

1 **Dry season greening and water stress in Amazonia: the role of**
2 **modeling leaf phenology**

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6 **Key Points:**

- 7 • A mechanistic description of tropical leaf-phenology for ecosystem models is pre-
8 sented
9 • Model simulations for 32 sites in the Amazon realistically reproduce carbon/water
10 fluxes
11 • Leaf phenology explains dry-season greening with little impact on evapotranspira-
12 tion fluxes

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Abstract

Large uncertainties on the sensitivity of Amazon forests to drought exist. Even though water stress should suppress photosynthesis and enhance tree mortality, a green-up has been often observed during the dry season. This interplay between climatic forcing and forest phenology is poorly understood and inadequately represented in most of existing Dynamic Global Vegetation Models (DGVMs) calling for an improved description of Amazon seasonal dynamics. Recent findings on tropical leaf phenology are incorporated in the state-of-the-art eco-hydrological model *Thetys & Chloris* (T&C). The new model accounts for a mechanistic light-controlled leaf development, synchronized dry season litterfall and an age-dependent leaf photosynthetic capacity. Simulation results from 32 sites in the Amazon basin over a 15 year period successfully mimic the seasonality of gross primary productivity (GPP), evapotranspiration (ET), as well as leaf area index (LAI), leaf age and leaf productivity. Representation of tropical leaf phenology reproduces the observed dry season greening, reduces simulated GPP and does not alter ET, when compared with simulations without phenology. Tolerance to dry periods, with the exception of major drought events, is simulated by the model. Deep roots rather than LAI regulation mechanisms control the response to short-term droughts but legacy effects can exacerbate multi-year water stress. Our results provide a novel mechanistic approach to model leaf phenology and flux seasonality in the tropics, reconciling the generally observed dry season greening, ET seasonality and decreased carbon uptake during severe droughts.

Introduction

The metabolic rhythm of Amazon rainforests (phenology of vegetation, seasonality of carbon and water fluxes) is a key component of the global carbon cycle [Phillips *et al.*, 2009] with impacts on tropical moist convection [Knox *et al.*, 2011] and important consequences on global climate [Cox *et al.*, 2000; Huete *et al.*, 2006; Alden *et al.*, 2016; Wu *et al.*, 2016]. The importance of the Amazon in the Earth system is therefore unquestionable [Malhi *et al.*, 2008; Davidson *et al.*, 2012] but its vulnerability to drought and the risks associated with a drying climate [Malhi *et al.*, 2008; Meir *et al.*, 2009; Ahlström *et al.*, 2017] is unclear, as conflicting results have been reported [Brando *et al.*, 2010].

Dry periods, i.e. when precipitation is below potential evapotranspiration, alter forest metabolism. When severe water stress is generated, drought can reduce or reverse the carbon sink [Phillips *et al.*, 2009; Lewis *et al.*, 2011; Gatti *et al.*, 2014] and lead to accelerated forest mortality [Malhi *et al.*, 2009; Meir *et al.*, 2009; da Costa *et al.*, 2010; Lewis *et al.*, 2011; Liu *et al.*, 2018]. However, evidence of both positive [e.g. Saleska *et al.*, 2003, 2007] and negative [e.g. Nepstad *et al.*, 2007; Meir *et al.*, 2009] impacts of drought on forest functioning exists. The severe drought event that affected the Amazon basin in 2005 is a clear example of such conflicting results: while Phillips *et al.* [2009] reported a significant decrease in carbon uptake and concluded that Amazon forests are vulnerable to increasing moisture stress, remote sensing observations revealed a basin-wide increase in photosynthetic activity, suggesting a biome resilience (defined as the capability to sustain carbon/water fluxes during extremely dry periods) higher than originally thought [Saleska *et al.*, 2007; Ahlström *et al.*, 2017].

Such unexpected dry season greening, associated with an increase in leaf area timed to solar radiation [Huete *et al.*, 2006; Myneni *et al.*, 2007], has been confirmed by a large number of remote sensing, eddy flux tower and field observations [Saleska *et al.*, 2003; Huete *et al.*, 2006; Huttyra *et al.*, 2007; Myneni *et al.*, 2007; Saleska *et al.*, 2007; Brando *et al.*, 2010; Samanta *et al.*, 2012; Restrepo-Coupe *et al.*, 2013; Morton *et al.*, 2014; Guan *et al.*, 2015; Saleska *et al.*, 2016; Wu *et al.*, 2016], suggesting that light, rather than water, may regulate forest seasonality in tropical wet climates. However, seasonal variations of temperature and radiation are fairly moderate in the tropics and understanding whether the carbon fluxes are controlled by hydro-climate [e.g. Borchert, 1998; Guan *et al.*, 2015] or

64 variations in the forest photosynthetic machinery (leaf area, leaf demography, photosyn-
65 thetic capacity) [e.g. *Huete et al.*, 2006; *Brando et al.*, 2010; *Restrepo-Coupe et al.*, 2013]
66 has been a subject of debate [*Morton et al.*, 2014; *Saleska et al.*, 2016; *Hayek et al.*, 2018;
67 *Liu et al.*, 2018].

68 The different theories have been recently reconciled by camera observations and
69 leaf-level measurements revealing a synchronization of dry season litterfall with the onset
70 of new leaves having higher photosynthetic capacity and therefore light use efficiency [*Wu*
71 *et al.*, 2016; *Albert et al.*, 2018]. Such a coordinated leaf development explains observed
72 seasonal variations of leaf area index (LAI), photosynthetic capacity (PC) and gross pri-
73 mary productivity (GPP), demonstrating that canopy phenology plays an important role
74 in regulating forest fluxes during the dry season [*Wu et al.*, 2016]. However, the interplay
75 between phenologic and climatic factors regulating the overall forest response to dry pe-
76 riods and droughts (i.e., during the dry periods of 2005 and 2010 [*Lewis et al.*, 2011]) is
77 still unclear and the compound effects of leaf phenology and plant water stress on car-
78 bon/water fluxes remain elusive, framing the scope here.

79 The fact that seasonality in photosynthetic capacity is driven by changes in leaf
80 quality and quantity (younger leaves and changes in LAI), can also explain the reported
81 discrepancies between observations and model simulations [*Wu et al.*, 2016; *Restrepo-*
82 *Coupe et al.*, 2017]. Most of existing Dynamic Global Vegetation Models, DGVMs (and,
83 similarly, Eco-Hydrological Models, Terrestrial Biosphere Models and Land Surface Mod-
84 els [*Fatichi et al.*, 2014]) assume simple or no phenology for tropical evergreen biomes
85 and they account for variability of the climate drivers only [*Wu et al.*, 2016; *Restrepo-*
86 *Coupe et al.*, 2017]. Thus, models systematically fail to reproduce the seasonality of car-
87 bon fluxes and the observed dry season greening [*Restrepo-Coupe et al.*, 2017]. Tropical
88 forest description in DGVMs has been continuously improved [*Baker et al.*, 2008; *Galbraith*
89 *et al.*, 2010; *Verbeeck et al.*, 2011; *De Weirdt et al.*, 2012; *Kim et al.*, 2012; *Ivanov et al.*,
90 2012; *Von Randow et al.*, 2013; *Christoffersen et al.*, 2014], but these models still produce
91 inaccurate GPP predictions at timescales from days to decades [*Restrepo-Coupe et al.*,
92 2017]. Despite limitations in reproducing GPP seasonality, DGVMs generally capture the
93 observed seasonality of ET fluxes and have provided insights into the importance of deep
94 rooting systems, hydraulic redistribution, root niche separation, and groundwater fluxes to
95 explain the observed tolerance of Amazon forests to extended droughts [*Baker et al.*, 2008;
96 *Ivanov et al.*, 2012; *Miguez-Macho and Fan*, 2012; *Christoffersen et al.*, 2014]. Hence,
97 given the assumption of an aseasonal photosynthetic infrastructure, it is unclear whether
98 model simulations provide the right answers for the right reasons [*Restrepo-Coupe et al.*,
99 2017]. Recently *Wu et al.* [2017a] have proposed a two-fraction leaf (sun/shade), two-
100 layer canopy model for representing tropical photosynthetic seasonality in DGVMs and *Xu*
101 *et al.* [2017] have shown that cross-species variations in leaf longevity can be explained
102 by a trait-driven carbon optimality model. However, the impact of such dynamics on car-
103 bon/water relations was not addressed, leaving the following questions open: (i) what is
104 the impact of leaf phenology on ecosystem carbon and water fluxes in the Amazon basin?
105 (ii) does photosynthetic seasonality enhance or decrease forest resilience to drought? (iii)
106 is the accuracy of model simulations, in terms of carbon and water fluxes, different when
107 the forest photosynthetic machinery is allowed to vary seasonally?

108 To answer these questions a novel eco-hydrological model description of phenol-
109 ogy in tropical biomes is developed here and used to investigate carbon and water fluxes
110 seasonality across the Amazon basin. The specific approaches of this study are: (i) the
111 development of a mechanistic light-controlled leaf phenology model for tropical ever-
112 green forests based on recent experimental observations, (ii) the use of model simula-
113 tions to assess the impact of leaf phenology on the seasonality of biosphere-atmosphere
114 exchanges in the Amazon, and (iii) a multi-site and multi-year analysis of water/carbon
115 fluxes to evaluate the interplay between leaf phenology and water stress controls on forest
116 responses to dry periods.

117 In summary, given the projected increase in Amazonian dry season length towards
 118 the end of this century [Malhi et al., 2008; Marengo et al., 2011; Lintner et al., 2012; Fu
 119 et al., 2013; Boisier et al., 2015], the need of realistically describing biosphere-atmosphere
 120 interactions under future climate [Fatichi et al., 2016a], and the fact that tropical leaf phe-
 121 nology is not accounted for in the existing DGVMs [Wu et al., 2016; Restrepo-Coupe
 122 et al., 2017], the overarching goal of this study is to improve the representation of wa-
 123 ter/carbon fluxes in the tropics, quantify the role of photosynthetic seasonality, and disen-
 124 tangle the role of between phenology and water stress.

125 **Materials and Methods**

126 **Study sites**

127 Local observations from 32 tropical forest sites in the Amazon basin are consid-
 128 ered here (Tab. 2). Flux tower data for 6 sites (Bananal, CAX, km34, km67, km83, RJA)
 129 are obtained from the LBA-ECO Flux Tower Network Data Compilation and LBA-Model
 130 Intercomparison Project [De Gonçalves et al., 2013; Restrepo-Coupe et al., 2013; Christof-
 131 fersen et al., 2014], freely available online ([ftp://saleskalab.eebweb.arizona.edu/
 132 pub/BrasilFlux_Data/](ftp://saleskalab.eebweb.arizona.edu/pub/BrasilFlux_Data/)). Additional meteorological data (temperature, precipitation,
 133 relative humidity, radiation, pressure, wind speed) from 8 LBA-ECO weather stations (Bel-
 134 terra, Embrapa, Guarana, Jamaragua, km117, Mojui, Sudam, Vilafranca) [Fitzjarrald et al.,
 135 2008] and 18 meteorological stations (A101, A109-113, A117, A120-126, A128, A133-
 136 134) run by the Brazilian Meteorological Institute, INMET (Instituto Nacional de Meteo-
 137 rologia - Ministério da Agricultura, Pecunária e Abastecimento) are also used as input for
 138 model simulations (see next subsections). Overall, LBA-ECO data are available for the pe-
 139 riod 1999-2006 while INMET meteo stations cover the period 2008-2015 with site A101
 140 spanning from 2000 to 2014.

141 Solar Induced Fluorescence (SIF) observations from the Global Ozone Monitoring
 142 Instrument 2 (GOME-2) are also used to assess model performance (monthly data at a
 143 spatial resolution of $0.5^\circ \times 0.5^\circ$ [Joiner et al., 2013]). SIF has been shown to provide
 144 good estimates of GPP [e.g. Yang et al., 2015; Zhang et al., 2016a,b] and forest response
 145 to drought [e.g. Lee et al., 2013; Joiner et al., 2013]. For instance, SIF correlates with
 146 GPP at diurnal and seasonal scales (with r^2 values larger than 0.7 for spring and sum-
 147 mer season in North America [Zhang et al., 2016a]), thus providing an additional piece of
 148 information to evaluate the seasonality of carbon fluxes at the study sites.

149 **Model Formulation**

150 **Phenological metrics**

151 Seasonal observations of GPP, LAI, photosynthetic capacity, and new leaf produc-
 152 tion at sites km34 and km67 have been digitized from Wu et al. [2016] (Fig. 1). Photo-
 153 synthetic efficiency e_{rel} is estimated from PC data as $e_{rel} = PC/PC_{max}$, with PC being
 154 the canopy photosynthesis per unit incoming light under reference climatic conditions [Wu
 155 et al., 2016], which can be interpreted as a metric of the ecosystem-scale photosynthetic
 156 capacity [Wu et al., 2017b], and PC_{max} is the annual maximum of PC. The partitioning
 157 of total LAI [$m^2_{leaf} m^{-2}_{ground}$] into young, mature, and old leaves presented by Wu et al.
 158 [2016] is used to estimate the average leaf age A_L [mo] and the fraction of new leaves
 159 (see Fig. 1b,c for details). Note that A_L in the model is prognostically estimated and rep-
 160 represents the average of the entire canopy, since the model does not track different leaf co-
 161 horts (see next subsections). The observations show consistent seasonal patterns at both
 162 sites (Fig. 1b-e) with increased leaf production at the end of the wet-season, followed
 163 by leaf rejuvenation and an increase in photosynthetic capacity as the dry season devel-
 164 ops. Specifically, the peak of new leaf production and the minimum leaf age occur during
 165 the dry season over a span of 1-2 months (Fig. 1c-e), while the largest PC is obtained for

166 mature leaves (i.e. intermediate age at the end of dry season, see also model simulations
167 in the Supporting Information), as young and old leaves are less photosynthetically effi-
168 cient [Wu *et al.*, 2016].

169 Combining such leaf production data with estimated canopy leaf age and observed
170 photosynthetic capacity, provides a two-dimensional relation for e_{rel} (Fig. 1f):

$$e_{rel}(A_L, f_{NL}) = 1.61 - 0.06 \cdot A_L - 1.20 \cdot f_{NL} \quad (1)$$

171 where the coefficients have been estimated by a least-square fit of the data, $f_{NL} = k_c \frac{NB_L^*}{LAI}$
172 [mo^{-1}] is the monthly fraction of newly generated leaves (i.e. age < 1 month) acting to
173 decrease e_{rel} , NB_L^* is the new leaf production [$\text{m}^2 \text{m}^{-2} \text{mo}^{-1}$] (as observed by Wu *et al.*
174 [2016]) and k_c is a correction factor to ensure consistency between NB_L^* and LAI. Specif-
175 ically, $k_c = \frac{d_{leaf} \cdot \overline{LAI}}{\sum NB_L^*}$, where \overline{LAI} is the mean annual LAI, d_L is the turnover rate of
176 green aboveground biomass from litterfall estimates [month^{-1}] and NB_L^* is summed over
177 a year. Note that k_c is introduced here to to preserve consistency (mass conservation) be-
178 tween observations of standing LAI, annual litterfall, and monthly leaf biomass production
179 estimates (Fig. 1e) which indicate that leaf average turnover is about 270 days. In the case
180 of model simulations carbon mass is conserved and therefore $k_c = 1$. Given that Eq. 1 ad-
181 mits values above 1, a limit $e_{rel} \leq 1$ is imposed (Fig. 1f). The overall good fit of Eq. 1
182 ($R^2=0.93$) with data reveals a linear dependence of photosynthetic capacity on canopy leaf
183 age and the fraction of new leaves (in accordance with the results by Wu *et al.* [2017a]
184 and Xu *et al.* [2017]). Specifically, e_{rel} is maximum at an average leaf age of 8-9 months
185 given that the carbon assimilation rates are low for young leaves and reach a peak at ma-
186 turity before decreasing with age [Wu *et al.*, 2017a; Xu *et al.*, 2017].

187 Eq. 1 provides a simple description of phenology-driven changes in PC, explaining
188 the role of quality (age) in regulating seasonal carbon fluxes. To include this information
189 into models that use an aseasonal photosynthetic scheme, the maximum Rubisco capacity
190 can be modified as:

$$V_{c,max25}^* = V_{c,max25} \cdot e_{rel}(A_L, f_{NL}) \quad (2)$$

191 where $V_{c,max25}$ is the maximum Rubisco capacity at 25°C and e_{rel} is the photosynthetic
192 efficiency defined according to Eq. 1, but computed with simulated quantities (i.e. A_L ,
193 LAI and NB_L^*).

