

1 **Surface Urban Energy and Water Balance Scheme (v2020a) in vegetated areas:**
2 **parameter derivation and performance evaluation using FLUXNET2015 dataset**

3 Hamidreza Omidvar¹, Ting Sun^{1,✉}, Sue Grimmond^{1,✉}, Dave Bilesbach², Andrew Black³, Jiquan Chen⁴,
4 Zexia Duan⁵, Zhiqiu Gao^{5,6}, Hiroki Iwata⁷, Joseph P. McFadden⁸

5 ¹ Department of Meteorology, University of Reading, Reading, RG6 6ET, UK

6 ² Biological Systems Engineering Department, University of Nebraska, Lincoln, NE, 68588, USA

7 ³ Faculty of Land and Food System, University of British Columbia, Vancouver, BC, V6T 1Z4, CA

8 ⁴ Center for Global Change and Earth Observation, Department of Geography, Michigan State University, East Lansing, MI,
9 48824, USA

10 ⁵ Collaborative Innovation Centre on Forecast and Evaluation of Meteorological Disasters, School of Atmospheric Physics,
11 Nanjing University of Information Science and Technology, Nanjing, 210044, China

12 ⁶ State Key Laboratory of Atmospheric Boundary Layer Physics and Atmospheric Chemistry, Institute of Atmospheric Physics,
13 Chinese Academy of Sciences, Beijing, 100029, China

14 ⁷ Department of Environmental Science, Faculty of Science, Shinshu University, Nagano 390-8621, Japan

15 ⁸ Department of Geography, University of California, Santa Barbara, CA, 93106 USA

16

17 ✉ Correspondence to: ting.sun@reading.ac.uk; c.s.grimmond@reading.ac.uk

18 **ORCID:**

19 Hamidreza Omidvar: <https://orcid.org/0000-0001-8124-7264>

20 Ting Sun: <https://orcid.org/0000-0002-2486-6146>

21 Sue Grimmond: <https://orcid.org/0000-0002-3166-9415>

22 Dave Bilesbach: <https://orcid.org/0000-0001-8661-9178>

23 Andrew Black: <https://orcid.org/0000-0001-9292-1146>

24 Jiquan Chen: <https://orcid.org/0000-0003-0761-9458>

25 Zexia Duan: <https://orcid.org/0000-0003-2822-7066>

26 Zhiqiu Gao: <https://orcid.org/0000-0001-8256-005X>

27 Hiroki Iwata: <https://orcid.org/0000-0002-8962-8982>

28 Joseph P. McFadden: <https://orcid.org/0000-0002-5869-7774>

29

30 **Abstract**

31 To compare the impact of surface-atmosphere exchanges from rural and urban areas, fully vegetated areas
32 (e.g. deciduous trees, evergreen trees and grass) commonly found adjacent to cities need to be modelled.
33 Here we provide a general workflow to derive parameters for SUEWS (Surface Urban Energy and Water
34 Balance Scheme), including those associated with vegetation phenology (via leaf area index, LAI), heat
35 storage and surface conductance. As expected, attribution analysis of bias in SUEWS modelled Q_E finds
36 the surface conductance (g_s) plays the dominant role, hence there is need for more estimates of surface
37 conductance parameters. The workflow is applied at 38 FLUXNET sites. The derived parameters vary
38 between sites with the same plant functional type (PFT), demonstrating the challenge of using a single set
39 of parameters for a PFT. SUEWS skill at simulating monthly and hourly latent heat flux (Q_E) is examined
40 using the site-specific derived parameters, with the default NOAH surface conductance parameters (Chen
41 et al. 1996). Overall evaluation for two years has similar metrics for both configurations: median hit rate
42 between 0.6 and 0.7, median mean absolute error less than 25 W m^{-2} , and median mean bias error $\sim 5 \text{ W}$
43 m^{-2} . Performance differences are more evident at monthly and hourly scales, with larger mean bias error
44 (monthly: $\sim 40 \text{ W m}^{-2}$; hourly $\sim 30 \text{ W m}^{-2}$) results using the NOAH-surface conductance parameters,
45 suggesting that they should be used with caution. Assessment of sites with contrasting Q_E performance
46 demonstrates how critical capturing the LAI dynamics is to the SUEWS prediction skills of g_s and Q_E .
47 Generally g_s is poorest in cooler periods (more pronounced at night, when underestimated by $\sim 3 \text{ mm s}^{-1}$).
48 Given the global LAI data availability and the workflow provided in this study, any site to be simulated
49 should benefit.

50 **Keywords:** SUEWS, FLUXNET, NOAH, LAI, surface conductance, Penman-Monteith equation

51 **1 Introduction**

52 The Surface Urban Energy and Water Balance Scheme (SUEWS, Grimmond et al., 1986, 1991,
53 Grimmond & Oke 1991, Järvi et al., 2011) is widely used to simulate urban surface energy and
54 hydrological fluxes, with heat and water released by anthropogenic activities accounted for (Grimmond et
55 al., 1986; Grimmond, 1992). SUEWS characterises the heterogeneity of urban surfaces allowing an
56 integrated mix of seven land covers within a grid cell (neighbourhood scale: $O(0.1\text{--}10 \text{ km})$) of impervious
57 (buildings, paved) and pervious (evergreen trees/shrubs, deciduous trees/shrubs, grass, soil, water) types.
58 Although SUEWS has been evaluated in cities around the globe (e.g. Karsisto et al., 2016, Ward et al.,
59 2016, Ao et al., 2018, Kokkonen et al., 2018, Harshan et al., 2018) with varying mixes of integrated

60 impervious-pervious land covers, its performance has not been comprehensively examined in fully
61 vegetated areas that commonly occur adjacent to cities.

62 One common and demanding application of urban climate models, including SUEWS, is to examine the
63 very well-known canopy layer urban heat island effects – parts of cities are often warmer than their
64 surroundings at night – and to understand the causes (Oke 1973, 1982). This requires both the “rural”
65 context – usually characterised by pervious land cover – to be simulated appropriately ideally using the
66 same modelling framework. As SUEWS v2020a (Tang et al. 2021) can diagnose near surface
67 meteorology in the roughness sub-layer and canopy layer (e.g., air temperature and humidity at 2 m agl
68 (above ground level), wind speed at 10 m agl), it is essential to ensure that any urban-rural comparison in
69 these diagnostics has the proper rural skill and parameters (i.e. coefficient values used in
70 parameterisations).

71 For meso-scale numerical weather prediction (NWP) of an urban region, both rural and urban areas need
72 to be simulated. With plans to couple SUEWS to a meso-scale model (e.g. Weather Research and
73 Forecasting (WRF), Skamarock and Klemp (2008)), most regions have extensive areas that have
74 completely pervious grid cells. As these need to be simulated using a consistent surface scheme, it is
75 essential to have appropriate parameters for these areas.

76 Central to the SUEWS biophysics, is the Penman-Monteith approach (Penman 1948; Monteith 1965) with
77 a Jarvis-type (Jarvis 1976) surface moisture conductance (Grimmond and Oke 1991). Parameters for
78 different types of urban areas (e.g. land cover differences) and regions (e.g. high/mid-latitude) have been
79 derived. However, both limited observations and lack of a standard workflow for deriving parameters
80 remains a constraint. This is evident in the availability of conductance and storage heat flux related
81 parameters (e.g. Järvi et al. 2011, 2014; Ward et al. 2016). Other land surface schemes have parameters
82 for a wide range of plant functional types (PFT) (e.g. NOAH within WRF, Chen et al. 1996, Chen and
83 Dudhia 2001) but are often derived from a small number of observational sites and their widespread
84 applicability is unexamined. For example, NOAH largely adopted values from the HAPEX-MOBILHY
85 observational program (Andre et al. 1986) following Noilhan and Planton (1989).

86 FLUXNET (Baldocchi et al., 2001) is a global network of sites that monitor surface-atmosphere
87 exchanges (e.g. carbon, water, and energy using the eddy covariance technique for the turbulent fluxes).
88 These data provide unprecedented possibilities to advance process-based land surface modelling, through
89 both development (e.g. Stöckli et al. 2008) and evaluation (e.g. Zhang et al. 2017). Extensive analysis of
90 FLUXNET datasets for the variety of terrestrial PFTs have considered various surface atmosphere
91 controls (e.g., albedo: Cescatti et al. 2012; latent heat flux: Ershadi et al. 2014; spatiotemporal

representativeness: Chu et al. 2017, Villarreal and Vargas 2021; energy balance closure: Franssen et al. 2010; landscape heterogeneity: Göckede et al. 2008, Stoy et al. 2013) to enhance understanding of land-atmosphere interactions. As such, this is an ideal data source for deriving widely applicable parameters and assessing performance of SUEWS over different land cover types.

In this work, we develop general workflows (Fig. 1) to derive vegetation related parameters associated with phenology, the storage heat flux and surface moisture conductance; and comprehensively examine model skill in modelling latent heat fluxes. We briefly review the key vegetation biophysics schemes in SUEWS (Sect. 2), describe the FLUXNET2015 (Pastorello et al. 2020) and auxiliary datasets used (Sect. 3), and outline the workflows for deriving parameters (Sect. 4). To assess the quality of the derived parameters the SUEWS modelled latent heat flux is evaluated (Sect. 5). Model parameters related to surface conductance are derived for NOAH at the PFT level (Appendix A) as well as those related to surface roughness based on FLUXNET2015 dataset at the site level (Appendix B). Other model parameters derived following workflows (Sect. 4) are also provided (Appendix C). The source code, input data and model simulations analysed are provided in Sun et al. (2021).

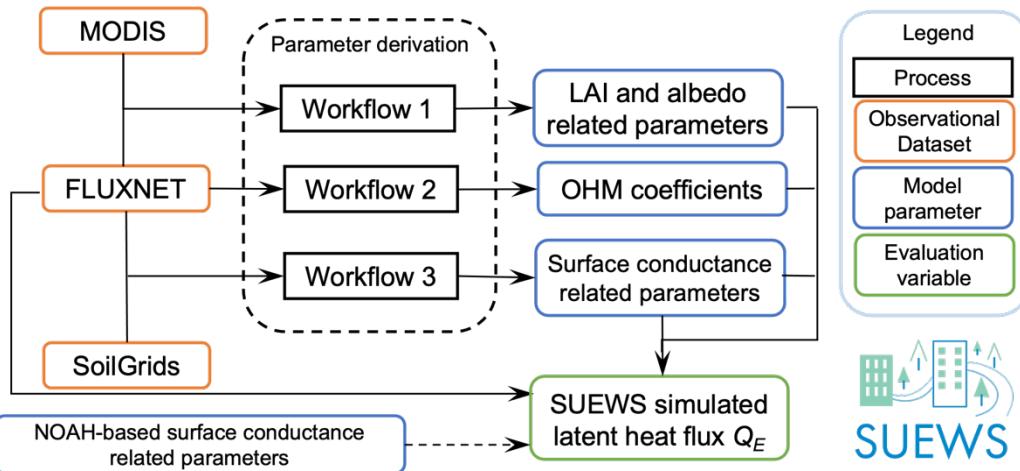


Figure 1 Overview of workflows to derive parameters, to undertake and to evaluate simulations. Acronyms are defined in Sect. 2 and 3. More details are provided in Figures 3, 5, and 6.

106

107

108

109

110 2 SUEWS model

111 2.1 Overview of SUEWS physics for vegetated areas

112 Surface Urban Energy and Water Balance Scheme (SUEWS) is a local-scale land surface model for
113 simulating the surface energy and hydrological fluxes (Grimmond and Oke 1986, 1991; Järvi et al. 2011,
114 2014; Offerle et al. 2003; Ward et al. 2016) without requiring specialised computing facilities. It has been

extensively evaluated and applied in many cities (Lindberg et al.'s (2018) Table 3, Sun and Grimmond's (2019) Table 1). Other details of how SUEWS computes the surface energy, water and carbon fluxes are given in recent model description papers (Järvi et al., 2011; Ward et al., 2016; Järvi et al., 2019).

