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This is an accepted version of an article by Swails, E., Yang, X., Asefi, S. et al. 2019. **Linking soil respiration and water table depth in tropical peatlands with remotely sensed changes in water storage from the gravity recovery and climate experiment.** *Mitigation and Adaptation Strategies for Global Change*, 24 (4): 575-590. DOI: <https://doi.org/10.1007/s11027-018-9822-z>



1 **Running head:** Linking soil respiration and remotely sensed changes in water storage

2 **Article type: SI:** Tropical Peatlands Under Siege

3

4 **Linking soil respiration and water table depth in tropical peatlands with remotely sensed**
5 **changes in water storage from the Gravity Recovery and Climate Experiment**

6

7 **Abstract**

8 CO₂ emissions from peatlands in Southeast Asia are contributing substantially to global
9 anthropogenic emissions to the atmosphere. Peatland emissions associated with land-use change
10 and fires are closely related to changes in the water table level. Remote sensing is a powerful tool
11 that is potentially useful for estimating peat CO₂ emissions over large spatial and temporal
12 scales. We related ground measurements of total soil respiration and water table depth collected
13 over 19 months in an Indonesian peatland to remotely sensed GRACE Terrestrial Water Storage
14 Anomaly (TWSA) data. GRACE TWSA can be used to predict changes in water storage on land
15 relative to a time-mean baseline. We combined ground observations from undrained forest and
16 drained smallholder oil palm plantations on peat in Central Kalimantan to produce a
17 representation of the peatland landscape in one 0.5° x 0.5° GRACE grid cell. In both ecosystem
18 types, total soil respiration increased with increasing water table depth. Across the landscape
19 grid, monthly changes in water table depth were significantly related to fluctuations in GRACE
20 TWSA. GRACE TWSA explained 75% of variation in total soil respiration measured on the
21 ground. By facilitating regular sampling across broad spatial scales that captures essential
22 variation in a major driver of soil respiration, our approach could improve information available

23 to decision makers to monitor changes in water table depth and peat CO₂ emissions. Testing over
24 larger regions is needed to operationalize this exploratory approach.

25

26 **Key words:** Indonesia, land-use, oil palm, greenhouse gas emissions, climate change

27

28 **1. Introduction**

29 Over the past several decades the area of tropical peat swamp forest converted to other uses has
30 increased substantially. Oil palm expansion is a major driver of peatland conversion, accounting
31 for 73% of industrial plantations on peat in Peninsular Malaysia, Sumatra, and Borneo, while
32 pulp wood plantations account for the remaining area under industrial management (Miettinen et
33 al. 2016). Smallholdings are equally important as industrial plantations, covering 22% of
34 peatlands in insular Southeast Asia versus 27% for industrial plantations (Miettinen et al. 2016).
35 Available estimates indicate that CO₂ emissions from converted peatlands in Southeast Asia
36 contribute substantially to global anthropogenic emissions to the atmosphere (Harris et al. 2012;
37 Miettinen et al. 2017). Peatland drainage and conversion increase CO₂ emissions as a
38 consequence of decreased organic matter inputs and increased rates of decomposition of organic
39 peat soils (Hergoualc'h & Verchot, 2014). Fires used for clearing lands and fertilization of
40 nutrient-poor peat soils also constitute a major source of emissions (Gaveau et al. 2014;
41 Miettinen et al. 2017).

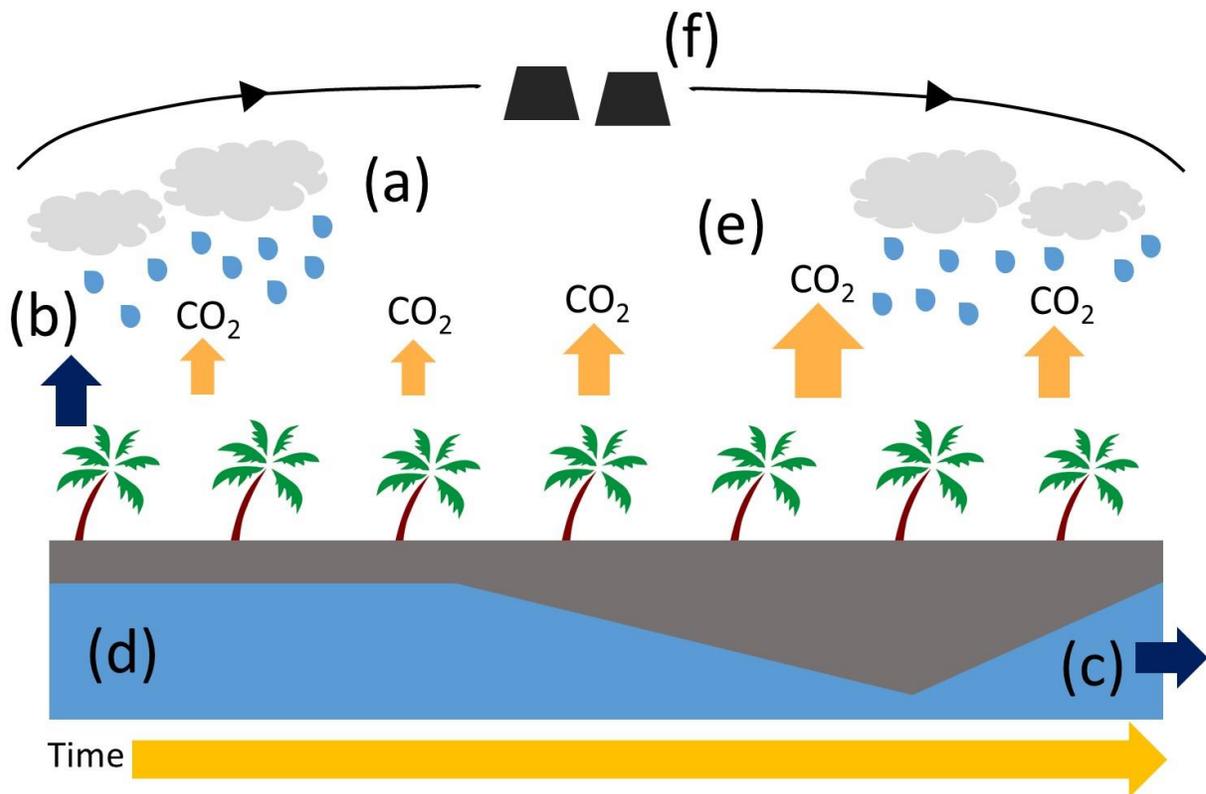
42 To accurately estimate peat CO₂ emissions and to understand how they may change in the
43 future, frequent measurements over months, seasons, and years are needed, as are measurements
44 that span the entire sequence of land-use change. In addition to understanding the impacts of
45 land-use change on emissions, we must assess how CO₂ emissions in tropical peatlands respond

46 to climate change. The frequency and severity of El Niño events is projected to increase in the
47 future (Cai et al. 2014) and may influence emissions from both converted and forested tropical
48 peatlands. Studying seasonal and interannual changes in temperature and moisture is essential to
49 understand microbial responses to land-use and climate changes, and can provide insight on peat
50 emissions of CO₂. Remote sensing can be a powerful tool for predicting spatial and temporal
51 variation in environmental conditions influencing peat C storage and loss.

