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1 **Reconciling simulations of seasonal carbon flux and soil water with**
2 **observations using tap roots and hydraulic redistribution; a multi-biome**
3 **FLUXNET study**

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6 **1 Abstract**

7 Understanding the response of plants to soil moisture stress is important given a future climate subject
8 to greater extremes, including drought. Nevertheless, major discrepancies still exist between observed and
9 simulated seasonal carbon, water and energy fluxes at the vegetated land-surface. For tropical forest,
10 these discrepancies have been reduced, especially during the dry season, by taking account of tap roots
11 and hydraulic redistribution. The expanding FLUXNET open-access archive allows the current study to
12 extend the investigation of seasonal drought-stress to ten different vegetation types. A state-of-the-art land-
13 surface model is enhanced to take account of tap roots and hydraulic redistribution in order to compare
14 with traditional simulations. Carbon fluxes and fractional soil water content are simulated and compared
15 against observations. We find that a traditional approach, by neglecting tap roots, simulates a seasonal
16 drought for trees and shrubs which is generally too severe compared to observed net carbon flux. The
17 introduction of a tap root benefits tropical broadleaf forest and other ecosystems with high annual potential
18 evapotranspiration in reducing observation-model discrepancies. Our simulations suggest a minor role for
19 hydraulic redistribution, modifying weekly soil moisture rather than substantially changing seasonal water
20 flux totals.

21 **Keywords**

22 carbon cycle; water cycle; land-surface modelling, Moderate Resolution Imaging Spectroradiometer (MODIS);
23 FLUXNET; plant functional types; drought

2 Introduction

Assessing the resilience of plants to soil moisture stress and seasonal drought is not only important for understanding ecosystem functioning and its role within the carbon cycle. The feedback of water and heat fluxes from vegetation to the atmosphere can change regional climate, surface temperature and land-surface cover (Denman et al. 2007; Richardson et al. 2013) and is key to predicting the response of a future biosphere subject to greater climatic extremes (Fischer & Schär 2010).

Nevertheless, major discrepancies still exist between observed and simulated seasonal carbon, water and energy fluxes at the vegetated land-surface. For example, standard land-surface models (LSMs) predict a drought-induced reduction in both ecosystem carbon assimilation and evapotranspiration during the tropical dry season (Baker et al. (2008)). In contrast, FLUXNET observations at one tropical forest reveal a 25% *increase* in evapotranspiration and sustained ecosystem carbon assimilation during this period (Goulden et al. 1996; Da Rocha et al. 2004). Examining a number of factors, Baker et al. (2008) conclude that access to deep (>3.5 m) soil water via tap roots is important to sustain gross productivity during the tropical dry season, although a simultaneous moisture-limited reduction in heterotrophic respiration is also implicated. Likewise, growing season evapotranspiration at four Californian FLUXNET sites simulated by Ichii et al. (2009) is reconciled with observations by the introduction of roots that are much deeper (e.g. 4 m for needleleaf forest) than values measured in the literature. This latter study, whilst thought-provoking, is based on a bucket model (single soil layer, no baseflow and linear root distribution) which is much simpler than the soil and plant hydrology adopted in most LSMs. Nevertheless, the aforementioned studies suggest our understanding of plant hydrology is incomplete, or at the very least poorly formulated in LSMs, and that plants might be more resilient to drought than has been hitherto supposed.

Deep roots have been excavated in the tropics and are believed to play an important role in drought-avoidance (Nepstad et al. 1994). Outside the tropics, 2-5 m tap roots are recorded at some boreal and mediterranean sites (Dawson & Pate 1996). However, the prevalence and importance of tap roots amongst different Plant Functional Types (PFTs) is not well established. (Acronyms and abbreviations used in the text are listed in Tab. 1). Compilations of multibiome measurements reveal that vast majority of root biomass lies in the upper metre (Jackson et al. 1996). Schenk & Jackson (2005) estimate that only 10% of global vegetation has >5% of root biomass deeper than 2 m, deep roots being most likely in seasonal (sub-)tropics for medium

54 texture soils. Even for trees, the majority of roots are constrained to the near-surface layers to allow com-
55 petitive nutrient recycling. Shallow rooting appears to be even more prevalent in grassland (Oliveira et
56 al. (2005); Jipp et al. (1998)). For example, Puecheta et al. (2004) record a scale depth of only 0.12 m in
57 temperate grassland.

58

59 Lee et al. (2005) argue that, given the small fraction of root biomass in deep tap roots, another mechanism
60 must operate in order to sustain photosynthesis and evapotranspiration during the dry season. They claim
61 that water from the lower, moist soil layers is redistributed to upper, drier soil layers in a process known
62 as Hydraulic Redistribution (HR). HR operates via the root system, occurs mostly at night and potentially
63 allows water to move more quickly through the soil profile compared to standard Darcian flow. Estimates
64 of HR and its importance vary. One model simulation predicts that 20% of Amazonian evapotranspiration
65 originates from HR (Lee et al. 2005). However, nocturnal recharge of the upper soil layers measured at one
66 tropical broadleaf site indicates that only 10% evapotranspiration is provided by HR (Da Rocha et al. 2004).
67 Sap flow measurements in arid savanna suggest that $\sim 10\%$ of annual transpiration is supplied by HR (Scott
68 et al. 2008). However, a simulation for arid shrubland predicts that HR supplies only 4% of total transpi-
69 ration (Ryel et al. 2002).

70

71 The expansion of the FLUXNET open access database allows a more extensive investigation into the preva-
72 lence of tap roots and HR across many global PFTs and how their implementation into standard LSMs may
73 reduce discrepancy between modelled and observed carbon fluxes. This may also relate to the long-standing
74 enigma that standard LSMs systematically underestimate fractional soil water content (SWC) in the upper
75 soil profile by 0.05-0.10 over a wide range of PFTs (Guo and Dirmeyer (2006)). This underestimation could
76 spuriously increase simulated drought-stress. The bearing of HR and tap roots on this problem is currently
77 unknown.

78

79 This study modifies a state-of-the-art LSM to take account of tap roots and HR. The overarching goal is
80 to compare revised simulations at 79 FLUXNET sites (482 siteyears and 10 vegetational types) against
81 observed Net Ecosystem Exchange (NEE) and fractional SWC. Note that tap roots and HR have hitherto
82 been implemented in only one or, at most, a few sites (e.g. Lee et al. 2005; Baker et al. 2008; Ichii et
83 al. 2009). Further, the simultaneous analysis of fluxes and soil water has seldom been attempted in the

84 past, although the carbon and water cycles are strongly coupled through the process of photosynthesis and
85 transpiration. In contrast to many previous studies, the current investigation also focuses on the ability of
86 a state-of-the-art model to reproduce *seasonal* rather than diurnal fluxes and states. Our specific objectives
87 are:

- 88 1. to determine whether the inability of a standard LSM to reproduce dry season NEE in the tropics
89 extends to other PFTs or climate zones;
- 90 2. conversely, to identify PFTs where drought is evident in observed fluxes and may or may not be
91 reproduced by the simulation;
- 92 3. to reduce observation-model discrepancies for both seasonal carbon flux and soil water by implementing
93 ecophysiological and field-based modifications for tap root and HR hydrology.

94 **3 Material and Methods**

95 The methodology consists of 3 experiments: (1) a standard, default simulation with traditional, shallow
96 roots based on average field measurements (Jackson et al. 1996); (2) as (1) but adding a tap root; and (3)
97 as (2) but allowing for HR between soil layers. First, the LSM and its modification are introduced. Then
98 the datasets are described which serve either as model input (parameterisation and forcing) or for validation
99 (fluxes and soil water content). Finally, the modelling protocol is explained.

100 **3.1 LSM and its Modification**

101 The current study uses the Joint UK Land Environmental Simulator (JULES-SF) which is an enhanced
102 version of the new UK Met.Office Surface Exchange Scheme (Cox et al. 1999). Key equations for JULES-SF
103 are given in the Appendix of Alton & Bodin (2010) with the exception of a subsequent reformulation of
104 plant maintenance respiration which is summarised below. In the following model overview we focus on
105 changes made to below-ground plant hydrology for the purposes of this study.

106
107 JULES-SF takes account of diffuse and direct sunlight at multiple heights within the canopy and is one of
108 most elaborate LSMs which operates globally in terms of light interception (Alton et al. 2007). The energy
109 calculation central to JULES-SF is the standard Penman-Monteith approach (Monteith 1965), ensuring the
110 balance of ingoing and outgoing energy fluxes at the land-surface. Photosynthesis is calculated separately

111 within each of 5 leaf layers according to a biochemical co-limitation model (Collatz et al. 1991), before
112 summing to produce a canopy total. Leaf photosynthesis is linked to transpiration through a Ball-Berry
113 stomatal model (Ball et al. 1987). Plant respiration depends on maintenance and growth terms (Ryan 1991).
114 The former includes separate, additive terms for leaf and root respiration according to Q_{10} relationships
115 based, respectively, on canopy and soil temperature (Law et al. 1999). Stem respiration depends on the
116 ratio of stem-to-leaf nitrogen concentration (Cox et al. 1999; 2004). Surface albedo is estimated according
117 to the two-stream approximation of Sellers et al. (1996).

118

119 Within JULES-SF, the soil is divided into 4 layers of thickness (top downwards) of 0.1, 0.25, 0.65, 2.0 m. The
120 total soil column is therefore 3 m. In the standard simulation (JULES-def), plant water extraction depends
121 on the exponential fine root distribution which declines rapidly with depth. The exponential scale-depths
122 are taken as averages ($d_{root}=0.1-0.3$ m) from Jackson et al. (1996) who collate and average measurements
123 for a wide range of PFTs. Most LSMs possess a similar shallow rooting depth although sometimes a bucket
124 model is adopted in which a single soil layer defines the maximum depth to which the linear, rather than
125 exponential, rootstock extends (e.g. Ichii et al. 2009).