The surface energy and water balances are directly linked by the turbulent latent heat flux (Q_E) or its mass equivalent evaporation (E) (Grimmond and Oke 1986, 1991):

$$Q^* + Q_F = Q_H + Q_E + \Delta Q_S \quad (1)$$

$$P + I_e = E + R + \Delta S \quad (2)$$

where Q^* is the net all-wave radiation flux, Q_F is the anthropogenic heat flux, Q_H is the turbulent sensible heat flux, ΔQ_S the net storage heat flux, and P , I_e , ΔS and R are precipitation, external water use, net change in the water storage (e.g. canopy, soil moisture, water bodies) and runoff, respectively. The sites selected in this work are assumed to have no irrigation, so I_e is assumed to be 0 mm s^{-1} .

In SUEWS, a modified Penman-Monteith equation (Penman, 1948; Monteith, 1965) is used to compute Q_E with an expectation in cities that the anthropogenic heat flux (Q_F) is greater than zero (Grimmond and Oke, 1991):

$$Q_E = \frac{s(Q^* + Q_F - \Delta Q_S) + \frac{\rho c_p VPD}{r_a}}{s + \gamma \left(1 + \frac{r_s}{r_a}\right)} \quad (3)$$

However, with our current focus on extensive (non-urban) pervious areas Q_F is assumed to be 0 W m^{-2} . The atmospheric state is obtained from the slope of saturation water vapour pressure curve with respect to air temperature (s , units: Pa K^{-1}), density of air (ρ , kg m^{-3}), specific heat of air at constant pressure (c_p , $\text{J K}^{-1} \text{ kg}^{-1}$), vapour pressure deficit (VPD , Pa), psychrometric 'constant' (γ , Pa K^{-1}), and the aerodynamic resistance for water vapour (r_a , units: s m^{-1}).

Under given ambient meteorological conditions (e.g., incoming solar radiation K_L , air temperature T_a , humidity) at an extensive vegetated site, Q_E from this method is sensitive to the estimation of available energy (i.e. $Q^* - \Delta Q_S$), aerodynamic resistance r_a and surface resistance r_s . Hence, the critical vegetation related parameters (Table 1) are addressed with these caveats and/or assumptions:

- surface emissivity ε_0 and canopy water storage capacity S_i are assumed to the same as reported in Ward et al. (2016)
- aerodynamic resistance r_a is highly dependent on aerodynamic parameters that vary with canopy height (H_c) and leaf area index (LAI) (Kent et al., 2017; Appendix B). The temporal varying H_c is obtained from FLUXNET2015 (Sect. 2.2.3). LAI varies with phenology (Sect. 2.2.1)

Table 1 Parameters and the first process they are used in by SUEWS (i.e. most impact multiple variables). Sources (S) include this study (*), Ward et al. (2016) (W16) and FLUXNET2015 (F15,

146 *Pastorello et al. 2020) where values are given (Table: T#, Sect.: S#) or used in individual*
 147 *equations (E). Two key phenology periods are related to growing and senescence degree days*
 148 *(GDD, SDD).*

Category	Symbol	Definition	Value	E	S
Leaf Area Index (LAI)	LAI_{min}	Minimum LAI	TC1	3	*
	LAI_{max}	Maximum LAI	TC1	3	*
	$T_{base,GDD}$	Base temperature for SDD	TC1	4	*
	$T_{base,SDD}$	Base temperature for GDD	TC1	4	*
	GDD_{full}	Ending GDD at LAI_{max}	TC1	5	*
	SDD_{full}	Ending SDD at LAI_{min}	TC1	5	*
	$\omega_{1(2),GDD}$ (SDD)	Curve factors used in the LAI model dependent on GDD (SDD)	TC1	3	*
Radiation	$\alpha_{LAI_{min}}$	Albedo at LAI_{min}	TC1	6	*
	$\alpha_{LAI_{max}}$	Albedo at LAI_{max}	TC1	6	*
	ε_0	Emissivity	EveTr 0.98	DecTr 0.98	Grass 0.93
Storage heat flux	a_1, a_2, a_3	Objective Hysteresis Model (OHM) coefficients	TC2	7	*
Aerodynamic resistance	H_c	Vegetation height	F15 varies	F15	
	z_{0m}	Roughness length for momentum	S2.2.3/B	9/B1	*
	z_d	Zero plane displacement	S2.2.3/B	9/B1	*
Surface resistance	g_{max}	Maximum surface conductance	TC3	14	*
	G_K	Solar radiation related parameter	TC3	15	*
	$G_{q,base},$	Specific humidity related parameters	TC3	16	*
	$G_{q,shape}$	for base value and curve shape			
	G_T	Air temperature related parameter	TC3	17	*
	T_H, T_L	Temperature limits for switching off evaporation	TC3	17	*
	G_θ	Soil moisture related parameter	TC3	18	*
Water storage	$\Delta\theta_{WP}$	Soil moisture deficit at wilting point	TC3	18	*
	S_i	Canopy water storage capacity (mm)	EveTr 0.8	DecTr 1.3	Grass 1.9
				21	W16

149 2.2 Q_E related sub-schemes in SUEWS

150 2.2.1 Leaf Area Index (LAI) and Radiation

151 In SUEWS, leaf growth is triggered by reaching a critical growing degree days (GDD) threshold
 152 ($T_{base,GDD,i}$), and similarly for leaf fall by senescence degree days (SDD, $T_{base,SDD,i}$) using daily (d) mean
 153 air temperatures (T_d) based on the previous day ($d - 1$) for each vegetation type i (one of evergreen trees,
 154 deciduous trees and grass). For forests and grass we use (Järvi et al., 2011):

$$155 \quad LAI_{d,i} = \begin{cases} \min(LAI_{max,i}, LAI_{d-1,i}^{\omega_{1,GDD,i}} GDD_{d,i} \omega_{2,GDD,i} + LAI_{d-1,i}), & T_{base,SDD,i} < T_{d-1} < T_{base,GDD,i} \\ \max(LAI_{min,i}, LAI_{d-1,i} \omega_{1,SDD,i} (1 - SDD_{d,i}) \omega_{2,SDD,i} + LAI_{d-1,i}), & T_{base,GDD,i} < T_{d-1} < T_{base,SDD,i} \end{cases} \quad (4)$$

156 with $\omega_{1/2,GDD/SDD,i}$ curve factors needing to be derived. T_{d-1} is derived from the daily maximum
 157 (T_a^{\max}) and minimum (T_a^{\min}) air temperature of the previous day:

$$T_{d-1} = \frac{T_a^{\max} + T_a^{\min}}{2} \quad (5)$$

159 For each site and vegetation type i , the maximum and minimum LAI values ($LAI_{max,i}$, $LAI_{min,i}$) and
 160 $T_{base,GDD}$ and $T_{base,SDD}$ are determined for each site (Sect. 4.1). For sites at higher latitude (e.g. $> 60^\circ$),
 161 other characteristics – such as day-length and photo period – are helpful to account for corresponding LAI
 162 controls (Bauerle et al., 2012; Gill et al., 2015).

163 LAI influences several processes in SUEWS – such as dynamics of surface conductance (later in Sect.
 164 2.2.4) and albedo – the latter varies with daily *LAI* between a minimum ($\alpha_{LAI_{\min}}$) and maximum
 165 ($\alpha_{LAI_{\max}}$) by vegetation type:

$$\alpha_{d,i} = \alpha_{d-1,i} + (\alpha_{\text{LAI,max},i} - \alpha_{\text{LAI,min},i}) \frac{LAI_{d,i} - LAI_{d-1,i}}{LAI_{\text{max},i} - LAI_{\text{min},i}} \quad (6)$$

167 We note the SUEWS urban snow module (Järvi et al., 2014) is not used in this work, so focus on snow-
168 free conditions. This may bias some modelled α and subsequent fluxes, but evaluating the snow module is
169 a large task in its own right.

Within SUEWS the albedo is used with the observed incoming shortwave radiation and longwave radiation to obtain Q^* . In the current analyses, the observed incoming longwave (L_\downarrow) and modelled outgoing longwave radiation ($L_\uparrow = (1 - \varepsilon_0)L_\downarrow + \varepsilon_0\sigma T_s^4$ where ε_0 is the surface emissivity, σ is the Stefan Boltzmann constant ($\text{W m}^{-2} \text{ K}^{-4}$), and T_s is the surface temperature (K)) are used. Table 1 gives the emissivity values used.

175 2.2.2 Storage heat flux

176 Storage heat flux ΔQ_S is simulated with the objective hysteresis model (OHM (Grimmond et al., 1991)):

$$177 \quad \Delta Q_S = \sum_i f_i \left[a_{1,i} Q^* + a_{2,i} \frac{\partial Q^*}{\partial t} + a_{3,i} \right] \quad (7)$$

where f_i is the plan area (or 3-dimensional fraction area, Grimmond et al. 1991, Grimmond and Oke 1999) fraction of surface i , a_{I-3} the OHM coefficients (Sect. 4.2), and t time.

180 2.2.3 Aerodynamic resistance

181 Aerodynamic resistance r_a is obtained from (Järvi et al., 2011; van Ulden and Holtsslag, 1985):

$$182 \quad r_a = \frac{\left[\ln \left(\frac{z_m - z_d}{z_{0m}} - \psi_m(\zeta) \right) \right] \left[\ln \left(\frac{z_m - z_d}{z_{0v}} - \psi_v(\zeta) \right) \right]}{\kappa^2 u}, \quad (8)$$

183 where z_m is the measurement height for mean wind speed (u) and κ the von Kármán constant (0.4
 184 assumed); the aerodynamic parameters z_d (zero plane displacement height) and z_{0m} (roughness length for

185 the momentum) are estimated as a function of canopy height H_c (Garratt 1990; Grimmond and Oke,
 186 1999):

$$187 \quad z_{0m} = f_0 H_c \quad (9)$$

$$188 \quad z_d = f_d H_c \quad (10)$$

189 with f_0 and f_d being vegetation-based coefficients (see Appendix B for derivation details). The stability
 190 parameter $\zeta (= (z_m - z_d)/L)$ depends on the Obukhov length L . The atmospheric stability functions of
 191 momentum (ψ_m) and water vapour (ψ_v) for unstable condition are (Campbell and Norman, 1998):

$$192 \quad \begin{aligned} \psi_v &= 2 \ln \left[\frac{1 + (1 - 16\zeta)^{1/2}}{2} \right], \\ \psi_m &= 0.6\psi_v \end{aligned} \quad (11)$$

193 and for stable condition (Campbell and Norman, 1998; Högström, 1988):

$$194 \quad \begin{aligned} \psi_v &= -4.5 \ln(1 + \zeta) \\ \psi_m &= -6 \ln(1 + \zeta) \end{aligned} \quad (12)$$

195 2.2.4 Surface resistance (r_s) or conductance (g_s)

196 For completely wet surfaces, the surface resistance r_s is assumed to be 0 s m⁻¹ (i.e. potential evaporation is
 197 calculated from Eq. 3). Otherwise r_s , or its inverse, surface conductance g_s , is parameterised with a Jarvis-
 198 type formulation (Jarvis 1976) in SUEWS (Grimmond and Oke 1991; Järvi et al. 2011; Ward et al. 2016):

$$199 \quad r_s^{-1} = g_s = \sum_i \left(g_{\max,i} \cdot f_i \cdot g(LAI_i) \right) g(K_\downarrow) g(\Delta q) g(T_a) g(\Delta\theta_{soil}). \quad (13)$$

200 where g_s is determined from the i -th land cover areally weighted maximum surface conductance ($g_{\max,i}$)
 201 (with $f_i = 1$ for a “homogeneous” site) and environmental (x) rescaling functions ($g(x)$) ranging between
 202 [0, 1], including:

- 203 • Leaf area index (LAI) (Ward et al. 2016):

$$204 \quad g(LAI_i) = \frac{LAI_i}{LAI_{\max,i}} \quad (14)$$

205 is relative to the maximum LAI of land cover i ($LAI_{\max,i}$). For bare soil surfaces (i.e. no vegetation),
 206 when LAI is irrelevant $g(LAI_i) = 1$.