194 **T&C model**

195 To simulate soil water dynamics and vegetation functioning, the eco-hydrological
196 model *Tethys & Chloris* (T&C) is used [Fatichi, 2010; Fatichi *et al.*, 2012a,b]. T&C com-
197 bines a dynamic vegetation model accounting for plant physiology, phenology and car-
198 bon pool dynamics with a land surface and hydrologic module solving the surface en-
199 ergy balance, soil-vegetation-atmosphere exchanges and subsurface water dynamics. T&C
200 does not use plant functional types (PFTs) and its vegetation parameterization is tailored
201 to each site and potentially for multiple species at each site, even though many parame-
202 ters may be equal across species and sites [Fatichi *et al.*, 2016b; Mastrotheodoros *et al.*,
203 2017]. The T&C model can be thus listed as a trait-based vegetation model accounting
204 for inter- and intra-specific plant trait variability. Trait-based approaches typically offer
205 a better representation of ecosystem functioning than models grouping plant traits into
206 broad categories [Pappas *et al.*, 2016]. T&C has been successfully applied to simulate wa-
207 ter and carbon fluxes in various ecosystems worldwide [Fatichi and Ivanov, 2014; Fatichi
208 *et al.*, 2015, 2016b; Paschalis *et al.*, 2015, 2016; Pappas *et al.*, 2016] and is applied here
209 in a revised form to the Amazon rainforests. Consistently with other DGVMs [Restrepo-
210 Coupe *et al.*, 2017], in the case of evergreen biomes the original formulation of T&C does
211 not simulate a phenologic cycle of photosynthetic efficiency, which is maintained fixed
212 throughout the year. A modified T&C version incorporating the phenology of tropical ev-
213 ergreen ecosystems (i.e. Eq. 1) is therefore introduced next. Direct simulation of SIF is

214 also implemented in T&C according to *Lee et al.* [2015]. Additional information on model
 215 equations are provided in the Supporting Information (SI) while a list of variables and ab-
 216 breviations is provided in Table 1.

217 *T&C with leaf phenology*

218 To describe the observed seasonality of photosynthesis, three phenological states (Φ)
 219 are employed (Fig. 1a): preparation to the new season ($\Phi=1$), initial growth ($\Phi=2$, cor-
 220 responding to the beginning of a new season), and normal growth ($\Phi=3$). This tropical
 221 phenology model describes a succession of periodic plant life cycles similar to the stages
 222 adopted for temperate excosystems [*Arora and Boer*, 2005; *Fatichi*, 2010], but is modi-
 223 fied to consider the peculiarities of tropical biomes, i.e. observed synchronization of new
 224 leaf growth and litterfall with sunlight during the dry season [*Huete et al.*, 2006; *Wu et al.*,
 225 2016].

226 Given that dry season greening closely tracks sunlight seasonality [*Huete et al.*,
 227 2006; *Wu et al.*, 2016], changes in photosynthetic active radiation (PAR) are used as the
 228 driver of leaf development. A new season ($\Phi = 1 \rightarrow 2$) is set to begin when $\overline{\Delta PAR} >$
 229 ΔPAR_{th} , where $\overline{\Delta PAR} = \left\langle \langle PAR(t) \rangle_{30} - \langle PAR(t) \rangle_{45} \right\rangle_{10}$ is a smoothed time derivative
 230 of PAR and ΔPAR_{th} is a specific threshold. The smoothing procedure is employed to
 231 remove the daily and sub-daily oscillations. This is achieved by computing the 10 days
 232 average of the difference between $\langle PAR(t) \rangle_{30}$ and $\langle PAR(t) \rangle_{45}$, i.e. PAR averages over
 233 30 and 45 preceding days, respectively. $\overline{\Delta PAR}$ is negative when PAR (on average) de-
 234 creases with time, positive otherwise. This choice is guided by the hypothesis that veg-
 235 etation “senses” the arrival of a new light-rich dry season by detecting an increase in
 236 sunlight availability [*Wright and Van Schaik*, 1994] and is in accordance with observa-
 237 tions of maximum leaf production one to two months before the peak in PAR [*Wu et al.*,
 238 2016]. Note that a similar mechanism based on light controls was used to explain ob-
 239 served synchronous flowering in the tropics [*Borchert et al.*, 2005]. The signal ($\overline{\Delta PAR}$)
 240 is a non-instantaneous sunlight control on rainforest greening as the new season starts when
 241 the threshold ΔPAR_{th} is reached. The threshold ΔPAR_{th} is theoretically zero (i.e. the
 242 new season starts when $\overline{\Delta PAR}$ switches from negative to positive) but values of 0.75-1
 243 [$\text{W m}^{-2} \text{d}^{-1}$] are used here to account for the remaining noise in $\overline{\Delta PAR}$ (see Fig. 1 and
 244 Fig. S1 in the SI). At the end of stage $\Phi=1$ and during $\Phi=2$ a large fraction of the assim-
 245 ilated carbon is allocated to new leaf biomass NB_L to support the observed light-controlled
 246 green-up.

247 The preliminary carbon allocation fraction to leaves is computed as $f'_L = 1 - d_{flo}/A_{L,cr}$
 248 where $A_{L,cr}$ is the critical leaf age [d], which is a model parameter and d_{flo} [d] is a phe-
 249 nological index counting the days after the beginning of the new season and computed
 250 as $d_{flo}(t + dt) = d_{flo}(t) + dt$, with $dt = 1$ day (see Fig. 1a). The remaining assimilated
 251 carbon is partitioned among fine roots, living sapwood, carbohydrate reserves, and repro-
 252 ductive organs using functional allocation fractions and considering allometric constraints
 253 that define final allocation fractions as in the original T&C [*Fatichi et al.*, 2012a,b]. Tropi-
 254 cal evergreen forests do not experience proper senescence and dormant phases and carbon
 255 is allocated to reproductive organs year-round. The transition to the normal growth phase
 256 ($\Phi = 2 \rightarrow 3$) takes place when $d_{flo} > d_{mg}$, where d_{mg} [d] is a prescribed number of days,
 257 while the transition $\Phi = 3 \rightarrow 1$ occurs when $d_{flo} > A_{L,cr}$. The parameters $A_{L,cr}$ and d_{mg}
 258 are employed in T&C also for other biomes and their values for tropical forests have been
 259 estimated, respectively, from observations and during model calibration (see next subsec-
 260 tion). Even though allocation dynamics are variable throughout the year (Fig. S1 in the
 261 SI), from a modeling perspective phase $\Phi=1$ is identical to normal growth ($\Phi=3$) with the
 262 only difference that it allows for the preparation to a new season. The criterion used for
 263 the transition to $\Phi=1$ (i.e. $d_{flo} > A_{L,cr}$) ensures that the new season cannot start before
 264 the leaves produced in the previous year have reached maturity. During phase $\Phi=1$, d_{flo} is

265 scaled back as $d_{fio}(t + dt) = d_{fio}(t) - \frac{365}{365 - A_{L,cr}} dt$ to progressively increase allocation to
 266 new leaves and prepare for phase $\Phi=2$ (Fig. 1 and Fig. S1 in the SI).

267 To increase litterfall with leaf onset [Wu *et al.*, 2016], the turnover rate of leaves d_L
 268 [d^{-1}] is modified to include NB_L [$gC\ m^{-2}\ d^{-1}$] as follows:

$$d_L(t) = \begin{cases} \frac{NB_L(t) \cdot A_{L,cr}}{C_L(t)} \cdot \frac{A_L(t)}{A_{L,cr}^2} & \text{if } NPP > 0 \\ \frac{A_L}{A_{L,cr}^2} & \text{if } NPP \leq 0 \end{cases} \quad (3)$$

269 where A_L [d] is the prognostic leaf age, C_L is the leaf carbon pool [$gC\ m^{-2}$]. Leaf age
 270 A_L is calculated as [Krunner *et al.*, 2005; Fatichi, 2010]:

$$A_L(t) = \frac{[LAI(t) - N_{LAI}(t)] \cdot [A_L(t - dt) + dt] + N_{LAI}(t)dt}{LAI(t)} \quad (4)$$

271 where N_{LAI} is the new leaf area increment [$m^2\ m^{-2}$] on a time step and dt is the daily
 272 time step. For seasonal tropical evergreens, the turnover rate of leaves is assumed to be
 273 proportional to the ratio of newly produced leaves to the total biomass ($\frac{NB_L(t)}{C_L(t)}$), thus gen-
 274 erating faster turnover times during leaf production and mimicking the observed behavior
 275 of shedding old leaves to create space for new ones [Wu *et al.*, 2016]. For an aseasonal
 276 forest $\frac{NB_L(t)}{C_L(t)} = \frac{1}{A_{L,cr}}$ and d_L becomes equal to the original T&C version without tropical
 277 phenology.

278 Equations 1-4 provide a novel mechanistic approach for the simulation of phenology-
 279 controlled seasonality in tropical evergreen forests. Compared to the original T&C formu-
 280 lation, the new approach introduces only one additional model parameter (ΔPAR_{th}).

281 **Simulation setup**

282 To assess the impact of leaf phenology on carbon/water fluxes in the Amazon basin,
 283 both the original (T&C) and new (T&C with tropical phenology) model formulations
 284 are employed here. Meteorological forcings measured at the 32 study sites are used as
 285 model inputs. Partition of solar radiation into diffuse and direct components and in two
 286 wavebands is carried out by using the weather generator AWE-GEN [Fatichi *et al.*, 2011].
 287 Model parameters are calibrated at one site (km67) and results are validated at three loca-
 288 tions (km34, CAX, RJA) for both model formulations with only few changes in the param-
 289 eters set to tailor the application to site-specific characteristics (e.g. rooting depth, see Ta-
 290 ble S1 in the SI). Based on literature values [e.g. Baraloto *et al.*, 2010; Bahar *et al.*, 2017],
 291 calibration was carried out by manually adjusting the most sensitive parameters for photo-
 292 synthesis and transpiration [Mastrotheodoros *et al.*, 2017]. Calibrated parameters are then
 293 used to form two sets of average biome-specific parameters (one for each model version)
 294 and applied to the remaining 30 sites (Table S1 in the SI). To be consistent with the theo-
 295 ry of a common phenological mechanism operating across climatic gradients [Wu *et al.*,
 296 2016], physiological/phenological parameters are kept constant among sites and only cli-
 297 mate drivers and soil properties are varied. Soil hydraulic parameters (saturated hydraulic
 298 conductivity and soil water retention curves) are estimated from soil textural properties
 299 (clay, sand and organic matter content) obtained for the site or retrieved from the Soil-
 300 Grids250m database [Hengl *et al.*, 2017], using the pedotransfer functions by Saxton and
 301 Rawls [2006] with proper changes to account for tropical clay specificity (see SI for de-
 302 tails).

303 Changes in the generic flux or variable Y (i.e. $Y = \{GPP, ET, LAI\}$) due to leaf
 304 phenology (ΔY [%]) are then estimated as:

$$\Delta Y = \frac{Y_{T\&C\ with\ phenology} - Y_{T\&C}}{Y_{T\&C}} \cdot 100 \quad (5)$$

where $Y_{T\&C}$ and $Y_{T\&C \text{ with phenology}}$ are the simulation results obtained with the original and modified T&C model versions, respectively.

The two model versions are run with a few different calibrated parameters and ΔY thus represents possible discrepancies due to tropical leaf phenology but also model parameters. To ensure that the calibration procedure does not confound the effects of leaf phenology, we run additional model simulations using a single set of calibrated parameters (see SI for details). Results are very similar, suggesting that the introduction of phenology rather than small differences in parameters is the main source of difference between the two numerical experiments.

To ensure good quality of the meteorological forcing, only data from flux towers and meteorological stations are considered. A basin-wide analysis could be performed by using model-derived reanalysis data. However, the large bias in precipitation generally found in the tropics [e.g. *Bosilovich et al.*, 2008] motivates our choice of a plot-scale multi-site analysis rather than a distributed analysis with incorrect local climatic forcing.

Results

Calibration and validation

Calibration and validation results are illustrated in Fig. 2. The original model version (without leaf phenology) assume a fixed photosynthetic efficiency throughout the year ($e_{rel} = 1$) and provides seasonal fluxes comparable with other DGVMs (see *Restrepo-Coupe et al.* [2017]): the seasonality of ET fluxes is generally correct but the dry season increase in GPP is not captured. When leaf phenology is introduced, model simulations successfully reproduce PC seasonality and capture the observed dry season greening. In particular, the correlation coefficient (r) between modeled and observed hourly GPP increased from 0.20 and 0.41 to 0.34 and 0.52 for km67 and km34, respectively (see SI). At monthly time scales and across the different sites, r increased from 0.2 to 0.5 (Fig. S6 in the SI). Note that the same set of parameters is used for all of the sites and, considering the uncertainties of flux tower observations in the tropics, the result can be considered to be a significant improvement. Interestingly, despite the changes in PC and GPP seasonality, simulated ET fluxes are only slightly affected by leaf phenology, thus preserving a good agreement with observations and reproducing coherently the seasonality of ET and GPP. This result is explained by the limited variability of LAI (Fig. 3). While the production of new leaf biomass modifies mean leaf age (thus affecting the photosynthetic efficiency through e_{rel}), the synchronization of leaf onset and litterfall limits LAI changes and, consequently, the impact on ET fluxes (see SI). All these processes are well captured by the modified model version, T&C with phenology (Fig. 3 and Fig. S1 in the SI), which has only one additional parameter. Additional comparisons between observations and model results are illustrated in the SI for energy fluxes, GPP and soil moisture dynamics.

Multi-site analysis

Model simulations are then used to evaluate the seasonal and interannual variability of carbon and water fluxes in the Amazon. An overview of GPP, ET and LAI as well as soil and pre-dawn leaf water potential across the study sites from year 1999 to 2015 is provided in Fig. 4 and 5. Note that different sites cover different periods of time. Also, pre-dawn leaf water potential is a model quantity that integrates soil water potential over the root zone weighted to account for fine root vertical distribution and expresses an ecosystem scale quantity that does not necessarily correspond to leaf-level observations of different species and thus should be interpreted with care.

GPP is shown to be lower at the beginning of the dry season and reach a maximum by the end of the dry season, with values generally ranging between 6 and 10 gC m⁻² d⁻¹. GPP dynamics are delayed compared to ET fluxes that increase early in the dry season (ET > 5 mm d⁻¹) and then decrease as the dry season progresses. However, monthly averages of forest ET never fall below 2 mm d⁻¹. Model simulation show ET values larger than observations, but flux tower measurements are likely to considerably underestimate evaporation from ground and intercepted water, especially after precipitation [Leuning *et al.*, 2012; Gerken *et al.*, 2017; Hirschi *et al.*, 2017]. Overall, the dry season increase in GPP, timed with LAI and ET increments, is consistent across sites (Fig. 4b,d,h) but clear spatial patterns of GPP and ET with mean annual rainfall (MAP) are not observed (see next section). The water use efficiency $WUE = GPP/ET$ [gC m⁻² mm⁻¹] is low at the end of the wet season and then increases during the dry months, indicating a more efficient water consumption linked to leaves with higher photosynthetic capacity as the ET demand increases.

Plant water stress (Fig. 4j) can occur at end of the dry season causing a reduction in ET, but ET is generally modulated by incoming radiation. Model simulations clearly illustrate that several sites likely have experienced water stress with major drought events in 2005 and 2010 [Liu *et al.*, 2018]. However, leaf water potential is close to zero (i.e. no water stress) for most places most of the time and only major droughts are evident with simulated pre-dawn leaf water potential $\Psi_L < -1$ MPa at several locations (Fig. 4i). Our results suggest that the 2010 drought was an “independent” severe event, while plant water stress in 2005 was the result of successive dry seasons that exacerbated drought through legacy effects. These results are consistent with the observed increase in tree mortality during the 2005 drought event [Meir *et al.*, 2009; Phillips *et al.*, 2009] and the greater anomalies in vegetation water content recorded in 2005 compared to 2010 [Liu *et al.*, 2018] but, given the difficulties in comparing modeled Ψ_L with observations and the paucity of Ψ_L measurements, results cannot be rigorously confirmed.

The decrease in LAI at the end of the wet season (Fig. 3 and 4h) reduces ET thus saving soil water for the upcoming dry months but the impact on the magnitude of ET is minimal. LAI dynamics show little seasonality, the variability across sites is higher than seasonal variations and LAI values range between 4 and 5.5 m². The dry season increase in LAI and GPP (i.e. greening during August-November) is clearly reproduced in Fig. 5, where simulated and observed SIF are also illustrated for comparison. During the 2005 drought, some sites (e.g. A101) show no water stress and a dry season increase in GPP, while other locations (e.g. km117) experience severe stress with a substantial decrease in productivity and, potentially, forest mortality [Phillips *et al.*, 2009]. Even though fewer locations across the study sites seem to have experienced stress in 2010, the severity of drought in some locations is clearly illustrated by the temporal evolution of the soil water potential (Fig. 5d) which caused a sharp GPP reduction (see site km117 and A123).

The role of leaf phenology

The impact of leaf phenology on water/carbon fluxes is now evaluated by comparing simulation results from the original and modified model versions (T&C and T&C with tropical phenology, respectively). Hourly values of GPP, ET, LAI and Ψ_L simulated with and without leaf phenology are illustrated in Fig. 6. When phenology is neglected, model results generally overestimate the total carbon uptake ($\Delta GPP < 0$) as the GPP reduction before the dry season is not captured (see Fig. 2, Fig. 6a and Restrepo-Coupe *et al.* [2017]). As expected little variations are observed in the ET fluxes and, given the changes on both GPP and ET, no appreciable deviations in WUE are simulated (Fig. 6b). Negative LAI changes (ΔLAI) are also obtained (Fig. 6c) but they are relatively small (<1 m²) and, at each site, LAI oscillates within a small range of values [Myneni *et al.*, 2007]. Overall the onset of new leaves at the beginning of the dry season can potentially increase

404 forest resilience to drought (i.e., its ability to maintain unaltered carbon and water fluxes
 405 under extremely dry conditions) by maintaining more favorable leaf water potentials dur-
 406 ing drought (Fig. 6d) and sustain water fluxes during the dry season. This mechanism is
 407 explained by a decrease in LAI at the end of the wet season that reduces ET, maintain fa-
 408 vorable soil water conditions, and sustain ET maxima during the dry season [Wu *et al.*,
 409 2016]. However, our results suggest that such a phenology-induced increase in forest re-
 410 siliance should be relatively limited and additional field measurements are required to test
 411 this assertion and support it with more quantitative evidence. Note that model simulations
 412 with and without phenology are run considering different sets of calibrated parameters but
 413 calibration was tested to have a negligible effect on the phenology-induced changes ob-
 414 served in Fig. 6 (see SI).

