a portable gas exchange system (LI 6400, Li-Cor
202 Biosciences, Lincoln, NE, USA) to measure leaf-level gas exchange. After returning to the
203 central lab building, leaf dark respiration (R_{dark}) was measured by covering branches with an

204 opaque bag for at least 20 minutes prior to measurement at a cuvette temperature of 30° C. After
205 this, branches were exposed to sunlight and light-saturated leaf photosynthesis was measured
206 (A_{sat} ; 1200 $\mu\text{mol m}^{-2} \text{s}^{-1}$ PPF, 400 ppm CO_2 , at 30° C). With A_{sat} ; 1200 $\mu\text{mol m}^{-2} \text{s}^{-1}$ chosen
207 because photosynthetic capacity in most tropical leaves saturates above light levels of 1200 μmol
208 $\text{m}^{-2} \text{s}^{-1}$ PPF (Both et al., 2019; Gvozdevaite et al., 2018)(Doughty & Goulden, 2009b). We
209 waited for gas exchange values to stabilize before starting a measurement, recorded data every 2
210 seconds and averaged the results after eliminating the first 20 measurements. We excluded
211 photosynthesis measurements less than 0 $\mu\text{mol m}^{-2} \text{s}^{-1}$ (as this was indicative of a failure to
212 maintain hydraulic connectivity in the sampled branch resulting in stomatal closure) and dark
213 respiration measurements more negative than -1.5 $\mu\text{mol m}^{-2} \text{s}^{-1}$ (as this was considered indicative
214 of a failure to truly represent R_d , or in some cases operator error). Most physiological
215 measurements were collected between 07:00 and 14:00 local time and branches were cut from
216 tree between 06:00 and 13:00 local time. An online supplement includes our averaged \pm sd data
217 for each leaf measured for transpiration rate ($\text{mmol H}_2\text{O m}^{-2} \text{s}^{-1}$), vapor pressure deficit based on
218 leaf temp (kPa), intercellular CO_2 concentration ($\mu\text{mol CO}_2 \text{mol}^{-1}$), conductance to H_2O (mol
219 $\text{H}_2\text{O m}^{-2} \text{s}^{-1}$), and photosynthetic rate ($\mu\text{mol CO}_2 \text{m}^{-2} \text{s}^{-1}$).

220 **Leaf spectroscopy** – We randomly selected five leaves within an hour of each branch being cut
221 and measured hemispherical reflectance near the mid-point between the main vein and the leaf
222 edge. We used an ASD Fieldspec 4 with a fibre optic cable, contact probe and a leaf clip
223 (Analytical Spectral Devices High Intensity Contact Probe and Leaf Clip, Boulder, Colorado,
224 USA). The spectrometer records 2175 bands spanning the 325–2500 nm wavelength region.
225 Measurements were collected with 136-ms integration time per spectrum. To ensure
226 measurement quality, the spectrometer was calibrated for dark current, stray light and white
227 referenced to a calibration panel (Spectralon, Labsphere, Durham, New Hampshire, USA) after
228 each branch. The spectrometer was optimized after every branch. For each measurement, 25
229 spectra were averaged together to increase the signal-to-noise ratio of the data.

230 **Data analysis** - We used the Partial Least Squares Regression (PLSR) modelling approach to
231 predict leaf traits with spectral information, (Geladi & Kowalski, 1986). PLSR incorporates all
232 the spectral information within each leaf reflectance measurement, eventually reducing all
233 spectral data (400-2500 nm) down to a relatively few, uncorrelated latent factors. This approach
234 has been used successfully to predict plant traits across a wide range of ecosystems, including
235 tropical forests (Asner & Martin, 2008)(Serbin et al., 2014). We used the PLSregress command
236 in Matlab (Matlab, MathWorks Inc., Natick, MA, USA) to establish predictive models for LMA,
237 A_{sat} , wood density and tree mortality. We minimized the mean square error with K-fold cross
238 validation to avoid over-fitting the number of latent factors. To create a completely independent
239 testing dataset, we used the above method on 70% of our data to calibrate our model and then the
240 remaining 30% to test the accuracy of our model. We evaluated the accuracy of our modelled
241 estimates using two main metrics: r^2 and root mean square error (RMSE)/mean. We grade our
242 results as high precision and accuracy ($r^2 > 0.70$; %RMSE $< 15\%$), medium precision and
243 accuracy ($r^2 > 0.50$; %RMSE $< 30\%$), low precision and accuracy ($r^2 > 0.50$; %RMSE $> 30\%$).

244 **Statistical tests** – For our leaf spectral measurements, for each 1 nm bandwidth, we determined
245 statistical significance ($P < 0.05$) with a paired t-test. To understand significant differences
246 between differences of LMA, R_{dark} , and A_{sat} , we used a t-test. To understand the impact of the
247 girdling over time, we used a repeated measures ANOVA.

248

249 **Results**

250

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

259 There was little change in leaf reflectance (400-2500 nm) between C1 and C2 (Figure 2)
260 in both the drought and girdle plots. We expected few spectral changes during this short interval
261 between C1 and C2 (Jan-21 to Feb-10) for the natural drought plots, but we were surprised there
262 were also few changes for the girdled plots since these trees experienced a significant trauma.
263 In the later campaigns (C3 to C5 01-Mar to 08-Jun), there were large (~0.03 albedo units)
264 decreases in NIR reflectance (750-1500 nm) in both the girdled and natural drought plots (Figure
265 2 a and b). Reflectance in the visible wavelengths were greater during the peak natural drought
266 (C3) than after the rains returned (C4 and C5). The girdled plots showed a consistent decrease in
267 the visible bands. The SWIR bands also differed between girdled and drought (non-girdled),
268 with large decreases in the drought plots and little change in the girdle plot except for the final
269 campaign where there was an increase. However, changes in spectral properties in the girdled
270 plot might also have resulted from species changes because certain tree species died sooner than
271 others, thus changing the species composition as the experiment continued.