52 Water table depth and soil moisture are critical environmental parameters affecting soil C
53 storage and loss in tropical peat ecosystems (Hirano et al. 2007). Water table depth, determined
54 by rainfall, evapotranspiration, and discharge, influences soil moisture throughout the soil
55 column, and controls to some extent soil respiration across tropical peatlands (Hergoualc'h &
56 Verhot 2014). NASA Gravity Recovery and Climate Experiment (GRACE) data provide
57 spaceborne observations of monthly changes in the Earth's gravity field. Changes in gravity
58 measured by GRACE over land are caused by mass fluctuations attributed to changes in water
59 storage by terrestrial ecosystems over time. GRACE Terrestrial Water Storage Anomaly
60 (TWSA) data can be used to predict changes in water storage on land relative to a time-mean
61 baseline. GRACE may provide a new tool for predicting spatio-temporal variations in water table
62 depth and soil moisture and support the monitoring of variables contributing to peat CO₂ losses,
63 in particular soil respiration. GRACE data have been used to estimate depletion of ground water
64 in aquifers around the world (Rodell et al. 2009, Famiglietti et al. 2011, Voss et al. 2013) but
65 have never been tested for assessing changes in water storage in tropical peatlands. Application
66 of GRACE to assess trace gas fluxes from soils have largely been limited to studies on methane
67 (Bloom et al. 2010; Bloom et al. 2012).

68 In this study we use GRACE TWSA data to predict changes in total respiration and water
69 table depth in peat soils. Our objective was to develop a new method for linking soil respiration –
70 a process that is difficult and expensive to measure in the field over time and space – and water
71 table depth, to readily available, spatially extensive, satellite-based estimates of changes in soil
72 water storage. Therefore, we tested for potentially useful relationships among soil respiration,
73 our parameter of interest, and water table depth, a physical driver of soil respiration in tropical
74 peatlands. Then we tested how variations in soil respiration and water table depth on a broader
75 landscape scale can be inferred from GRACE TWSA (Figure 1).

76 If soil respiration is related to soil moisture regime, and if water table depth is related to
77 TWSA, then TWSA could be used to predict total soil respiration in tropical peatlands. Since soil
78 respiration is a key component of the peat C budget (Hergoualc'h & Verchot 2014), successful
79 operationalization and application of our remote sensing approach at large spatial scales could
80 improve understanding of the influence of seasonal and interannual variation in water storage on
81 the C cycle.



82

83 Figure 1. Conceptual model of links among total soil respiration, water table depth, GRACE
 84 TWSA and climate drivers in an Indonesian peatland. Precipitation (a), evapotranspiration (b),
 85 and discharge (c) influence water table depth (d). Water table depth increases under conditions of
 86 reduced precipitation during dry periods, and total soil respiration increases (e). GRACE TWSA
 87 (f) indicates monthly changes in soil water storage ultimately driven by variation in precipitation,
 88 evapotranspiration, and discharge.

89

90 **2. Materials and methods**

91 *2.1 Site description*

92 We collected ground measurements at permanent plots in peat forest and smallholder oil palm
 93 plantations in Central Kalimantan Province, approximately 50 km from the city of Pangkalan
 94 Bun, in and around Tanjung Puting National Park (-2.82806, 111.813, Figure 2a). The climate of

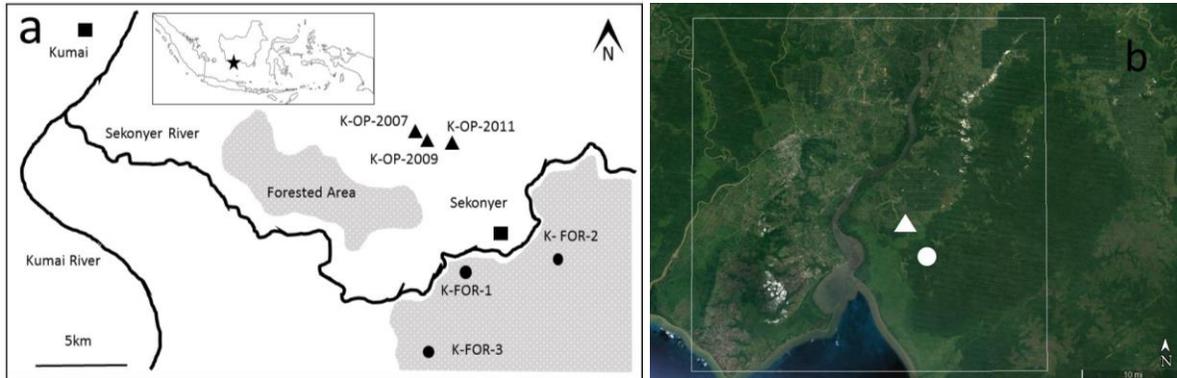
95 the region is humid tropical, with little variation in temperature throughout the year and high
 96 annual rainfall. We used weather observations from Iskandar airport in Pangkalan Bun during
 97 2004-2013 to describe climate at the study area. Mean annual temperature in Pangkalan Bun is
 98 27.4°C. Mean annual rainfall is 2058 mm and September is typically the driest month (85 mm).

99 Three plots were established in forest, and three in oil palm plantations, for a total of six
 100 plots. The plots were located 1-10 km apart, representing a range of peat depths, land use
 101 histories and vegetation ages (Table 1). All plots fell within a roughly 10 km x 10 km area in one
 102 GRACE grid cell, 0.5° x 0.5° or 55 km x 55 km (Figure 2b). Forest plots were situated at varying
 103 distances from river's edge and thus differed in peat depth. Two of the plots (K-FOR-2, K-FOR-
 104 3) were mature forest whereas the plot closest to the river (K-FOR-1) was a 30 year old
 105 secondary forest, likely formerly used as an agroforestry garden (Novita 2016). Oil palm
 106 plantations were planted in 2007 (K-OP-2007), 2009 (K-OP-2009), and 2011 (K-OP-2011). Oil
 107 palm plots underwent multiple fires.

Table 1. Characteristics of the sample plots in Central Kalimantan, Indonesia. (after Swails et al. 2017)

Code	Landuse	Location		Clearance Year	Plantation Age	Fires	Distance to River	Peat Depth
K-FOR-1	Forest	-2.82360	111.813	pre 1982	-	Multiple	0.5 km	27 cm
K-FOR-2	Forest	-2.82220	111.807	-	-	-	1 km	155 cm
K-FOR-3	Forest	-2.83080	111.802	-	-	-	2 km	290 cm
K-OP-2011	Oil palm	-2.82310	111.810	1989	4 year	Multiple	3.5 km	20 cm
K-OP-2009	Oil palm	-2.82170	111.803	2005	6 year	Multiple	3.5 km	47 cm
K-OP-2007	Oil palm	-2.82060	111.801	2005	8 year	Multiple	3.5 km	47 cm

108



109
 110 Figure 2. Research sites and sampling design. Location of the three plots in the undrained forest
 111 site and three plots in the nearby drained smallholder oil palm site (a) in Central Kalimantan,
 112 Indonesia (inset, a). Oil palm (triangle) and forest (circle) sampling sites were located in an
 113 approximately 10km by 10km area within the 0.5° GRACE grid cell (b).