415 The spatial distribution of carbon/water fluxes and phenology induced changes in
 416 GPP, ET and LAI is illustrated in Fig. 7. On average (yearly and among sites), the addi-
 417 tion of leaf phenology results in GPP, ET and LAI changes of -2.56%, +0.4%, and -1.3%,
 418 respectively (with $\Delta GPP \in [-7.6; 5.9]$), $\Delta ET \in [-4.1; 5.9]$, and $\Delta LAI \in [-14.0; 10.8]$).
 419 While GPP is consistently overestimated when leaf phenology is neglected, changes in ET
 420 and LAI are small and no clear spatial pattern can be identified.

421 Discussion

422 Leaf phenology in DGVMs

423 Global estimates of GPP are still highly uncertain [Badgley *et al.*, 2017] and tropi-
 424 cal carbon fluxes are poorly resolved in existing DGVMs [Restrepo-Coupe *et al.*, 2017].
 425 Tropical forest GPP is a major component of the global carbon cycle [Musavi *et al.*, 2017]
 426 and understanding its seasonal and interannual variability is crucial to predict global cli-
 427 mate dynamics. Here we have provided a novel mechanistic approach to represent leaf
 428 phenology and GPP seasonality that requires a single parameter and is general enough
 429 to be used in any DGVM that has a prognostic phenology and simulates leaf age. Its in-
 430 clusion can improve the assessment of carbon and water fluxes in the tropics. We have
 431 shown that carbon uptake is likely to be biased by current DGVMs simulations and, in
 432 the absence of leaf phenology, model parameterization can lead to both an underestima-
 433 tion and overestimation of photosynthesis (as happened here, Fig. 2a-d). Previous efforts
 434 to include tropical phenology in DGVMs focused on parameterizing $V_{c,max}$ as a function
 435 of leaf age [De Weirdt *et al.*, 2012; Kim *et al.*, 2012] and introducing a radiation-dependent
 436 leaf turnover rate [Kim *et al.*, 2012]. These modifications improved the ability of models
 437 to capture the seasonality of litterfall [De Weirdt *et al.*, 2012] and carbon fluxes [Kim *et al.*,
 438 2012]. Here we introduced a mechanistic link between light controls, leaf demography,
 439 and photosynthetic efficiency and we have shed light on seasonal dynamics of forest ET
 440 and ecosystem responses to drought. This approach is consistent with recent field obser-
 441 vations showing that mature leaves have “better quality” (i.e. higher $V_{c,max}$) than young
 442 and old leaves and their quantity increases during the dry season [Wu *et al.*, 2016; Al-
 443 bert *et al.*, 2018]. Building on this knowledge, future model improvements could focus on
 444 the explicit representation of different leaf age classes which are encoded here in a single
 445 canopy age, A_L , and another variable, which is the fraction of young leaves f_{NL} . Such a
 446 modification might improve the timing of simulated leaf flush (Fig. 3) and allow a direct
 447 comparison with available data for young, mature and old leaves [Albert *et al.*, 2018]. In
 448 this regard, more resolved litterfall and biomass production data as well as observations
 449 from more locations in the tropics are needed to better assess the performance of tropical
 450 phenology schemes.

451 Leaf phenology and water stress in the Amazon rainforest

452 Coordinated ecosystem scale phenology is likely to be an evolutionary strategy to
 453 maximize photosynthesis during drier but light-richer periods [Myneni *et al.*, 2007] and

454 optimize carbon gain in year-round warm climates [Wu *et al.*, 2016]. On evolutionary
 455 timescales, producing leaves and flowers in synchronous flushes during the dry season
 456 could also be an “escape” strategy to reduce the damages from herbivores, which are more
 457 abundant at the beginning of the wet season [Aide, 1988, 1992] or the result of biotic in-
 458 teractions between plants and pollinators [Borchert *et al.*, 2005]. However, these responses
 459 to biotic pressures are largely neglected in the context of DGVMs, and seasonal variation
 460 in rainfall, light, and soil water availability are generally accepted as the major causes of
 461 observed tropical phenology [Wright and Van Schaik, 1994; Borchert *et al.*, 2004; Brando
 462 *et al.*, 2006; Kim *et al.*, 2012; Wu *et al.*, 2016]. Our results confirm the hypothesis that leaf
 463 phenology may act to facilitate dry season maxima in water fluxes [Chavana-Bryant *et al.*,
 464 2016; Wu *et al.*, 2016] since we found little evidence of soil moisture stress in most of the
 465 locations with ET fluxes supported by deep root water uptake. Existing evidence suggests
 466 that such late dry season fluxes are key to activating shallow convection and initiate the
 467 dry-to-wet season transition [Machado *et al.*, 2004; Wright *et al.*, 2017]. In this framework
 468 leaf phenology can help enhancing resilience to drought by reducing LAI at the end of
 469 the wet-season, thus “saving” soil water for the upcoming dry months but quantitative ev-
 470 idence is minimal. The impact on ET is relatively small (+0.4%), indicating that tropical
 471 leaf phenology may have little impact on forest tolerance to drought, and implications for
 472 simulated rainfall recycling [Eltahir and Bras, 1994; Betts *et al.*, 2004; Bonetti *et al.*, 2015]
 473 and climate teleconnections [Stark *et al.*, 2016; Wu *et al.*, 2016; Wright *et al.*, 2017] should
 474 be limited. However, the simulated seasonality of WUE suggest that leaf development and
 475 synchronized dry season litterfall are in agreement with evolutionary strategies aimed at
 476 increasing the efficiency of photosynthesis and water consumption during periods of ab-
 477 undant light but potentially low water availability (i.e. at the end of the dry season).

478 The small sensitivity of ET to leaf phenology is explained by the fact that changes
 479 in the maximum Rubisco capacity ($V_{c,max25}^*$) due to seasonality (i.e. e_{rel}) have direct ef-
 480 fects on carbon assimilation (A_n) and GPP (according to the Farquhar model A_n is propor-
 481 tional to $V_{c,max25}^*$ in light-rich environments [Farquhar *et al.*, 1980; Collatz *et al.*, 1991;
 482 Bonan *et al.*, 2011], see SI) but only an indirect impact on ET through changes in the
 483 stomatal conductance (g_s) of sunlit and shaded leaves (modeled according to Leuning
 484 [1995] in T&C). In particular, while e_{rel} affects g_s , the impact of leaf phenology on tran-
 485 spiration is buffered by canopy-atmosphere decoupling [De Kauwe *et al.*, 2017], significant
 486 for tall broadleaf tropical forests, and concomitant LAI changes, which reduce the changes
 487 in ET as compared to ΔGPP (see SI for details).

488 Our results also show that Amazonian forests experienced a severe water stress in
 489 2005 due to a legacy effect of deficient rainfall in previous dry/wet seasons that aggra-
 490 vated water stress by systematically decreasing soil-plant water potentials (Fig. 4i). Such
 491 legacy effects were not visible in 2010, probably due to a very wet 2009 [Marengo *et al.*,
 492 2011]. Thus, the hypothesis that tropical forest are resilient to short-term climatic anoma-
 493 lies [Saleska *et al.*, 2007] but vulnerable to prolonged (i.e. multi-year) drought events [Nep-
 494 stad *et al.*, 2007; Ivanov *et al.*, 2012] is generally supported here. Furthermore, these re-
 495 sults are consistent with the observations of severe drought events in the Amazon region
 496 in 2005 and 2010 [Lewis *et al.*, 2011; Marengo *et al.*, 2011]. After the 2005 drought an in-
 497 crease in tree mortality was observed [Phillips *et al.*, 2009] and a suppression of photosyn-
 498 thesis caused a neutralization of the carbon sink in 2010 [Gatti *et al.*, 2014]. A multi-site
 499 analysis by Doughty *et al.* [2015] also revealed that trees’ allocation to maintenance and
 500 defence tissues decreased during the 2010 drought, thus increasing the risk of post-drought
 501 mortality.

502 Basin-wide drought assessments based on satellite-derived rainfall data have con-
 503 siderable uncertainty as compared to plot-scale analyses that are also better representing
 504 effects of local soil conditions and soil-moisture temporal and vertical variability. As a
 505 matter of fact, ecosystem functioning and productivity are directly linked to soil water
 506 availability rather than rainfall [Fatichi *et al.*, 2016a; Bonetti *et al.*, 2017]. Hence, despite

the spatial limitation of our analysis (performed at the plot-scale in multiple sites), the simulation of coupled soil-plant-atmosphere processes here provides an insightful quantification of the mechanisms regulating dry season greening and water stress in the Amazon. In particular, we show that depending on complex interactions between rainfall variability, soil water content and canopy phenological state, plot-scale forest productivity can both increase or decrease during the dry season (see simulated GPP in 2005 and 2010, Fig. 5). These results are consistent with the observed heterogeneities of basin-wide responses to drought reported in the literature [Phillips *et al.*, 2009; Lewis *et al.*, 2011].

Conclusions

A novel approach to model GPP seasonality in the tropics and a multi-site, multi-year analysis relying on locally observed meteorological data only and illustrating forest responses to climate variability across the Amazon basin over a 15 year period has been presented. Our results provide a first mechanistic description of tropical leaf phenology, reconciling observed dry season greening and water limitations in the Amazon and paving the way for future model analyses accounting for photosynthetic seasonality in the tropics. Leaf phenology is shown to influence considerably ecosystem carbon fluxes with little impact on evapotranspiration and resilience to short-term drought. Phenology-related inaccuracies in the simulation of water and energy fluxes are unlikely but existing DGVMs generally overestimate or underestimate GPP, because they lack a seasonal cycle of photosynthetic efficiency. Accounting for the effects of leaf quality and quantity on photosynthesis is therefore crucial to accurately describe the Amazon carbon balance from hourly to decadal timescales.

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Symbol	Description	Units
A_L	Leaf age	months (mo)
$A_{L,cr}$	Critical leaf age	days (d)
A_n	Net carbon assimilation	$\mu \text{ mol CO}_2 \text{ m}^{-2} \text{ s}^{-1}$
C_L	Leaf carbon pool	gC m^{-2}
$\overline{\Delta PAR}$	Smoothed PAR time derivative	$\text{W m}^2 \text{ d}^{-1}$
ΔPAR_{th}	Threshold for $\overline{\Delta PAR}$	$\text{W m}^2 \text{ d}^{-1}$
d_{f1o}	Phenological index counting the days after new season beginning	d
d_L	Turnover rate of leaves	d^{-1}
d_{mg}	phenological parameter (days of initial growth)	d
e_{rel}	Photosynthetic efficiency	-
ET	Evapotranspiration	mm d^{-1}
f_L	Carbon allocation fraction to leaves	-
f'_L	Preliminary carbon allocation fraction to leaves	-
f'_{NL}	monthly fraction of young (< 1 month) leaves	mo^{-1}
GPP	Gross Primary Productivity	$\text{gC m}^{-2} \text{ d}^{-1}$
g_s	Stomatal conductance	$\text{mol CO}_2 \text{ m}^{-2} \text{ s}^{-1}$
k_c	Correction factor	-
LAI	Leaf Area Index	$\text{m}^2_{leaf} \text{ m}^{-2}_{ground}$
NB_L	New leaf biomass production	$\text{gC m}^{-2} \text{ mo}^{-1}$
NB'_L	New leaf production	$\text{m}^2 \text{ m}^{-2} \text{ mo}^{-1}$
N_{LAI}	New leaf area increment	$\text{m}^2 \text{ m}^{-1} \text{ d}^{-1}$
Φ	Phenological state	-
Ψ_L	Pre-dawn leaf water potential	MPa
PAR	Photosynthetic Active Radiation	W m^{-2}
PC	Photosynthetic Capacity	$\text{molCO}_2 \text{ mol}^{-1}_{photons}$
PC_{max}	Maximum Photosynthetic Capacity	$\text{molCO}_2 \text{ mol}^{-1}_{photons}$
SIF	Solar Induced Fluorescence	$\text{W m}^{-2} \text{ sr}^{-1} \mu\text{m}^{-1}$
S_L	Specific leaf area	$\text{m}^2 \text{ gC}^{-1}$
$V_{c,max25}$	Maximum Rubisco capacity at 25°C	$\mu \text{ mol CO}_2 \text{ m}^{-2} \text{ s}^{-1}$

869

Table 1. Variables used in the tropical phenology module and listed in the text.

Site	Latitude	Longitude	MAP [mm yr ⁻¹]	n_{dry}	Monitoring Method	References
A101-134 (18 sites)	[-8.76; -0.11]	[-69.86; -56.75]	1738 - 3223	0 - 4	Meteo station	Instituto Nacional de Meteorologia, Brazil
Bananal	-9.82	-50.16	1714	6	Flux tower	<i>De Gonçalves et al. [2013]; Restrepo-Coupe et al. [2013]; Christoffersen et al. [2014]</i>
Belterra	-2.64	-54.94	1642	6	Meteo station	<i>Fitzjarrald et al. [2008]</i>
Caxiuna (CAX)	-1.72	-51.47	2022	4	Flux tower	<i>Restrepo-Coupe et al. [2013]</i>
Embrapa	-2.39	-54.33	2411	8	Flux tower	-
Guarana	-2.68	-54.32	1579	6	Meteo station	<i>Fitzjarrald et al. [2008]</i>
Jamaraua	-2.81	-55.04	1590	7	Meteo station	<i>Fitzjarrald et al. [2008]</i>
km34 (Manaus)	-2.61	-60.21	2735	2	Flux tower	<i>De Gonçalves et al. [2013]; Restrepo-Coupe et al. [2013]; Christoffersen et al. [2014]</i>
km67 (Santarem)	-2.86	-54.96	1649	5	Flux tower	<i>De Gonçalves et al. [2013]; Restrepo-Coupe et al. [2013]; Christoffersen et al. [2014]</i>
km83 (Santarem)	-3.02	-54.96	1716	5	Flux tower	<i>De Gonçalves et al. [2013]; Restrepo-Coupe et al. [2013]; Christoffersen et al. [2014]</i>
km117	-3.35	-54.92	1356	6	Meteo station	<i>Fitzjarrald et al. [2008]</i>
Mojui	-2.77	-54.58	1618	5	Meteo station	<i>Fitzjarrald et al. [2008]</i>
Reserva Jaru (RJA)	-10.08	-61.93	2325	5	Flux tower	<i>De Gonçalves et al. [2013]; Restrepo-Coupe et al. [2013]; Christoffersen et al. [2014]</i>
Sudam	-2.54	-54.09	1278	7	Meteo station	<i>Fitzjarrald et al. [2008]</i>
Vilafranca	-2.35	-55.03	2367	4	Meteo station	<i>Fitzjarrald et al. [2008]</i>

870

Table 2. Name and location of the study sites, mean annual precipitation (MAP), number of dry months

871

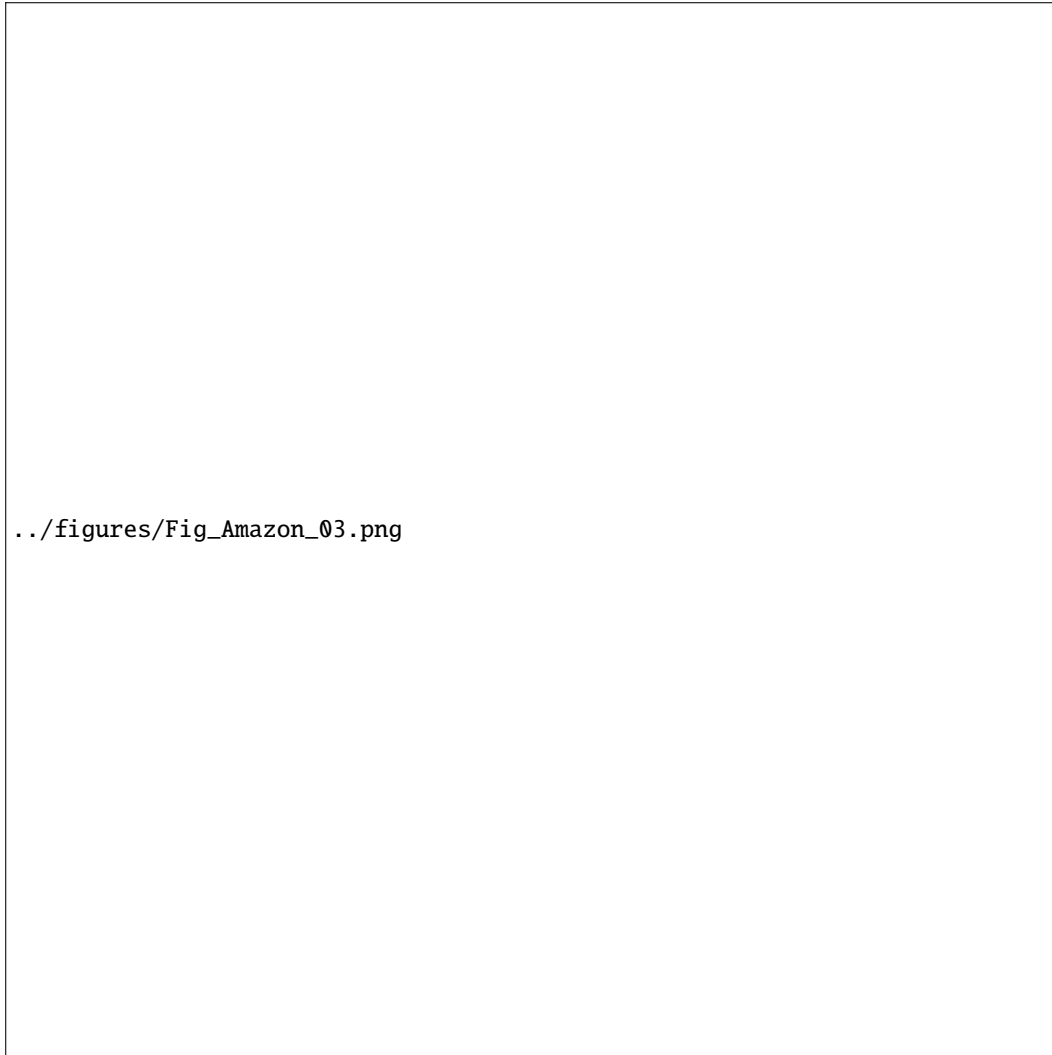
 n_{dry} (i.e. monthly precipitation < 100 mm), and monitoring method.