126

127 In the second experiment, we add a single tap root to the standard model (JULES-tap). This tap root
128 is placed within the lowest soil layer (depth 1-3 m). There are few measurements of the partitioning of
129 biomass between shallow root stock and tap roots which can be used directly to parameterise our model.
130 From numerous compiled measurements, Jackson et al. (1996) estimate that root biomass below 1 m ranges
131 from $<1\%$ in tundra to 8-9% in deserts and temperate needleleaf forest, with a median across all 11 biomes
132 of only 2%. From a similar compilation, Schenk & Jackson (2005) estimate that only 10% global vegetation
133 has $>5\%$ of root biomass deeper than 2 m. However, for broadleaf trees in a mediterranean climate, 17%
134 of total root biomass is found at depths of 0.9m (Kurz-Besson et al. 2006). Further, nearly one third of
135 roots have been found below 2 m from excavations at one tropical forest (Nepstad et al. 1994; Jackson et
136 al. 1996). In order to assess the maximum impact of deep rooting we adopt a high value for the fraction of
137 tap biomass (1/3).

138

139 The properties of roots (specific hydraulic conductivity, diameter, length etc) differ considerably between
140 shallow rootstock and deep tap roots (McElrone et al. 2004). However, these kind of detailed and differen-

141 tiated properties are not yet formulated explicitly in JULES-SF or any other global LSM. Extraction from
 142 each soil layer depends simply on the fraction of total root mass (shallow plus tap) present in that layer.
 143 This Ohm’s Law analogy to root conductance (Tyree & Ewers 1991; Sellers et al 1996), which is also adopted
 144 below for HR (see Eq. 1 in Appendix), is a necessary simplification but one that we examine critically in
 145 the Results.

146

147 In the third experiment, we modify JULES-tap to allow for transport of water from wetter to drier soil layers
 148 *via* the root system (JULES-tap-HR). This hydraulic redistribution is in addition to the bulk Darcian soil
 149 flow present in all LSMs. The formulation of HR is based on Lee et al. (2005) and is described in detail in
 150 the Appendix. Note that HR can be either upwards or downwards according to whether the upper soil layers
 151 are subject to drought or heavy precipitation. We assume HR only takes place at night since transpiration
 152 is expected to drive water transport in the roots during the daytime.

153

154 For all 3 experiments, the moisture content within each soil layer is determined as the balance between
 155 water input (precipitation) and water output. The latter consists of evapotranspiration (i.e. soil and canopy
 156 evaporation as well as transpiration) and runoff (both above and below-ground). The below-ground runoff
 157 or baseflow is missing in bucket models but present in most standard LSMs. The model can store water in
 158 the soil (ΔSMC), on top of the soil surface as snow (ΔSNOW) and on the surface of canopy leaves (ΔCAN).
 159 ΔCAN relates linearly to LAI. Both ΔSNOW and ΔCAN are small compared to ΔSMC . Fig. 1 given an
 160 overview of model hydrology and the key water-balance equation.

161

162 The model contains 10 PFTs defined in Tab. 2. Based on site description, each FLUXNET location is
 163 attributed to one of these PFTs and simulations are conducted separately for each site.

164 3.2 Datasets

165 As described separately below, datasets serve either as model input or as validation of model output.

166 3.2.1 Model Input

167 As input, JULES-SF requires biophysical parameter values, meteorological forcing and a Leaf Area Index
 168 (LAI) timeseries or phenology. Many of the biophysical parameters are PFT-specific and include plant

169 attributes which are either structural (e.g. rooting depth, canopy height), optical (e.g. leaf absorptance)
 170 or physiological (e.g. photosynthetic capacity, minimum stomatal conductance). They are assigned using
 171 average collated field measurements (Alton & Bodin 2010). For the most influential parameter on modelled
 172 carbon fluxes, photosynthetic capacity (V_{cmax}^0), we adopt the mean of Wright et al. (2004) and Kattge et
 173 al. (2009), weighting for the number of measurements for each PFT. Before doing so, we convert the mea-
 174 surements of leaf nitrogen collated by Wright et al. (2004) into estimates of V_{cmax}^0 using the same procedure
 175 as Kattge et al. (2009). Although there may be overlap in measurements contained in Wright et al. (2004)
 176 and Kattge et al. (2009), removing duplicates from such large samples is beyond the scope of the present
 177 study. Furthermore, our approach yields measured V_{cmax}^0 averages per PFT which agree well with values
 178 retrieved in calibration experiments (Alton 2011). It is often advantageous to tune parameters such as V_{cmax}^0
 179 to each site or at least for each PFT as part of the model calibration. However, the current study tests the
 180 impact of model changes and, hypothetically, a separate calibration in each experiment could offset differ-
 181 ences produced by reformulation of the model. Therefore, for the current investigation, we adopt constant
 182 values for each PFT based on the best average measurements available in the literature. Average soil com-
 183 position measured at each site is taken from the FLUXNET ancillary database (Agarwal 2012). Recorded
 184 clay and silt contents determine soil hydraulic properties (e.g. conductance at saturation, Clapp-Hornberger
 185 exponent) based on the soil categorisation in Campbell & Norman (1998).

186

187 Model forcing consists of standard meteorological variables and LAI. Site meteorology is provided in the
 188 FLUXNET database and this is averaged to the 3-hourly model timestep. Although the FLUXNET meteo-
 189 rology is gap-filled (Falge et al. 2002), some siteyears contain a hiatus e.g. in winter. We fill these extended
 190 gaps with the Princeton global reconstructed climatology (Sheffield et al. 2006) using the 3-hourly mete-
 191 orology within the corresponding 1° grid square. This allows the model to simulate total *annual* fluxes
 192 where necessary. However, our focus is the growing season for which the tower-based site meteorology is
 193 usually fairly complete. The main model calculation (Penman energy balance and simulation of sites fluxes)
 194 is 3-hourly, consistent with the Princeton forcing used to fill extended gaps in the site meteorology. This
 195 also provides sufficient temporal resolution to simulate precipitation infiltration and Darcian flow in the
 196 soil. However, HR allows for faster moisture transfer and we modify the model so that it updates moisture
 197 in the soil layers on a half-hourly basis. This is an internal ministep which does not increase the overall
 198 computational burden significantly (an important consideration in a model that is normally run globally)

199 but provides additional numerical stability in the calculation of water balance when HR is occurring rapidly.
 200
 201 For LAI, we adopt the Collection 5 MODIS MCD15A2 product (Schaaf et al. 2002). A $7\text{km}\times 7\text{km}$ subset
 202 (49 pixels) centred on the site location is used to mean average pixels of good quality (i.e. main algorithm,
 203 no significant cloud and $>50\%$ detectors working; Yang et al. 2006). The satellite phenology is normalised
 204 to maximum *in situ* LAI where available (2/3 of sites). MODIS data are only available from 2002. For
 205 earlier siteyears (one third of sample), we create a satellite phenology based on the median value acquired
 206 for the same day-of-year over the period 2002-2008. The error introduced by this approximation is small
 207 compared to other model errors stemming from, for example, parameter calibration.

208 3.2.2 Validation

209 To validate model output we compare against NEE, SWC and, to a lesser extent, latent heat flux (LE), all
 210 recorded in the main FLUXNET database. Measurements are available to the general modelling commu-
 211 nity for 79 sites and encompass 482 siteyears between 1991-2010, though the bulk (93%) range 1997-2009
 212 (Falge et al. 2002; Yuan et al. 2010). Sites are distributed worldwide but are biased towards forest in
 213 North America and Europe. To minimise the impact of incomplete energy closure (Foken 2008), we exclude
 214 fluxes recorded under low frictional velocity ($<0.16\text{ ms}^{-1}$; Goulden et al. 1996; Reichstein et al. 2003) or, if
 215 frictional velocity is unrecorded, where windspeed $<2\text{ ms}^{-1}$ (Medlyn et al. 2003). To compare with model
 216 output, good quality observed NEE is averaged over a 3hr interval in the first instance, although much of our
 217 seasonal analysis relies on weekly averages of both modelled and observed fluxes, as discussed in the Results.

218
 219 SWC is measured at an average depth of 8 cm (SWC1) and 19 cm (SWC2). Coverage is quite low. Thus,
 220 SWC1 and SWC2 are only available for, respectively, 46% and 32% of the eddy covariance fluxes. No valid
 221 measurements are available for tundra, shrubs and C4 crops. To filter out spurious (unreasonable) observa-
 222 tions, we reject the 1% of SWC1 and SWC2 values in excess of 0.55.

223
 224 Tab. 2 shows the number of sites per PFT whilst Tab. 3 summarises the main datasets.

225 3.3 Modelling Protocol

226 A simulation is conducted for each site using JULES-def, JULES-tap and JULES-tap-HR. Model soil mois-
227 ture is spun-up by a 3yr pre-simulation using the site meteorology placed back-to-back where necessary (<3
228 siteyears available). Initially, the model is validated against seasonal moisture content and, to that end,
229 both modelled and observed NEE and SWC are averaged over weekly bins.