114 *2.2 Monthly ground measurements*

115 We collected measurements of total soil respiration and water table depth from plots once each
 116 month from January 2014 through June 2015 and again in September 2015. Plots were measured
 117 on consecutive days between the hours of 0800 and 1200 usually during the last week of the
 118 month. We measured water table depth concomitantly with CO₂ measurements. Daily
 119 precipitation data for the area were obtained from Iskander Airport in Pangkalan Bun. Our
 120 measurements covered one year with normal precipitation (2014) and one El Niño year (2015).

121 Our ground sampling approach was designed to account for spatial heterogeneity in soil
 122 respiration and environmental conditions while capturing temporal heterogeneity. Sixteen
 123 months before the beginning of this study, we inserted sets of two PVC collars to 5 cm depth at
 124 six locations per plot. In forest plots, we installed one collar on a hummock and one collar in the
 125 adjacent hollow at locations roughly 10 meters apart. In oil palm plots, we installed one collar at
 126 the base of a palm (near) and one collar at mid-distance between two adjacent rows of palm (far),
 127 at locations 7-9 meters apart (the distance between palms determined by the planting density,

128 Swails et al. 2017). Total soil respiration was measured by the dynamic closed chamber method
129 (Pumpanen et al. 2009) with a portable infrared gas analyzer/EGM-4 (Environmental Gas
130 Monitor) connected to a Soil Respiration Chamber (SRC-1) (PP System, Amesbury, USA)
131 placed on the permanent PVC collar. Water table depth was measured in a dipwell permanently
132 installed next to each CO₂ collar. The dipwells were perforated PVC pipe (2.5 cm diameter)
133 inserted to 2 m depth below the peat surface.

134 With the goal of creating a single monthly value of soil respiration and water table depth
135 against which to compare remotely sensed data, we combined data in a way appropriate to the
136 scale of the measurements. First, we calculated plot-level weighted averages of total soil
137 respiration and water table depth measurements. The weighting was based on the spatial extent
138 of conditions within the plot (hummock/hollow and near/far). In forest plots, we measured the
139 length of hummocks and hollows along two perpendicular 50 m transects and divided the total
140 length of hummocks by the total length of hollows to calculate the ratio of hummock to hollow
141 area in each forest plot. In oil palm plots, we assume that measurements at collars near palms are
142 representative of the area within a 2 m radius of the base of the palms. This is the zone where
143 smallholders apply fertilizers and root density (Comeau et al. 2016; Khalid et al. 1999) and
144 activity (Nelson et al. 2006) are usually highest. In forest plots, the ratios of hummock to hollow
145 area were 48:52 (K-FOR-1), 52:48 (K-FOR-2), and 63:37 (K-FOR-3). In oil palm plots, the
146 ratios of the area within a 2 m radius of palms (near) to the area outside of this radius (far) were
147 25:75 (OP-2011), 27:73 (OP-2009), and 37:63 (OP-2007). For each plot, we multiplied the mean
148 value of hummock/near measurements by the hummock/near ratio, and the mean value of
149 hollow/far measurement by the hollow/far ratio. Then, we summed the two numbers to yield a
150 single value for each plot. To calculate mean monthly values, we pooled the weighted averages

151 from each plot in each month to yield a single value for each land use (three plots, n=3 per land
152 use). Detailed soil respiration rates for each plot are reported elsewhere (Swails et al. in
153 preparation).

154 Finally, we combined data from the two land uses to estimate a single value of soil
155 respiration and water table depth for comparison with GRACE TWSA and precipitation. We
156 multiplied the mean respiration rate by the proportional coverage of the two land uses in our 0.5°
157 x 0.5° GRACE grid cell. We estimated the proportional coverage of oil palm and forest by
158 overlaying a 0.05° x 0.05° grid on the GRACE cell boundaries in Google Earth (Figure 2b). The
159 proportional coverage of forest (60%) and oil palm (30%) in each of the .05° x .05° cells was
160 determined by visual inspection. We inspected each of the 100 cells individually, and tallied the
161 coverage by land use in each cell. The actual factors used in weighting (forest, 2/3 and oil palm,
162 1/3) spread the residual effect of the area in water, urban areas, or other crops (10%)
163 proportionally across the two land uses. We weighted data for water table depth in the same
164 manner to generate a single landscape-scale value representative of the 0.5° x 0.5° GRACE grid
165 cell. We related these weighted average monthly values for the landscape—derived from
166 measurements in oil palm and forest—to GRACE TWSA and precipitation.

167 *2.3 GRACE data acquisition*

168 We extracted GRACE TWSA values for our study site from one 0.5° x 0.5° grid cell (-2.75000
169 111.750, Figure 2b) in JPL-RL05 GRACE monthly mass grids (Watkins et al. 2015; Wiese
170 2015). JPL-RL05 uses a-priori constraints in space and time to estimate global, monthly gravity
171 fields in terms of equal area 3-degree spherical cap mass concentration functions. A Coastal
172 Resolution Improvement (CRI) filter is applied in post-processing to separate land and ocean
173 portions of mass. The mass grids, updated monthly, provide surface mass changes relative to a

174 baseline average over January 2004 to December 2009 with a spatial sampling of 0.5°
175 (approximately 55 km at the equator). After oceanic and atmospheric effects are removed,
176 monthly and interannual variations in Earth's gravity field are mostly accounted for by changes
177 in terrestrial water storage. The vertical extent of these changes can be considered as a thin layer
178 of water concentrated at the Earth's surface, measured in units of centimeters equivalent water
179 thickness. Scaled uncertainty estimates are also provided on a 0.5° global grid in the JPL-RL05
180 product.

181 About one month of satellite measurements are required to generate the GRACE monthly
182 mass change data, although occasionally, values represent less than a month of observations.
183 Nevertheless, the temporal resolution of GRACE TWSA is fixed at one month. The mass
184 changes reported for a given month were usually estimated as the average of measurements
185 collected from day 16 of the previous month to day 16 of the present month. We matched these
186 data with the observations of soil respiration and water table depth closest in time, most often
187 taken at the end of the month, within a week or two of the GRACE value determined by
188 integrating over the last half of the previous month and the first half of the current month.

189 Rather than the January 2004 – December 2009 baseline, we used a January 2014 –
190 September 2015 baseline to match the time of our study. To calculate TWSA relative to 2014 –
191 2015, we calculated an average of TWSA values over our study period relative to the Jan 2004 –
192 Dec 2009 baseline, and subtracted that value from the TWSA value for each month. TWSA data
193 were not available for the months of February, July, and December 2014, and June 2015 due to
194 satellite battery management.