- 207 • incoming shortwave radiation (K_\downarrow) (Stewart 1988):

$$208 \quad g(K_\downarrow) = \frac{\frac{K_\downarrow}{G_K + K_\downarrow}}{\frac{K_{\downarrow,\max}}{G_K + K_{\downarrow,\max}}} \quad (15)$$

209 where the G_K parameter modifies the K_{\downarrow} response, relative to $K_{\downarrow,\max}$ the maximum observed incoming
 210 shortwave radiation ($= 1200 \text{ W m}^{-2}$): when K_{\downarrow} approaches G_K , $g(K_{\downarrow})$ reaches 50% of

211 $g_{s,\max} \left(\frac{K_{\downarrow,\max}}{G_K + K_{\downarrow,\max}} \right)^{-1}$ (i.e., $g_{s,\max}$ normalised by $\frac{K_{\downarrow,\max}}{G_K + K_{\downarrow,\max}}$). At night $g(K_{\downarrow})$ goes to 1.

212 • specific humidity deficit (Δq) (Ogink-Hendriks 1995):

$$213 \quad g(\Delta q) = G_{q,base} + (1 - G_{q,base})G_{q,shape}^{\Delta q} \quad (16)$$

214 where the specific humidity related parameters are for the ‘base’ $G_{q,base}$ and curve shape $G_{q,shape}$: the
 215 former indicates the limit of $g(\Delta q)$ when Δq approaches extremely large values, while the latter
 216 determines the curvature of the $g(\Delta q)$ (e.g., Fig. 9c)

217 • air temperature (T_a) (Stewart 1988):

$$218 \quad g(T_a) = \frac{(T_a - T_L)(T_H - T_a)^{T_c}}{(G_T - T_L)(T_H - G_T)^{T_c}} \quad (17)$$

219 where $T_c = \frac{T_H - G_T}{G_T - T_L}$ is a function of the lower (T_L) and upper (T_H) limits when the evaporation occurs, and
 220 G_T the optimal temperature for evaporation to reach its potential maximum.

221 • soil moisture deficit ($\Delta\theta_{soil}$, difference between soil water capacity and soil moisture content) (Ward
 222 et al. 2016):

$$223 \quad g(\Delta\theta_{soil}) = \frac{1 - \exp(G_\theta(\Delta\theta_{soil} - \Delta\theta_{WP}))}{1 - \exp(-G_\theta\Delta\theta_{WP})} \quad (18)$$

224 both the wilting point ($\Delta\theta_{WP}$) and a soil type dependent parameter (G_θ) vary with soil and plant type.
 225 Appendix A gives the equivalent form used in the NOAH model for Eqn. 13.

226 SUEWS has a running water balance that accounts for the multiple surface types. The amount of water on
 227 the canopy of each surface (C_i) (Grimmond & Oke 1991) is used to vary the surface resistance between
 228 dry and wet ($r_s = 0 \text{ s m}^{-1}$) by replacing r_s with r_{ss} (Shuttleworth, 1978):

$$229 \quad r_{ss} = \left[\frac{W}{r_b(s/\gamma + 1)} + \frac{(1 - W)}{r_s + r_b(s/\gamma + 1)} \right]^{-1} - r_b(s/\gamma + 1), \quad (19)$$

230 where W is a function of the relative amount of water present on each surface to its water storage capacity
 231 (S_i , Table 1):

$$232 \quad W = \begin{cases} 1 & C_i \geq S_i \\ \frac{K - 1}{K - S_i/C_i} & C_i < S_i \end{cases} \quad (20)$$

233 K depends on the aerodynamic and surface resistances:

$$234 \quad K = \frac{(r_s/r_a)/(r_a - r_b)}{r_s + r_b(s/\gamma + 1)}, \quad (21)$$

235 where r_b , the boundary layer resistance, is a function of friction velocity u_* (Shuttleworth, 1983):

$$r_b = 1.1u_*^{-1} + 5.6u_*^{\frac{1}{3}}. \quad (22)$$

Eqn. 19-22 ensure that the surface resistance r_{ss} has a smooth transition from 0 (a completely wet surface) to r_s (a dry surface).

239 3 Global observational datasets used

We use three global datasets FLUXNET2015 (Pastorello et al. 2020), MODIS (Myneni et al., 2015) and SoilGrids (Hengl et al. 2014) to derive the parameters. The FLUXNET2015 surface energy fluxes and other meteorology observations are used for three purposes: to derive parameter values, force simulations and evaluate simulations. The remotely sensed (MODIS) derived LAI products are used for the LAI related parameters. To derive soil moisture related parameters the SoilGrids data are used. Unlike the FLUXNET2015 data, the latter two datasets are spatially continuous.

246 3.1 FLUXNET2015

The FLUXNET2015 dataset (Pastorello et al. 2020) is the newest version of the FLUXNET data products. The gap-filled dataset includes 212 flux sites from around the world. Although the FLUXNET focus is on local scale ecosystem CO₂ eddy covariance (EC) fluxes, it also includes water and energy EC fluxes plus other meteorological and biological data. The biosphere-atmosphere exchange dataset contains more than 1500 site-years for the period to the end of 2014. The open source package ONEFlux (Open Network-Enabled Flux processing pipeline; <https://github.com/fluxnet/ONEFlux>) is used to produce FLUXNET2015 (Pastorello et al. 2020).

254 Half-hourly observations (Table 2) are used from 38 sites (Table 3) in three regions (Fig. 2). These sites
255 are selected to meet the following criteria (number of remaining sites that met the criteria):

- 256 1) sites with CC-BY 4.0 license (206/212).
257 2) data availability (56/206): require both MODIS LAI data (available from 2002, Sect. 3.2) and long-
258 term continuity (defined here as ≥ 3 years for the multiple needs).
259 3) model capacity (38/56): the SUEWS v2020a LAI scheme is forced with only air temperature and not
260 other variables (e.g., rainfall) which may strongly influence phenology at some sites (Appendix D).
261 Hence, these sites are excluded.

Unfortunately, no datasets are left after selection based on the above criteria for some regions (Fig. 2), including Africa, Asia and South America.

264 As SUEWS allows any grid cell to have three vegetation or plant functional types (PFT), with the sub-
 265 type or properties varying between grids, we subdivide the 38 sites into three classes using IGBP (Table
 266 3) (code, number of sites):
 267 a) Evergreen trees/shrubs (EveTr, 13): Evergreen Needleleaf Forests (ENF, 12), Evergreen Broadleaf
 268 Forests (EBF, 1)
 269 b) Deciduous trees/shrubs (DecTr, 11): Mixed Forests (MF, 2), Deciduous Broadleaf Forests (DBF, 5),
 270 Open Shrublands (OSH, 1), Woody Savannas (WSA, 1), Savannas (SAV, 2).
 271 c) Grass (14): Grasslands (GRA, 8), Croplands (CRO, 6).

272 The landscape heterogeneity of many FLUXNET EC flux measurements sites have been systematically
 273 examined by Stoy et al. (2013) using satellite imagery. Of the sites they examined, they found them to be
 274 located within homogeneous parts of the targeted PFT, but the larger landscape (~ 20 km) may have
 275 considerable variability. As a FLUXNET site is typically assigned to one PFT for land surface model
 276 development/evaluation (e.g. Stöckli et al. 2008, Zhang et al. 2017, Chu et al. 2021), we configure each as
 277 a homogeneous grid cell and assume $f_i=1$.

278 **Table 2** FLUXNET2015 (Pastorello et al. 2020) variables used in this work to derive parameters (P),
 279 to force (F) model simulations and to evaluate (E) models.

Variable	Unit	Description	Usage
H_c	m (agl)	Canopy height	P
K_\uparrow	W m^{-2}	Outgoing solar radiation	P
K_\downarrow	W m^{-2}	Incoming solar radiation	P, F
L_\uparrow	W m^{-2}	Outgoing longwave radiation	P
L_\downarrow	W m^{-2}	Incoming longwave radiation	F
P	mm h^{-1}	Precipitation rate	P, F
PA	Pa	Station atmospheric pressure	P, F
Q^*	W m^{-2}	Net all-wave radiation	P
Q_E	W m^{-2}	Latent heat flux	P, E
Q_H	W m^{-2}	Sensible heat flux	P
RH	%	Relative humidity	P, F
T_a	°C	Air temperature	P, F
u	m s^{-1}	Wind speed	P, F
u^*	m s^{-1}	Friction velocity	P
VPD	Pa	Vapour pressure deficit	P
θ	$\text{m}^3 \text{m}^{-3}$	Volumetric soil water content	P

280
 281

282 **Table 3** Key information about the FLUXNET2015 sites (Pastorello et al. 2020), and their DOI reference) used in this work: site name
 283 (country-name) with altitude above sea level (asl)) or anemometer sensor height above ground level (agl). More details about the
 284 simulation and analyses given in Sect. 5.1. The land cover type as defined based on IGBP (International Geosphere–Biosphere
 285 Programme) by the FLUXNET curators (<https://fluxnet.org/data/badm-data-templates/igbp-classification/>) with the crops (CRO) being: 1 -
 286 Rotation: cereal, potato, sugar beet (Moureaux et al., 2006), 2 - Rotation: winter barley, rapeseed, winter wheat, maize and spring barley
 287 at DE-Kli (Prescher et al., 2010), 3 - Continuous maize (<https://doi.org/10.18140/FLX/1440084>); 4 - Rotation: maize and soybean
 288 (<https://doi.org/10.18140/FLX/1440085>), 5- Rotation: maize and soybean (<https://doi.org/10.18140/FLX/1440086>). The SUEWS
 289 recommended vegetation/PFT class (informed by IGBP) data as used in this paper are given in Sun et al. (2021).