230

231 For most sites, SWC1 and SWC2 do not provide sufficient coverage either in time or depth to reconstruct
232 seasonal total soil moisture content (SMC in kg m^{-2}). Therefore, we sought a proxy for total SMC or
233 soil moisture stress. We explored the MODIS mid-infrared to near-infrared reflectance ratio (Ceccato et
234 al. 2001; Cheng et al. 2006) and the evaporative fraction ratio, the latter based on observed sensible and
235 latent heat fluxes (Schwalm et al. 2010). However, both ratios correlate strongly with LAI ($R^2=0.07-0.44$
236 and $R^2=0.35-0.86$, respectively; $p<0.01$) making them unreliable as proxies. Both Zhao & Running (2010)
237 and Angert et al. (2005) rely on the Palmer Drought Index but this is a modelled variable using a bucket
238 approach to soil water balance. Reichstein et al. (2007) define an index of water availability as the ratio of
239 actual evapotranspiration to potential evapotranspiration. However, as the authors themselves admit, this
240 index does not isolate the limitation by water availability since actual evapotranspiration, though measured,
241 depends on LAI. Furthermore, potential evapotranspiration is partly modelled. To compare moisture stress
242 in a range of LSMs, Guo & Dirmeyer (2006) use simulated Plant Available Water (PAW) defined as the
243 difference between current soil moisture content and the plant wilting point. In lieu of a suitable observed
244 variable, we adopt a dual approach to broaden our perspective. Firstly, we examine NEE (measured fluxes)
245 against simulated fractional Soil Water Content (SWC) across the total soil column. Then, we examine
246 Gross Primary Product (GPP; derived from fluxes) against simulated PAW for the total soil column. GPP
247 is derived as $R_E - \text{NEE}$ where R_E is the ecosystem respiration, which is modelled separately for each
248 sitemonth as a quadratic function of air temperature and best-fit to observed nighttime NEE (Medlyn et
249 al. 2003). The PAW is derived assuming a wilting point of -4 MPa in soil water potential.

250 4 Results and Discussion

251 4.1 Carbon fluxes

252 In Figs. 2 and 3, we plot modelled and observed NEE against the deficit in fractional SWC (Δ SWC)
 253 for the default model (JULES-def) and the tap root model (JULES-tap), respectively. To separate the
 254 approximate seasonal change in peak carbon assimilation and respiration, NEE is shown separately for
 255 canopy light saturation (shortwave irradiance $>300 \text{ Wm}^{-2}$; NEE(sat)) and for nighttime (NEE(night)). A
 256 similar approach has been adopted by previous authors (e.g. Goulden et al. 2004) who wish to focus on
 257 measured (NEE) rather than derived (e.g. GPP) fluxes. Observation minus model differences in NEE un-
 258 der light-saturation, Δ NEE(sat), correlate inversely and strongly with observation minus model differences
 259 in LE under light-saturation, Δ LE(sat) (Δ NEE(sat)[$\mu\text{mol m}^{-2} \text{ s}^{-1}$]= -0.12Δ LE(sat)[Wm^{-2}]-2.9; $R^2=0.64$;
 260 $p<0.001$), suggesting that both are driven by the same process (photosynthesis and transpiration).

261

262 Focusing firstly on measurements for trees and shrubs, observed NEE(sat) is largely neutral with respect to
 263 increasing seasonal soil moisture deficit (Fig.2). However, there is an increase in NEE(sat) for natural grass.
 264 For C3 grass this may be partly attributable to increased seasonal ecosystem respiration, which is reflected
 265 in increasing NEE(night). Expressing carbon fluxes as GPP against PAW provides a somewhat different
 266 perspective (Fig. 4). There is a steady decrease in GPP as PAW is reduced, the decline being gentle for
 267 broadleaf trees but somewhat steeper for needleleaf trees. For mediterranean needleleaf trees there appears
 268 to be an inconsistency between Fig.2 and Fig. 4. On closer inspection, we find that PAW is more sensitive
 269 than Δ SWC to soil type and its assumed properties (for example, the wilting point differs quite a lot between
 270 sand or loam soils) and this tends to produce steeper gradients across the dependent variable. Fig. 4 shows
 271 the role of the tap root in sustaining GPP to lower PAW, at least for broadleaf and tropical broadleaf trees.
 272 However, there is often an offset present e.g. for shrubs and tropical broadleaf, possibly owing to an absence
 273 of model calibration in the current study.

274

275 Both Schwalm et al. (2010) and Reichstein et al. (2007) claim a drop in gross productivity under drought.
 276 However, both these studies are based on annual fluxes, either comparing sites for different climate zones
 277 or comparing several years for the same site. Relative few studies quantify the response *across* the season
 278 for the same site or PFT under changing soil moisture deficit. For a temperate deciduous broadleaf forest,

279 Wilson & Baldocchi (2000) claim to detect the onset of seasonal drought in both the ratio of measured
280 sensible and latent heat and the inferred surface conductance. However, both these quantities are sensitive
281 to LAI and the seasonal response is therefore convoluted by phenology. Likewise, Fig. 2 cannot be purely
282 interpreted as a response to soil moisture stress. For example, the concomitant change in average LAI with
283 Δ SMC is strong for crops. Furthermore, crop phenologies recorded *in situ* and by satellite often match
284 poorly owing to the mosaic of vegetation covered by the satellite footprint. This gives rise to large differ-
285 ences between observed and modelled NEE(sat) for C3 crops (Cr3) in Fig. 2 since the model is primarily
286 driven by satellite (MODIS) phenology.

287
288 Reichstein et al. (2003) infer a reduction in seasonal photosynthetic capacity from eddy covariance fluxes
289 recorded at 3 mediterranean sites, comprising two forests and one shrubland. However, this drought stress
290 is only detected at very low soil moisture (SWC \sim 0.07) which occurs only infrequently at most of our sites
291 (\leq 6% of measurements; see panel (a) of Fig. 7, which is discussed in detail below in §4.2). For the dry season
292 within a tropical broadleaf forest, Goulden et al. (2004) measure a small systematic decrease in ecosystem
293 respiration ($2 \mu\text{mol m}^{-2} \text{s}^{-1}$) and a gross productivity which is either sustained or increasing owing to access
294 to deep (10 m) water (Baker et al. 2008).

295
296 Our results are somewhat ambiguous according to how we define soil moisture status (Δ SWC or PAW).
297 However, for trees and shrubs, there is an apparent absence of stress on observed NEE at light saturation
298 over a large range of soil moisture conditions (Fig. 2) and a generally gentle decline in GPP. In contrast,
299 NEE(sat) simulated by the default model exhibits an increase with soil moisture deficit for most PFTs and a
300 marked reduction in GPP. Compared to the observations, the model is oversensitive to drought, particularly
301 for trees and especially for tropical broadleaf forest. This behaviour is also reflected in the corresponding
302 seasonal profiles for LE (not shown). In tropical broadleaf forest, for example, an increase in modelled
303 NEE(sat) at Δ SWC $<$ -0.07 (reduction in carbon assimilation) is mirrored by a one third reduction in mod-
304 elled LE at light saturation.

305
306 The implementation of a tap root yields a better match between model and observed NEE for trees and
307 shrubs (Fig. 3; see also Tab. 4). It also produces a shallower gradient with respect to PAW and sustains
308 GPP to lower PAW. This is particularly beneficial to simulations of tropical broadleaf forest. The deep root

309 allows plants to access water in the lowest soil layer (1-3 m) which would otherwise remain in the lower soil
 310 column or drain out of the system as baseflow runoff. With the tap root implemented, there is no obvious
 311 improvement for crops because of the limiting accuracy of phenology, discussed above. Furthermore, there
 312 is no obvious improvement for grassland (Fig. 2-4). Depth-resolved soil moisture measurements indicate
 313 that grass roots are short compared to trees (Oliveira et al. 2005; Jipp et al. 1998; Pucheta et al. 2004) and
 314 long-term eddy-covariance studies reveal that grassland gross productivity and ecosystem respiration are
 315 very sensitive to drought (Scott et al. 2010). Using compiled global root measurements, Schenk & Jackson
 316 (2005) claim that perennial herbs are five times less likely to be deeply rooted compared to shrubs and trees.
 317 For tropical broadleaf forest, some stress is still apparent in the model even after implementation of a tap
 318 root (Fig. 3).

319

320 With HR implemented, seasonal NEE does not differ significantly from Fig. 3 for JULES-tap (Tab. 4). As
 321 discussed below, the main impact of HR appears to be on weekly rather than seasonal timescales. Although
 322 HR can move water around the soil profile to irrigate roots in the drier layers, once water has been removed
 323 from the total soil column, either by evapotranspiration or baseflow, HR does little to alleviate soil moisture
 324 stress. Thus, HR acts to delay rather than to preclude drought-stress. Both the reduction in observation-
 325 model NEE discrepancies with tap root implementation and the largely neutral seasonal impact of HR are
 326 quantified in Tab. 4.

327

328 Although the improvement in model performance with tap root implementation depends to some extent
 329 on PFT (trees/shrubs versus grass), climate also plays important a role. Fig. 5 shows the change in Root
 330 Mean-Square Error (RMSE) between JULES-def and JULES-tap when sites are plotted against annual po-
 331 tential evapotranspiration. There is an improvement with tap root implementation (Δ RMSE decreasing) for
 332 sites experiencing a higher atmospheric demand for water (higher potential evapotranspiration). However,
 333 the systematic improvement is small ($1 \mu\text{mol m}^{-2} \text{s}^{-1}$) compared to the typical RMSE of the default sim-
 334 ulation ($4 \mu\text{mol m}^{-2} \text{s}^{-1}$). High RMSE is caused by the large observational errors which characterise eddy
 335 covariance fluxes ($1.5\text{-}3 \mu\text{mol m}^{-2} \text{s}^{-1}$; Goulden et al. 1996; Medlyn et al. 2005). Furthermore, model bias is
 336 evident, even when drought stress is minimal (e.g. at $\Delta\text{SWC}=0$ in Fig. 2 for tropical broadleaf forest), and
 337 our simulations (necessarily) use PFT averages for biophysical parameters such as photosynthetic capacity
 338 which are known to vary greatly even within PFTs (Wright et al. 2004). Somewhat surprisingly, inclusion

339 of annual precipitation into the water balance of Fig. 5 (e.g. potential evapotranspiration minus precipita-
 340 tion) does not yield a stronger relationship against ΔRMSE . However, the Princeton dataset providing our
 341 estimate of annual precipitation possesses only a coarse spatial resolution (~ 100 km).