272 Our average A_{sat} values across the campaigns for the girdled plot ($3.7 \mu\text{mol CO}_2 \text{ m}^{-2} \text{ s}^{-1}$)
273 and the drought plot ($4.7 \mu\text{mol CO}_2 \text{ m}^{-2} \text{ s}^{-1}$) were slightly lower, but within 95% confidence
274 intervals of values from a nearby campaign in Borneo of community weighted mean and 95%
275 confidence interval of $4.08 \mu\text{mol CO}_2 \text{ m}^{-2} \text{ s}^{-1}$ (2.7–5.5) for the old growth plots and $7.0 \mu\text{mol}$
276 $\text{CO}_2 \text{ m}^{-2} \text{ s}^{-1}$ (5.7–8.4) for the selectively logged plots (Both et al., 2019). Our average R_{dark} values
277 across the campaigns for the girdled plot ($-0.82 \mu\text{mol CO}_2 \text{ m}^{-2} \text{ s}^{-1}$) and the drought plot (-0.83
278 $\mu\text{mol CO}_2 \text{ m}^{-2} \text{ s}^{-1}$) were likewise slightly lower than the values from Both et al 2019 of -1.0
279 $\mu\text{mol CO}_2 \text{ m}^{-2} \text{ s}^{-1}$ (-0.9 to -1.2) for the old growth plots and $-1.3 \mu\text{mol CO}_2 \text{ m}^{-2} \text{ s}^{-1}$ (-1.1 to -1.4)
280 for the selectively logged plots. Light saturated leaf photosynthesis and R_{dark} showed strong
281 seasonality in both plots over the measurement period (Figure 3). For instance, A_{sat} increased in
282 both the drought and girdled plots in campaign 5 following the return of the rains. Surprisingly,
283 the surviving girdled trees had the highest photosynthetic rates of the campaign in C5 despite the
284 damaged phloem. Dark respiration was at its lowest in C3 and 4 during the peak of the drought.
285 In both groups, changes in R_{dark} matched those in A_{sat} meaning that as A_{sat} increased so did dark
286 respiration. The ratio $R_{\text{dark}}/A_{\text{sat}}$ showed a similar seasonal cycle, with the exception of C4,
287 which was less efficient in the drought plot. A repeated measures ANOVA showed no
288 significant differences between A_{sat} , R_{d} , and LMA over time between the girdled and drought
289 plots across the five campaigns suggesting the girdling had little overall impact of on leaf
290 physiology.

291 Details of the trees that died (i.e. size, species, functional traits) is the topic of a
292 companion paper (Nottingham et al in prep), but functional traits, such as wood density, may
293 explain some of the timing of tree mortality in our study (see companion paper). To understand

294 how the drought and girdling impacted leaf spectral properties in different ways according to
295 functional traits, we binned our results into groups of trees with either high ($>0.5 \text{ g cm}^3$) or low
296 wood density ($<0.5 \text{ g cm}^3$) (Figure 4). Tree species with lower density wood showed a much
297 stronger reaction to the drought in the NIR and SWIR bands than tree species with higher density
298 wood, with fewer significant changes ($P<0.05$) in the visible bands. In contrast, the high wood
299 density tree species show a stronger reaction to the girdling than the low wood density species,
300 again with most of the change in the NIR and SWIR bands.

301 We then compared near death leaf reflectance (within 50 days of dying) to leaf
302 reflectance from the same trees not near to death (Figure 5). We found that as death approaches
303 in the girdled trees, there are large, significant reductions in reflectance in the visible, the red
304 edge and most of the NIR ($P<0.05$). By C5, 38 trees or 18% percent of all girdled trees had died.
305 There were large (0.03-0.05 reflectance units) and significant decreases ($P<0.05$) in leaf
306 reflectance in the visible bands and the red edge as tree death approached. There were also large
307 (0.02) and significant increases ($P<0.05$) in leaf reflectance in NIR and SWIR bands too. Next,
308 we investigated how drought conditions, precipitated by the ENSO event, affected leaf spectral
309 properties in trees which died naturally in the non-girdled control plot. Only one tree died from
310 drought in the control that was intensively sampled for functional traits. We observed similar
311 significant changes in this tree as observed in the trees that died following the girdling treatment:
312 reductions in reflectance occurred in the red, the NIR and SWIR bands. However, there was a
313 significant peak in the red edge in the opposite direction compared to the girdling study. The
314 wavelengths that show similarities for both types of death are: red (650-700nm), the NIR (1000 -
315 1400nm) and SWIR bands (2000-2400nm).

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

327 Finally, we used PLSR to predict changes in physiology and time to death with
328 spectroscopy (Figure 7). We used the primary weighting (right side of figure 7) to understand
329 which spectral regions are most important (deviations from 0). Spectroscopy predicted LMA
330 with an r^2 of 0.70 and RMSE/mean of 0.14 (similar to many other studies with high precision
331 and high accuracy (Asner and Martin 2008, Doughty et al 2011)). The primary weighting is in
332 the NIR and SWIR bands which is typical of traits relating to structure. Spectroscopy predicted
333 maximum photosynthetic rate (A_{sat}) with an r^2 of 0.65 and RMSE/mean of 0.69 (medium
334 precision but low accuracy) and wood density with an r^2 of 0.45 and RMSE/mean of 0.24 (low

335 precision but medium accuracy). The primary weighting of A_{sat} was in the visible bands (likely
336 related to chlorophyll content) and for wood density in NIR and SWIR >1000 nm (likely related
337 to variations in LMA and leaf structure). Finally, we predicted to time to death with spectroscopy
338 and the PLSR technique with an r^2 of 0.65 and RMSE/mean of 0.58 (medium precision and low
339 accuracy). The primary weighting shows similarity with Figure 5 with important spectral
340 regions in the visible (related to photosynthetic characteristics), the NIR (related to structure) and
341 SWIR bands (related to water bands).