Site	Latitude (°)	Longitude (°)	Altitude (m asl)	Measurement height z_m (m agl)	Parameter derivation period	Evaluation period	Temporal resolution (min)	No. of valid entries	IGBP	SUEWS	DOI
AT-Neu	47.1167	11.3175	970	3.0	2005 – 2012	2002 – 2004	30	33582	GRA	Grass	10.18140/FLX/1440121
AU-ASM	-22.283	133.249	607	11.7	2013 – 2014	2010 – 2012	30	33710	SAV	DecTr	10.18140/FLX/1440194
AU-DaS	-14.1593	131.388	73	21.0	2011 – 2014	2008 – 2010	30	34022	SAV	DecTr	10.18140/FLX/1440122
AU-Gin	-31.3764	115.714	51	15.0	2011 – 2011	2011 – 2013	30	28766	WSA	DecTr	10.18140/FLX/1440199
AU-Wom	-37.4222	144.094	705	30.0	2013 – 2014	2010 – 2012	30	34434	EBF	EveTr	10.18140/FLX/1440207
BE-Lon	50.5516	4.74623	167	2.7	2007 – 2014	2004 – 2006	30	34486	CRO ¹	Grass	10.18140/FLX/1440129
CA-Gro	48.2167	-82.1556	340	43.3	2006 – 2014	2003 – 2005	30	32669	MF	DecTr	10.18140/FLX/1440034
CA-Oas	53.6289	-106.198	530	39.0	1995 – 2010	2002 – 2004	30	34885	DBF	DecTr	10.18140/FLX/1440043
CA-Qfo	49.6925	-74.3421	382	24.0	2006 – 2010	2003 – 2005	30	32980	ENF	EveTr	10.18140/FLX/1440045
CA-SF2	54.2539	-105.878	520	9.1	2005 – 2005	2002 – 2004	30	31701	ENF	EveTr	10.18140/FLX/1440047
CA-SF3	54.0916	-106.005	540	20.0	2005 – 2007	2002 – 2004	30	34618	OSH	DecTr	10.18140/FLX/1440048
CA-TP4	42.7102	-80.3574	184	28.0	2005 – 2014	2002 – 2004	30	34533	ENF	EveTr	10.18140/FLX/1440053
CH-Cha	47.2102	8.41044	393	2.4	2006 – 2014	2005 – 2007	30	34480	GRA	Grass	10.18140/FLX/1440131
CH-Dav	46.8153	9.85591	1639	35.0	2005 – 2014	2002 – 2004	30	24456	ENF	EveTr	10.18140/FLX/1440132
CH-Oe1	47.2858	7.73194	450	1.2	2005 – 2008	2002 – 2004	30	34768	GRA	Grass	10.18140/FLX/1440135
DE-Gri	50.95	13.5126	385	3.0	2007 – 2014	2004 – 2006	30	34659	GRA	Grass	10.18140/FLX/1440147
DE-Hai	51.0792	10.4522	430	42.0	2005 – 2012	2002 – 2004	30	35028	DBF	DecTr	10.18140/FLX/1440148
DE-Kli	50.8931	13.5224	478	3.5	2007 – 2014	2004 – 2006	30	33933	CRO ²	Grass	10.18140/FLX/1440149
DE-Lkb	49.0996	13.3047	1308	9.0	2012 – 2014	2009 – 2011	30	29726	ENF	EveTr	10.18140/FLX/1440214
DE-Obe	50.7867	13.7213	734	30.0	2011 – 2014	2008 – 2010	30	33872	ENF	EveTr	10.18140/FLX/1440151
FI-Hyy	61.8474	24.2948	181	24.0	2005 – 2014	2002 – 2004	30	30979	ENF	EveTr	10.18140/FLX/1440158
FR-LBr	44.7171	-0.7693	61	41.5	2005 – 2008	2002 – 2004	30	34364	ENF	EveTr	10.18140/FLX/1440163
IT-Col	41.8494	13.5881	1560	32.0	2005 – 2014	2002 – 2004	30	22918	DBF	DecTr	10.18140/FLX/1440167
IT-Sro	43.7279	10.2844	6	22.5	2005 – 2012	2002 – 2004	30	26961	ENF	EveTr	10.18140/FLX/1440176
IT-Tor	45.8444	7.57806	2160	2.7	2008 – 2014	2008 – 2010	30	33126	GRA	Grass	10.18140/FLX/1440237
NL-Loo	52.1666	5.74356	25	26.0	2005 – 2014	2002 – 2004	30	34098	ENF	EveTr	10.18140/FLX/1440178
US-AR1	36.4267	-99.42	611	2.8	2012 – 2012	2009 – 2011	30	35024	GRA	Grass	10.18140/FLX/1440103
US-CRT	41.6285	-83.3471	180	2.0	2014 – 2014	2011 – 2013	30	34895	CRO ³	Grass	10.18140/FLX/1440117
US-Goo	34.2547	-89.8735	87	4.0	2005 – 2007	2002 – 2004	30	30848	GRA	Grass	10.18140/FLX/1440070

US-IB2	41.8406	-88.241	226.5	3.8	2005 – 2011	2004 – 2006	30	34339	GRA	Grass	10.18140/FLX/1440072
US-Me6	44.3233	-121.608	998	12.0	2013 – 2015	2010 – 2012	30	32141	ENF	EveTr	10.18140/FLX/1440099
US-MMS	39.3232	-86.4131	275	46.0	2005 – 2014	2002 – 2004	60	17508	DBF	DecTr	10.18140/FLX/1440083
US-Ne1	41.1651	-96.4766	361	3.0	2005 – 2013	2002 – 2004	60	17450	CRO ³	Grass	10.18140/FLX/1440084
US-Ne2	41.1649	-96.4701	362	3.0	2005 – 2013	2002 – 2004	60	17407	CRO ⁴	Grass	10.18140/FLX/1440085
US-Ne3	41.1797	-96.4397	363	3.0	2005 – 2013	2002 – 2004	60	17351	CRO ⁵	Grass	10.18140/FLX/1440086
US-NR1	40.0329	-105.546	3050	21.5	2005 – 2014	2002 – 2004	30	35023	ENF	EveTr	10.18140/FLX/1440087
US-Oho	41.5545	-83.8438	230	32.0	2007 – 2013	2004 – 2006	30	31180	DBF	DecTr	10.18140/FLX/1440088
US-Syv	46.242	-89.3477	540	36.0	2005 – 2014	2002 – 2004	30	27276	MF	DecTr	10.18140/FLX/1440091

290



291
292
293
294
295

Figure 2 Location of FLUXNET sites (Table 3) coded by into three land cover types: deciduous trees (DecTr), evergreen trees (EveTr), and grass (Grass). Source of base map: © OpenStreetMap contributors 2021. Distributed under the Open Data Commons Open Database License (ODbL) v1.0.

296 **3.2 MODIS LAI**

297 The NASA Moderate Resolution Imaging Spectroradiometer (MODIS, (Nishihama et al., 1997)) four-day
298 composite product MCD15A3H (Myneni et al., 2015) with 500 m resolution is treated as ‘observed’ LAI.
299 Product data are available from 2002. We use the Fixed Sites Subsetting and Visualization Tool (ORNL
300 DAAC 2018) for FLUXNET dataset to extract the MCD15A3H time series. To obtain a daily timeseries
301 we linearly interpolate between values, for parameter derivation (Sect. 4.1).

302 **3.3 Soil information**

303 The SoilGrids (Hengl et al. 2014) database provides soil properties (i.e., organic carbon, bulk density,
 304 Cation Exchange Capacity (CEC), pH, soil texture fractions and coarse fragments) at seven depths (0,
 305 0.05, 0.15, 0.30, 0.60, 1.00 and 2.00 m), as well as a bedrock depth prediction, World Reference Base
 306 (WRB) and USDA soil classes. We use the SoilGrids250m (Hengl et al. 2017) version, with its ~280
 307 raster layers, to obtain the parameters (Table 4) to derive soil moisture deficit at wilting point ($\Delta\theta_{wp}$ in
 308 mm) for soil moisture related calculations (e.g. Eqn. 18).

309 The difference in soil moisture between field capacity (θ_{FC} in mm) and wilting point (θ_{WP} in mm) are used
 310 with parameters defined as (Saxon and Rawls 2006):

$$311 \quad \Delta\theta_{wp} = \theta_{FC} - \theta_{WP} = (W_{FC} - W_{WP})(1 - f_{CF}) d_r \quad (23)$$

312 with

$$313 \quad W_{FC} = k_{FC} + (1.283 \cdot k_{FC}^2 - 0.374 \cdot k_{FC} - 0.015) \quad (24)$$

314 using the weight fractions of sand f_{sand} , clay f_{clay} and f_{OM} organic matter

$$315 \quad \begin{aligned} k_{FC} = & -0.251 \cdot f_{sand} + 0.195 \cdot f_{clay} + 0.011 \cdot f_{OM} \\ & + 0.006 \cdot (f_{sand} f_{OM}) \\ & - 0.027 \cdot (f_{clay} f_{OM}) \\ & + 0.452 \cdot (f_{sand} f_{clay}) + 0.299 \end{aligned} \quad (25)$$

316 and

$$317 \quad W_{WP} = k_{WP} + (0.14 \cdot k_{WP} - 0.02) \quad (26)$$

318 where

$$319 \quad \begin{aligned} k_{WP} = & -0.024 \cdot f_{sand} + 0.487 \cdot f_{clay} + 0.006 \cdot f_{OM} \\ & + 0.005 \cdot (f_{sand} f_{OM}) \\ & - 0.013 \cdot (f_{clay} f_{OM}) \\ & + 0.068 \cdot (f_{sand} f_{clay}) + 0.031 \end{aligned} \quad (27)$$

320 **Table 4** Soil related parameters obtained from the SoilGrids (Hengl et al. 2014) database for each
 321 site (Table 3) at 250 m resolution for seven depths (Sect. 3.3). Values for each site (Table 3) are
 322 given in Sun et al. (2021).

Parameter	Unit	Description
d_r	mm	Soil depth
f_{CF}	$m m^{-3}$	coarse fragment fraction
f_{clay}	$kg kg^{-1}$	clay fraction
f_{sand}	$kg kg^{-1}$	sand fraction
f_{silt}	$kg kg^{-1}$	silt fraction
f_{OM}	$kg kg^{-1}$	organic carbon fraction
ρ_{bulk}	$kg m^{-3}$	Bulk density

323 **4 Parameter derivation for vegetated land covers: workflows and results**

324 **4.1 Leaf area index (LAI) and albedo related parameters**

325 LAI is a key phenology parameter in SUEWS, it moderates albedo (α) and therefore surface radiative
 326 exchanges. LAI changes also modify both aerodynamic roughness parameters (roughness length z_0 , zero
 327 plane displacement height z_d) (e.g. Kent et al. 2017) impacting aerodynamic resistance (r_a) and surface
 328 resistance (r_s). LAI directly moderates Q_E and canopy interception capacity, which modifies when
 329 potential evaporation occurs and aspects of the water balance.

330 As the SUEWS LAI equation (Eqn. 4) makes global optimisation techniques numerically challenging to
 331 derive all the required parameters, we take a two-step approach (Fig. 3):

332 *I) Approximating growing stages using an asymmetric Tukey window function:*

333 Tukey or cosine-tapered window (TW) is used in signal processing applications when data needs to be
 334 processed in short segments. It is defined (Bloomfield 2000):

$$335 \quad TW(x, a) = \begin{cases} 1 & (0 < a < 1 \wedge a - 2x - 1 \leq 0 \wedge a + 2x - 1 \leq 0) \vee (a = 1 \wedge x = 0) \vee \left(a \leq 0 \wedge -\frac{1}{2} \leq x \leq \frac{1}{2}\right) \\ \frac{1}{2}(\cos(2\pi x) + 1) & a > 1 \wedge -\frac{1}{2} \leq x \leq \frac{1}{2} \\ \frac{1}{2} \left(\cos \left(\frac{2\pi \left(-\frac{a}{2} + x + \frac{1}{2} \right)}{a} \right) + 1 \right) & 0 < a \leq 1 \wedge x \geq -\frac{1}{2} \wedge a - 2x - 1 > 0 \\ \frac{1}{2} \left(\cos \left(\frac{2\pi \left(\frac{a}{2} + x - \frac{1}{2} \right)}{a} \right) + 1 \right) & 0 < a \leq 1 \wedge a + 2x - 1 > 0 \wedge x \leq \frac{1}{2} \\ 0 & |x| > \frac{1}{2} \end{cases} \quad (28)$$

336 where x is the independent variable and a the curve shape factor. We propose an asymmetric form of
 337 Tukey window (aTW) to approximate the intra-annual LAI dynamics:

$$338 \quad aTW(x, a, b, x_0, l) = \begin{cases} TW\left(\frac{x - x_0}{l}, a\right) & x < x_0 \\ TW\left(\frac{x - x_0}{l}, b\right) & x \geq x_0 \end{cases} \quad (28)$$

339 where b is a curve shape factor for different segments, x_0 the segment parameter, and l the rescaling
 340 factor.

341 To demonstrate this we use the US-MMS site (Table 3), to fit the intra-annual LAI dynamics using an
 342 aTW curve (blue line, Fig. 4) to determine different phenological stages (shading, Fig. 4) and
 343 subsequently derive several related parameters:

- 344 ▪ LAI_{min} : 5th percentile of LAI values before the growth and after the senescence
- 345 ▪ LAI_{max} : 75th percentile of LAI values after the growth and before the senescence

- 346 □ $T_{\text{base,GDD}}$: 99th percentile of air temperatures before the growth
 347 □ $T_{\text{base,SDD}}$: 10th percentile of air temperature after the growth and before the senescence.
 348 □ GDD_{full} : GDD at the end of growth based on $T_{\text{base,GDD}}$
 349 □ SDD_{full} : SDD at the end of senescence based on $T_{\text{base,SDD}}$
 350 □ $\alpha_{\min} / \alpha_{\max}$: 10th/90th percentile of daily albedo values after the growth and before the senescence. A
 351 daily albedo is calculated from 30/60 min FLUXNET observations of incoming and outgoing
 352 shortwave radiation for the period 10:00 to 14:00 (local standard time). To remove outliers a
 353 clustering method is applied (*ClusterClassify* of *Mathematica* v12.3.1 Wolfram Research 2020).
 354 For example, at some high-latitude sites (e.g. CA-Oas) snow occurs, the winter values are based on
 355 data from shortly after senescence to shortly before growth (next spring) and the clustering approach
 356 removes the snow period albedo values.