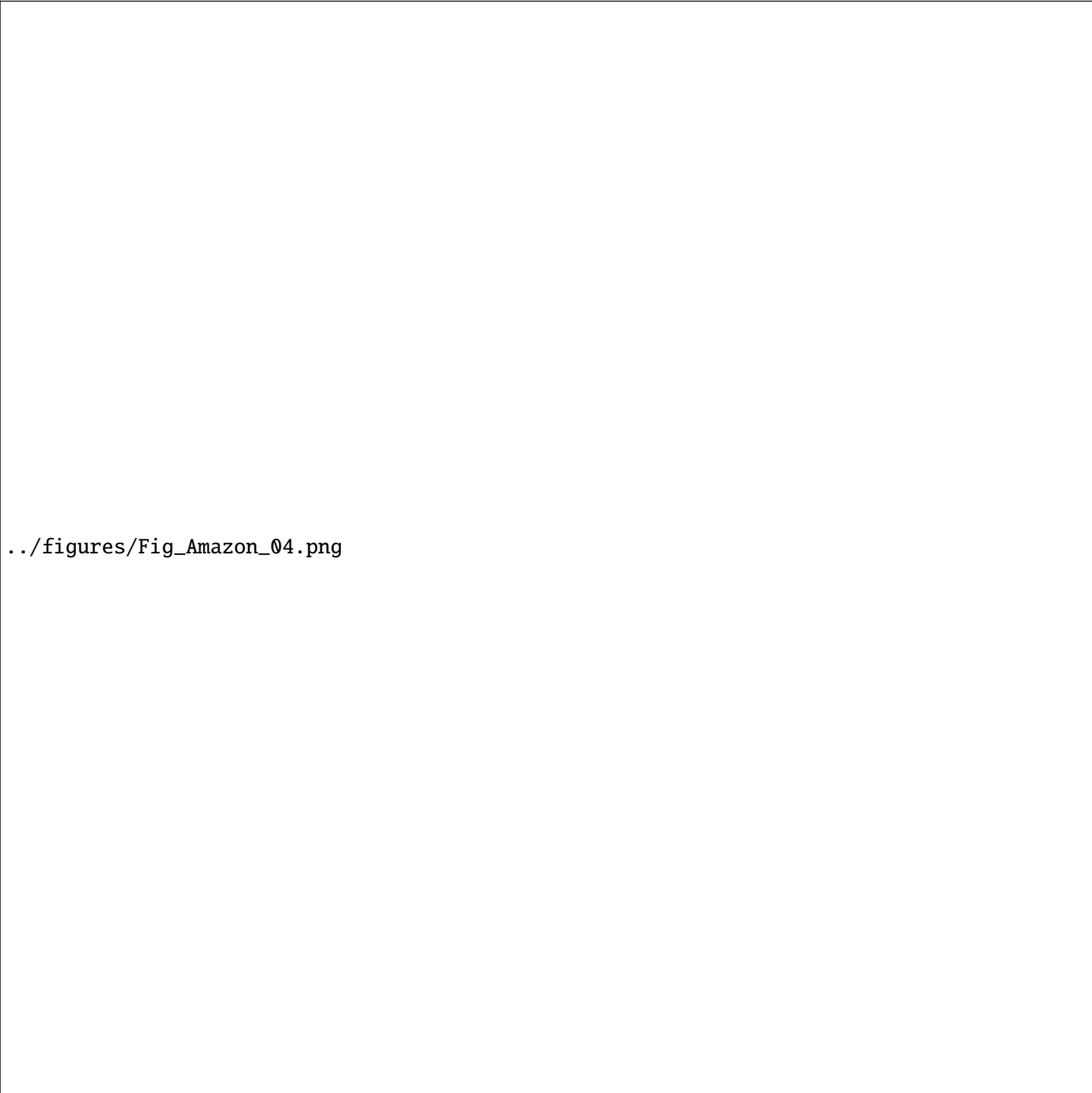
872 **Figure 1.** Conceptualization of the leaf phenology model developed for tropical rainforests (a), observa-
 873 tions from sites km34 and km67 (b-e), and parameterization of e_{rel} (f). Data are digitized from Wu *et al.*
 874 [2016]. Phenological states (Φ) and the count of days from the new season beginning (d_{f10}) are regulated by
 875 changes in PAR ($\overline{\Delta PAR}$) exceeding an assigned threshold (ΔPAR_{th}). See main text for details on the calcu-
 876 lation of ΔPAR_{th} . Canopy leaf age A_L [mo] (c) is estimated using a simple mixing model [Wu *et al.*, 2016]
 877 accounting for the partition of total LAI (squares in b) into young (dotted line), mature (solid line) and old
 878 (dashed line) leaves (b) and assuming average ages of 1.5, 6 and 12 months, respectively. Only data for km34
 879 are shown in (b) as similar trends are observed at km67 [Wu *et al.*, 2016]. Photosynthetic efficiency (e_{rel})
 880 and new leaf biomass production (NB_L^*) are illustrated in panels d and e, respectively. The dry season (i.e.
 881 monthly precipitation < 100 mm [Christoffersen *et al.*, 2014]) is denoted by gray shaded regions (dark gray
 882 for km34, light gray for km67 in panels c,d,e). The observed dependence of e_{rel} on A_L and NB_L^* is shown in
 883 panel f together with the interpolating plane (Eq. 1). Note that a limit $e_{rel} \leq 1$ is imposed. Given that sea-
 884 sonal changes in LAI are limited, the fraction of new leaves $f_{NL} = k_c \frac{NB_L^*}{LAI}$ follows the same trend illustrated
 885 in panel (e) for NB_L^* .



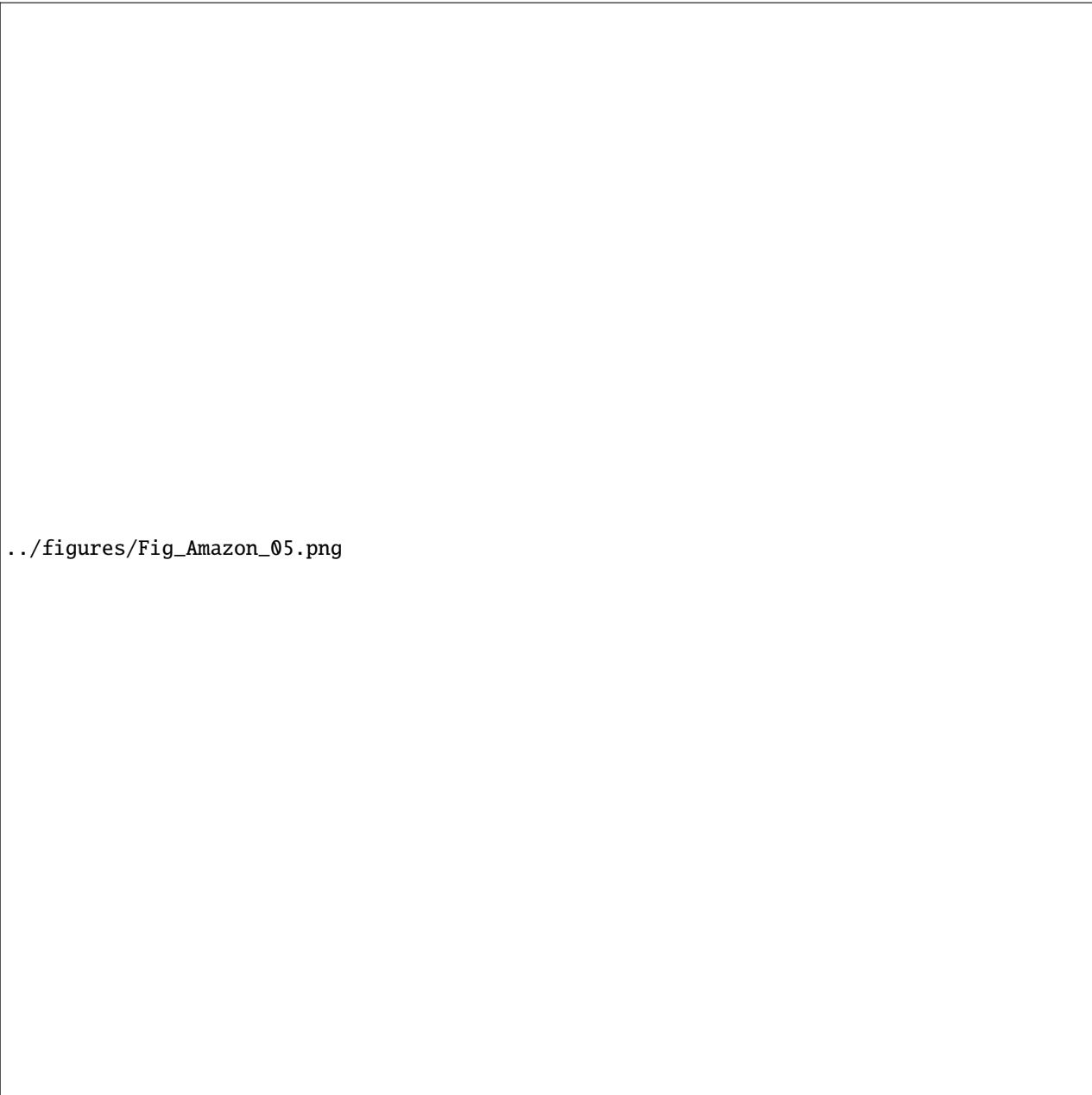
886 **Figure 2.** Observed and simulated GPP, e_{rel} , and ET for the calibration (km67) and validation (km34,
887 CAX and RJA) sites in the Amazon basin (blue and black boxes, respectively). Simulation results are shown
888 for both the original and modified (i.e. with phenology) model formulations (red and blue lines, respectively).
889 The dry season (i.e. monthly precipitation < 100 mm) is denoted by gray shaded regions. Error bars indicate
890 ± 1 standard deviation. In the case of digitized data (e_{rel} and GPP), the standard deviation is estimated from
891 the coefficient of variation of ET.



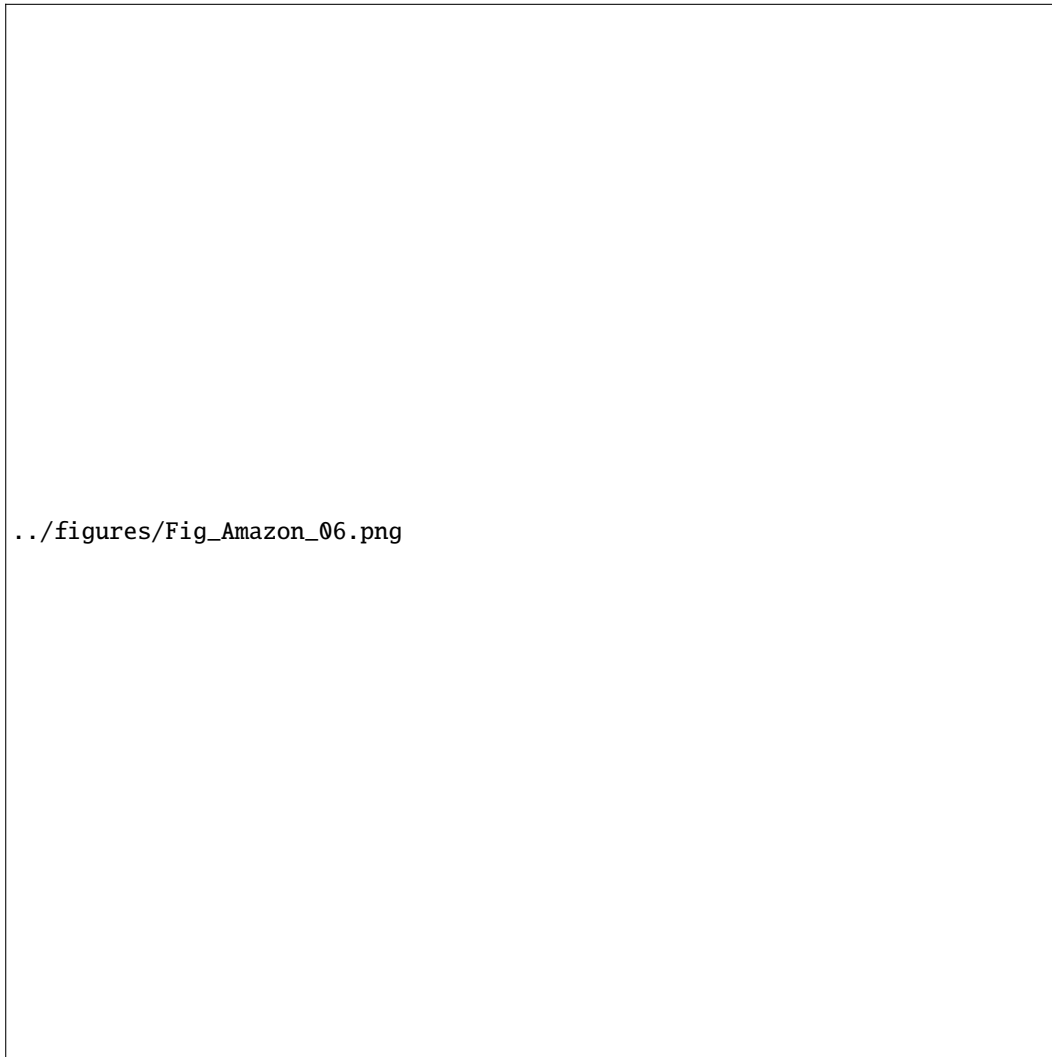
892 **Figure 3.** Observed and simulated LAI, new leaf production $NB_L^* = NB_L \cdot S_L$, i.e. new leaf mass times
893 specific leaf area (a-b), and leaf age A_L (c-d) at km34 and km67 sites. New leaf data (NB_L^*) are digitized
894 from *Wu et al.* [2016] and scaled by k_c to ensure consistency between LAI, litterfall and leaf production (see
895 main text for details). Simulation results are obtained using the modified model version (T&C with phenol-
896 ogy).