342

343

344 Discussion

345 **Leaf spectroscopy** - Identification of tropical trees susceptible to mortality through
346 hyperspectral imagery could provide a powerful tool in examining recently reported increases in
347 tree mortality rates across the tropics (Hubau et al., 2020)(Brienen et al., 2015). By contributing
348 to “environmental surveillance,” the use of hyperspectral data would have a wide range of
349 applications from the prediction of tree death from heat stress, pests, pathogens or illegal
350 logging. Moreover, this technique could enable us to identify potential tipping points in tropical
351 forests, with wider ramifications for the development of adaptive forest management strategies in
352 the future. Based on these preliminary results, future mortality is potentially predictable using
353 hyperspectral imagery for up to 50 days in advance of tree death (Figure 7). We also observed a
354 tree that died naturally from drought, and saw that there were regions of spectral overlap with the
355 signal from trees killed by girdling in terms of the wavelengths that changed prior to tree death;
356 e.g. red (650-700nm), the NIR (1000 -1400nm) and SWIR bands (2000-2400nm) (Figure 5).
357 This gives us some confidence that the spectral changes may be general to mortality and not
358 specific to girdling-induced mortality. We demonstrate only changes in leaf reflectance and not
359 overall canopy reflectance. It is important to differentiate between leaf versus canopy reflectance
360 (as seen from aircraft or space) because the latter also incorporates forest structural changes (like
361 variations in LAI and branch architecture), which we have not measured. Leaf spectral
362 properties strongly influence canopy spectral properties especially in certain wavelengths (Asner
363 and Martin 2008), but changes in other properties, like LAI, could confound the signal. Large
364 shifts in these spectral regions may be indicative of tree mortality and should be tested with
365 hyperspectral aircraft data in the region for confirmation (Swinfield et al., 2019).

366
367 Surprisingly, leaf spectral properties did not vary greatly during the period immediately
368 following tree girdling (~1 week). Previous studies have quantified changes in non-
369 photosynthetic vegetation to estimate regional selective logging (Asner et al., 2005). Here we
370 show that significant trauma to the trunk did not immediately result in changes to leaf spectral
371 properties but leaf spectral properties did change within 50 days of tree death. We hypothesize
372 that > 10 days is the time needed to change the biochemistry, physiology and metabolism of
373 leaves to respond to environmental stress. This indicates that >10 days but <50 are necessary
374 for leaf spectral changes to occur (Figure 5), which could constrain timing for a potential new
375 technique to identify damage to trees from selective logging.

376 It should be noted that our plots had been extensively logged, four times since the 1970’s
377 with 46 to 54 Mg C ha⁻¹ cumulative extracted biomass in the area (Riutta et al., 2018). This has
378 been shown with hyperspectral imagery to lower canopy foliar nutrient concentrations and
379 decrease nutrient availability (Swinfield et al., 2019). Our results are therefore biased towards
380 logged/low foliar nutrient forests, although our dataset does include late-successional species as
381 well. However, most forests (72%) in the region have been selectively logged, and our results
382 should be valid for these forests (Bryan et al., 2013).

383 **Leaf physiology** - Dark leaf respiration, R_{dark} , was at its lowest during the peak of the drought, in
384 campaigns C3 and C4. This stands in contrast to other leaf respiration studies during an artificial
385 drought that saw a strong increase in leaf respiration rates (Rowland et al., 2015), although recent
386 results suggest that this response may be taxon-specific result that is not observed across all

387 species (Rowland et al in review). Leaf R_{dark} also did not increase in the girdled leaves despite
388 potential increases in leaf NSCs (as they could not be transported towards the roots following the
389 girdling). Other studies have shown a decrease in overall respiration during drought periods as
390 compared to before a drought (Doughty et al., 2015), and this is a similar pattern shown at our
391 plots (Riutta et al 2020).

392 We also observed both increased R_{dark} and decreased A_{sat} 50 days prior to tree death,
393 which in combination are very likely to reduce the carbon available in leaf tissue (although net
394 carbon balance is also dependent on changes in stomatal conductance). Which in turn could
395 increase the likelihood of carbon starvation (McDowell et al., 2018) and reduce the availability
396 of carbon (or more accurately NSC) for embolism repair the of reversal of in the water
397 conducting xylem tissue (Sala et al., 2012). It is also interesting to note that the highest average
398 photosynthetic capacity (A_{sat}) for the girdled experiment were observed when the rains returned.
399 We speculate that might be due to a growth or sink driven response where, after the return of
400 available water increased growth (e.g. fine root growth and leaf flushing) to replace senesced
401 tissue results in a higher carbon sink leading to a higher demand for NSC with a consequent
402 increase in A_{sat} . Overall, this is more evidence that photosynthesis is robust despite
403 perturbations, and that growth may be maintained preceding a mortality event as the plant
404 attempts to recover damaged xylem capacity (L. Rowland et al., 2015; Lucy Rowland et al.,
405 2015).