342

343 Given the influence of climate on the inferred presence of tap root, we re-run the JULES-tap simulation,
 344 allowing the fraction of tap root (with respect to total root biomass) to be optimised for each site. This is
 345 done using a gradient-based Levenberg-Marquardt search algorithm (Press et al. 1992) which minimises the
 346 χ^2 differences between observed and modelled fluxes i.e. $\chi^2 = \sum(\text{obs} - \text{mod})^2/\sigma^2$ where σ is assumed to be
 347 $3 \mu\text{mol m}^{-2} \text{ s}^{-1}$ and 30 W m^{-2} for NEE and LE, respectively (Goulden et al. 1996; Medlyn et al. 2005).
 348 The retrieved optimised values of tap root fraction exhibit a large range (Fig. 6). However, only a third
 349 of our sites have more than 5% in tap roots. Extrapolating from site measurements, Schenk & Jackson
 350 (2005) estimate that only 10% global vegetation has $>5\%$ of root biomass deeper than 2 m. Thus we might
 351 expect at least 10% of our sites to possess $>5\%$ of roots in the lowest JULES soil layer (i.e. deeper than 1
 352 m). By far the PFT with the highest tap root fraction is tropical broadleaf forest (median value 0.4). This
 353 substantial fraction is approximately consistent with excavations at one tropical forest which reveal that one
 354 third of root biomass exists in deep roots (Nepstad et al. 1994; Jackson et al. 1996). Field measurements
 355 reveal that tap roots are present in 75% tropical trees (Canadell et al. 1996). Canadell et al (1996) compile
 356 the maximum rooting depth recorded in different biomes, rather than the proportion of root mass below 1
 357 m appropriate for parameterisation/validation of our model. Notably, however, they find that the deepest
 358 roots are present in deserts (not covered by present study) and tropical biomes.

359

360 McElrone et al. (2004) measure a hydraulic conductivity which is 2.3-6.0 (mean 3.8) times higher in deep
 361 roots compared to shallow roots for broadleaf and needleleaf trees in an environment which is susceptible to
 362 seasonal drought. All else being equal, increasing tap root conductivity by a factor of 3.8 would reduce the
 363 optimised tap root fraction by the same factor owing to the Ohm's law analogy formulated in JULES (see
 364 Eq. 1 in the Appendix which shows how water flow for HR, which works in a similar way, is proportional to
 365 the product of conductance and root fraction). However, a factor 3.8 is likely to be the maximum reduction
 366 since the water path length is longer for tap roots compared to shallow roots (e.g. factor ~ 2 in McElrone
 367 et al. 2004) which reduces the conductance for tap roots relative to shallow roots (conductance is propor-
 368 tional to the product of conductivity and path length; Tyree & Ewers 1991). In conclusion, our simulations

369 suggest that the tap root fraction could be as little as 11% for tropical broadleaf forest and even smaller for
370 other PFTs. The minor fraction within tap roots explains, in part, why deep roots have been overlooked in
371 standard LSMs despite their important function in relieving seasonal drought.

372

373 4.2 Soil moisture

374 Fig. 7 compares the fraction of soil water content at depths 8 cm and 19 cm (SWC1 and SWC2, respec-
375 tively) for both the model and observations using the median average within weekly bins. A median is
376 adopted to remove sensitive towards high precipitation events in the observations. Results are shown for
377 JULES-tap and JULES-tap-HR only. The result for the default simulation is similar to JULES-tap because
378 the tap root model extracts additional moisture from the lowest soil layer (depth 2.5 m) rather than from
379 the upper soil profile pertaining to SWC1 and SWC2. On average, the fractional moisture observed in the
380 lower soil level (SWC2) is 0.03 higher than the value measured in the upper layer (SWC1). The model has
381 difficulty reproducing this offset especially with HR implemented. We investigated whether the observed
382 offset was due to a vertical change in soil composition and associated hydraulic properties. However, there
383 is no evidence of an increase in clay content with depth from the FLUXNET ancillary database (Agarwal
384 2012) which, if present, might give rise to greater holding capacity at lower soil depth.

385

386 For JULES-tap there is quite a lot of dispersion between SWC1 and SWC2. This is partly explained by
387 clusters of points where the top soil layer has reached wilting point but moisture is still draining from the
388 lower layer. In HR, this situation does not arise since the roots equilibrate soil moisture across the vertical
389 soil layers. For the observations, the dispersion could be associated with the inherent diversity of soil hy-
390 draulic properties which are rather poorly known at individual sites and estimated in the model according
391 to silt and clay content. Furthermore, the observations often provide only an instantaneous measurement
392 that may fall either side of a heavy precipitation event, whereas the model averages all 3-hourly steps over
393 the duration of a week.

394

395 It is difficult to determine which revised model (JULES-tap or JULES-tap-HR) performs better against the
396 observations until the systematic offset between modelled and observed fractional SWC is removed and the
397 full diversity of soil hydraulic properties is accounted for at all sites. The systematic offset is highlighted in

398 Fig. 8, where modelled SWC2 is compared against measurement throughout the year. For model output,
399 only JULES-tap is shown. JULES-def exhibits a similar seasonal behaviour though slightly offset to lower
400 values (i.e. away from the observations). JULES-tap-HR is very similar to JULES-tap (see also Tab. 4 which
401 quantifies the RMSE for each simulation). Although the model often captures observed seasonal behaviour,
402 on average it is too dry with respect to the observations, even with tap root and HR enhancements. This
403 is a general problem of LSMs. A diverse range of models underestimate growing season fractional SWC in
404 the top metre by a significant amount (0.05-0.10) when compared against measurements in forest, grassland
405 and cropland (Guo & Dirmeyer 2006). Stöckli et al. (2008) implement a catchment-scale aquifer into the
406 Community Land Model to allow for water storage below the 3.5 m soil layer and irrigation of the root-zone
407 during drought. This novel enhancement significantly improves predicted LE at 15 FLUXNET sites but
408 the simulated fractional SWC, whilst increased, still lies 0.05-0.10 below observed values during the driest
409 part of the growing season. Furthermore, our simulations demonstrate that this offset is not eliminated
410 by implementing tap roots or HR. Clearly more work is required to resolve this systematic offset using
411 site-specific measurements of soil hydraulic properties, deep soil moisture (to monitor aquifer and tap root
412 sources) and bedrock features (which may alter baseflow runoff).

413

414 When tap roots and HR are implemented together (JULES-tap-HR), there is an average increase in annual
415 transpiration of 13% compared to shallow rooting. In a few cases, the additional transpiration is 100 mm
416 which is significant. Most of the 13% increase comes from the tap root, with HR contributing a mere 2% to
417 the annual total. HR seems to be more important on weekly (Fig. 7) rather than seasonal timescales.

418

419 Previous estimates of the importance of HR vary. Lee et al. (2005) simulate a 20% increase in annual evapo-
420 transpiration over Amazonia when HR is implemented although it is not clear how the roots are distributed
421 in their model. Measured nocturnal recharge of the upper soil layers at one tropical broadleaf site, Tapajos,
422 indicates that a maximum of 10% annual evapotranspiration is provided by HR (Da Rocha et al. 2004).
423 Sap flow measurements in arid savanna suggest that $\sim 10\%$ of annual transpiration is supplied by HR (Scott
424 et al. 2008) although a simulation of HR within arid shrubland predicts that only 4% annual transpiration
425 arises from HR (Ryel et al. 2002).

426

427 Some previous measurements and simulations suggest that HR could be important seasonally, at least in

428 combination with deep roots. Thus, isotope measurements within trees under a mediterranean climate
 429 indicate that a broad proportion of dry season transpiration (9-47%) originates from water lifted by deep
 430 roots (Dawson & Pate 1996). However, seasonally, our results suggest that it is the tap root, rather than
 431 nocturnal HR, which sustains carbon assimilation under soil moisture deficit (Figs. 2 and 3). Our simulations
 432 are rather insensitive to the parameter values adopted for HR. For example, a factor 2 increase in C_{sat} (Eq. 1
 433 in Appendix), covering the range used for HR in the literature (Becker et al. 1999; Ryel et al. 2002; Lee et
 434 al 2005), only produces a change of 2% in annual transpiration. Our simulations also confirm one problem
 435 already noted by Lee et al. (2005), that HR can lead to overestimates of nighttime evaporation as transported
 436 water is lost from the upper soil layer rather than transpired next day. We believe that more depth-explicit
 437 site measurements of root distribution and soil moisture are required in order to formulate HR correctly in
 438 the model.

439 4.3 Limitations of Study

440 Although providing some initial insights into the role that deep roots and HR could play in land-surface
 441 modelling, our study has significant limitations:

- 442 1. Dawson & Pate (1996) distinguish lateral, shallow, nutrient-acquiring fine roots from stouter, sinker tap
 443 roots, both categories having different hydraulic conductivities and efficiencies. Although we endeavour
 444 to account for some of these differences when estimating the tap root fraction, our experiment is
 445 necessarily a simple first step in representing dimorphic root systems in global LSMs;
- 446 2. Although inclusion of deep roots generally appears to improve simulations of seasonal NEE in trees
 447 and shrubs, we cannot exclude the possibility that other model enhancements could produce a similar
 448 effect (e.g. accounting for seasonal change in V_{cmax}^0). However, we know that deep roots are found in
 449 the field and that they are neglected in the vast majority of LSMs. Moreover, any seasonal increase
 450 in V_{cmax}^0 implies greater transpiration which requires better access to deep soil water (via tap roots);
- 451 3. Ultimately, in order to be useful to global simulations, we have analysed our sites according to PFT.
 452 However, within any given PFT, extraction from different parts of the soil profile may relate to life
 453 strategy (e.g. deciduous-evergreen habit) of individual species (Jackson et al. 1995).