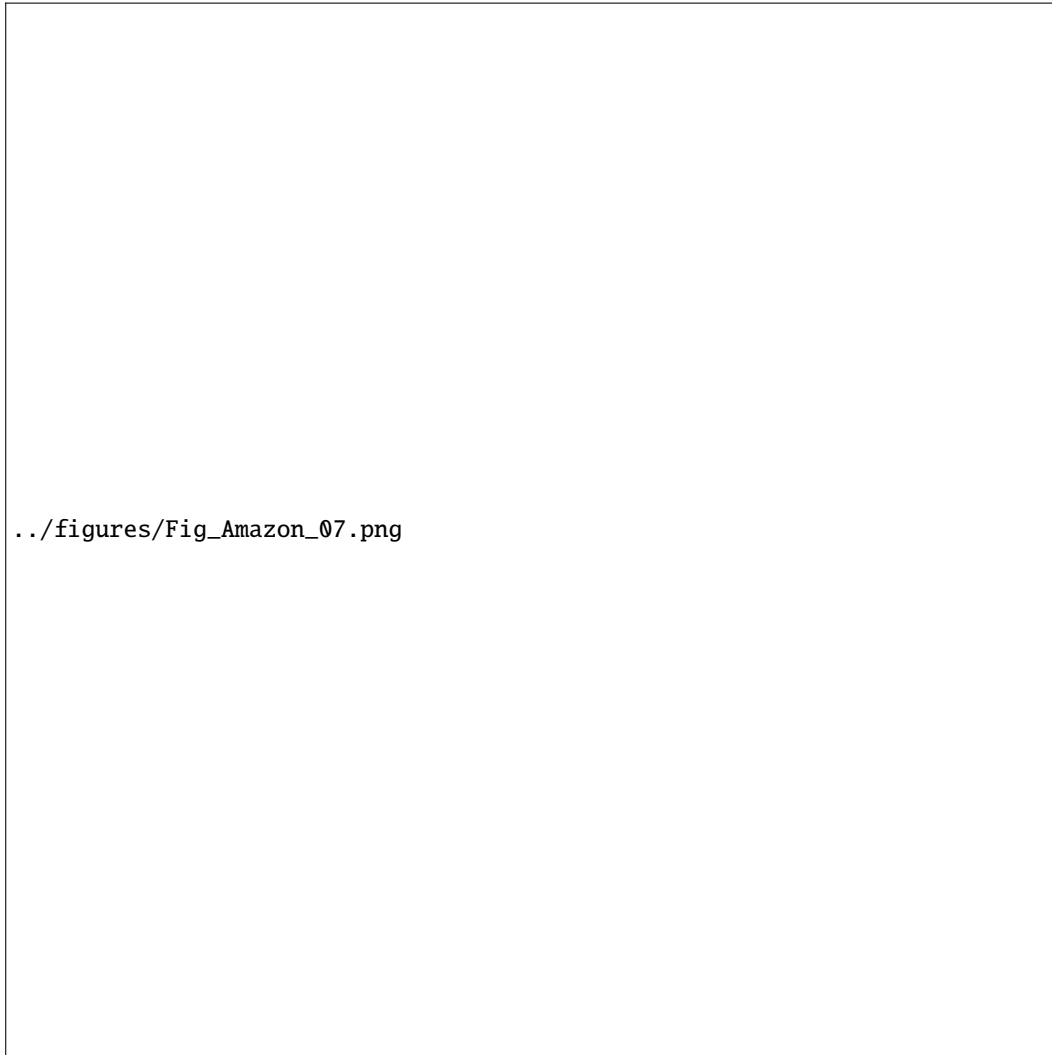
897 **Figure 4.** Daily simulated GPP (a,b), ET (c,d), WUE (e,f), LAI (g,h), and pre-dawn leaf water potential
898 Ψ_L (i,j) at the 34 study sites using the modified T&C model (T&C with phenology). Colors indicate the
899 magnitude of mean annual precipitation, MAP [mm yr^{-1}], at the different study sites.



900 **Figure 5.** Simulated monthly averages of GPP (a), SIF (b) and soil water potential (c,d) at sites A101,
901 km117 and A123. SIF observations from GOME-2 [Joiner *et al.*, 2013] at the 32 sites are also illustrated for
902 a qualitative comparison (grey lines in panel b). The inset in panel b shows the location of the selected study
903 sites.



904 **Figure 6.** Comparison of simulation results (daily values) with and without leaf phenology: GPP (a), ET
905 (b), LAI (c) and pre-dawn leaf water potential ψ_L (d). Water use efficiency ($WUE=GPP/ET$ [$gC\ m^{-2}\ mm^{-1}$])
906 is also shown (inset in panel b). Colors indicate mean annual precipitation values, MAP [$mm\ yr^{-1}$], at the
907 different study sites. The 1:1 line is illustrated for comparison (yellow line).



908 **Figure 7.** Land cover (a) and mean annual precipitation MAP (b) in tropical Amazonia. Simulated GPP,
909 ET, and LAI (mean annual values) at the 34 study sites using T&C with phenology are illustrated in panels
910 c, e, and g. Phenology induced changes in simulated GPP, ET and LAI are shown in panel d, f, and h. Land
911 cover data are derived from the Global Land Cover 2000 database (European Commission, Joint Research
912 Centre, 2003), while precipitation is based on the GPCC Full Data Reanalysis of monthly global land-surface
913 precipitation [Schneider *et al.*, 2015].

Figure 1.

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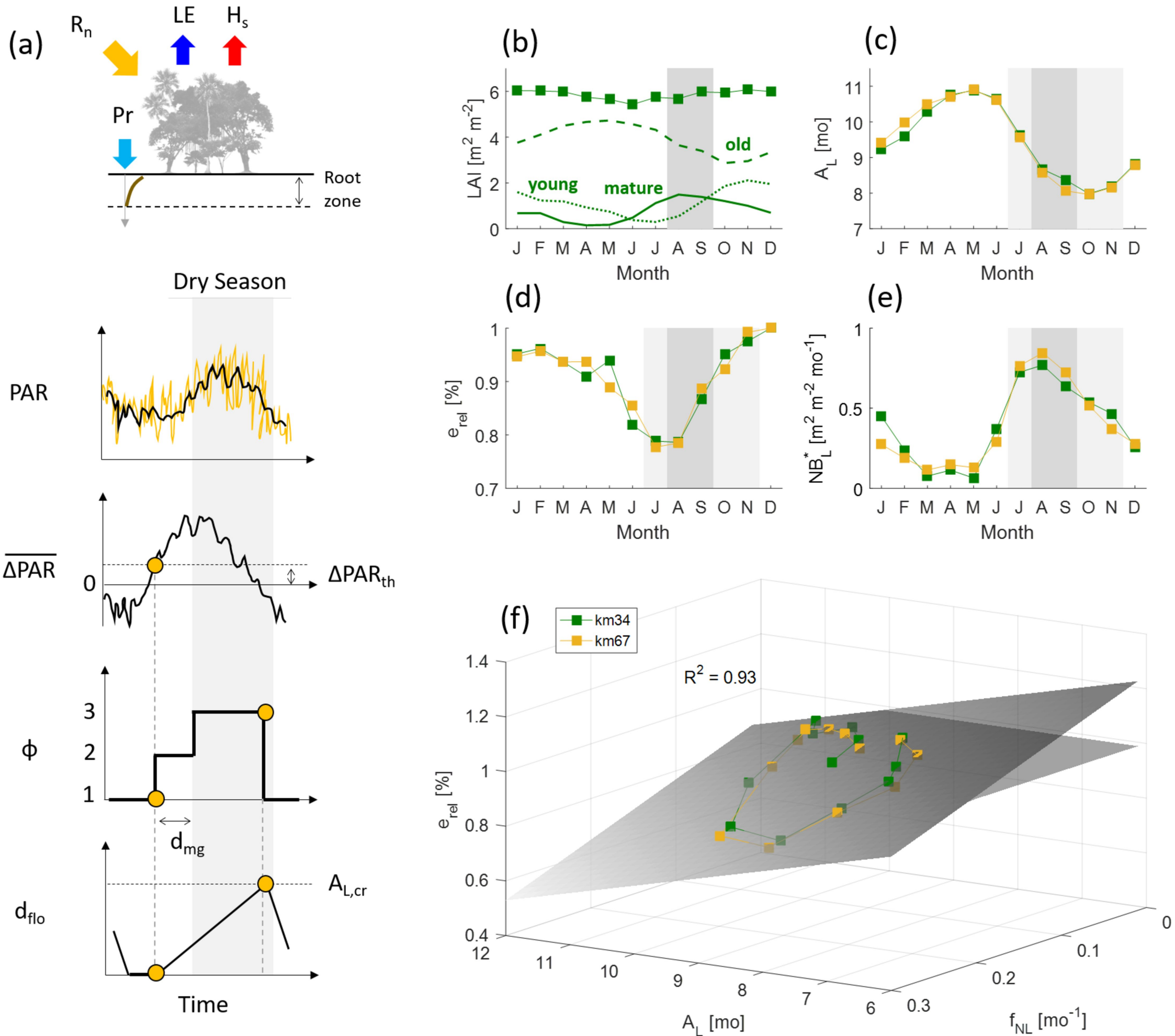


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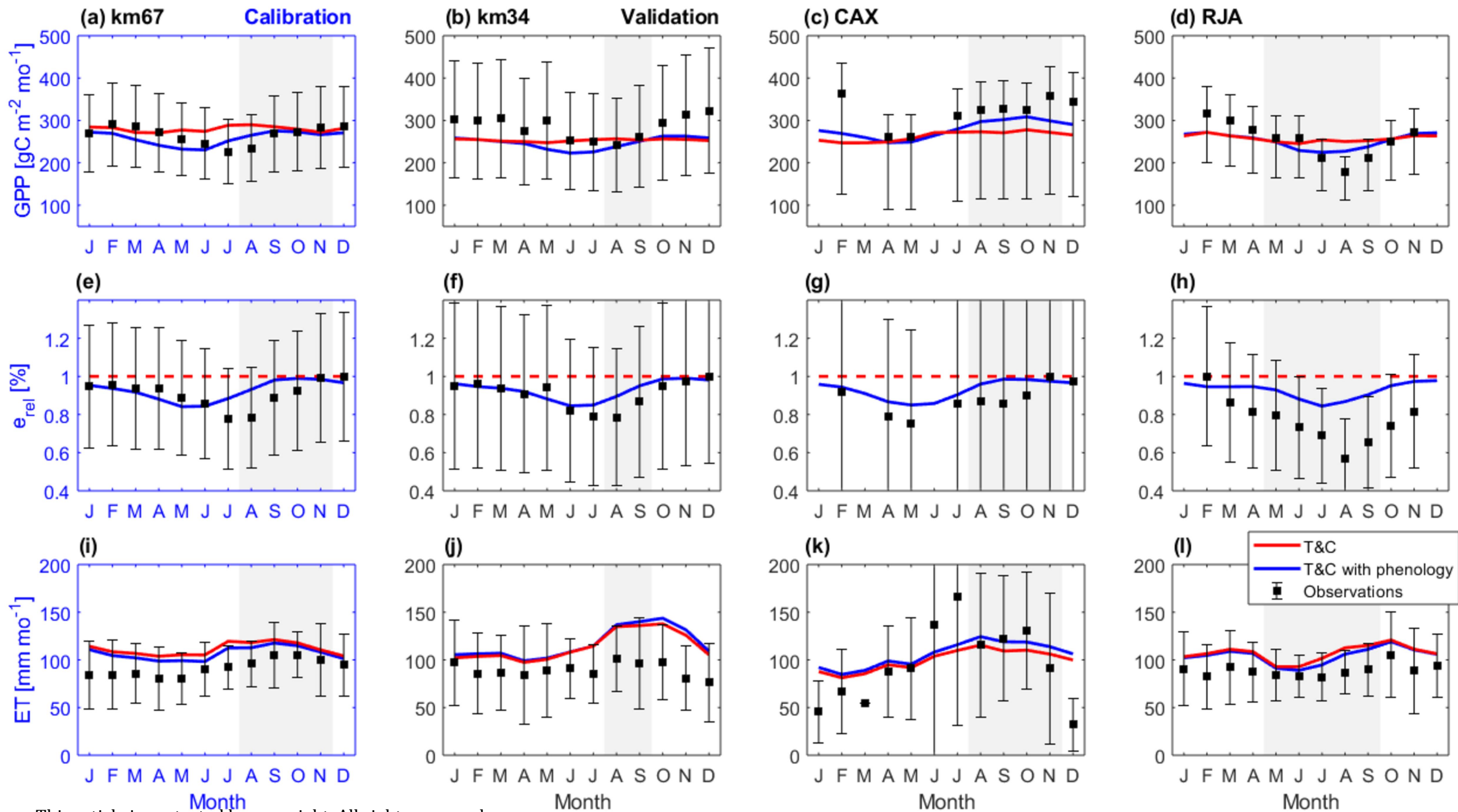


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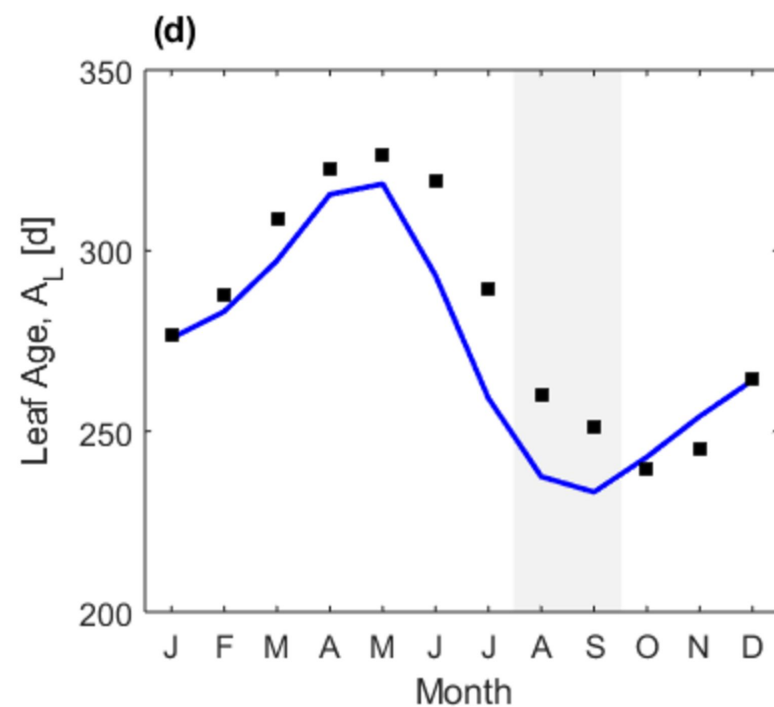
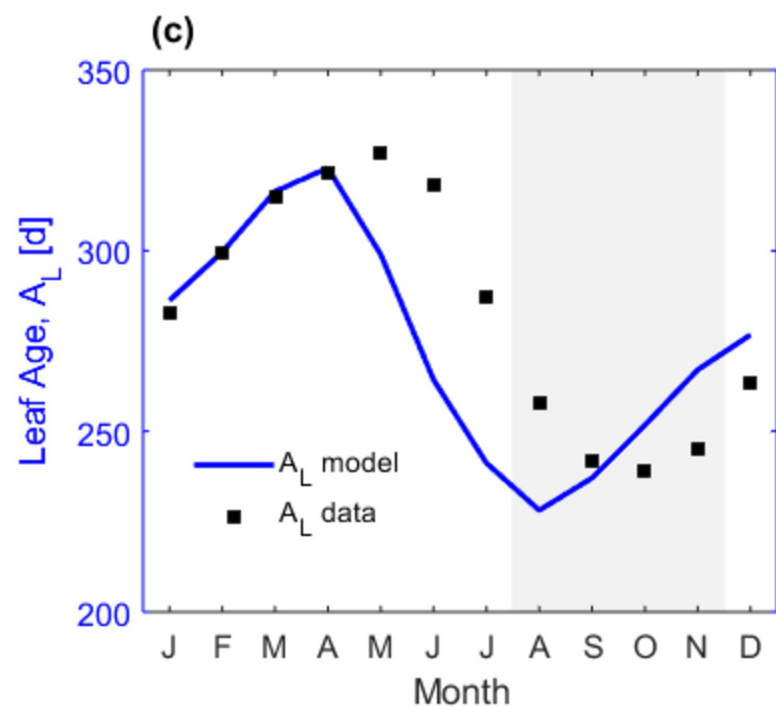
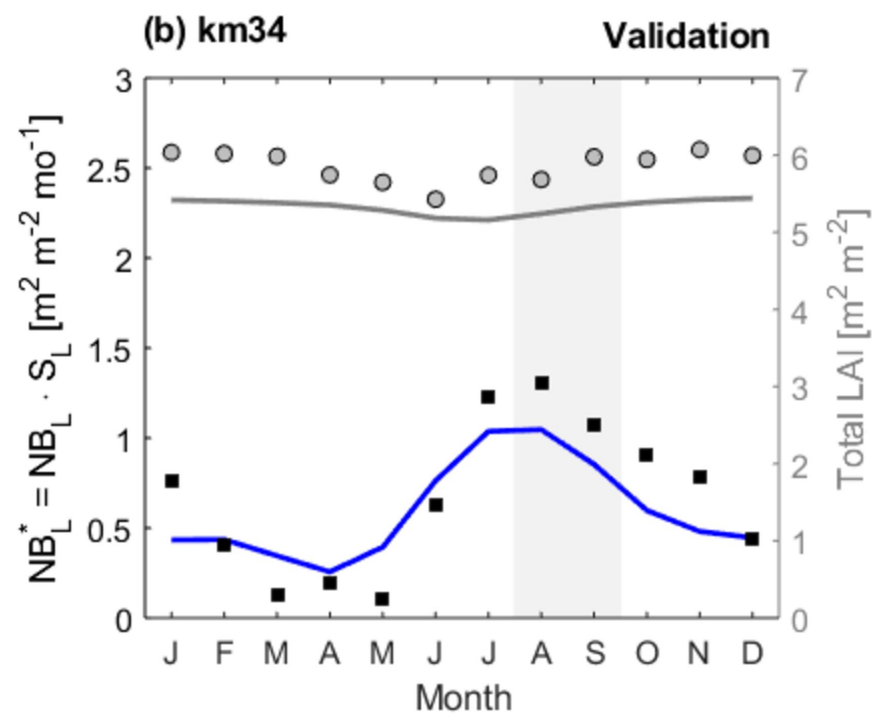
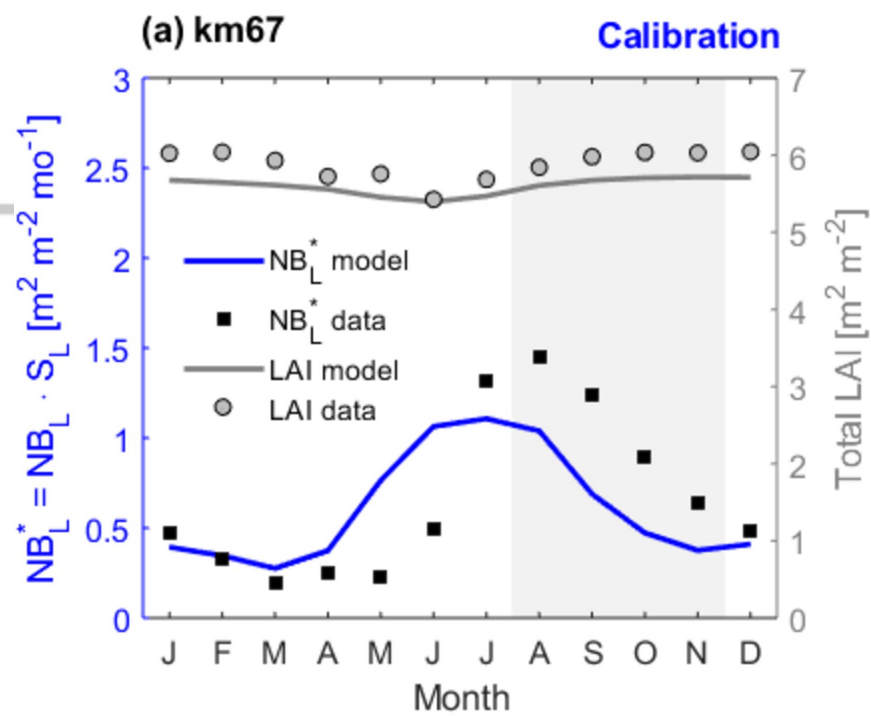