406 **Conclusion**

407 Our key finding is that remote sensing using spectral imagery shows potential to identify
408 trees at imminent risk of death (approximately 50 days prior). This technique has widespread
409 relevance and applicability for ecological/management surveillance, prediction of future
410 vegetation and forest carbon dynamics. We suggest aircraft campaigns search for a large shift in
411 visible, red edge, and NIR reflectance and compare this to observed tree mortality. For instance,
412 we hypothesize that comparing hyperspectral aircraft flights before and after the 2016 drought
413 might show large shifts in reflectance properties prior to tree mortality (Davies et al.,
414 2019)(Swinfield et al., 2019). This could also be of use for hyperspectral satellites (Krutz et al.,
415 2019). The large significant changes in leaf reflectance observed here that were shared by both
416 girdling- and drought-killed trees at the same timescale prior to mortality indicate that there
417 could be a spectral indication of tropical tree mortality that has regional or wider application.

418

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420 the SAFE experiment, Elelia Nahun, Dg Ku Shamirah binti Pg Bakar for their contributions to
421 the field campaign, Unding Jami, Ryan Gray, Rostin Jantan, Suhaini Patik and Rohid Kailoh and
422 the BALI and Lombok project research assistants.

423 **Tables**

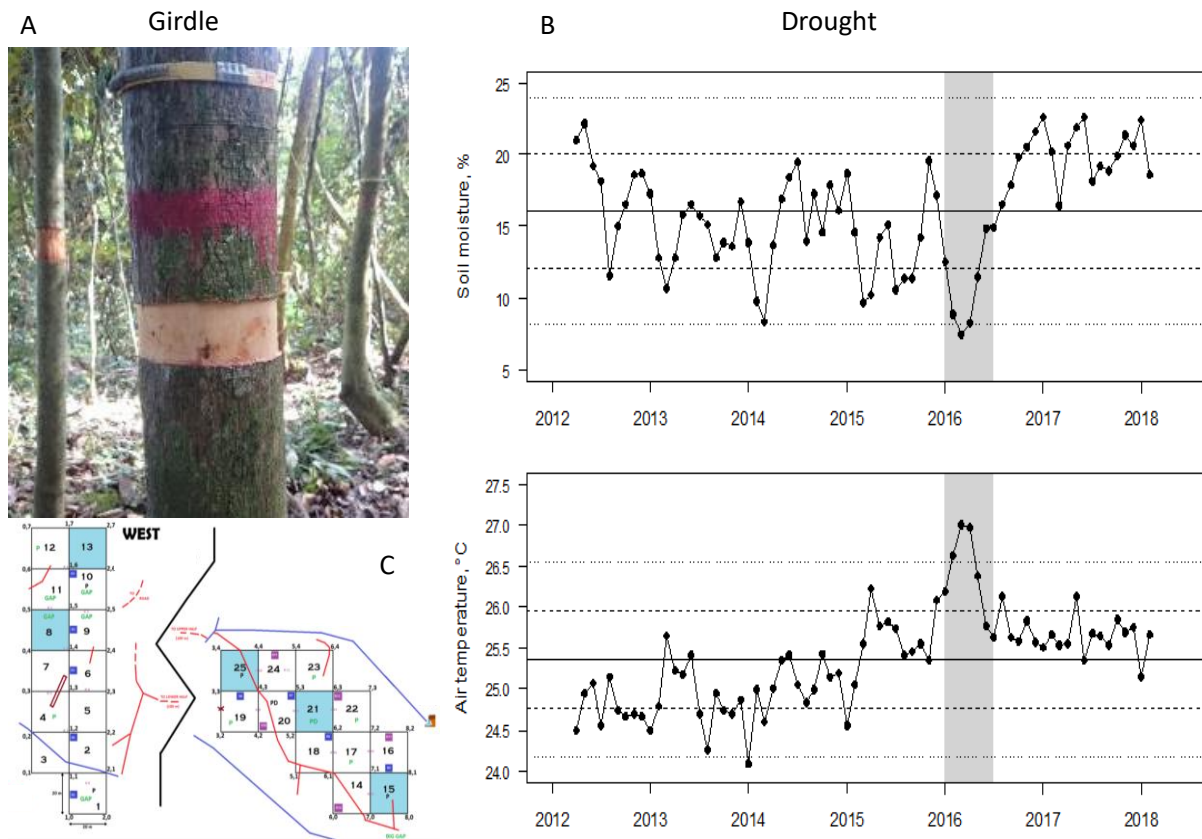
424 **Table 1** – Tree species measured intensively in the drought and girdled plot aligned to show
 425 which species were measured in both plots.