454 5 Summary and Conclusions

455 The current study investigates the prevalence of seasonal drought across 79 FLUXNET sites (482 siteyears)
456 using a state-of-the-art land-surface model, JULES-SF, enhanced to take account of tap roots and hydraulic
457 redistribution. We examine both carbon flux and fractional soil water content across a wide range of plant
458 functional types. Our most important findings are as follows:

- 459 1. Although somewhat sensitive to how we represent soil moisture deficit, the seasonal drought-stress
460 inferred from observed carbon fluxes is less severe for trees and shrubs than that simulated by a
461 traditional model using shallow rooting. The simulated drought-stress is reduced considerably by
462 implementation of a 2 m tap root.
- 463 2. The prevalence of deep roots also depends on climate. Sites with high potential evapotranspiration
464 rates appear to benefit most from the introduction of a tap root. A Levenberg-Marquardt optimisation
465 of the model suggests that only one third of our sites possess >5% root biomass within tap roots. Tap
466 roots appear most important in tropical broadleaf forest (40% root biomass). Note, however, that
467 assuming an enhanced hydraulic conductivity for deep roots, these tap root fractions could be as
468 much as four times lower i.e. a minor fraction of root biomass, which partly explains their neglect in
469 standard LSMs despite their important function.
- 470 3. The model simulates quite well the seasonal change in fractional soil water content. However, as
471 with other land-surface models, the current model, even with tap root and hydraulic redistribution
472 enhancements, is too dry with respect to the observations. This systematic offset makes it difficult
473 to establish whether the model performs better with hydraulic redistribution or not. In any case,
474 hydraulic redistribution appears to have more impact on weekly soil moisture rather than seasonal
475 totals. Thus, it is the tap root rather than hydraulic redistribution which extracts efficiently from the
476 deeper (1-3 m) soil layers, yielding an average increase in annual transpiration of 10% compared to
477 traditional shallow rooting.

478 6 Appendix

479 Hydraulic Redistribution (HR) is based on Lee et al. (2005). Thus, HR water flux ($\text{kg m}^{-2} \text{s}^{-1}$) is defined
480 as:

$$Q = -C_{sat} \frac{r\Delta\psi}{1 + \exp[0.02(\psi_{crit} - \psi)]} \quad (1)$$

481 where C_{sat} ($\text{kg m}^{-3} \text{ s}^{-1}$) is the root hydraulic conductance when the soil column is saturated. A value
 482 of $2.5 \times 10^{-6} LAI_{max}$ is adopted for C_{sat} (Becker et al. (1999); Ryel et al. (2002)), where LAI_{max} is the
 483 maximum Leaf Area Index ($\text{m}^2 \text{ m}^{-2}$) during the year. In Eq. 1, r is the root fraction in the uptake layer,
 484 $\Delta\psi$ (m) is the difference in soil water potential between the uptake (wet) and release (dry) layers. The
 485 denominator is a stress function which describes the steep reduction observed in water transport via the
 486 roots once soil water potential in the uptake layer (ψ in m) falls below a critical value ψ_{crit} (-200m; Sellers
 487 et al. 1996). HR constitutes a low-resistance conduit, relative to the bulk soil Darcian flow, between dry
 488 and wet soil layers.

489

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Table 1: An alphabetical list of acronyms and abbreviations used in the main text. Units are given where appropriate.

	Definition
GPP	Gross Primary Product ($\mu\text{m m}^{-2} \text{ s}^{-1}$)
HR	Hydraulic Redistribution
JULES-SF	Joint UK land environmental simulator
LAI	Leaf Area Index ($\text{m}^2 \text{ m}^{-2}$)
LE	Latent Energy flux (W m^{-2})
LSM	Land Surface Model
MODIS	Moderate Resolution Imaging Spectroradiometer
NEE	Net Ecosystem Exchange ($\mu\text{m m}^{-2} \text{ s}^{-1}$)
PFT	Plant Functional Type
RMSE	Root Mean Square Error
SMC	Soil Moisture Content (kg m^{-2})
SWC	fractional Soil Water Content (-)

Table 2: Plant functional types examined in the current study with the corresponding abbreviation (Desig.) adopted in subsequent figures and tables. The number of sites is given by n . Climate is described by average \pm standard deviation for latitude, Mean Annual Precipitation (MAP) and Mean Annual Temperature (MAT).

Plant Functional Type	Desig.	n	Latitude ($^{\circ}$)	MAP (mm)	MAT ($^{\circ}\text{C}$)
Non-tropical Broadleaf Forest	BL	17	44 \pm 7	850 \pm 294	10 \pm 4
Non-mediterranean Needleleaf Forest	NL	16	51 \pm 7	595 \pm 319	5 \pm 5
C3 Crop	Cr3	8	44 \pm 7	787 \pm 433	10 \pm 4
C4 Crop	Cr4	1	37 \pm 9	864 \pm 209	15 \pm 8
Tundra Shrub	Tu	2	69 \pm 1	158 \pm 231	-9 \pm 1
Tropical Broadleaf Forest	TBL	4	2 \pm 10	2150 \pm 631	27 \pm 2
C3 Grass	C3	14	43 \pm 8	651 \pm 383	10 \pm 6
C4 Grass	C4	4	-5 \pm 30	542 \pm 250	21 \pm 4
Non-tundra Shrub	SH	7	34 \pm 5	336 \pm 213	17 \pm 7
Mediterranean Needleleaf Forest	MNL	6	34 \pm 4	1370 \pm 572	16 \pm 4

Table 3: Main datasets adopted in the present study. Model input data also includes biophysical parameters for each PFT averaged from collated literature values (Alton & Bodin 2010). Note that the temporal resolution refers to the original dataset and does not necessarily correspond to that used either in the model simulations (3-hourly) nor in the analysis (weekly or annual). LAI, NEE, LE, SWC and PET refer, respectively, to Leaf Area Index, Net Ecosystem Exchange, Latent Energy heat flux, fractional Soil Water Content and Potential Evapo-Transpiration.

Purpose	Dataset	Source	Resolution		Reference
			Spatial	Temporal	
Model Input	LAI	MODIS	7 km	8-day	Schaaf et al. (2002)
	Main Met.	FLUXNET	<1 km	~ hourly	Falge et al. (2002)
	Gap-filling Met.	Princeton	1°	3hr	Sheffield et al. (2006)
	Soil composition	FLUXNET	<1 km	singular	Agarwal (2012)
Validation	NEE, LE	FLUXNET	<1 km	~ hourly	Falge et al. (2002)
	SWC1, SWC2	FLUXNET	<1 km	~ weekly	Falge et al. (2002)
	PET	Princeton	1°	annual	Sheffield et al. (2012)

Table 4: Root-mean square error (RMSE) in simulated Net Ecosystem Exchange at light saturation (NEE(sat)) and fractional soil water content (SWC2). Averaging is over weekly values for all siteyears comprising any given PFT. Designation for PFT follows Tab. 2. RMSE is shown separately for each model (JULES-def, JULES-tap, JULES-tap-HR). No SWC2 measurements are available for C4 crops, tundra and shrubs.

PFT	RMSE(NEE(sat)) [$\mu\text{mol m}^{-2} \text{s}^{-1}$]			RMSE(SWC2) [-]		
	JULES-def	JULES-tap	JULES-tap-HR	JULES-def	JULES-tap	JULES-tap-HR
BL	3.60	2.87	2.76	0.108	0.090	0.093
NL	2.31	2.02	2.19	0.063	0.060	0.085
Cr3	10.92	8.24	7.01	0.099	0.077	0.108
Cr4	2.64	3.13	3.65	–	–	–
Tu	0.12	0.06	0.10	–	–	–
TBL	7.77	5.23	4.75	0.130	0.110	0.096
C3	3.34	4.51	4.58	0.043	0.031	0.055
C4	14.05	12.99	14.61	0.039	0.044	0.033
SH	4.35	1.07	0.74	–	–	–
MNL	2.33	1.50	1.57	0.065	0.052	0.061

696 Figure Captions:

697

698 Fig.1: Schematic of JULES hydrology. Soil moisture content (kg m^{-2}) within each of n soil layers ($\text{SMC}(n)$;
 699 $n=4$) is determined by the balance between water input (precipitation (PPT)) and water output (Evapo-
 700 transpiration (ET) and Runoff (RUN)), as well as changes in two smaller reservoirs (SNOW and CAN). ET
 701 consists of transpiration (TR) and evaporation from soil and plant surfaces (ES). Soil depths (m) are given
 702 to the left of the depicted soil and root system. Dashed lines denote potential water flow between vertically
 703 adjacent soil layers.

704

705 Fig.2: Observed (solid line) and modelled (dashed line) weekly Net Ecosystem Exchange (NEE) against
 706 modelled deficit of soil water content (ΔSWC). For any given site, ΔSWC is the maximum value simu-
 707 lated for that site (approximately field capacity) minus the SWC in any given week. For NEE, we average
 708 fluxes into bins of 1 week and then average weekly bins from the same PFT into bins of ΔSWC . Model
 709 results pertain to the default model (JULES-def). Profiles above zero correspond to nighttime exchange
 710 ($\text{NEE}(\text{night})$) whilst negative profiles refer to NEE at light saturation ($\text{NEE}(\text{sat})$). Panel labels follow the
 711 PFT designation in Tab. 2. For tundra (Tu) insufficient data are available to create a profile.

712

713 Fig.3: As Fig.2 but plotting for JULES-tap. Note that ΔSWC is a modelled variable. Therefore, both
 714 observed and modelled NEE span a different range in ΔSWC compared to Fig.2.

715

716 Fig.4: Gross Primary Product (GPP) plotted against Plant Available Water (PAW) averaged over weekly
 717 bins as in Fig. 2. GPP is given under canopy light saturation as values inferred from observed carbon fluxes
 718 (obs) and from the JULES-def (def) and JULES-tap (tap) simulations.