195 *2.4 Calculations and statistical analysis*

196 All statistical analyses were completed using R (v 3.2.5). We used ordinary least squares (OLS)
197 linear regression to test for relationships among total soil respiration, water table depth, GRACE
198 TWSA, and monthly precipitation calculated as cumulative rainfall over the 30 days prior to
199 sampling. To test for a relationship between soil respiration and water table depth in forest and
200 oil palm, we related mean monthly soil respiration to water table depth in each land-use (n=19).
201 Finally, we related weighted average water table depth and weighted average soil respiration to
202 GRACE TWSA (n=16 for both regressions). We also related mean monthly water table depth
203 and soil respiration in forest and oil palm as well as weighted average water depth and soil
204 respiration to monthly precipitation. At 0.033, the ratio of area represented by the dependent
205 variable (roughly 10 km x 10 km covered by ground measurement plots = 100 km²) to the area
206 represented by the independent variable (roughly 55 km x 55 km for a 0.5° x 0.5° GRACE grid
207 cell at the equator= 3,025 km²) is small but not unprecedented. For example, Spruce et al. (2011)
208 validate a 250 m x 250 m MODIS product using 30 m x 30 m Landsat scenes, for a
209 dependent:independent area ratio of 0.014. There are many additional highly cited examples in
210 the literature where Landsat is used as reference data for assessing a MODIS product (see for
211 example Chen et al. 2005; Vina et al. 2008; Painter et al. 2009).

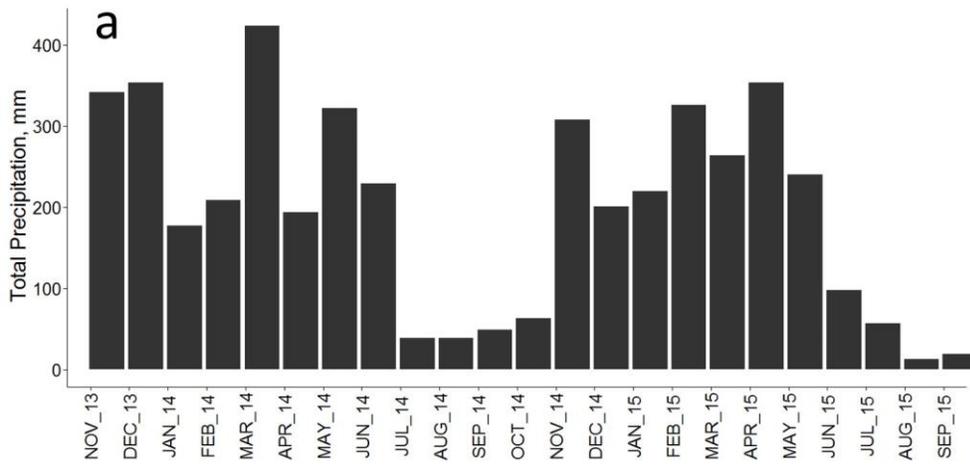
212 We used data transformation as necessary to adequately model the functional form of
213 dependent variables, e.g. we added 12 to GRACE TWSA to eliminate negative values to model
214 the relationship between combined total soil respiration and GRACE TWSA as a logarithmic
215 function. To assess the normality assumption of OLS regression we used normality probability
216 plots with a 95% confidence envelope produced using a parametric bootstrap. Durbin-Watson
217 test was used to test for autocorrelation. To test for heteroscedasticity we used a score test of the
218 hypothesis of constant error variance against the alternative that the error variance changes with

219 the level of the fitted values. We identified outliers for examination using Bonferroni adjusted p-
220 value for the largest absolute studentized residual. Data points with high leverage were identified
221 using the hat statistic p/n , where p is the number of parameters estimated and n is the sample
222 size. We examined observations with hat values greater than 3 times the average hat value. We
223 used Cook's D to identify influential observation.

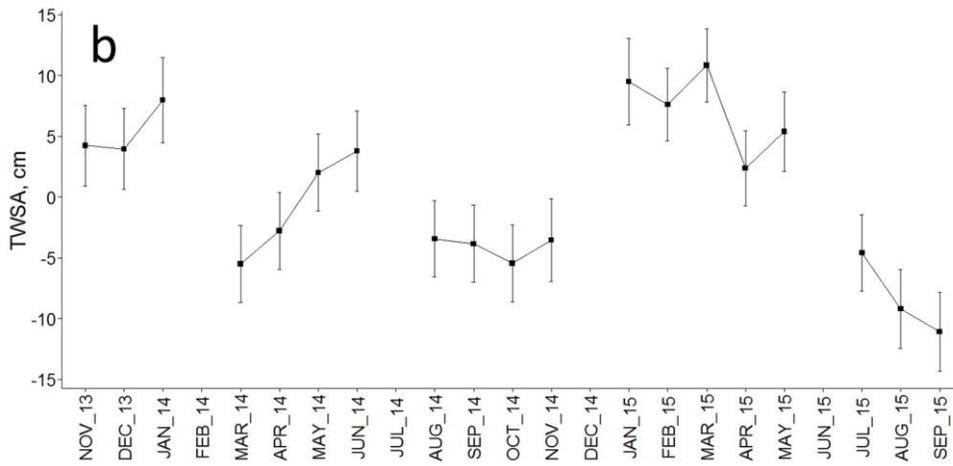
224 **3. Results**

225 *3.1 Variation in total soil respiration, water table depth, TWSA, and rainfall*

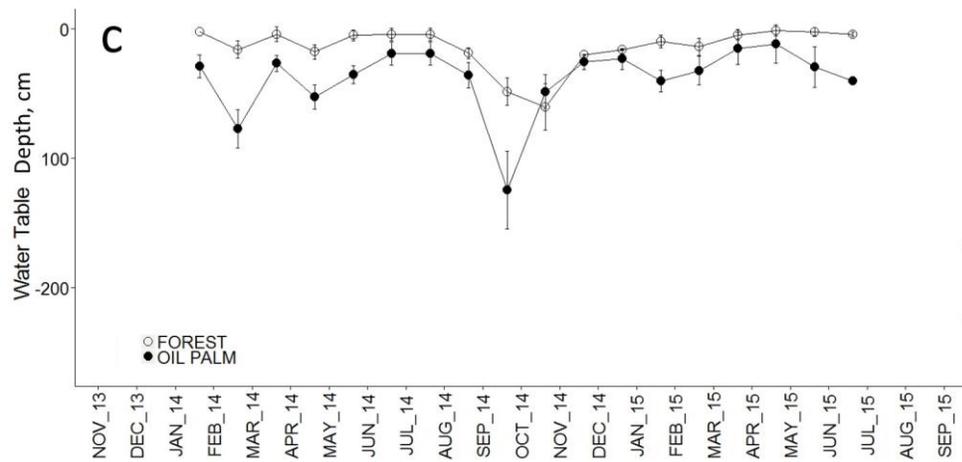
226 Precipitation, TWSA, water table depth, and total soil respiration showed clear seasonal variation
227 in both oil palm and forest sites. Monthly precipitation was ≤ 100 mm during the months of July
228 – October 2014 and June – September 2015. Precipitation reached a maximum of 424 mm in the
229 month of March 2014 (Figure 3a) and a minimum in August 2015 (13 mm). Monthly TWSA
230 ranged from 10.8 cm in March 2015 to -11.1 cm in September 2015 (Figure 3b), with
231 considerable interseasonal variation (Figure 4). In both forest and oil palm, the water table was
232 highest in April 2015 (-2.3 ± 3.5 cm and -13.7 ± 3.8 cm, respectively) and lowest in September
233 2015 (-167.9 ± 6.5 cm and -227.3 ± 9.0 cm, respectively). Total soil respiration was lowest in
234 April 2014 in the forest (0.36 ± 0.04 g CO₂ m⁻² hr⁻¹) and April 2015 in the plantations ($0.54 \pm$
235 0.07 g CO₂ m⁻² hr⁻¹). It was highest in September 2015 at the beginning of the most intense El
236 Niño Southern Oscillation event in recent history, in both forest (1.54 ± 0.23 g CO₂ m⁻² hr⁻¹) and
237 oil palm (1.07 ± 0.14 g CO₂ m⁻² hr⁻¹).