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

426

427

428 **Figures**

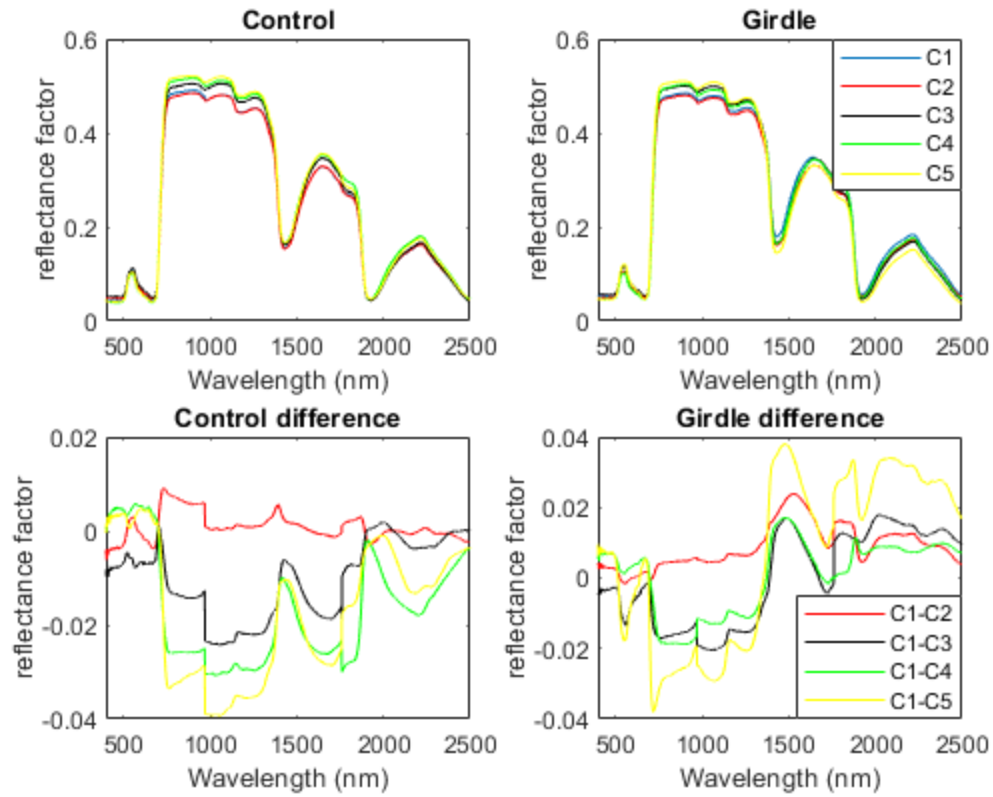


429

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

438

439

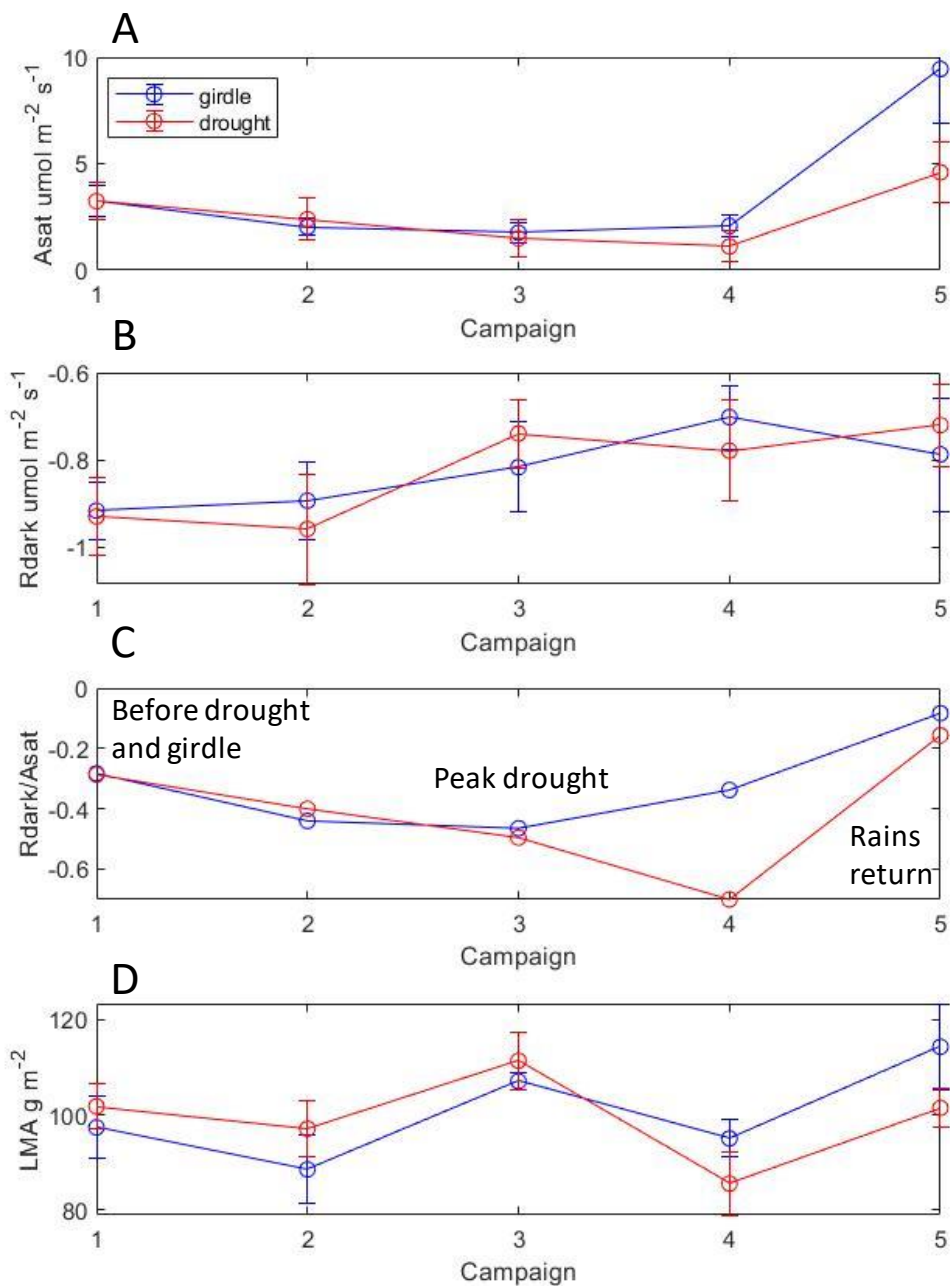


440

441 **Figure 2.** Leaf spectral properties (400-2500nm) for the drought (left) and girdled (right) plots for the 5
 442 campaigns (Jan-June 2015). (bottom) The difference (C1-CX, where X=2-5) in leaf spectral properties
 443 for the control (left) and the girdled (right) plots. In each campaign, we sampled the same trees unless the
 444 trees died. Reflectance factor is reflected incident light between 0-1.