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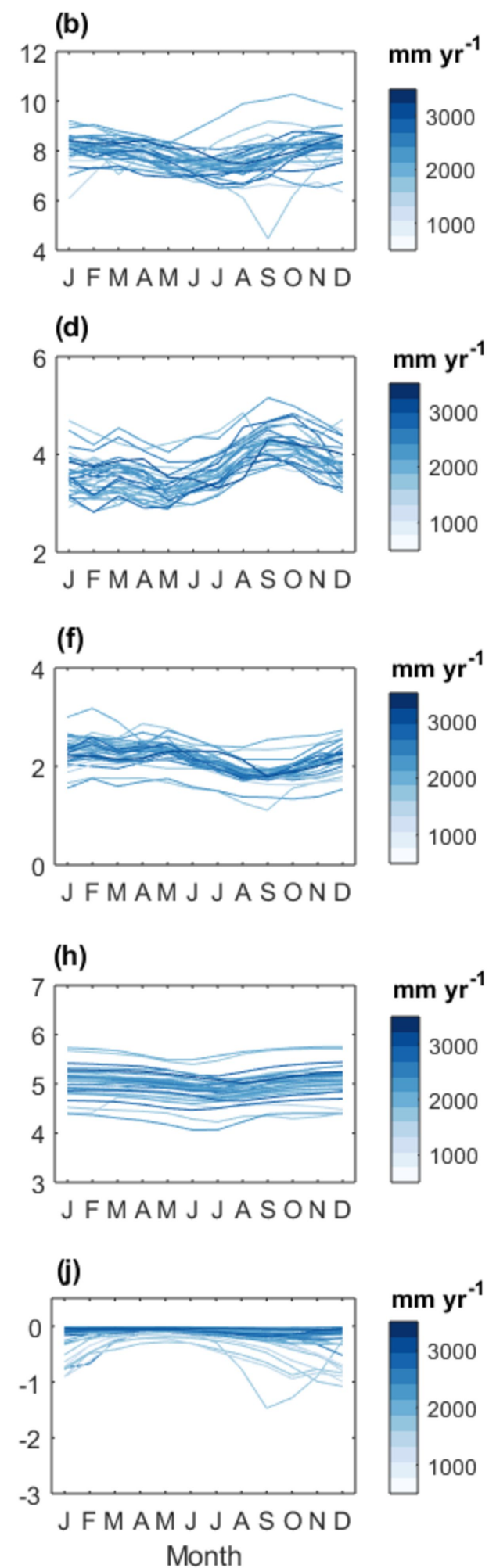
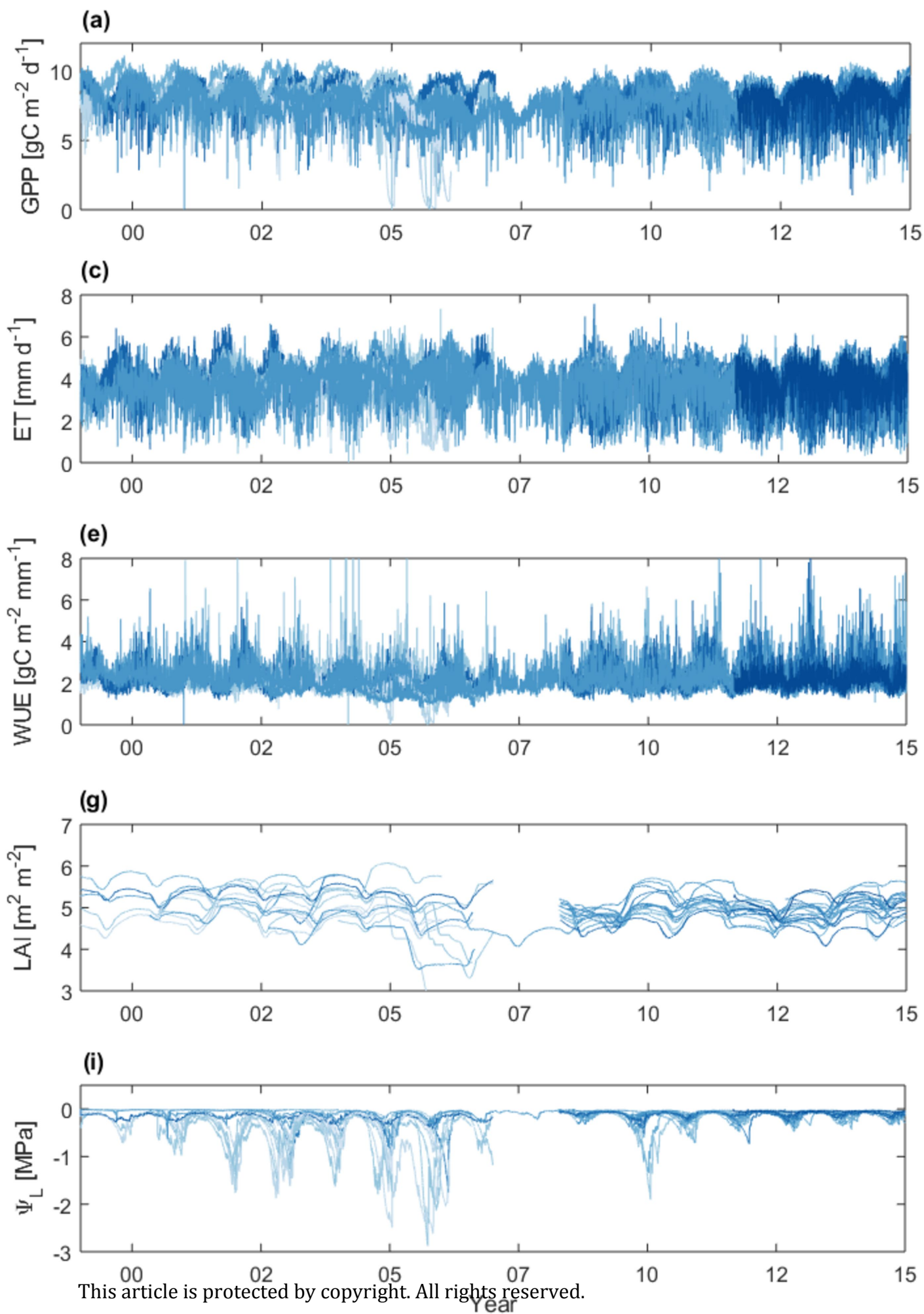


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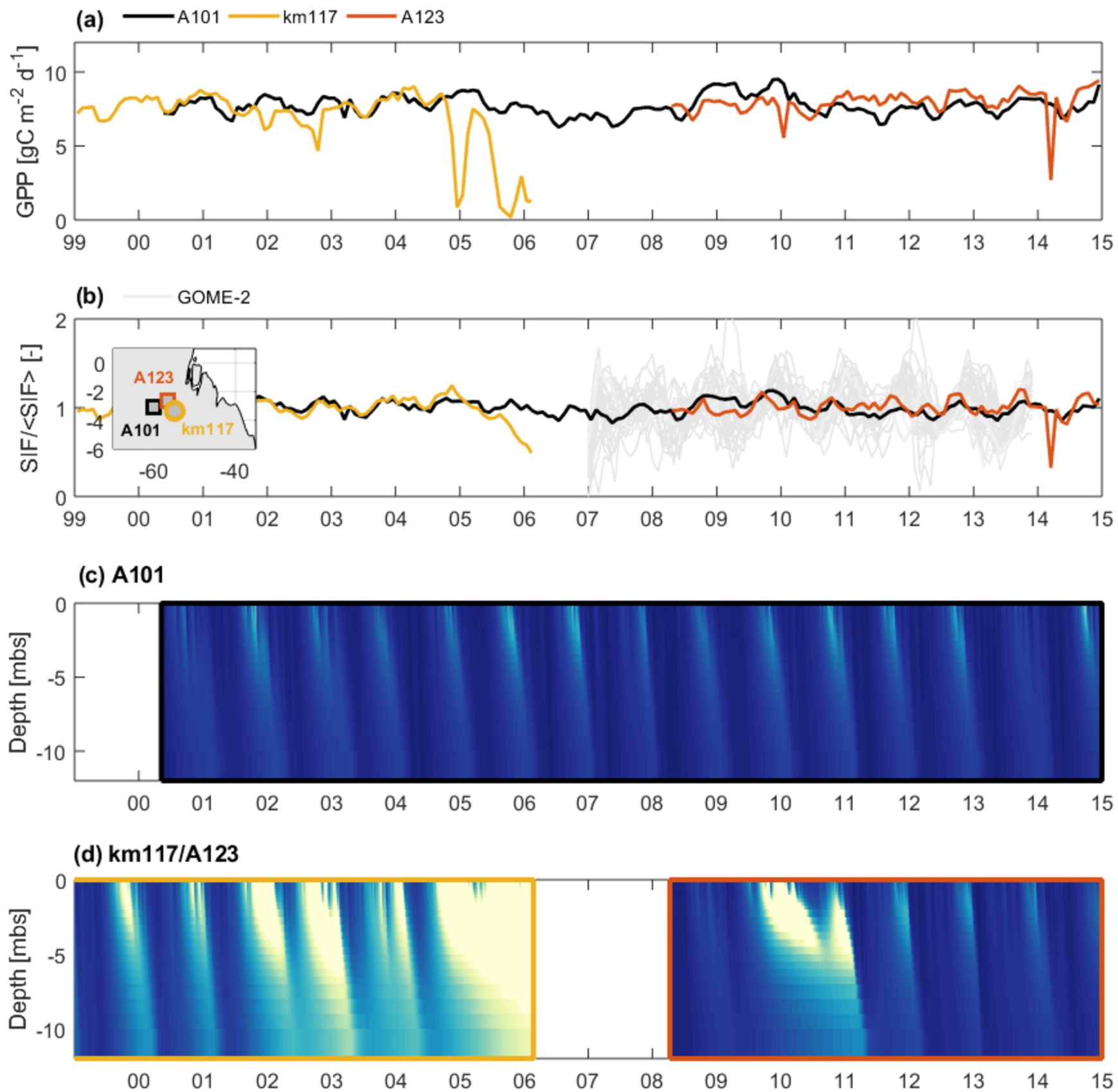