357 For evergreen and deciduous trees, $\alpha_{LAI,\min}$ ($\alpha_{LAI,\max}$) in Eqn. 6 typically corresponds to α_{\min} (α_{\max}), while
 358 for grassland a reverse relation holds (i.e. $\alpha_{LAI,\min}$ corresponds to α_{\max} and vice versa; see Cescatti et al.
 359 2012 for a detailed analysis of albedo dynamics at FLUXNET sites).

360 2) *Deriving curve factors used in SUEWS LAI scheme:*

361 With the parameters derived in step 1, we can determine the curve factors $\omega_{1/2,GDD/SDD}$ by minimising the
 362 bias between MODIS observed (open triangle, Fig. 4) and SUEWS simulated (red line, Fig. 4) LAI
 363 values.

364 The derived LAI related parameters for the 38 FLUXNET sites vary between different land cover groups
 365 (Table 5, Fig. 5). The derived $LAI_{\max/\min}$ results are consistent with those reported in the literature (Asaadi
 366 et al. 2018). For EveTr sites, the large contrast between LAI_{\max} and LAI_{\min} in the ENF sites analysed here
 367 is consistent with MODIS derived LAI for ENF having larger seasonal variability than EBF (Heiskanen et
 368 al. 2012), but some of this is caused by a known issue of particularly low winter values (Garrigues et al.
 369 2008).

370 Given the global availability of MODIS LAI and reanalysis-based air temperature datasets, we suggest
 371 the LAI related parameters be derived following this workflow (Fig. 3) to set parameters for SUEWS
 372 simulations. This can be done independent of the availability of flux tower observations.

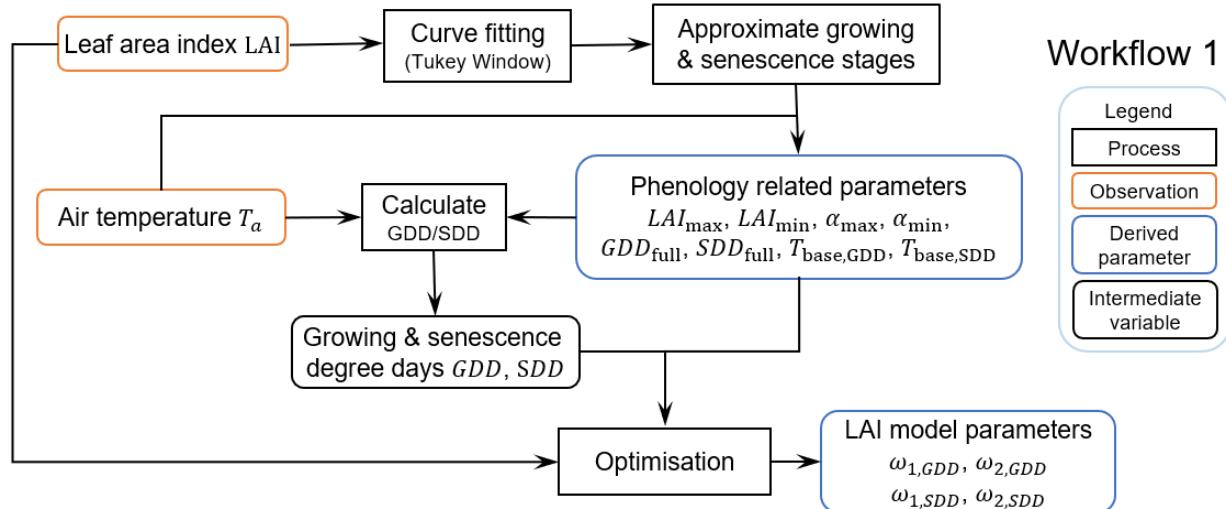


Figure 3 Workflow 1 (Fig. 1) for deriving LAI and albedo related parameters. Related Jupyter notebooks are provided in Sun et al. (2021).

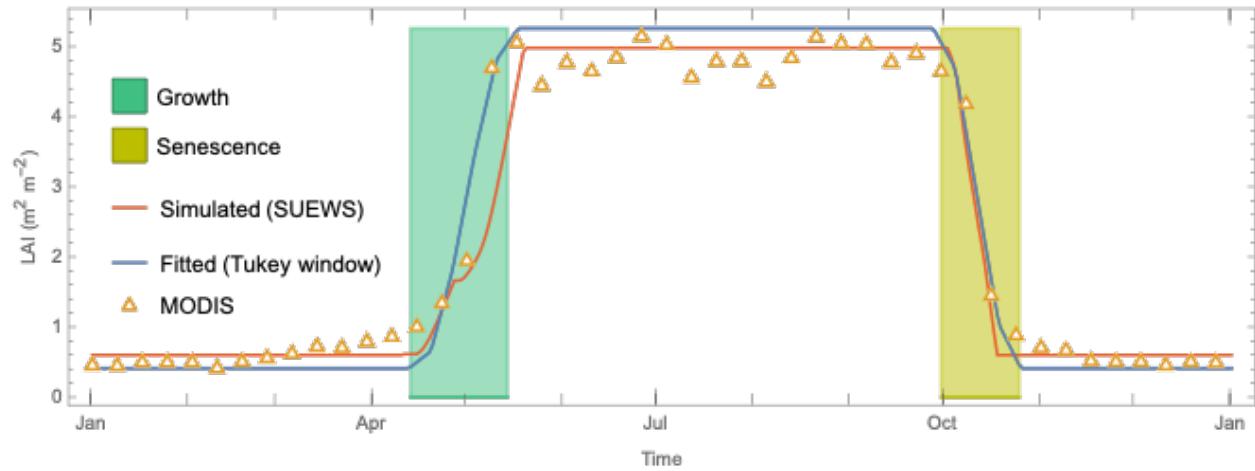
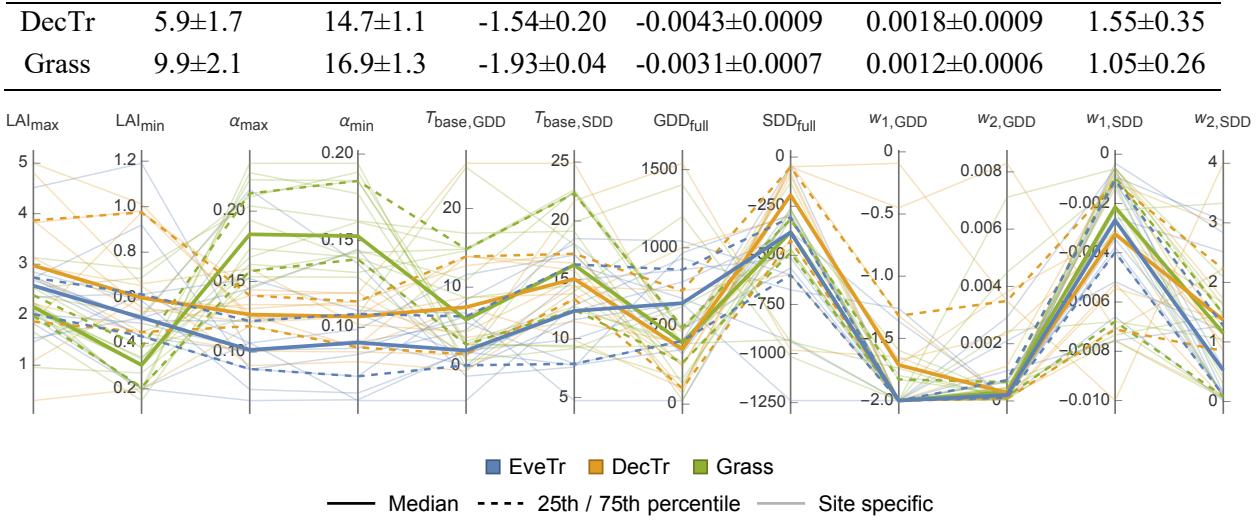


Figure 4 Intra-annual LAI dynamics at US-MMS multi-year (2002–2014) ensemble median derived from MODIS observations (open triangle, Sect. 3.2) and simulated by SUEWS temperature-based LAI scheme (Eqn. 4) (orange line) with Tukey window fit (blue line, Sect. 4.1) using to derive the leaf-on or growth period (green shading) and senescence (yellow shading) periods.

Table 5 Inter-site variability within the three vegetation classes of LAI and albedo related parameters (Eqn. 4, Sect. 4.1) shown by mean and standard deviation. For individual site and by PFT type parameters see Appendix C (for digital version see Sun et al. 2021). Median and interquartile range (IQR) see Fig. 5.

	α_{\min} [-]	α_{\max} [-]	LAI_{\max} [$m^2 m^{-2}$]	LAI_{\min} [$m^2 m^{-2}$]	GDD_{full} [$^\circ C day$]	SDD_{full} [$^\circ C day$]
EveTr	0.093 ± 0.007	0.113 ± 0.010	2.46 ± 0.20	0.55 ± 0.07	625 ± 83	-501 ± 87
DecTr	0.102 ± 0.004	0.125 ± 0.006	2.9 ± 0.4	0.66 ± 0.07	475 ± 137	-273 ± 89
Grass	0.156 ± 0.007	0.185 ± 0.009	2.15 ± 0.13	0.35 ± 0.06	484 ± 102	-482 ± 74
	$T_{base,GDD}$ [$^\circ C$]	$T_{base,SDD}$ [$^\circ C$]	$\omega_{1,GDD}$ [-]	$\omega_{1,SDD}$ [-]	$\omega_{2,GDD}$ [-]	$\omega_{2,SDD}$ [-]
EveTr	2.8 ± 1.2	12.5 ± 1.2	-1.89 ± 0.07	-0.0031 ± 0.0006	0.00067 ± 0.00023	0.96 ± 0.31



385
386
387
388

Figure 5 Variation in LAI related parameters (12 labelled vertical lines, Sect. 2.2.1) within three land cover classes (colour) showing median (thick line), interquartile range (IQR, 25th and 75th percentiles, dashed lines), site-specific values (thin lines).

389 4.2 Storage heat flux coefficients

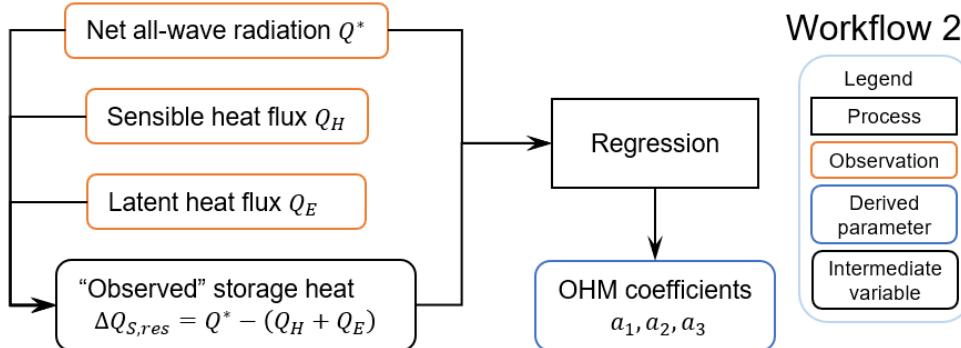
390 To calculate the storage heat flux ΔQ_S , the required OHM coefficients (Eqn. 7), can be determined from
391 observed net all-wave radiation and observed storage heat flux, using ordinary linear regression. As the
392 FLUXNET sites chosen are considered to be homogeneous, we derive coefficients for each site.