719

720 Fig.5: Change in Root-Mean Square Error (ΔRMSE) between the default and the tap root simulations
 721 (JULES-tap minus JULES-def). RMSE is calculated for a given site using all NEE fluxes recorded across all
 722 relevant siteyears and represents the difference between observed and modelled fluxes. ΔRMSE is plotted
 723 against the corresponding annual Potential Evapo-Transpiration (PET). The plot is produced using all sites
 724 with available NEE measurements with rejection of three 2σ outliers ($n=59$). The solid line shows the best
 725 linear fit.

726

727 Fig.6: Relative histogram of tap root fraction for individual sites retrieved from the model optimisation
728 (n=79).

729

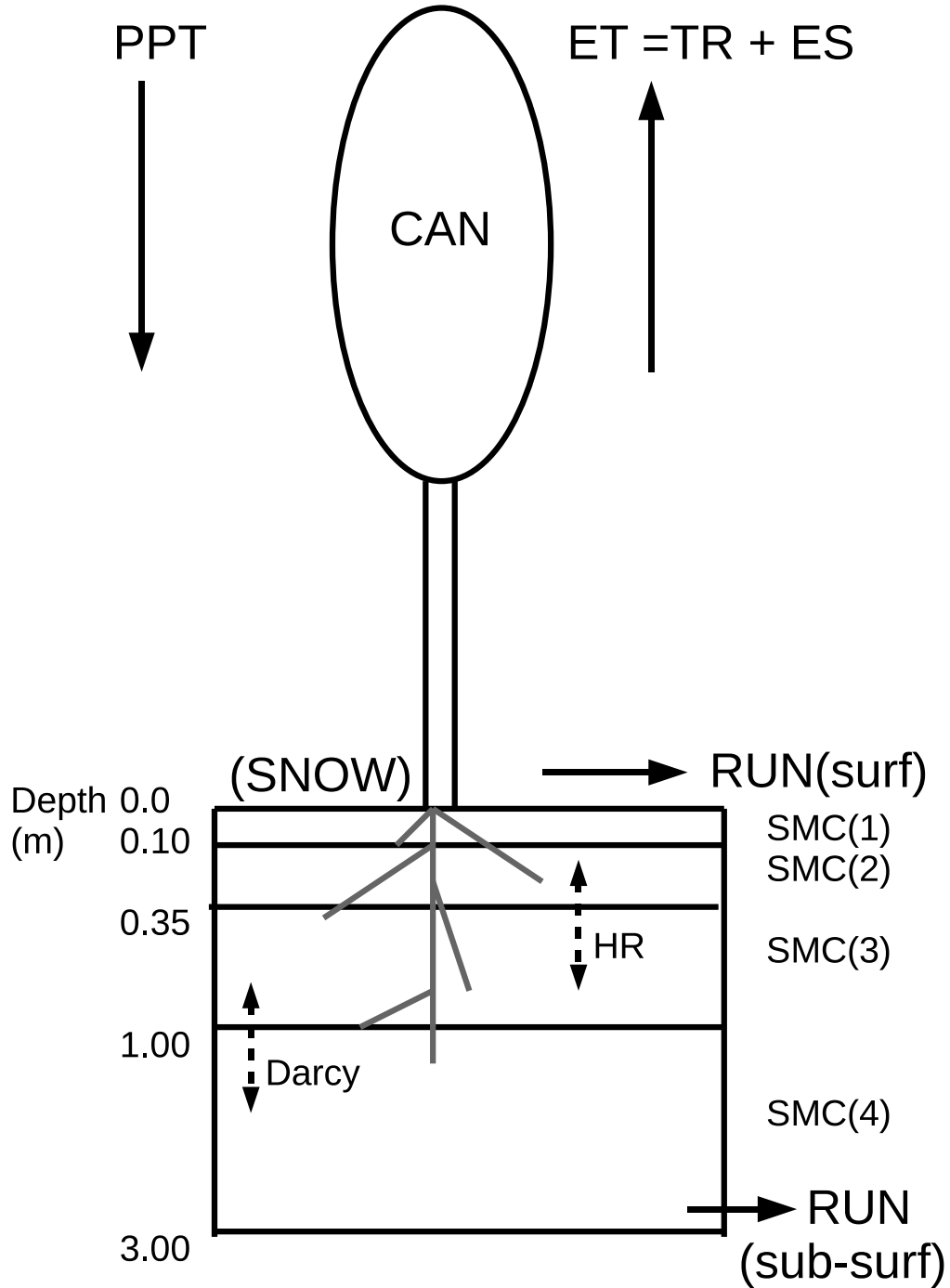
730 Fig.7: Observed (panel a) and modelled (panels b and c) fractional soil water content at average depths of
731 8 cm (SWC1) and 19 cm (SWC2). Points are pooled for all siteyears and PFTs for which observations are
732 available and represent median weekly averages for each siteyear.

733

734 Fig.8: Observed (solid line) and modelled (dashed line: JULES-tap) fractional soil water content at depth
735 19 cm (SWC2) against week of the year. The graphs uses the corresponding points in Fig. 7 mean-averaged
736 over each PFT. PFT designation follows Tab. 2.

737

Figure 1: Schematic of JULES hydrology. Soil moisture content (kg m^{-2}) within each of n soil layers ($\text{SMC}(n)$; $n=4$) is determined by the balance between water input (precipitation (PPT)) and water output (Evapotranspiration (ET) and Runoff (RUN)), as well as changes in two smaller reservoirs (SNOW and CAN). ET consists of transpiration (TR) and evaporation from soil and plant surfaces (ES). Soil depths (m) are given to the left of the depicted soil and root system. Dashed lines denote potential water flow between vertically adjacent soil layers.



$$\text{PPT} - \text{ET} - \text{RUN} = \sum \Delta \text{SMC}(n) + \Delta \text{SNOW} + \Delta \text{CAN}$$

Figure 2: Observed (solid line) and modelled (dashed line) weekly Net Ecosystem Exchange (NEE) against modelled deficit of soil water content (ΔSWC). For any given site, ΔSWC is the maximum value simulated for that site (approximately field capacity) minus the SWC in any given week. For NEE, we average fluxes into bins of 1 week and then average weekly bins from the same PFT into bins of ΔSWC . Model results pertain to the default model (JULES-def). Profiles above zero correspond to nighttime exchange (NEE(night)) whilst negative profiles refer to NEE at light saturation (NEE(sat)). Panel labels follow the PFT designation in Tab. 2. For tundra (Tu) insufficient data are available to create a profile.

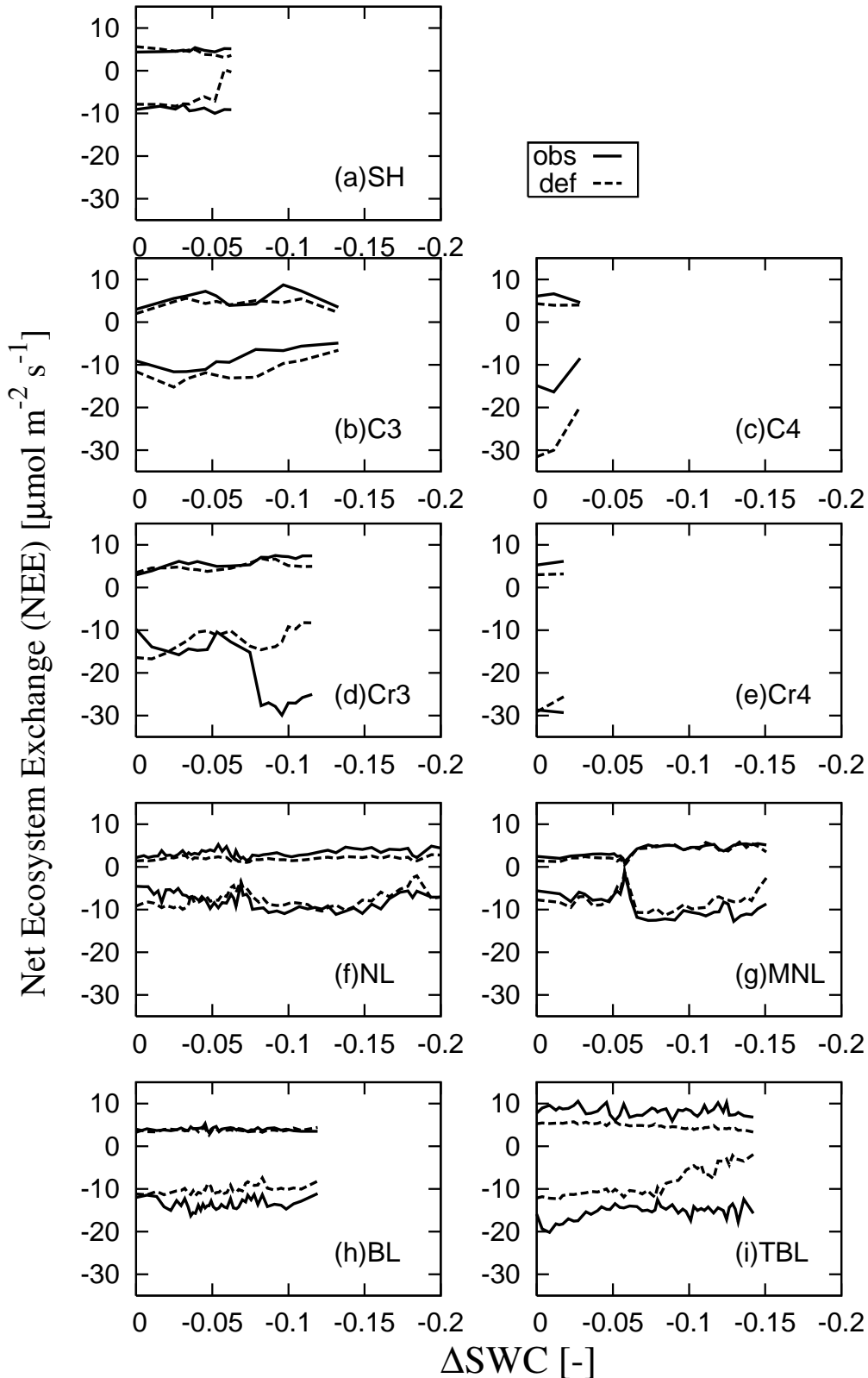


Figure 3: As Fig.2 but plotting for JULES-tap. Note that ΔSWC is a modelled variable. Therefore, both observed and modelled NEE span a different range in ΔSWC compared to Fig.2.