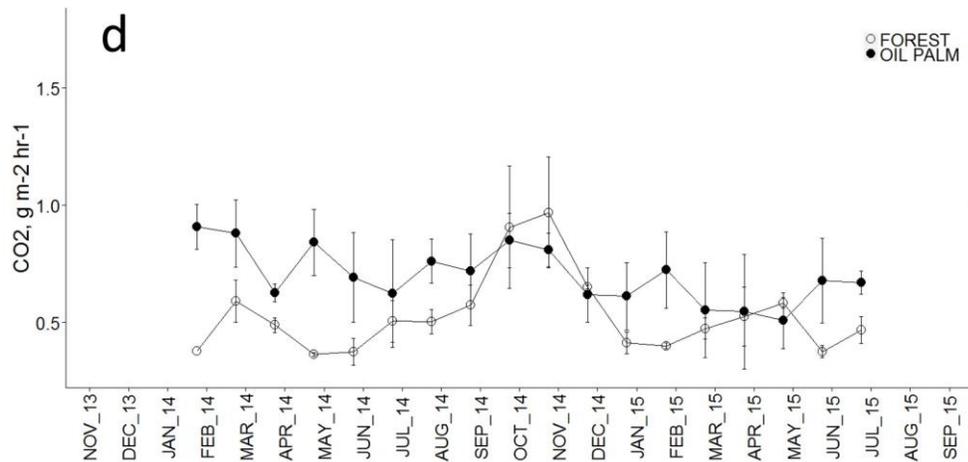
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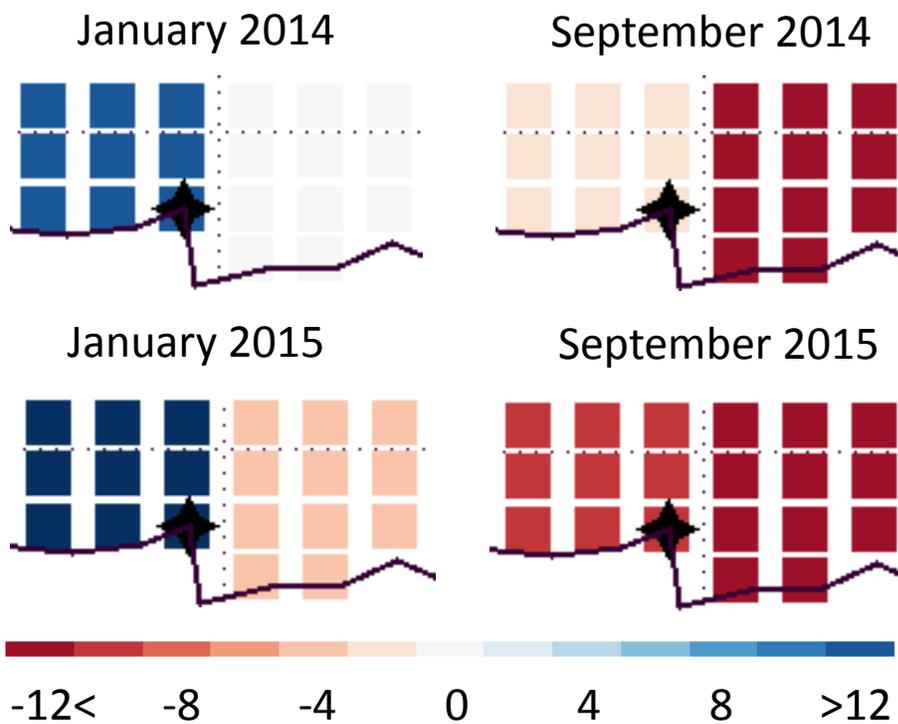


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241

242 Figure 3. Monthly precipitation (a), GRACE TWSA (b), mean water table depth (c) and mean
 243 total soil respiration in forest (solid circle) and oil palm (open circle) plots (d). Values in (b)
 244 represent the change in remotely sensed water storage at the sampling sites in centimeters liquid
 245 water equivalent. Error bars in (b) represent the scaled uncertainty associated with the 3^o mascon
 246 estimate (Weise et al. 2016). Error bars in (c) and (d) represent standard error of the mean (n=3).

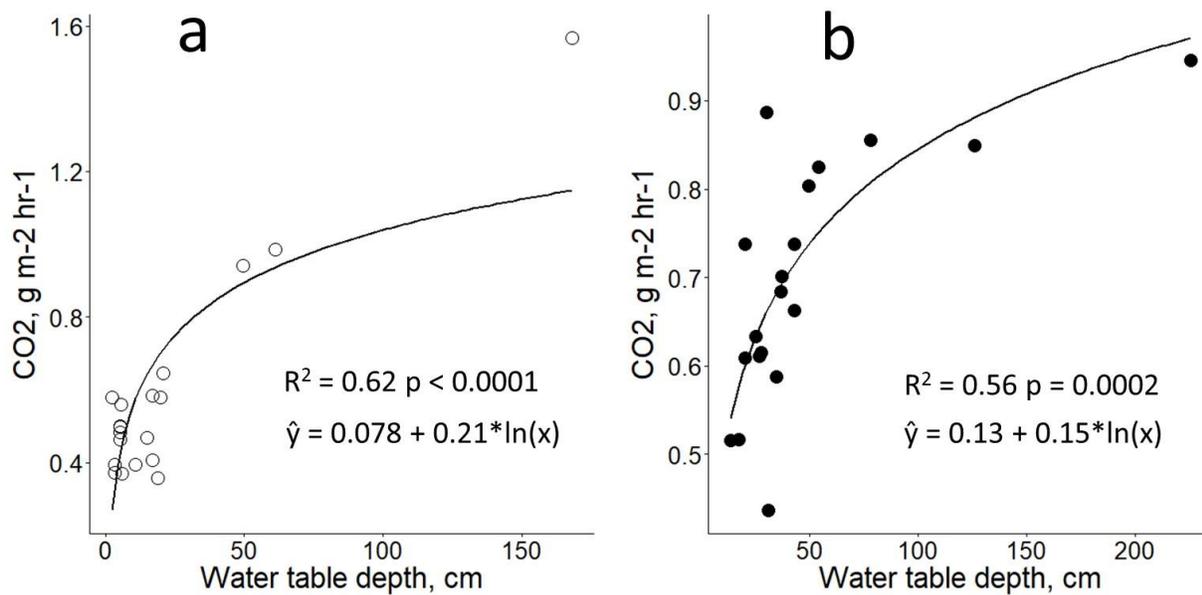


247

248 Figure 4. Gridded GRACE TWSA across southern Central Kalimantan, Indonesia during wet
249 months (precipitation > 100 mm) in January 2014 and 2015 and dry months (precipitation ≤ 100
250 mm) in September 2014 and 2015. September 2015 was the beginning of a very intense El Niño
251 Southern Oscillation across Indonesia. Colors represent the change in water thickness (units =
252 cm liquid water equivalent) relative to January 2004 to December 2009 average baseline. The
253 grid cell covering our study site is marked with a star. Dotted lines indicate -2 latitude and 112
254 longitude.