393 Ideally the storage heat flux measurements would include each of the components than are heating and
394 cooling down on a daily basis, such as the soil, trunk, branches, leaves and air volume in a forest (e.g.
395 McCaughey et al. 1985, Oliphant et al. 2004). However, these measurements are unavailable in the
396 FLUXNET2015 dataset. Hence, we calculate a residual flux $\Delta Q_{S,res} = Q^* - (Q_H + Q_E)$ by assuming
397 energy balance closure. This has the problem of accumulating the net measurement errors in this term
398 (Grimmond et al. 1991, Grimmond and Oke 1999).

399 The derived OHM coefficients (Fig. 6) can be determined by season (Anandakumar 1999; Ward et al.,
400 2016; Sun et al., 2017). We distinguish warm (“summer”) and cold (“winter”) seasons using months
401 (summer: Northern Hemisphere JJA; Southern Hemisphere: DJF; winter: DJF (JJA), respectively). For
402 simplicity, we omit periods when LAI may be changing rapidly. If the daily mean air temperature is
403 warmer/cooler than the annual mean of daily median temperature, then summer/winter OHM coefficients
404 are used in the simulations.

405 The OHM coefficients derived for the 38 FLUXNET sites (Table 6, Fig. 7) vary between land cover types
406 and seasons. For each land cover type, a_1 and a_3 are notably larger in winter than in summer while the
407 seasonal difference in a_2 is relatively small. Thus the overall fraction of heat stored does not vary much

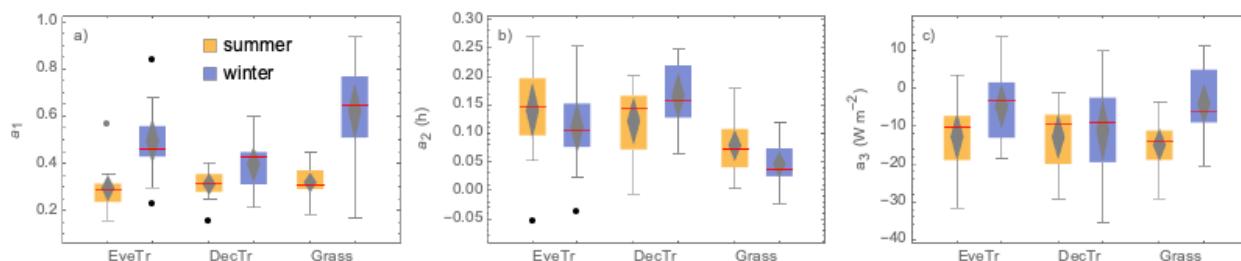
408 but diurnal hysteresis effect is weaker in winter. These results are consistent with previous analytical
 409 results (Sun et al., 2017). Within each PFT, there is larger variability in a_2 and a_3 (cf. a_1), notably for
 410 evergreen and deciduous trees, suggesting using the most appropriate site values (e.g. medians) may
 411 improve predictions of the storage heat flux. In addition to the values derived here, we note that more
 412 detailed ΔQ_S observations are available for vegetated sites to derive such OHM coefficients (e.g.
 413 McCaughey (1985), Oliphant et al. (2004)).



414
 415 **Figure 6** Workflow 2 (Fig. 1) to derive OHM coefficients. Related notebooks are provided in Sun et
 416 al. (2021).

417 **Table 6** As Table 5, but for OHM related parameters (Sect. 4.2). See Fig .7 for comparison and
 418 Table C2 for site specific values.

	$a_1 [-]$		$a_2 [h]$		$a_3 [W m^{-2}]$	
	summer	winter	summer	winter	summer	winter
EveTr	0.294 ± 0.027	0.49 ± 0.04	0.140 ± 0.023	0.110 ± 0.021	-12.7 ± 3.0	-4.8 ± 2.8
DecTr	0.312 ± 0.021	0.396 ± 0.035	0.122 ± 0.019	0.166 ± 0.019	-12.9 ± 2.8	-11.0 ± 4.0
Grass	0.318 ± 0.020	0.62 ± 0.06	0.079 ± 0.013	0.046 ± 0.011	-14.9 ± 2.0	-4.1 ± 2.5



419
 420 **Figure 7** Boxplots showing variability of OHM coefficients between land covers (EveTr, DecTr and
 421 Grass) and seasons (summer and winter): a) a_1 b) a_2 and c) a_3 . Boxes (25th and 75th percentiles),
 422 whiskers (5th and 95th percentiles), with median (red line) and mean (middle grey diamond, with
 423 95% confidence level (top and bottom) values, and outliers (dots).

4.3 Surface conductance related parameters

424 As the Jarvis-type formulation of stomatal/surface conductance is widely used for many land cover types,
 425 many parameter sets exist (e.g. Stewart 1988; Grimmond and Oke 1991; Ogink-Hendriks 1995; Wright et

427 al. 1995; Bosveld and Bonten 2001; Järvi et al. 2011). Hoshika et al.’s (2018) comprehensive meta-
428 analysis of published Jarvis-type stomatal conductance parameter values includes major woody and crop
429 plants broadly similar to PFTs examined here.

430 Conventionally, the surface conductance parameters are derived by minimising the bias between the
431 parameterised (Eqn. 14) and so-called “observed” values derived from an inverse form of Penman-
432 Monteith equation (Eqn. 3):

$$433 \frac{1}{g_s} = r_s = \left[\frac{s}{\gamma} \frac{Q_H}{Q_E} - 1 \right] r_a + \frac{\rho c_p VPD}{\gamma Q_E}. \quad (29)$$

434 This requires the surface be dry (Section 2.2.4) which we define as being without recorded rainfall in 24
435 h.

436 However, as the optimisation may not return values because of the complexity in Eqn. 14 and the
437 challenge of interpreting the derived parameter values, we adopt Matsumoto et al.’s (2008) approach to
438 derive these parameters. Rather than using all the data combinations for g_s , the upper boundary of each
439 forcing variable component (e.g. $g(K_{\downarrow})$) is considered as the response for unconstrained conditions.

440 Specifically, the workflow is (Fig. 8):

- 441 1) Calculate aerodynamic resistance r_a (Eqn. 8) with roughness length z_{0m} and displacement height z_d
442 derived from observed wind speed under neutral conditions (Appendix B).
- 443 2) Calculate “observed” surface conductance $g_{s,obs}$ (Eqn. 30).
- 444 3) Remove outliers from $g_{s,obs}$ data (step 2) iteratively (i.e. values larger than the 98th percentile until
445 difference between 98th and 99th percentiles is < 1 mm s⁻¹). The remainder are used for deriving
446 parameters.
- 447 4) Determine the upper boundaries of g_s curves with each component variable. To demonstrate this we
448 use the US-MMS site (Fig. 9). First, original data are binned (sizes: 50 W m⁻² for K_{\downarrow} , 2 °C for T_a , 2 kg
449 kg⁻¹ for Δq and 10 mm for $\Delta\theta$), the 95th percentiles of these bins are sampled 100 times (bootstrapped)
450 to determine anchor points (red dots, Fig. 9). Second, the parameters are fit to the g_s related curves
451 (Eqn. 14–17) using the anchor points using **NonlinearModelFit** of *Mathematica* v12.3.1 (Wolfram
452 Research 2008).

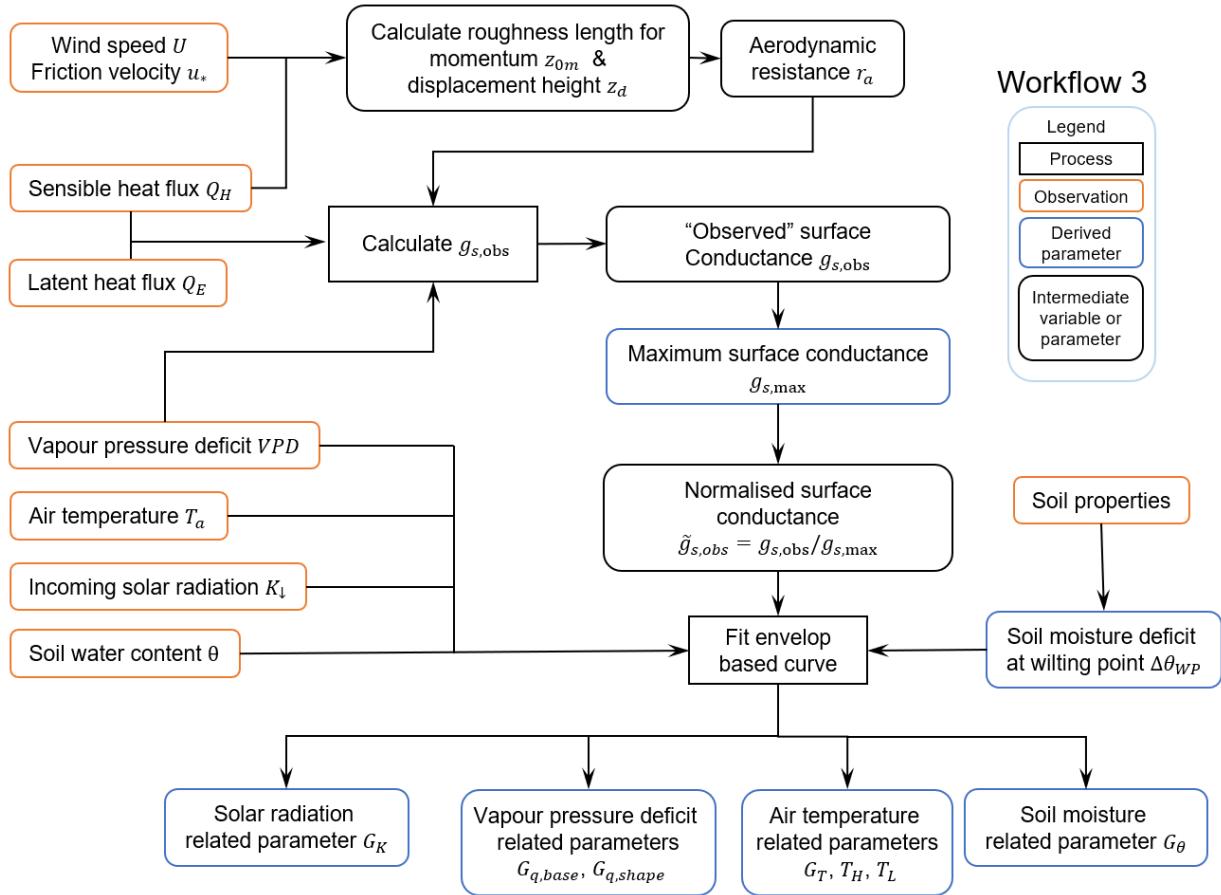
453 The derived surface conductance parameters for the 38 FLUXNET sites (Table 7 and C3) have different
454 intra-PFT variability based on the IQR (dotted lines, Fig. 10) and demonstrates the benefit of the
455 observations and of deriving site-values when possible. It may help in selecting appropriate PFT from
456 other sources (e.g. NOAH values in Appendix A). The g_{max} results are consistent with Hoshika et al.
457 (2018) in terms of inter-PFT ordering (Grass > EveTr and DecTr). The grass and crop values are

458 comparable (Table C3) to Hoshika et al. (2018); however, our derived deciduous trees values are smaller
459 (22 cf. 31 mm s⁻¹) and evergreen trees values larger (20 cf. 12 mm s⁻¹).

460 A consistent $G_{q,shape}$ (eqn 16) value (0.9 units) is obtained for all sites, implying potential for
461 improvements to the $g(\Delta q)$ relation between g_s and Δq (e.g. other formulations $g_s(\Delta q)$ in Matsumoto et al.
462 (2008)) in future SUEWS development. This would be beneficial as there is a clear “plateau” observed
463 for low Δq (Fig. 9c). Similar issues are found in $g(\Delta\theta)$ for soil moisture related parameters. Although the
464 parameters derived here are the ‘best’ fit to the g_s forms in SUEWS v2020a, for each component variable
465 multiple g_s formulations exist with a range of variable fitting performance (e.g. Fig A1 in Ward et al.
466 2016). Here, we focus on *deriving the parameters* rather than *proposing new or more appropriate
467 formulations*.