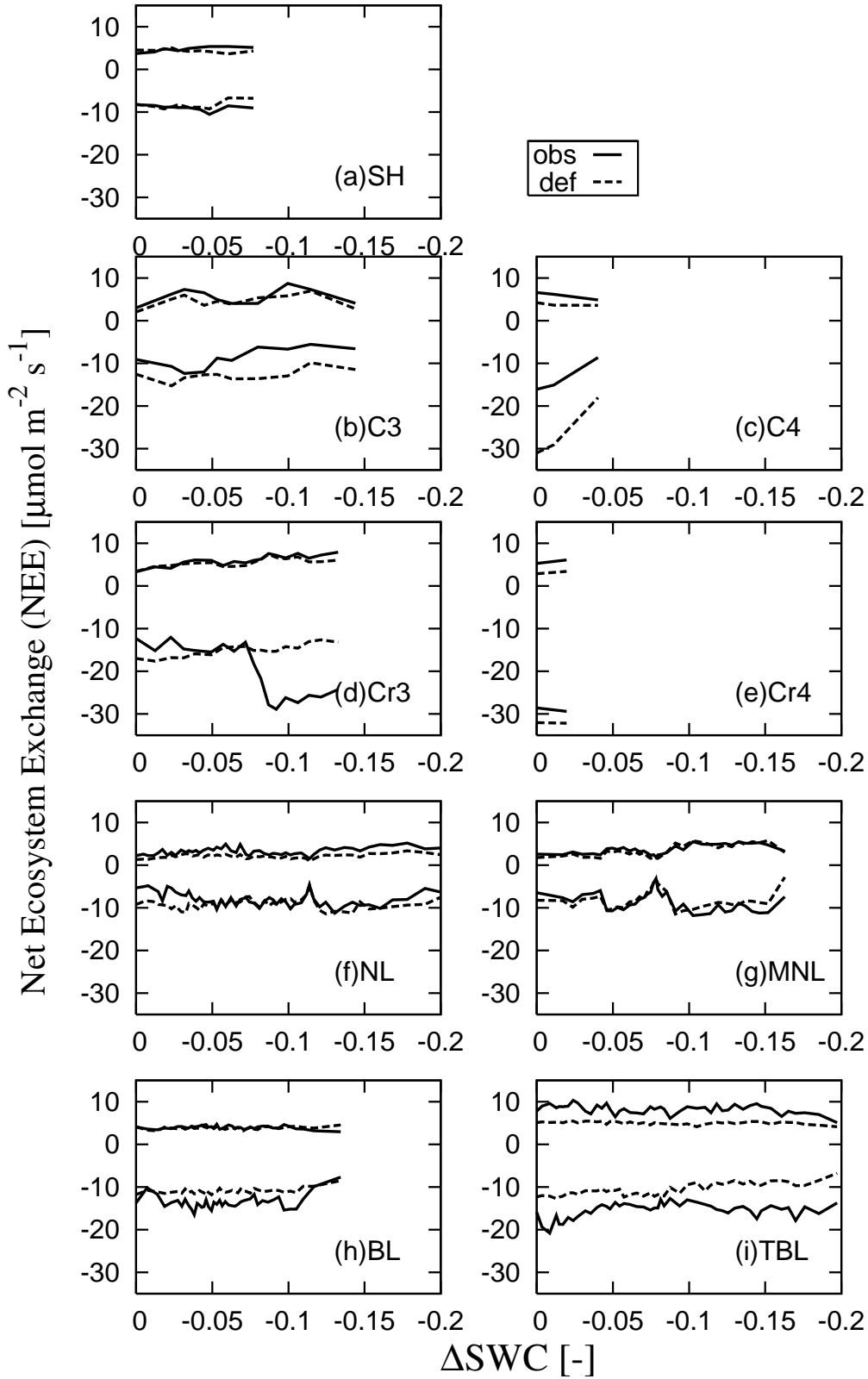


Figure 4: Gross Primary Product (GPP) plotted against Plant Available Water (PAW) averaged over weekly bins as in Fig. 2. GPP is given under canopy light saturation as values inferred from observed carbon fluxes (obs) and from the JULES-def (def) and JULES-tap (tap) simulations.

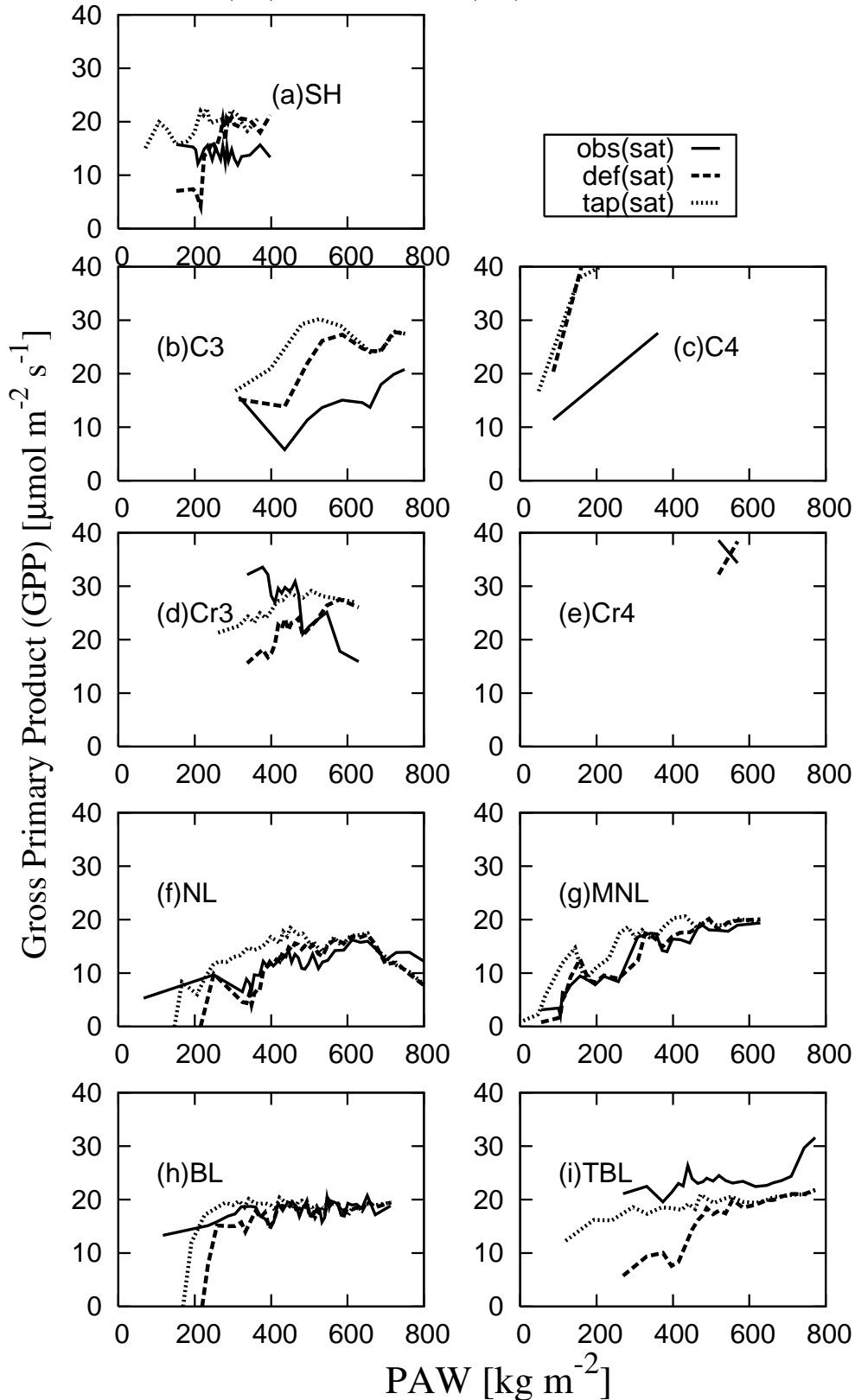


Figure 5: Change in Root-Mean Square Error (ΔRMSE) between the default and the tap root simulations (JULES-tap minus JULES-def). RMSE is calculated for a given site using all NEE fluxes recorded across all relevant siteyears and represents the difference between observed and modelled fluxes. ΔRMSE is plotted against the corresponding annual Potential Evapo-Transpiration (PET). The plot is produced using all sites with available NEE measurements with rejection of three 2σ outliers ($n=59$). The solid line shows the best linear fit.