445

446

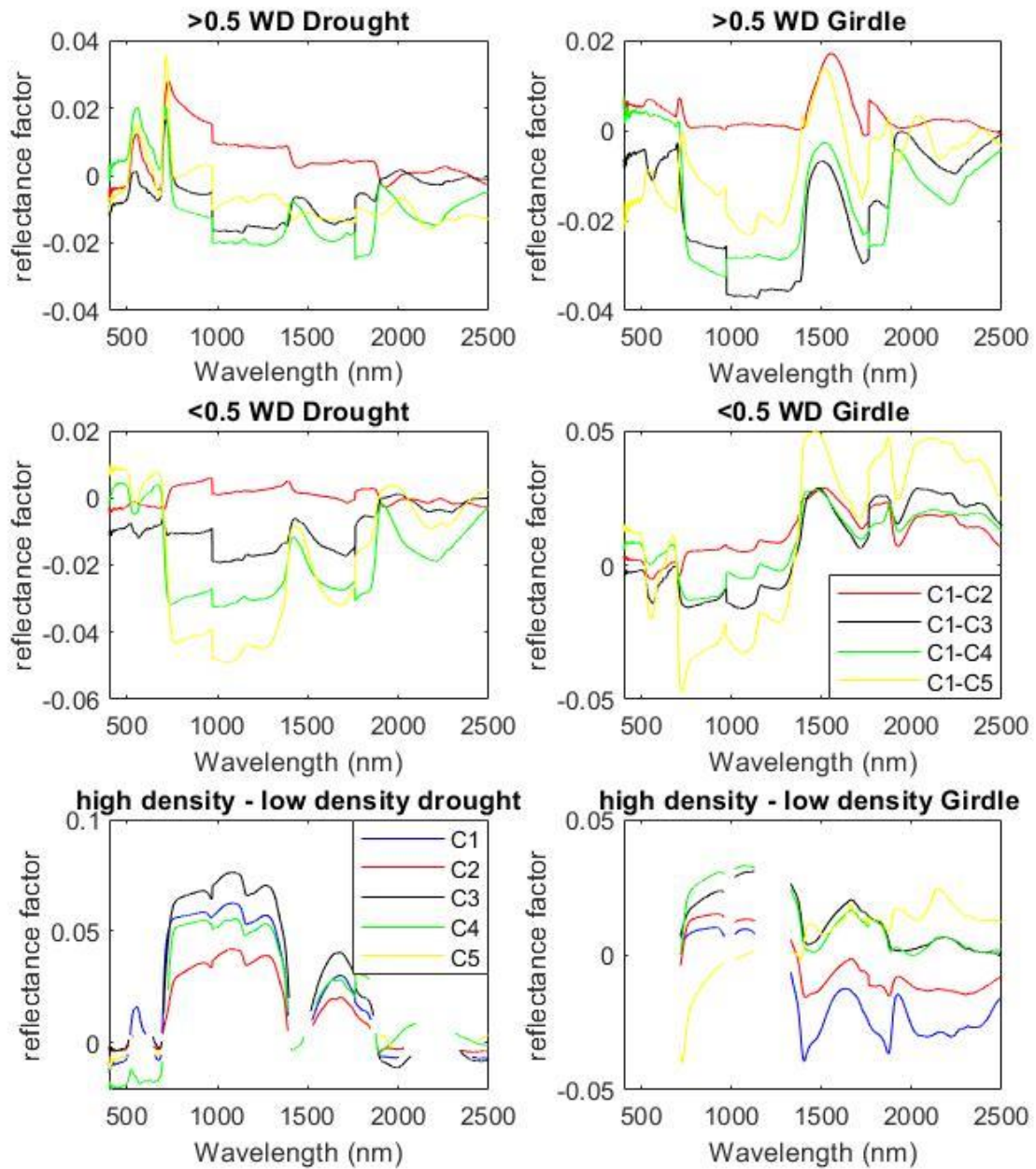


448

449 **Figure 3.** Average \pm se (A_{sat}) photosynthetic capacity (A), (R_{dark}) leaf dark respiration (B), $A_{\text{sat}} / R_{\text{dark}}$ (C)
 450 and (LMA) leaf mass area (D) for the 5 campaigns for the control site (red) and the girdled site (blue).
 451 A_{sat} and R_{d} were collected at a standard temperature (30 °C) during all campaigns. We subtracted the
 452 initial difference (2 $\mu\text{mol m}^{-2} \text{sec}^{-1}$) in the top panel between the average C1 values to better highlight the
 453 impact of the girdling.