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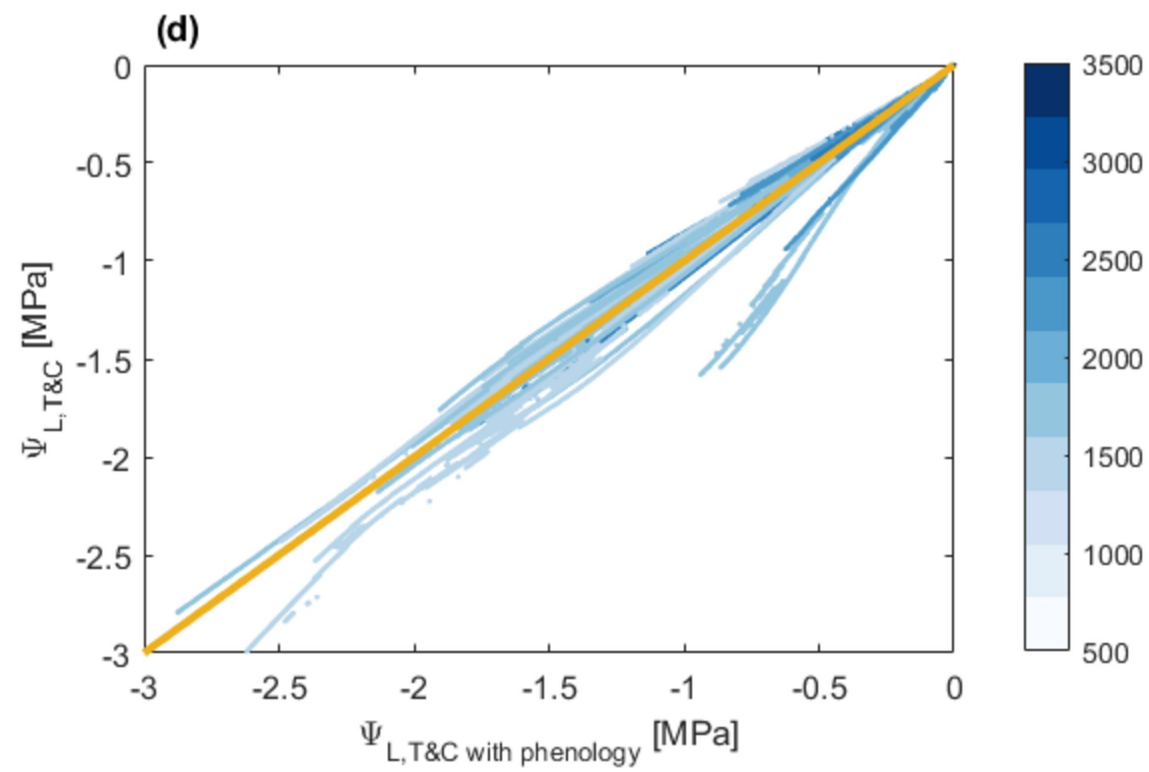
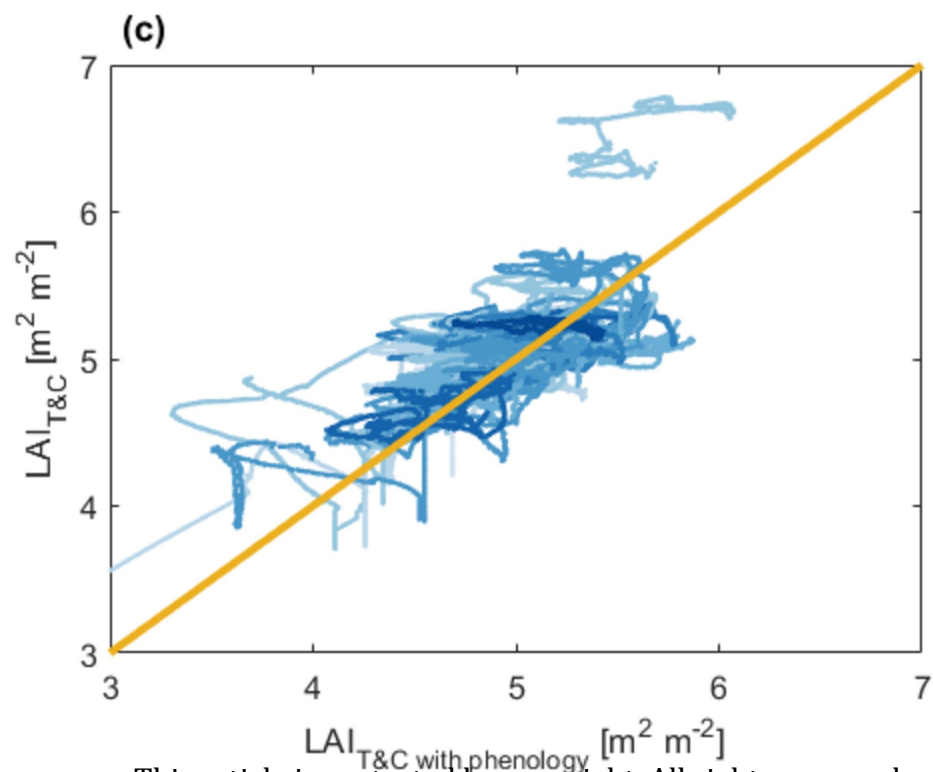
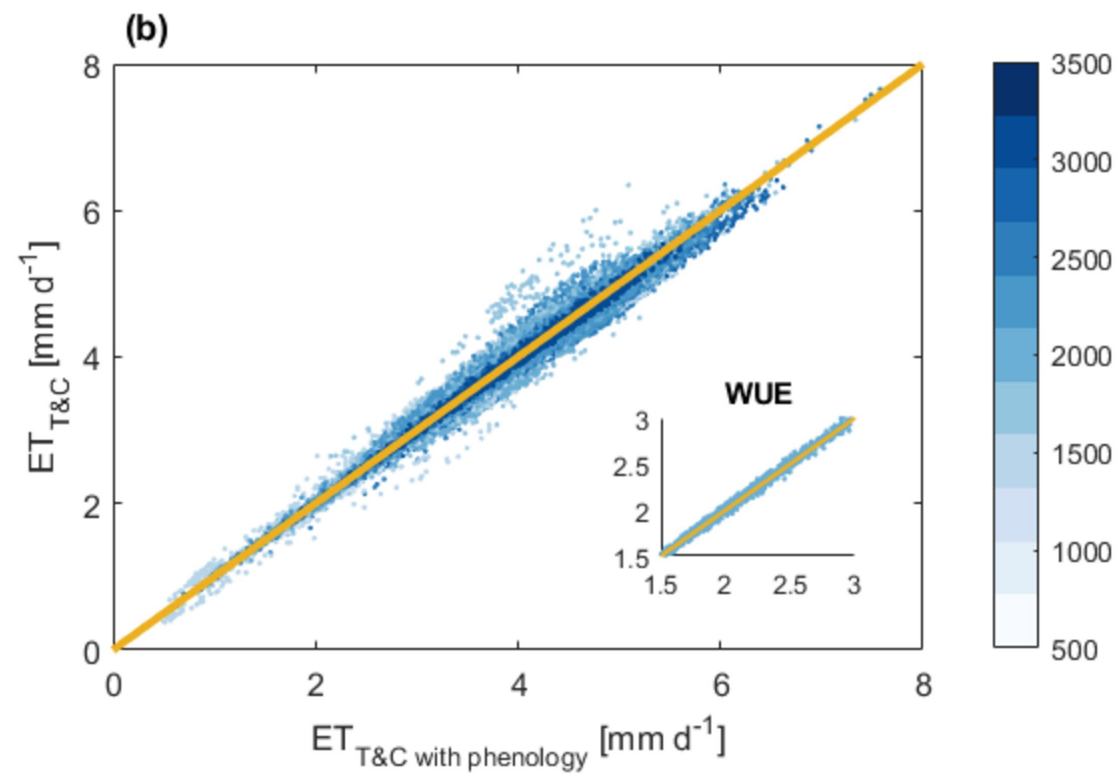
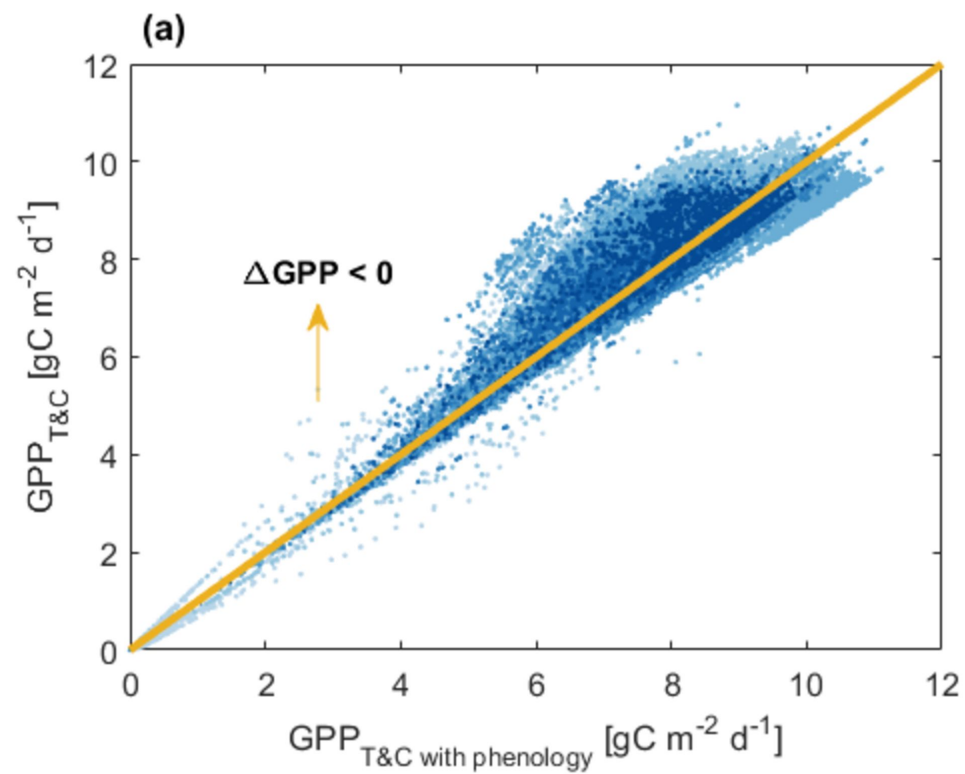
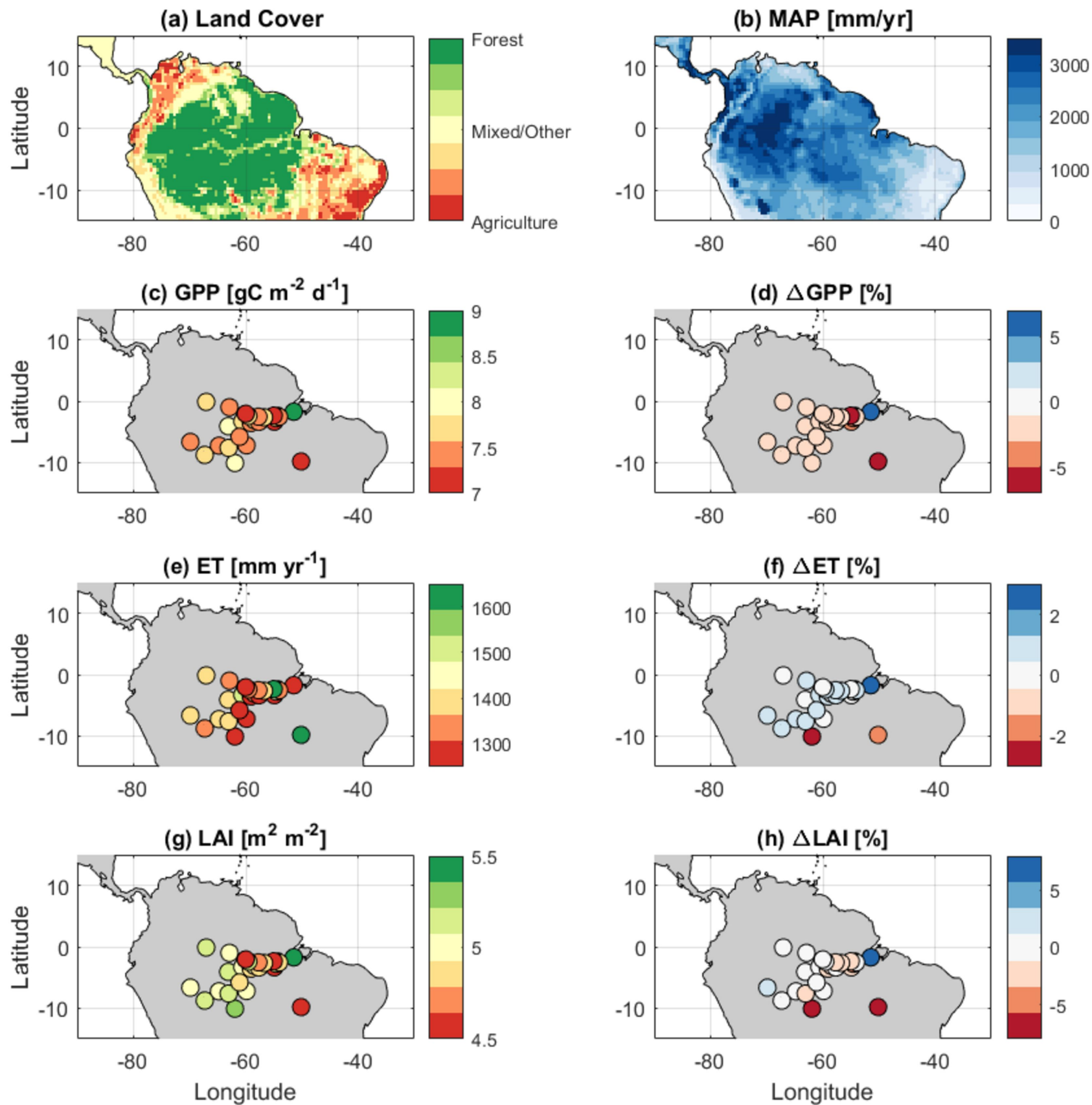
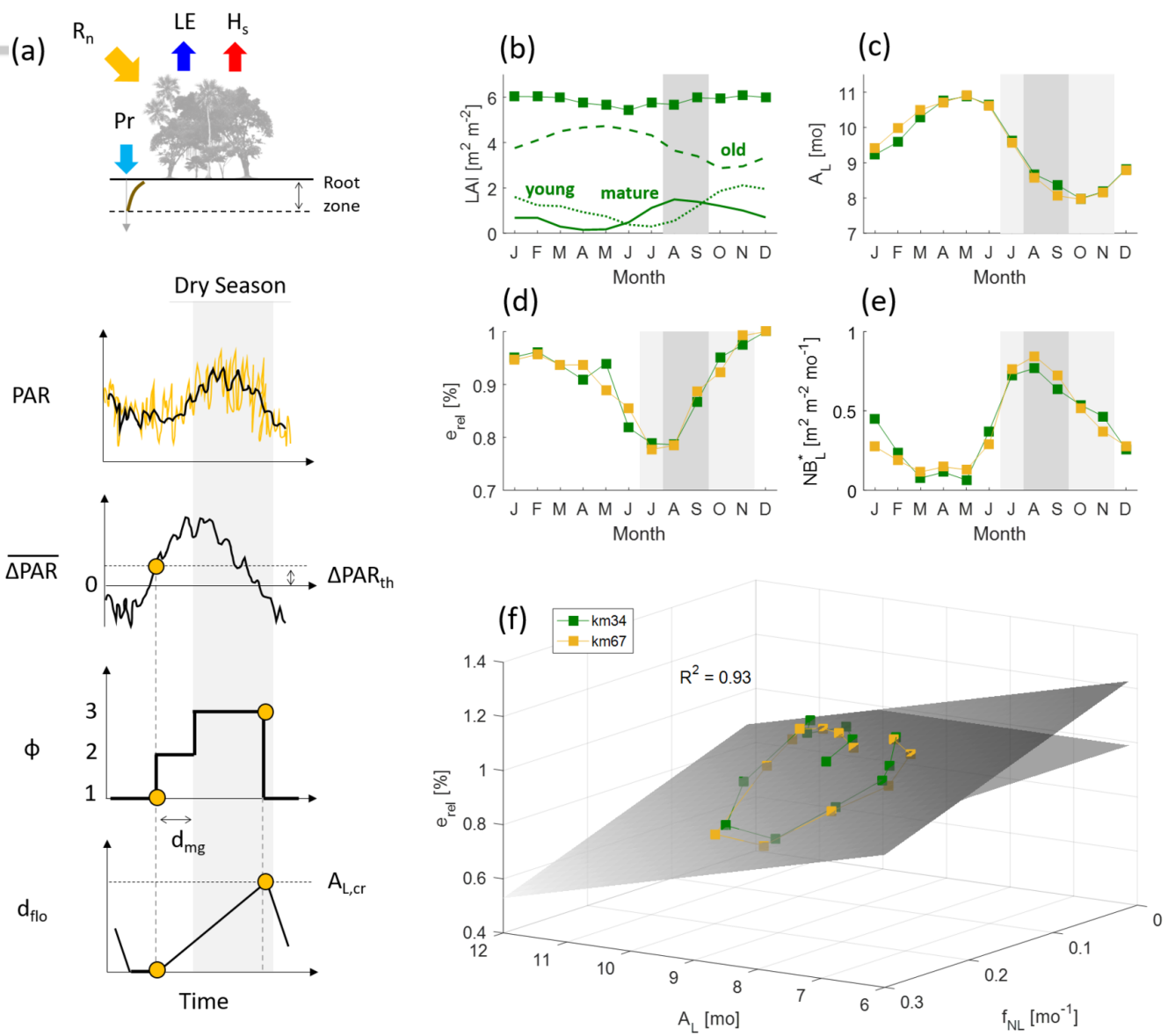


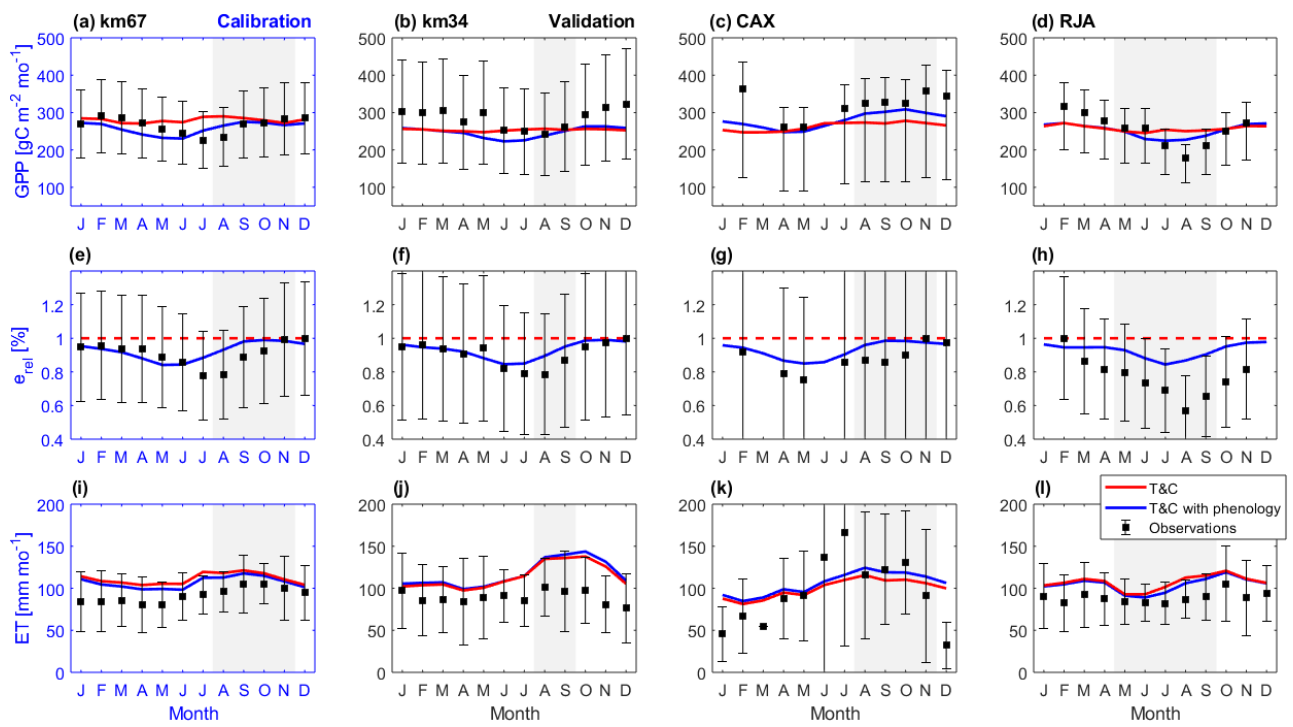
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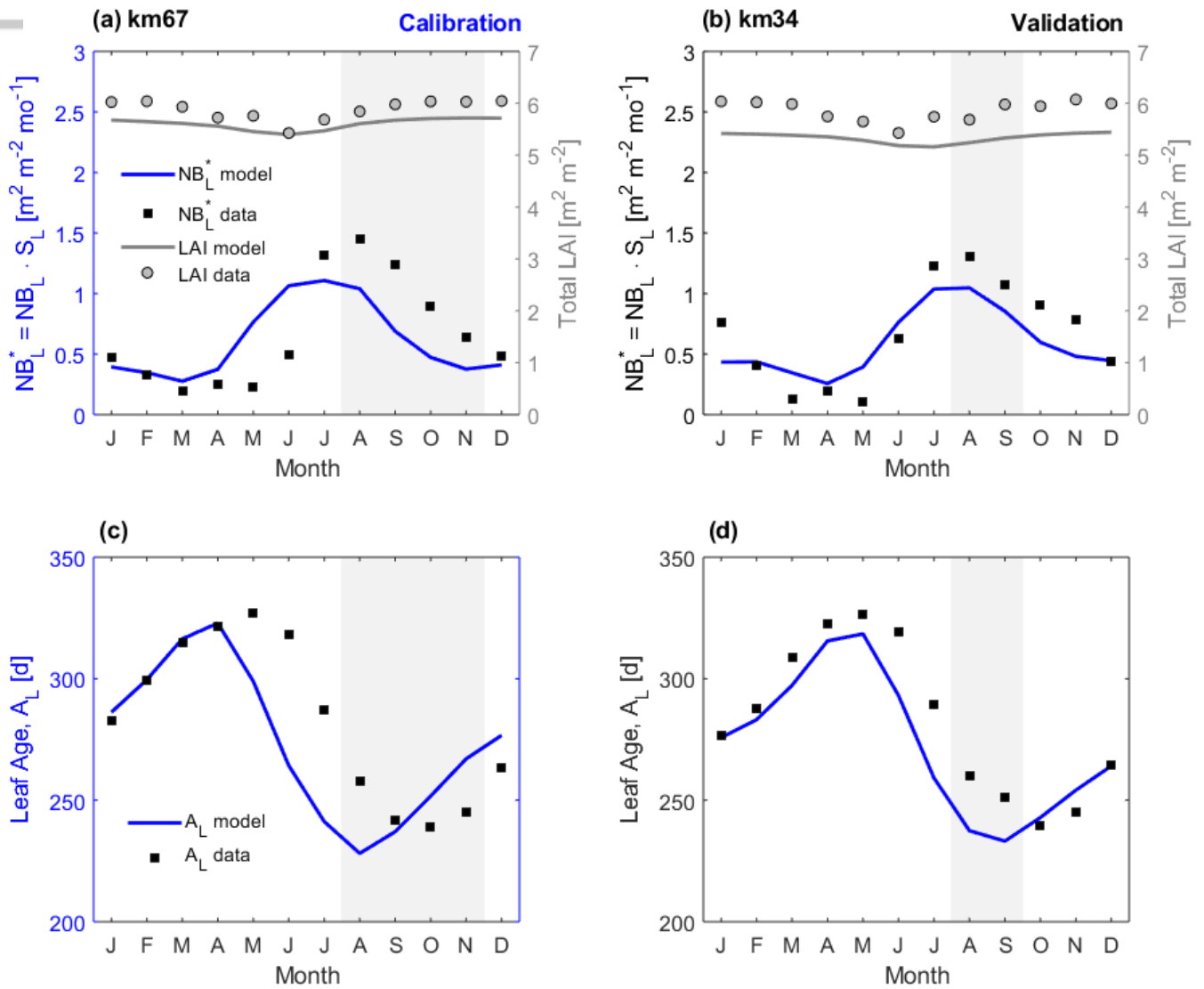