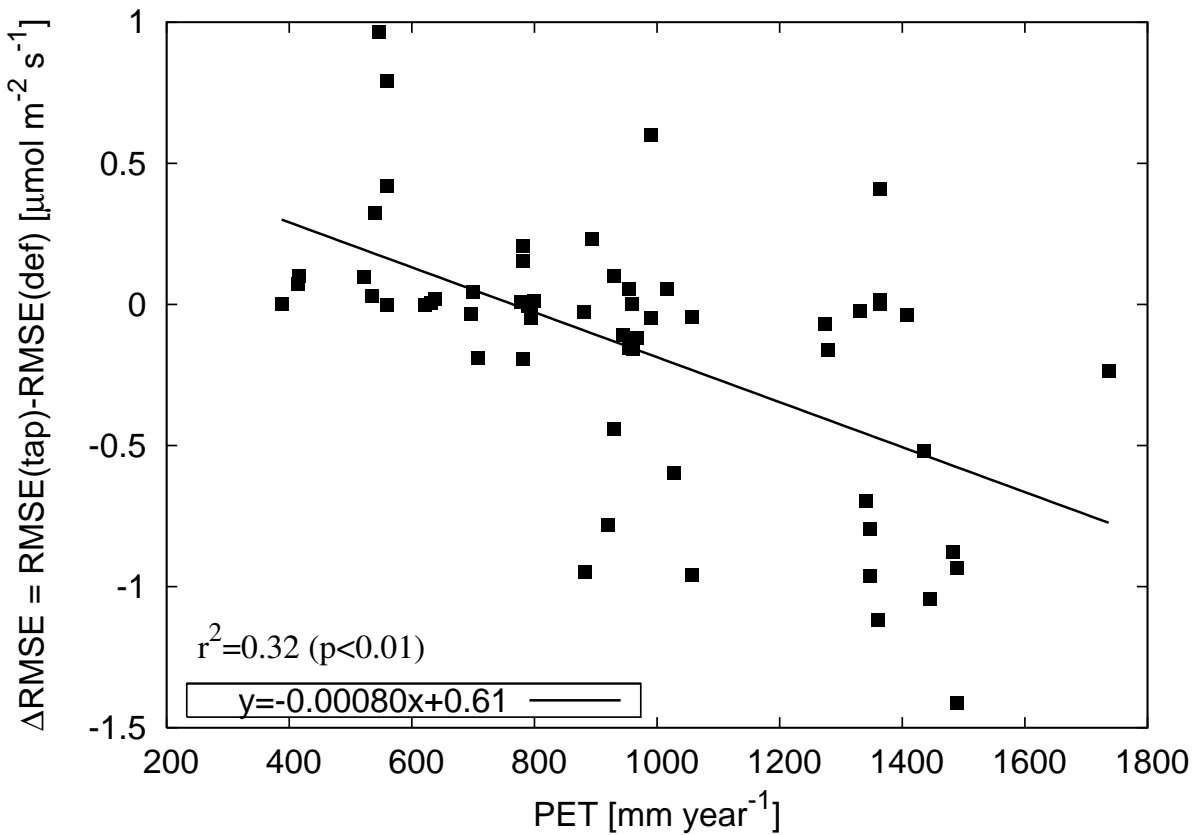


Figure 6: Relative histogram of tap root fraction for individual sites retrieved from the model optimisation (n=79).

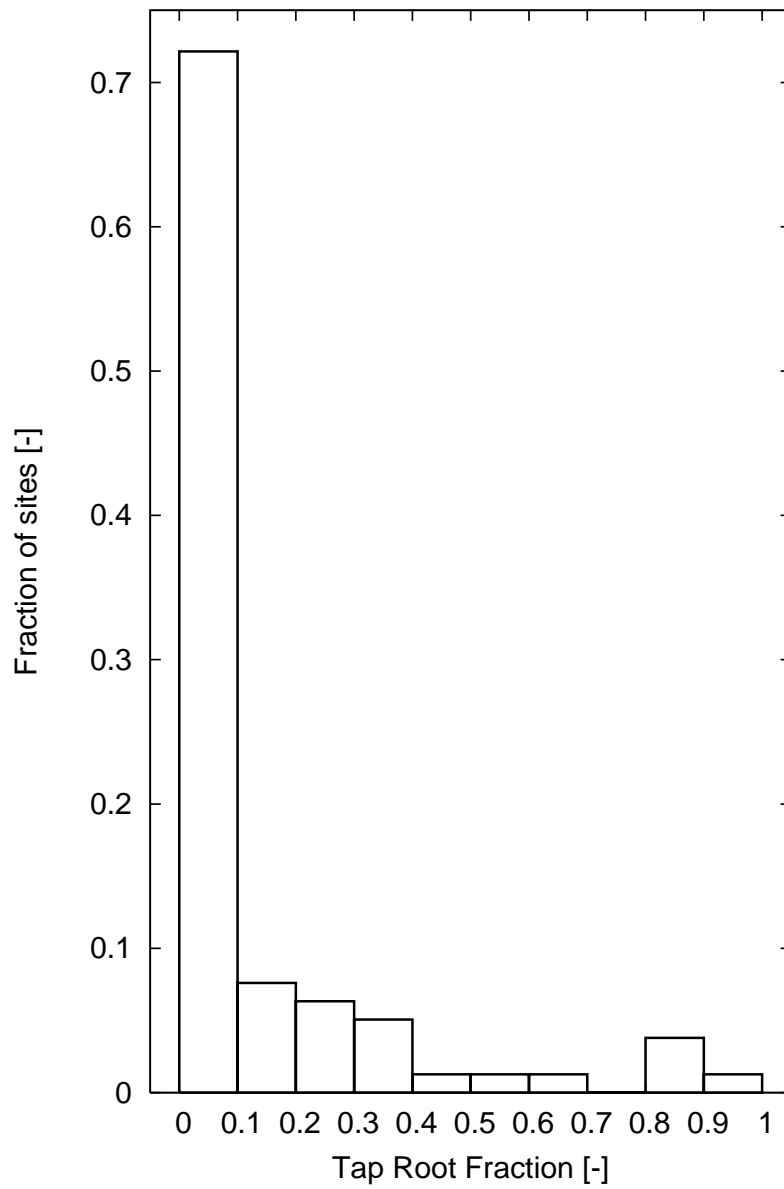


Figure 7: Observed (panel a) and modelled (panels b and c) fractional soil water content at average depths of 8 cm (SWC1) and 19 cm (SWC2). Points are pooled for all siteyears and PFTs for which observations are available and represent median weekly averages for each siteyear.

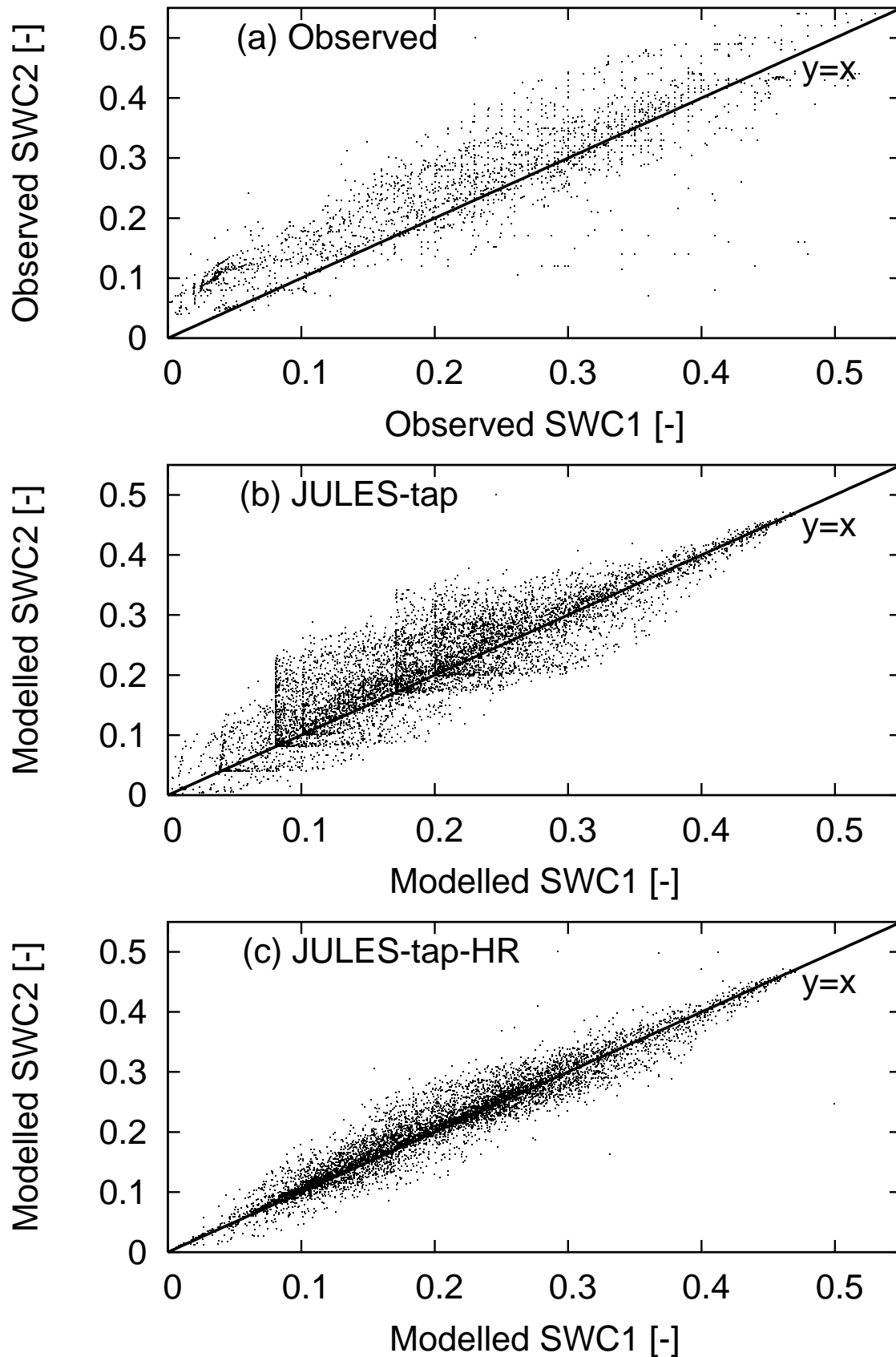


Figure 8: Observed (solid line) and modelled (dashed line: JULES-tap) fractional soil water content at depth 19 cm (SWC2) against week of the year. The graphs uses the corresponding points in Fig. 7 mean-averaged over each PFT. PFT designation follows Tab. 2.