255 *3.2 Relationships among total soil respiration, water table depth, and TWSA*

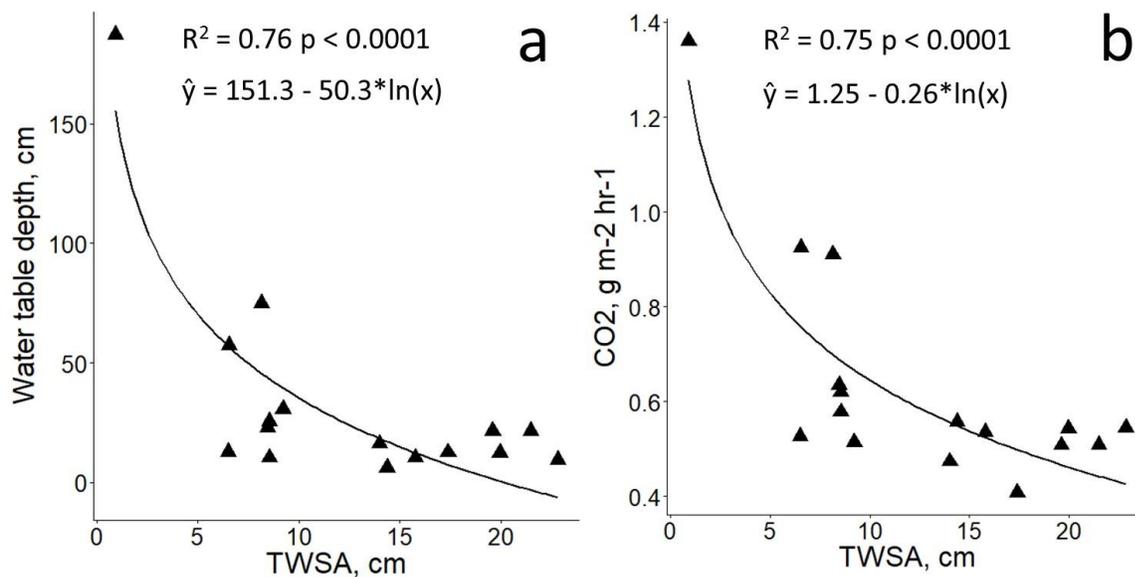
256 Total soil respiration increased with the natural log of concurrently measured water table depth
257 in both forest (Figure 5a) and oil palm (Figure 5b). As the water table dropped further below the
258 soil surface, soil respiration increased, in both oil palm and forest. The strong effect of ENSO-
259 induced drying and associated drop in the water table are evident in data from September 2015.
260 Extremely low rainfall during the two preceding months led to low water table levels in forest
261 and oil palm in September 2015 during the El Niño event. The data point corresponding to
262 measurements collected in September 2015 in forest plots (water table of -167.9 cm, soil
263 respiration of $1.54 \text{ g m}^{-2} \text{ hr}^{-1}$) was an outlier (Bonferroni adjusted $p=0.03$) with marginally
264 significant influence on the relationship between water table depth and soil respiration in forest
265 (Cook's $D=2.5$).



266

267 Figure 5. Mean total soil respiration as a function of mean water table depth (presented as a
 268 positive difference from the surface) in forest (a) and oil palm (b) from January 2014 through
 269 September 2015 (n = 19 months).

270 The relationships between TWSA and water table depth, and between TWSA and soil
 271 respiration, were also logarithmic in the independent variable. As water level approached the
 272 surface TWSA increased (Figure 6a). Total soil respiration declined with increasing TWSA
 273 (Figure 6b).



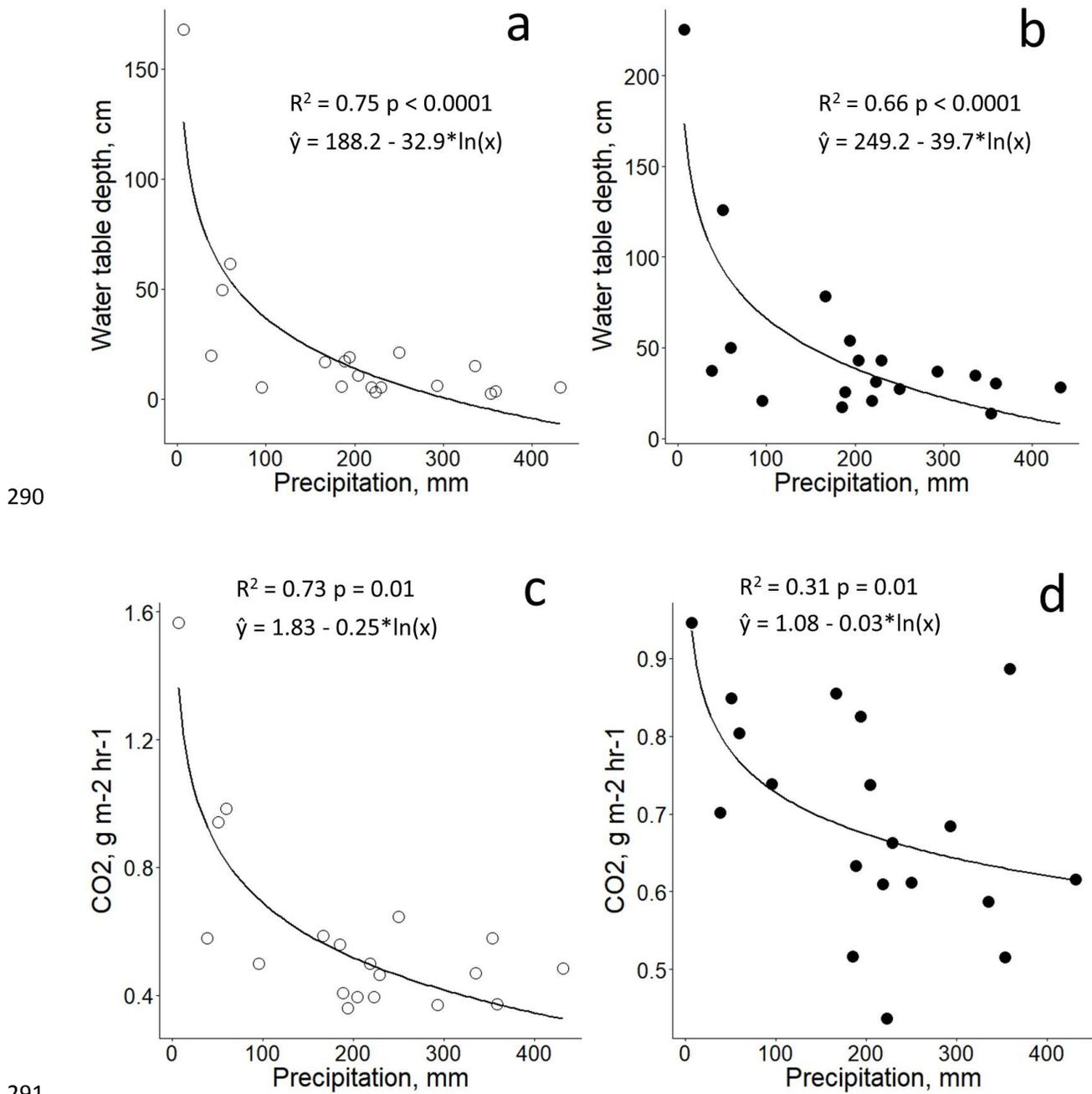
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275 Figure 6. Weighted average water table depth (presented as a positive difference from the
 276 surface) (a) and weighted average soil respiration (b) as a function of GRACE TWSA from
 277 January 2014 through September 2015 (n = 16 months). Note that TWSA is presented as
 278 anomaly values plus 12, to eliminate negative TWSA values. Smaller TWSA values indicate
 279 lower soil water storage (deeper water table) and larger values indicate higher soil water storage
 280 (shallow water table).