454

455



456

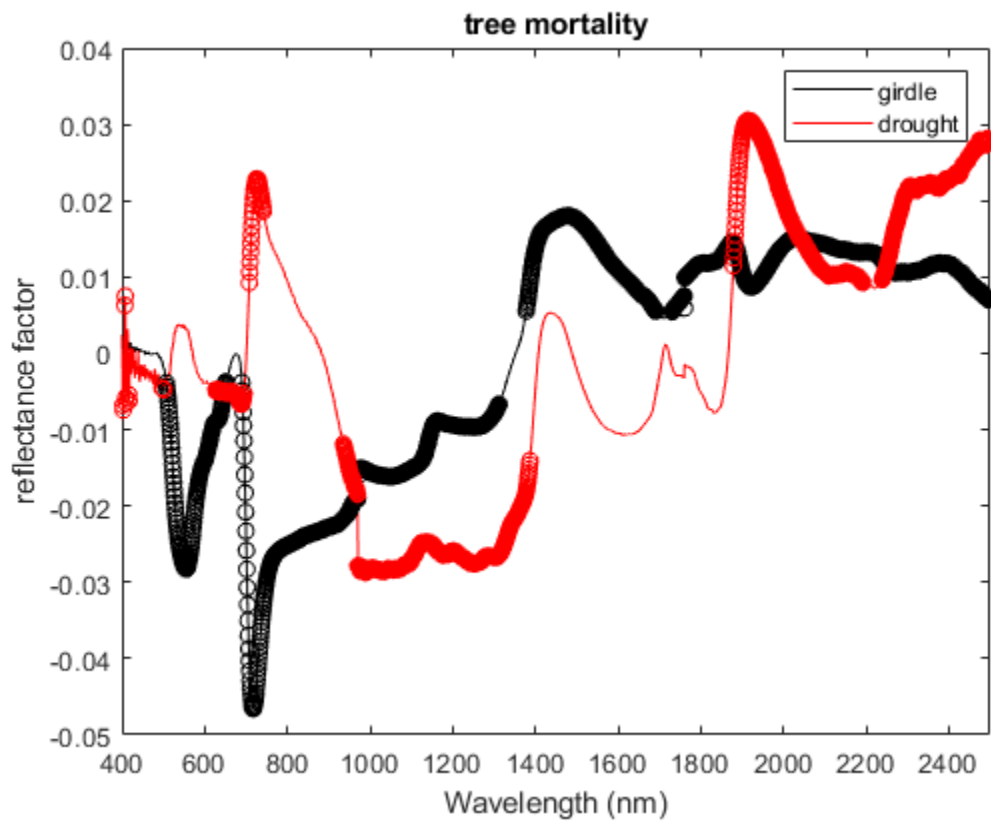
457 **Figure 4.** Leaf spectral properties (400-2500nm) comparing low wood density (density < 0.5 g cm⁻³, left)
 458 and high wood density species (density > 0.5 g cm⁻³, right) through the 5 Campaigns for the control plot
 459 (top) and the girdled plot (middle). For each campaign, we subtract dense wooded species from light
 460 wooded species (bottom). Only significant spectral regions are shown in the bottom.

461

462

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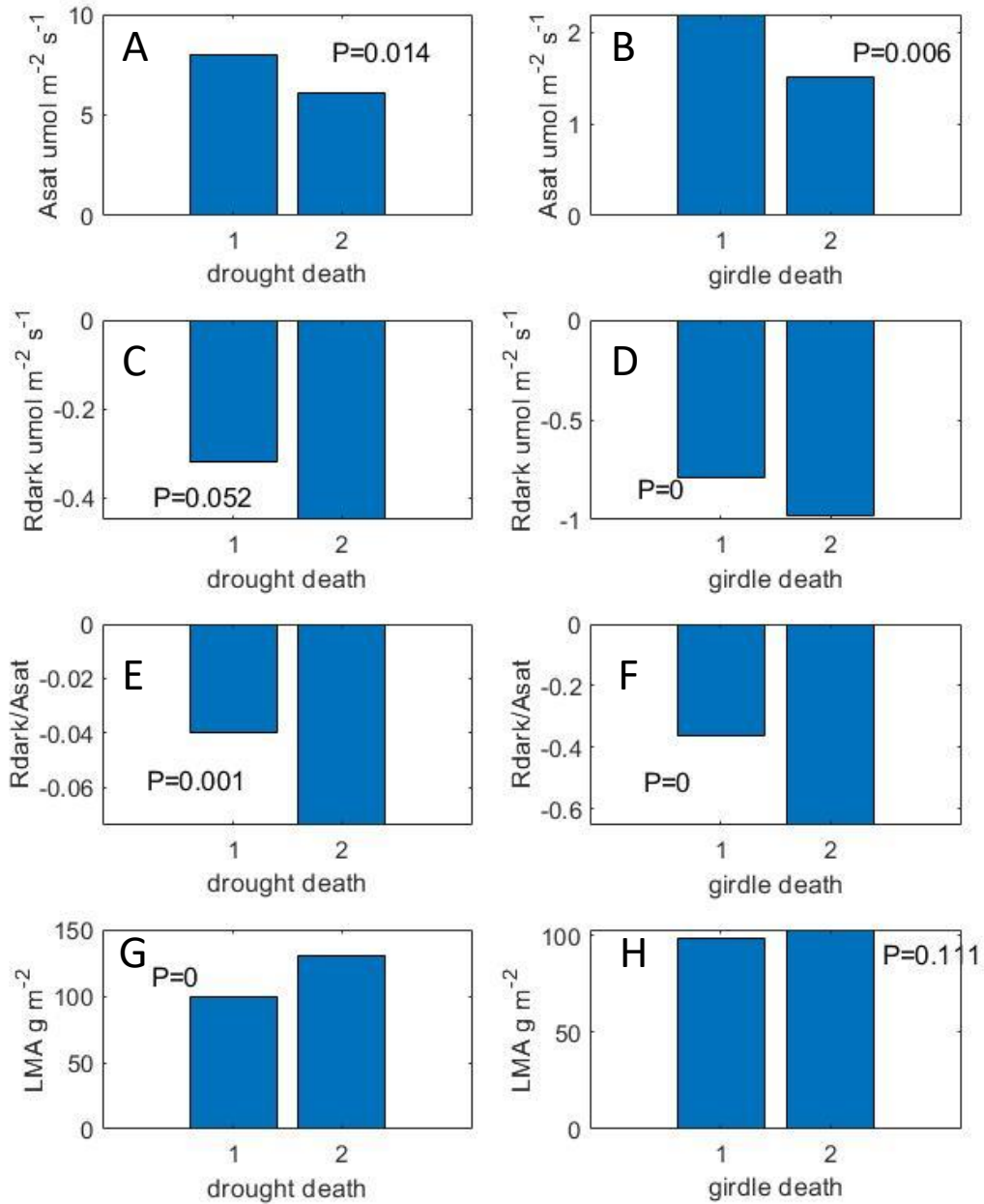