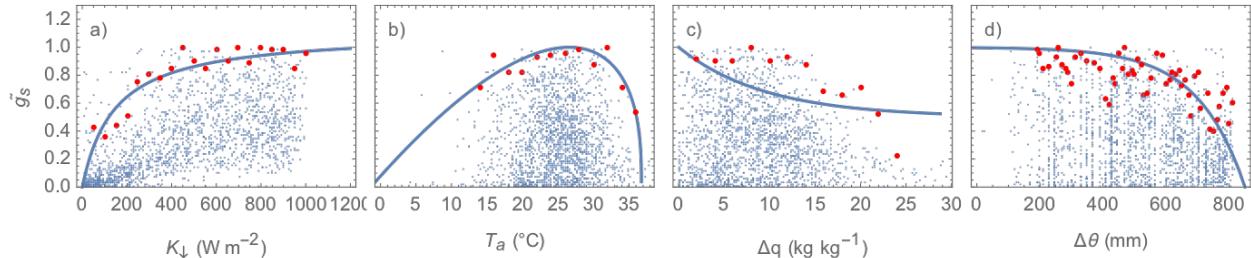
468 Solar radiation related G_K parameter is linked to the level of incoming solar radiation needed for
469 evapotranspiration to occur. Given incoming solar radiation intensity varies with latitude, we see G_K
470 generally decreases polewards (Fig. 11a), suggesting geographical location could be used as a proxy for
471 deriving G_K .

472 The air temperature related G_T parameter indicates the optimal temperature for evapotranspiration to
473 reach its probable maxima. G_T appears to have a negative relation with latitude, but the two other
474 temperature parameters (T_L and T_H) have a very weak (none) with latitude (Fig. 11b). This suggests a
475 universal temperature range between T_L and T_H might be applicable across different sites while G_T should
476 be determined on a site-by-site basis.



477

478 **Figure 8** Workflow 3 (Fig. 1) for deriving surface conductance related parameters. Related
 479 notebooks are provided in Sun et al. (2021).

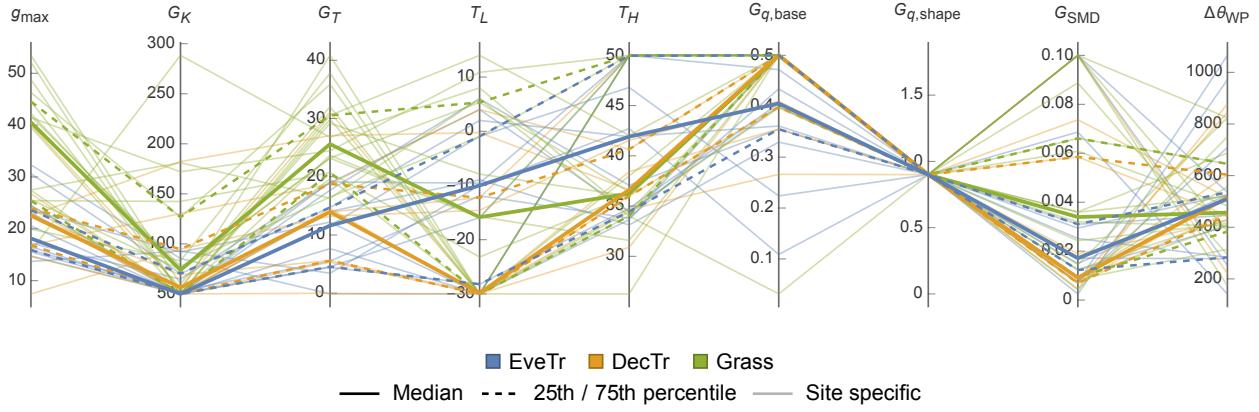


480

481 **Figure 9** Derived relations (blue lines) between normalised surface conductance \tilde{g}_s and (a) incoming
 482 solar radiation K_l , (b) air temperature T_a , (c) specific humidity deficit Δq , and (d) soil moisture
 483 deficit $\Delta\theta$ based on anchor data points (red dots) after bootstrapping of observations (blue dots)
 484 for an example site (US-MMS).

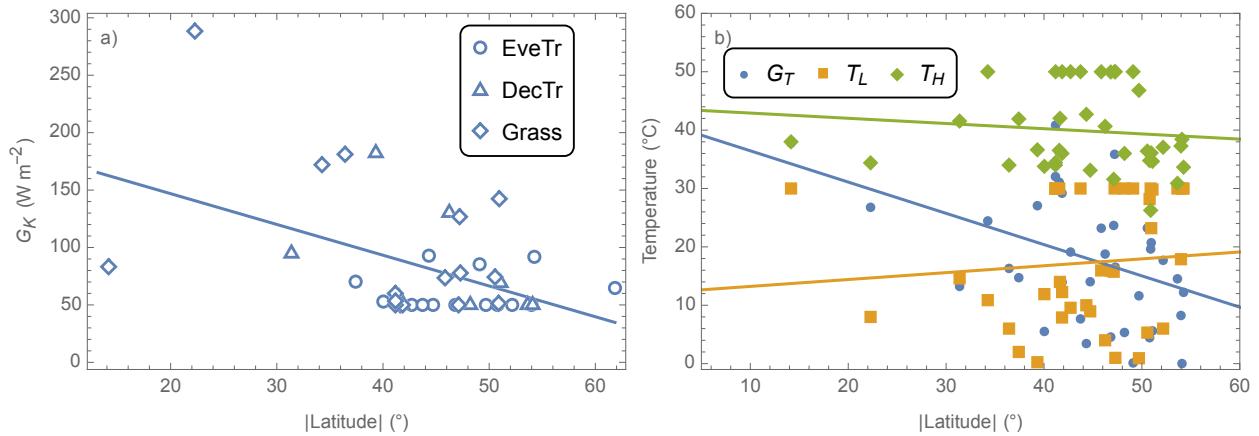
485 **Table 7** As Table 5, but for surface conductance related parameters (Sect. 4.3). See Fig. 10 and
 486 Appendix C.

	g_{max} [mm s ⁻¹]	G_K [W m ⁻²]	G_T [°C]	T_L [°C]	T_H [°C]	$G_{q,base}$ [-]	$G_{q,shape}$ [-]	G_θ [-]	$\Delta\theta_{WP}$ [mm]
EveTr	20.5 ± 1.7	62 ± 5	10.3 ± 1.8	-13 ± 4	41.4 ± 2.0	0.391 ± 0.033	0.9	0.033 ± 0.009	511 ± 75
DecTr	21.2 ± 2.5	100 ± 23	18.0 ± 4.0	-18 ± 5	38.0 ± 1.5	0.439 ± 0.024	0.9	0.029 ± 0.010	521 ± 58
Grass	38.6 ± 2.8	87 ± 13	26.1 ± 1.9	-13 ± 5	40.1 ± 2.2	0.467 ± 0.033	0.9	0.048 ± 0.010	521 ± 54



487
488

Figure 10 As Fig.5, but for surface conductance related parameters.



489
490
491
492

Figure 11 Relations between absolute latitude and derived parameters: (a) solar radiation related G_K by PFT (symbol) and (b) temperature related G_T , T_L and T_H . Lines are derived by ordinary linear regression. See text for notation definitions.

493 5 SUEWS performance in vegetated areas

494 5.1 SUEWS configuration and evaluation

495 SUEWS v2020a (Tang et al. 2021) is evaluated using its python wrapper SuPy v2021.3.18 (Sun and
496 Grimmond 2019) with parameters (Table 1) and gap-filled 30/60 min meteorological forcing data (Table
497 2) based on FLUXNET2015 dataset. Simulations are conducted, with forcing data interpolated to a 5 min
498 timestep (Ward et al. 2016), for three years (Table 3, *Evaluation period*) starting in mid winter. The first
499 year is discarded to allow for model spin-up. The two subsequent years are evaluated when observed
500 latent heat flux are available. In these model runs, the z_{0m} and z_{dm} values used are derived (Appendix B)
501 by LAI state using observations for each LAI season for each (approximately 9 values per site; see Sun et
502 al. (2021) for values). All other parameters (Table 1) are determined for the *parameter derivation period*

503 indicated in Table 3. At one site (AU-Gin), there are insufficient data for independent evaluation period
 504 from the parameter derivation period.

505 For the periods with 30(/60)-min Q_E EC observations (Y_{obs}) available, the 5 min simulated values (Y_{mod})
 506 are averaged to 30(/60)-min to evaluate the j cases between 1 and the number of data points (N). The
 507 following metrics are used:

508 1) hit rate (HR):

$$509 \quad \text{HR} = \frac{\sum_{j=1}^N H(\delta_{Y,j} - |Y_{\text{mod},j} - Y_{\text{obs},j}|)}{N} \quad (30)$$

510 with Heaviside step function H defined by

$$511 \quad H(x) = \begin{cases} 0, & x < 0 \\ 1, & x \geq 0 \end{cases} \quad (31)$$

512 and the threshold $\delta_{Y,j}$ being a value dependent on evaluation variable Y .

513 In particular, $\delta_{Y,j}$ for Q_E is determined as a function of net all-wave radiation Q^* following Hollinger and
 514 Richardson (2005) to be $\delta_{Y,j} = 0.1Q_j^* + 10$ (in W m^{-2}) based on measurement uncertainties.

515 2) mean absolute error (MAE):

$$516 \quad \text{MAE} = \frac{\sum_{j=1}^N |Y_{\text{mod},j} - Y_{\text{obs},j}|}{N} \quad (32)$$

517 3) mean bias error (MBE):

$$518 \quad \text{MBE} = \frac{\sum_{j=1}^N (Y_{\text{mod},j} - Y_{\text{obs},j})}{N} \quad (33)$$

519 Both the MAE and MBE would ideally be 0 (with units of parameter/variable assessed). Whereas if the
 520 HR=1 it indicates all model predictions fall within the acceptable threshold set, while HR =0 would suggest
 521 none are within the acceptance threshold.

522 A performance score PS as a function for each metric (x ; i.e. HR, MAE, |MBE|) is used to rank the sites:

$$527 \quad PS = \frac{1}{N} \sum_{k=1}^N (w_x \tilde{x})_k \quad (34)$$

523 where \tilde{x} is the rescaled ranking score a given metric after being ranked from poorest to best and w_x is a
 524 weight associated with the temporal analysis type k which varies from 1 to N (number of component
 525 periods; e.g., $N = 24$ for hourly results). Equal weights (1/3) are used in the PS calculations for HR, MAE
 526 and |MBE|.

528 **5.2 Impacts of model parameters on model performance**

529 Given the many parameters in SUEWS, first we assess the relative importance of the parameters. We
 530 assume in this analysis our derived parameters (Sect. 4) are “perfect”, so we can undertake a sensitivity
 531 analysis (McCuen 1974, Beven 1975) of the Penman-Monteith equation (i.e. Eqn. 3, denoted by PM
 532 hereafter):

$$537 \quad \Delta Q_E = PM(AE + \Delta AE, r_a + \Delta r_a, r_s + \Delta r_s) - Q_E \quad (35)$$

533 where $AE = Q^* - \Delta Q_S$ is the available energy, incorporating parameters influences related to LAI, albedo
 534 and OHM. Similarly, multiple parameters influence the resistance terms. In Eqn. 31 the prefix Δ indicates
 535 bias terms. For simplicity, we consider the direct impacts only (i.e., secondary impacts from parameters
 536 inter-dependence are ignored). Expanding Eqn. 31 in Taylor series, gives:

$$541 \quad \Delta Q_E \approx PM'(AE) \cdot \Delta AE + PM'(r_a) \cdot \Delta r_a + PM'(r_s) \cdot \Delta r_s \quad (36)$$

538 where $PM'(x)$, the first-order derivative of x , indicates the sensitivity of modelled Q_E . Note “ \approx ” implies
 539 the approximation of ΔQ_E as the sum of bias from the chosen parameters. To examine the influences of
 540 different parameters in model performance, we use two non-dimensional metrics derived from Eqn. 32:

542 1) *sensitivity coefficient* (SC) (McCuen 1974):

$$545 \quad SC = PM'(x) \cdot \frac{x}{Q_E} = \frac{\partial Q_E}{\partial x} \frac{x}{Q_E} \approx \frac{\Delta Q_E / Q_E}{\Delta x / x} \quad (37)$$

543 gives the fractional change in x causing a change in Q_E , indicating a relative sensitivity of PM to x .