281 3.3 Precipitation as a predictor variable of soil respiration and water table depth

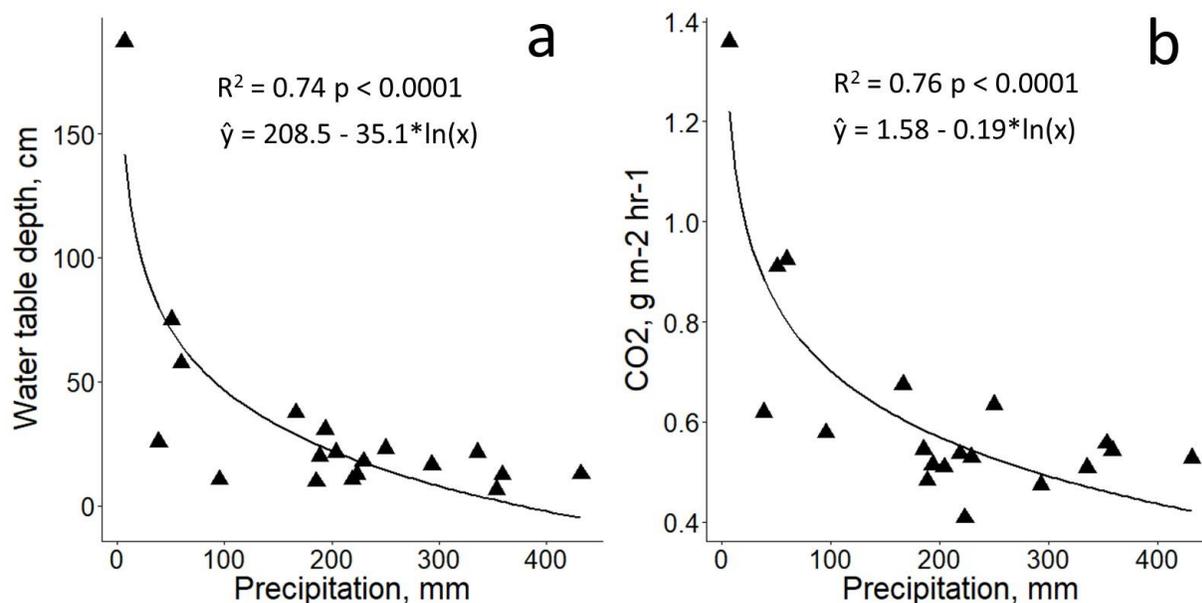
282 Precipitation explained variation in water table depth and soil respiration in forest and oil palm,
 283 as well as variation in the weighted average water table depth and soil respiration values. Water
 284 table depth decreased with increasing cumulative precipitation over the 30 days prior to sampling
 285 in forest (Figure 7a) and oil palm (Figure 7b), but precipitation explained more variation in water
 286 table in forest ($R^2 = 0.75$) than oil palm ($R^2 = 0.66$). Soil respiration also decreased with
 287 increasing precipitation in both forest (Figure 7c) and oil palm (Figure 7d). Precipitation

288 explained over two times more variation in soil respiration in forest ($R^2 = 0.73$) than oil palm (R^2
289 $= 0.31$).



291
292 Figure 7. Mean water table depth (presented as a positive difference from the surface) (a and b)
293 and soil respiration (c and d) as a function of cumulative precipitation during the 30 days prior to

294 the sampling date in forest (a and c) and oil palm (b and d) from January 2014 through
295 September 2015 (n = 19 months).
296 Precipitation explained 74% and 76% of variation in weighted average water table depth (Figure
297 8a) and soil respiration (Figure 8b) respectively.



298
299 Figure 8. Weighted average water table depth (presented as a positive difference from the
300 surface) (a) and weighted average soil respiration (b) as a function of cumulative precipitation
301 during the 30 days prior to sampling from January 2014 through September 2015 (n = 16
302 months).

303 4. Discussion

304 4.1 Linking total soil respiration and water table depth to GRACE observations

305 GRACE TWSA was well in phase with precipitation and water table depth (Figure 3). Water
306 table depth, influenced by precipitation (Hirano et al. 2007), is a reasonably good predictor of
307 total soil respiration in our test site (Figure 5 and Swails et al. in preparation), and other tropical
308 peatlands sites (Hirano et al. 2009; Jauhiainen et al. 2008). However, at larger spatial scales, the

309 relationship between peat soil respiration and water table depth loses strength (Hergoualc'h and
310 Verchot 2014). Additional work is needed to investigate other proxies and develop new
311 approaches allowing broader scale evaluations of total soil respiration. Soil moisture is another
312 critical variable influencing soil respiration and particularly important in drained peatlands
313 (Marwanto and Agus 2014; Comeau et al. 2016; Hergoualc'h et al. 2017). Because GRACE
314 TWSA tracks soil water storage, which includes water table depth and soil moisture, GRACE
315 data could be a useful tool to assess soil respiration, an important C flux from tropical peat soils.
316 GRACE TWSA data as a tool for monitoring water table depth might also serve as a fire-alert
317 system. Indeed, we found a significant relationship between total soil respiration and water table
318 depth (Figure 5), between water table depth and GRACE TWSA (Figure 6a), and between total
319 soil respiration and GRACE TWSA (Figure 6b) in our test site. GRACE TWSA was sensitive to
320 extreme dry down during the 2015 El Niño event associated with increased water table depth and
321 higher soil respiration in forest and oil palm. The most negative GRACE TWSA value was
322 associated with the lowest water table depth and highest soil respiration measurements in
323 September 2015. Broad scale monitoring of water table depth and soil respiration concomitantly
324 in peatlands would also benefit peat restoration efforts.