465

466 **Figure 5** –The change (negative is a reduction in reflectance close to death) in leaf spectral
467 properties from healthy leaves (>50 days from death) minus close to death leaves (<50 days from
468 death) on a tree that died of natural drought (red, N=14 leaves) and trees that died during the
469 girdling experiment (black, N=122 leaves). Dots show regions of significant change (P<0.05)
470 using a paired t-test.

471

472

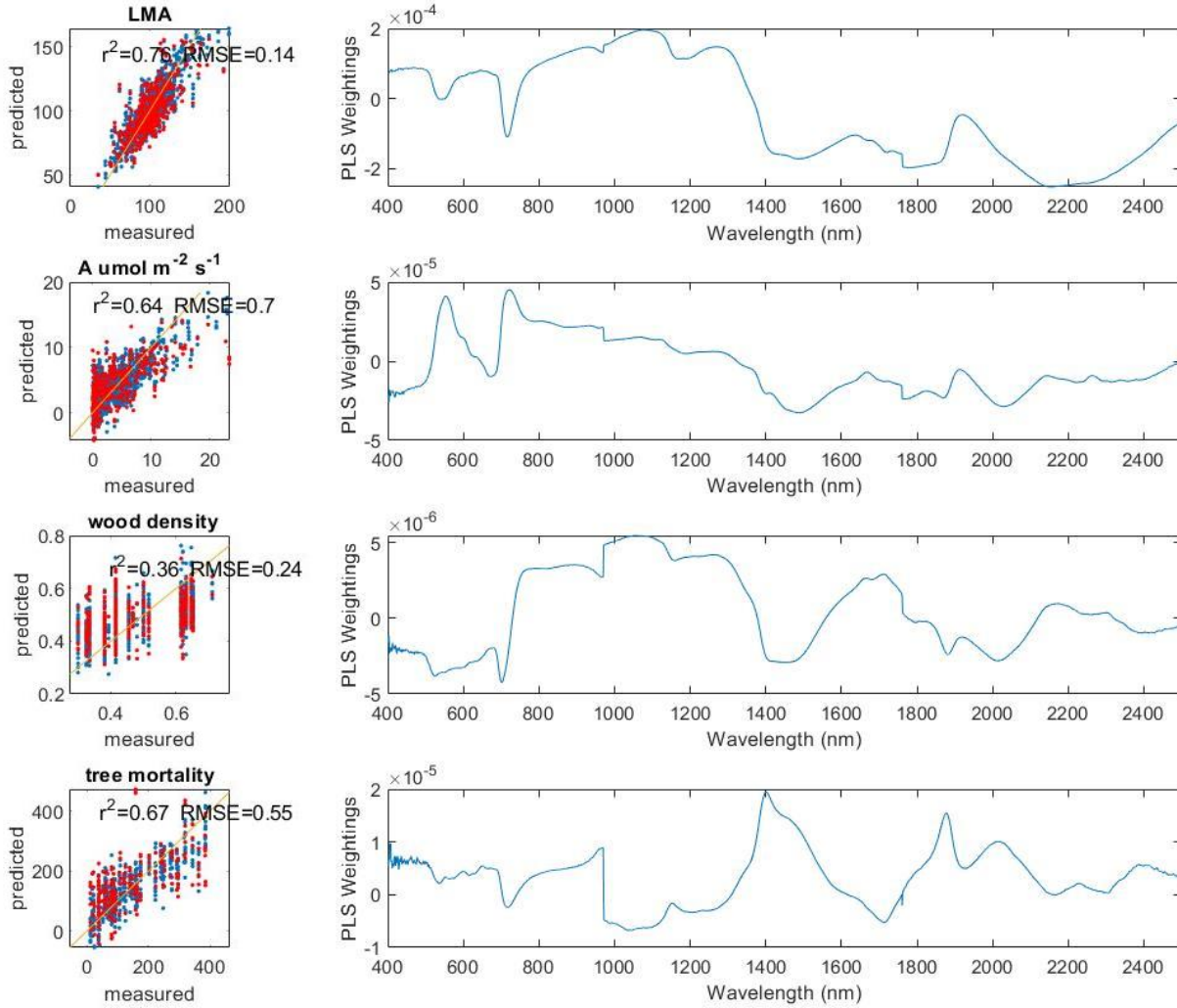


473

474 **Figure 6** – Comparison of A_{sat} (A), R_{dark} (C), R_{dark}/A_{sat} (E) and LMA (G) between initial values
 475 (1) and values within 50 days of death (2) for the girdling experiment (right) and the intensively
 476 monitored tree that died during the drought (left). The P value listed is the level of significance
 477 to three digits for a student's t-test.

478

479



480

481 **Figure 7.** Results from our PLSR analysis where we try and predict various traits including LMA,
 482 photosynthesis, wood density, and time to tree death. Red dots are the data to train the model (70%) and
 483 the blue dots are the independent dataset (30%). On the right is the primary weighting and on the left is
 484 the predictive power (measured vs predicted) with the r^2 and RMSE/mean.

485

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