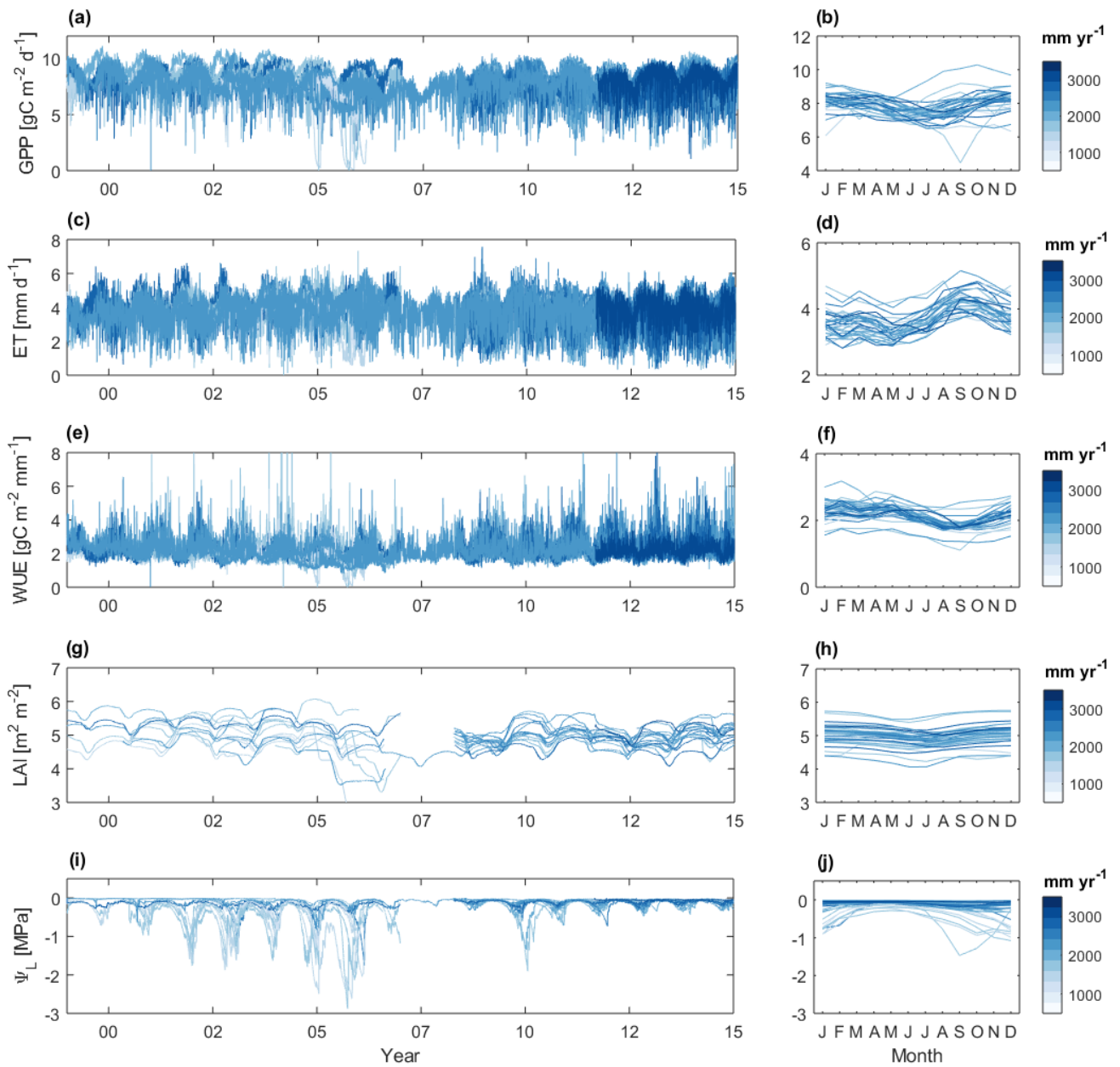
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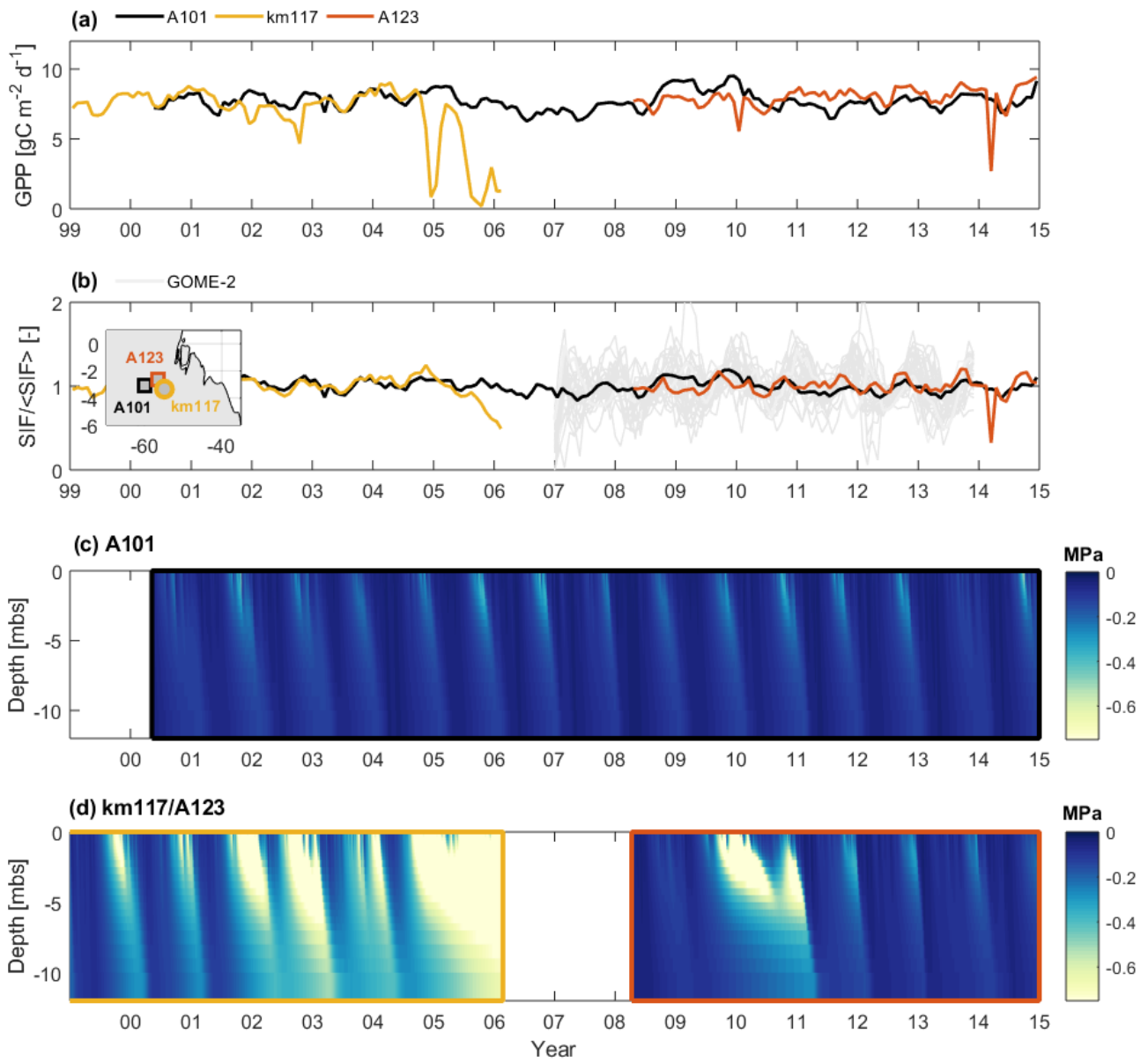
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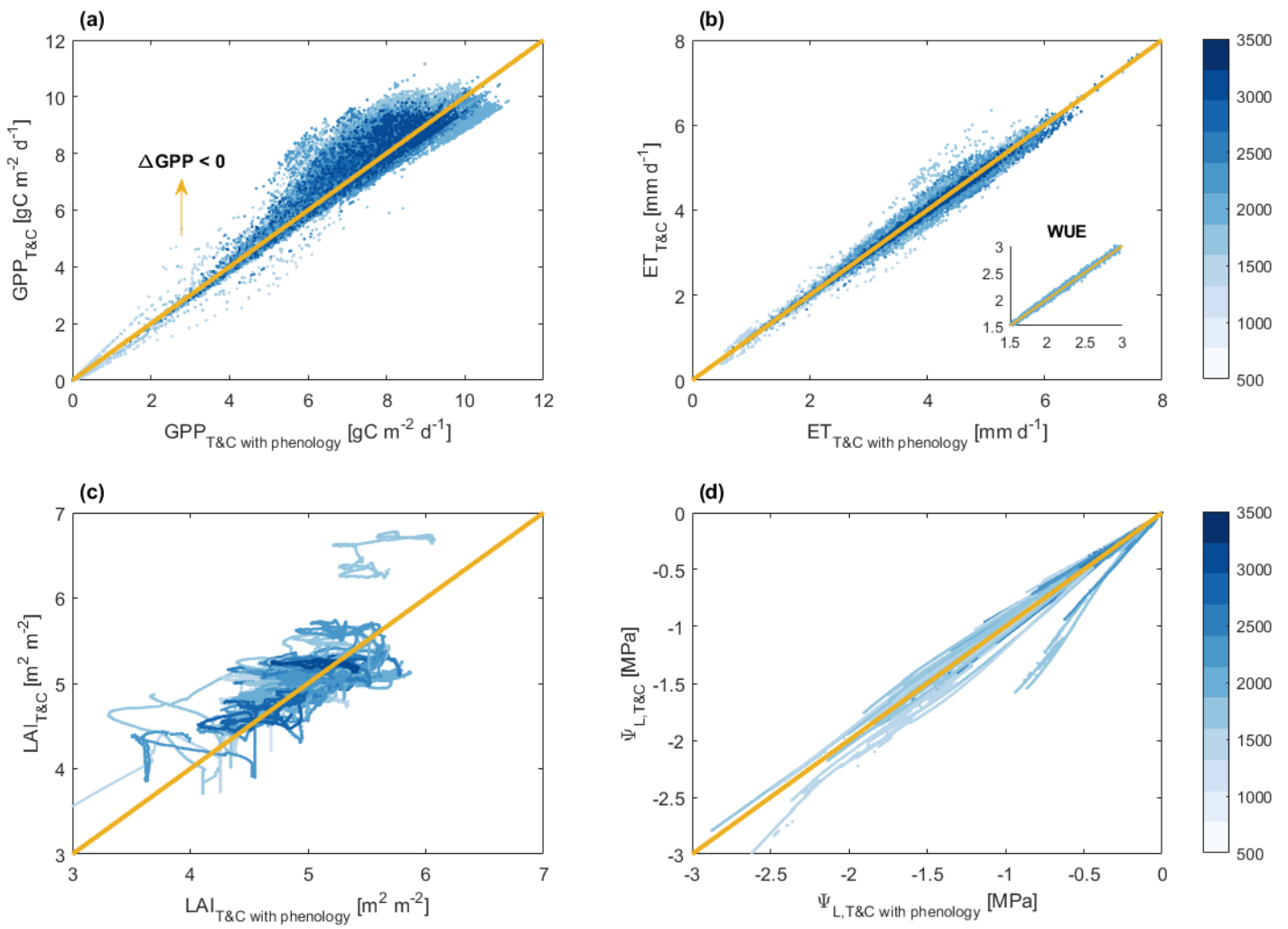
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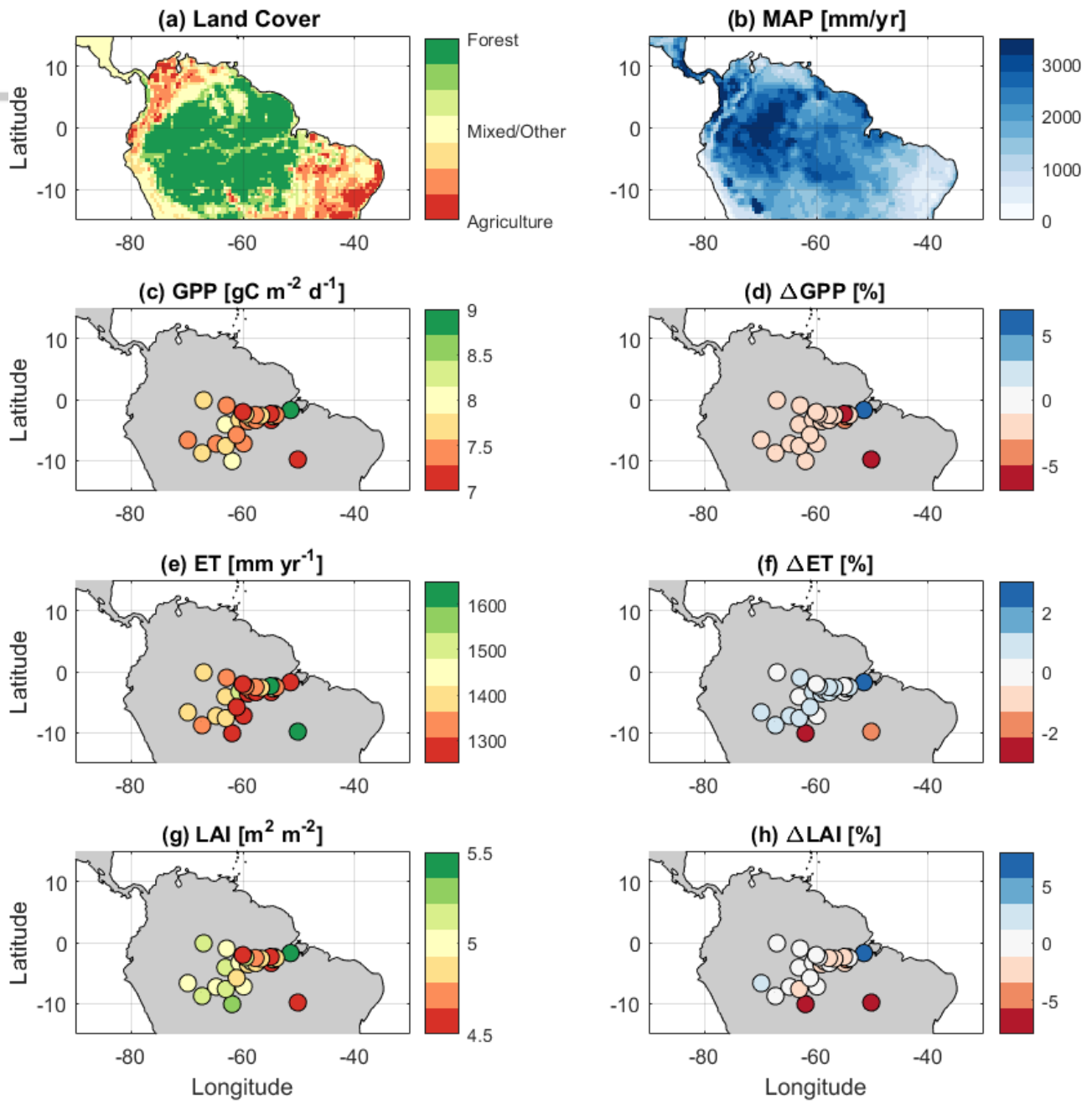
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