325 Understanding the hydrological processes driving variation in soil water storage is
326 important for interpreting relationships among precipitation, GRACE TWSA, and water storage
327 in tropical peatlands. GRACE TWSA is related to changes in water storage, which is a function
328 of precipitation, but also evapotranspiration and discharge, which were not accounted for in our
329 study. Relating total soil respiration to water table depth on the ground to GRACE TWSA is
330 constrained by many factors. For example, TWSA reported for March 2014 was strongly
331 negative. Despite extremely high rainfall in the latter half of March 2014, because the period

332 followed two relatively dry months, TWSA remained negative for April, and it did not become
333 positive again until May 2014. These data indicate that ground water reservoirs required several
334 months of rainfall to recharge after the relatively dry conditions in January and February 2014.
335 Careful consideration of antecedent conditions (wet to dry versus dry to wet transitions) and time
336 lags is necessary for determining a predictive relationship between soil respiration, hydroclimatic
337 drivers on the ground, and GRACE TWSA.

338 Another constraint on estimating relationships among critical hydroclimatic parameters
339 and soil respiration is the dearth of meteorological data. The precipitation recorded at Iskander
340 Airport in Pangkalan Bun may not have been representative of the climatic conditions
341 represented in the GRACE grid cell, which covers an area of approximately 3,025 km². The
342 spatial resolution of the current product, at 0.5°, is fairly coarse. Finally, missing days in the data
343 record due to instrument issues may have influenced the accuracy of TWSA observations.
344 Estimation of a good gravity field solution requires accumulation of satellite-to-satellite tracking
345 data for about one month, and there were many days missing from the record. Beginning in 2011
346 the GRACE mission has shut down battery power for consecutive weeks approximately every
347 six weeks to extend satellite lifetime. The anticipated GRACE follow-on mission will extend the
348 GRACE time series with minimal data gaps while significantly improving on the accuracy and
349 spatial resolution of the original mission (Fletcher et al. 2014).

350 *4.2 A new way to assess a critical CO₂ flux from tropical peatlands*

351 Smaller TWSA, indicating drier conditions, was associated with greater landscape-scale soil
352 respiration in our test site, one GRACE grid cell, comprised of roughly 1/3 oil palm and 2/3
353 intact peat swamp forest (Figure 6b). Using relationships among precipitation, GRACE TWSA,
354 and total soil respiration, soil water storage, an important driver of respiration in tropical peat

355 soils, could be related to seasonal and interannual climatic variation. This method of assessing
356 soil water status with GRACE TWSA would better characterize spatial and temporal variability
357 in total soil respiration in tropical peatlands compared to some other potential approaches using
358 satellites. For example, the Soil Moisture Active Passive (SMAP) mission L4-C product for
359 monitoring terrestrial ecosystem – atmosphere CO₂ exchange using L-band microwave
360 observations of soil moisture achieves 9 km resolution (Jones et al. 2016) compared to 0.5
361 degree resolution with GRACE JPL-RL05. However, SMAP, while useful for assessing soil
362 moisture status in other parts of the world (Piepmeier et al. 2017), cannot be used in densely
363 vegetated tropical peatlands. GRACE is uniquely appropriate for application in tropical peatlands
364 in that it is able to “see through” dense vegetation, unlike SMAP. Additionally, soil respiration in
365 tropical peatlands depends on water table depth in addition to soil moisture. Therefore GRACE
366 TWSA, as an integrated measure of groundwater and soil moisture, is particularly useful.
367 Satellite based rainfall data such as the Global Precipitation Mission (GPM) can be used in the
368 tropics to model soil water storage, and achieves higher spatial resolution than GRACE (e.g. 10
369 km x 10 km for GPM). However satellite based rainfall products may underestimate rainfall in
370 Southeast Asia during dry months (Vernimmen et al. 2012). Furthermore, rainfall remains one
371 step removed from soil water status which is the ultimate determinant of soil respiration.

372 The strength of relationships between the weighted average water table depth and soil
373 respiration and precipitation are similar to those of relationships between water table depth and
374 soil respiration and TWSA. This indicates that in our study area, precipitation was an equally
375 good predictor as TWSA for assessing landscape soil respiration and water table depth variation.
376 Notwithstanding, in oil palm where water table level is controlled by drainage, precipitation was
377 not a good predictor of soil respiration (Figure 7d). GRACE TWSA could therefore be useful for

378 predicting soil respiration in landscapes dominated by oil palm on peat. Further testing of this
379 application across larger spatial scales is needed, with additional ground measurements properly
380 designed to systematically test results presented here before they may be generalized. This case
381 study represents an early exploration of the potential of GRACE TWSA as a tool for assessing
382 total soil respiration and soil moisture regime. It should lead to further investigation of how
383 GRACE data can be used in a broader land-use change and climatic change context.

384 Several issues complicate the application of GRACE data for assessment of CO₂
385 emissions from tropical peatlands. Total soil respiration includes both heterotrophic and
386 autotrophic contributions, but only heterotrophic respiration is directly linked to peat
387 decomposition. The literature indicates that anywhere from 50-90% of the flux is likely due to
388 heterotrophic respiration (Comeau et al. 2016, Hergoualc'h et al. 2017). Furthermore, peat C
389 storage or loss results from the balance of C entering the peat – litterfall, root mortality, and
390 exudates, and C leaving the peat – heterotrophic respiration, dissolved organic carbon, methane,
391 and fire, if any. Also, GRACE data are coarse, and grid level TWSA represents the contribution
392 of changes in water storage in both undrained peat forest and drained oil palm. As we have done
393 here, using land cover data, GRACE grid level data could be weighted to represent coverage by
394 forest and oil palm to better predict soil respiration and water table depth with TWSA
395 observations. Finally, total soil respiration within a specific land use in tropical peatlands
396 responds to multiple factors in addition to soil water storage, such as temperature, soil organic
397 matter quality, and nutrients. For instance, higher peat substrate quality in forest than oil palm
398 may have contributed to the stronger response of soil respiration to increased water table depth in
399 forest than oil palm during the El Niño event in September 2015 (Swails et al. 2017).

400 Ultimately, a multi-factor model could be developed linking remotely sensed measures
401 with ground measurements for large scale assessments of soil respiration in tropical peatlands.
402 More work is needed to operationalize the application of GRACE TWSA for assessing CO₂
403 emissions from tropical peatlands. Additional ground measurements of soil respiration and
404 physical drivers are needed to increase the spatial extent of *in-situ* observations and scale the
405 relationship with coarse resolution GRACE data. The current sample size is very small and the
406 plot locations do not represent any randomized selection. While a small, non-randomized
407 sample is adequate for this exploratory study, for rigorous inference, a well-defined probability
408 sampling design would be necessary. Next, characterization of error and uncertainty of annual
409 emissions estimates at various scales from the plot to the plantation, district, province, and island
410 is needed. This will enable the identification of an optimal sampling strategy for monitoring CO₂
411 emissions from peat using limited ground based measurements and remotely sensed data.
412 Additional work is needed to account for other critical C fluxes. However GRACE data shows
413 great promise for providing an alternative approach for understanding the role of tropical
414 peatlands in the global C cycle and the combined influence of land-use change and climate
415 variability on peat C emissions. With further development and systematic testing of results
416 presented here, this new application could provide useful information to decision makers to
417 monitor changes in water table depth and peat CO₂ emissions in remote and inaccessible areas
418 with limited measurements on the ground.

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