544 For instance, $SC= 0.5$ suggests a 20% increase in x may increase Q_E by 10% ($=20\% \times 0.5$).

546 2) *attribution fraction* (AF): quantifies the fraction of model bias derived from a given parameter x :

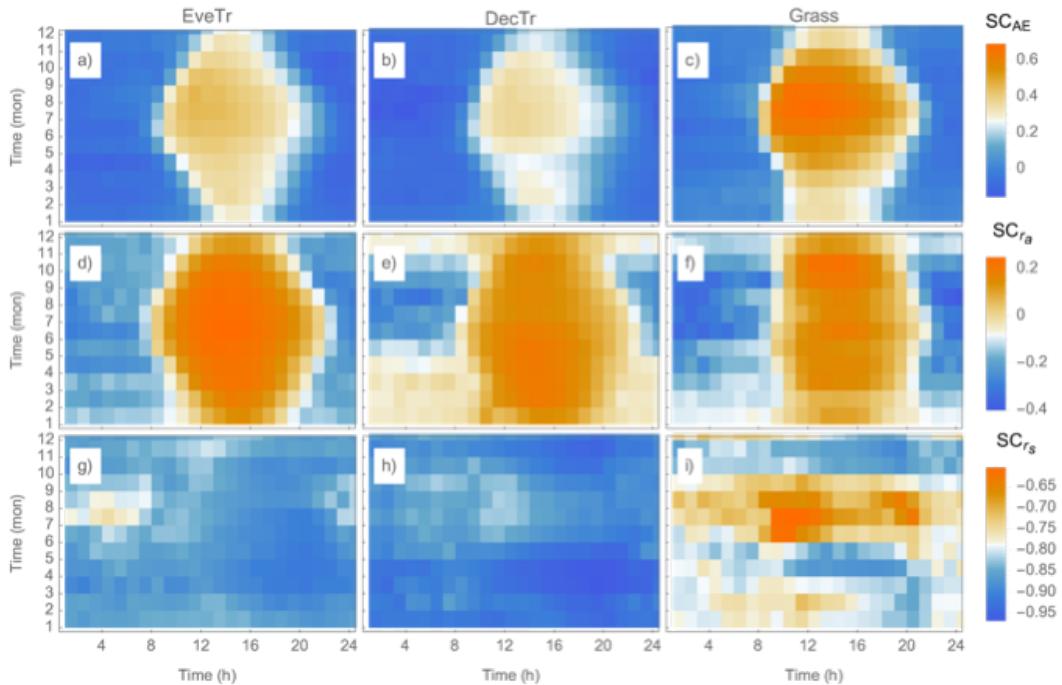
$$550 \quad AF = PM'(x) \cdot \frac{\Delta x}{\Delta Q_E} \quad (38)$$

547 Ideally, the sum of all AF contributors would equal one, but as we omit inter-dependence of impacts
 548 of parameters, this may not occur. However, comparing the different contributors is indicative of their
 549 relative importance in modelled Q_E .

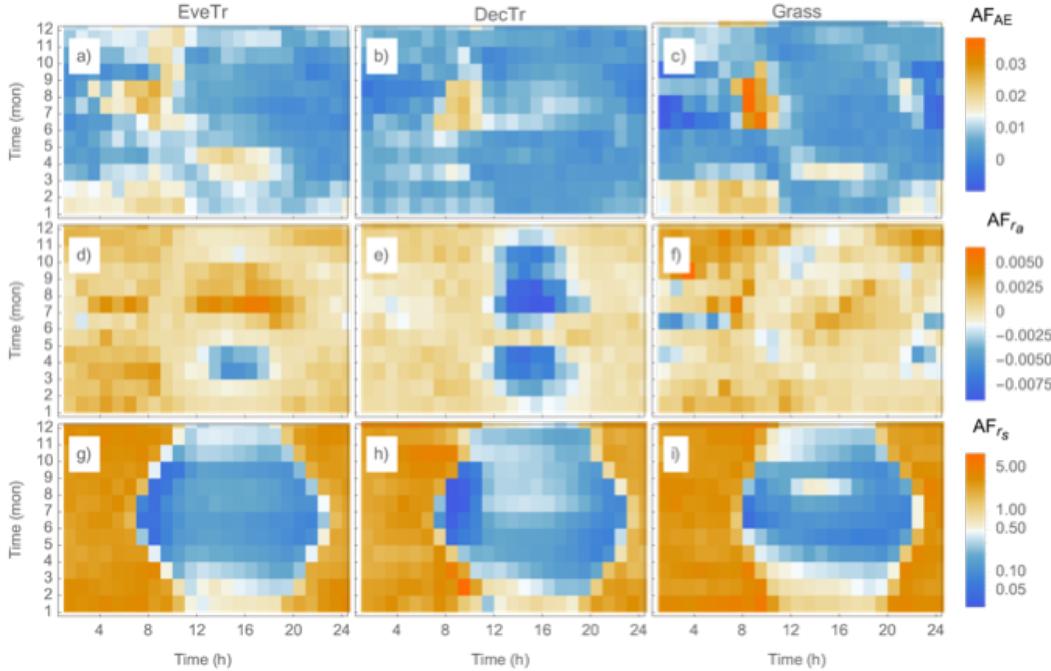
551 For both SC_{AE} and SC_{r_a} they are generally a similar type of patterns (Fig. 12a-f) with seasonal and diurnal
 552 variations for the three PFT. During warm periods (~summer and ~noon time), with an increase in ΔAE
 553 and Δr_a it is found to lead to larger positive bias in modelled Q_E ; whereas in cooler periods (~winter and
 554 ~night time) the ΔAE and Δr_a is found to increase the negative bias.

555 However, the temporal patterns in SC_{r_s} differ (Fig. 13g-i) from those in SC_{AE} (Fig. 13a-c) and SC_{r_a} (Fig.
 556 13d-f): the SC_{r_s} values are always negative, and consistently larger in magnitude (cf. SC_{AE} and SC_{r_a}),
 557 implying a particularly strong sensitivity of Q_E to r_s . This is consistent with Beven (1975), who found it to
 558 dominate the modelled summertime Q_E sensitivity in the PM framework.

559 The relative (cf. total) bias from the parameters is assessed in modelled Q_E at monthly and hourly
 560 temporal scales using the median AF (Fig. 13). AF_{r_s} is larger than both AF_{AE} and AF_{r_a} ; i.e., r_s imposes a
 561 dominant influence in modelled Q_E bias. There is more temporal variability in AF_{r_s} (cf. AF_{AE} and AF_{r_a})
 562 with cooler periods (morning and evening, whole winter) generally have values greater than one,
 563 indicating the bias in r_s dominates modelled Q_E . As AF_{r_s} is still generally larger than ~ 0.3 (except for
 564 transitional periods in summer, 8:00–9:00 in the morning, when $AF_{r_s} < \sim 0.3$), r_s remains an important
 565 control on modelled Q_E . These results together, indicate that it is critical to assign accurate r_s to obtain
 566 accurate estimates of Q_E .



567
 568 **Figure 12** Temporal variation in median (colour) sensitivity coefficient (SC, eq.38) of (a-c) available
 569 energy (AE, sect. 5.1), (d-f) aerodynamic resistance (r_a) and (g-i) surface resistance (r_s) for (a,d,g)
 570 evergreen trees (EveTr), (b,e,h) deciduous trees (DecTr), and (c,f,i) grassland and crops (Grass).



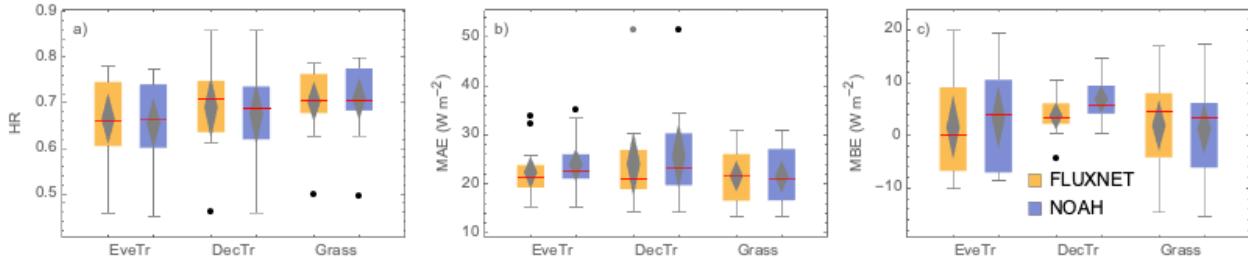
571
572

Figure 13 As Fig. 12, but the attribution fraction (AF, Eq. 39). Note AF_{rs} scale is logarithmic.

573 **5.3 Evaluation of SUEWS simulated Q_E with two different sources of g_s parameters**

574 Given the critical importance of surface resistance to model performance in Q_E (Sect. 5.2), we assess the
575 impact two different sources of g_s parameters (keeping all other site parameters the same, with the values
576 as indicated in section 5.1): (i) site-specific values derived from FLUXNET2015 data (Sect. 4); and (ii)
577 PFT-specific NOAH values modified for SUEWS (Appendix A). Errors in the other derived parameters
578 (e.g., LAI related parameters, storage heat flux coefficients via available energy) will impact both sets of
579 results but they are assumed to be equal, allowing the impacts of using site- and PFT-specific g_s
580 parameters on SUEWS simulated Q_E to be assessed. Given NOAH is extensively used in NWP systems
581 (e.g., WRF, Skamarock and Klemp, 2008), the result also allows the applicability of NOAH-based g_s
582 parameters at FLUXNET sites to be assessed.

583 Analysis using two years of Q_E EC flux data (after 1 year spin up) uses three metrics (Sect. 5.1). The
584 overall median results are similar between the two sets of parameters across the 38 sites split into the
585 three PFTs (Fig. 14, red lines). The median HR are between 0.6 and 0.7, median MAE are less than 25 W
586 m^{-2} , and median MBE are $\sim 5 W m^{-2}$. The Grass site, notably HR and MAE (Fig. 14a, b), performance is
587 very similar suggesting the NOAH-based parameters could be used for these sites at annual scales as a
588 first-order proxy.



589

590 **Figure 14** Simulated Q_E using two sets of parameters (colour, FLUXNET - Table C3, NOAH – Table
 591 A1 assigned based on Table 3 PFT class) at 38 sites (boxplots, as Fig. 9, subdivided into three
 592 land cover classes: EveTr, DecTr and Grass) evaluated for two years with observed 30/60-min
 593 fluxes using three metrics (Sect. 5.1): (a) HR, (b) MAE, and (c) MBE.

594 Evaluation using three different time periods (annual, monthly and hourly), shows differences in
 595 performance between using the FLUXNET2015 and NOAH-based parameters (Fig. 15). The HR is
 596 similar for all three temporal scales (Fig. 15a–c) for the three site types (colour). Both the MAE (Fig.
 597 15d–f) and MBE (Fig. 15g–i) indicate better model performance can be obtained using the
 598 FLUXNET2015-based parameters (i.e. not above the 1:1 line). When using the NOAH parameters (Fig.
 599 15h,i), some monthly MBE are $\sim 40 \text{ W m}^{-2}$ larger at EveTr sites for 8 of 156 cases and 5/312 for DecTr
 600 sites. Similarly, at the hourly scale the NOAH MBE are on occasions $\sim 30 \text{ W m}^{-2}$ larger (4/132 EveTr
 601 cases and 6/264 DecTr cases). However, the NOAH results have similar metrics at Grass sites. This
 602 suggests at the EveTr and DecTr sites, the NOAH-based g_s parameters may on occasion be less
 603 appropriate, suggesting that the individual sites values may be better.

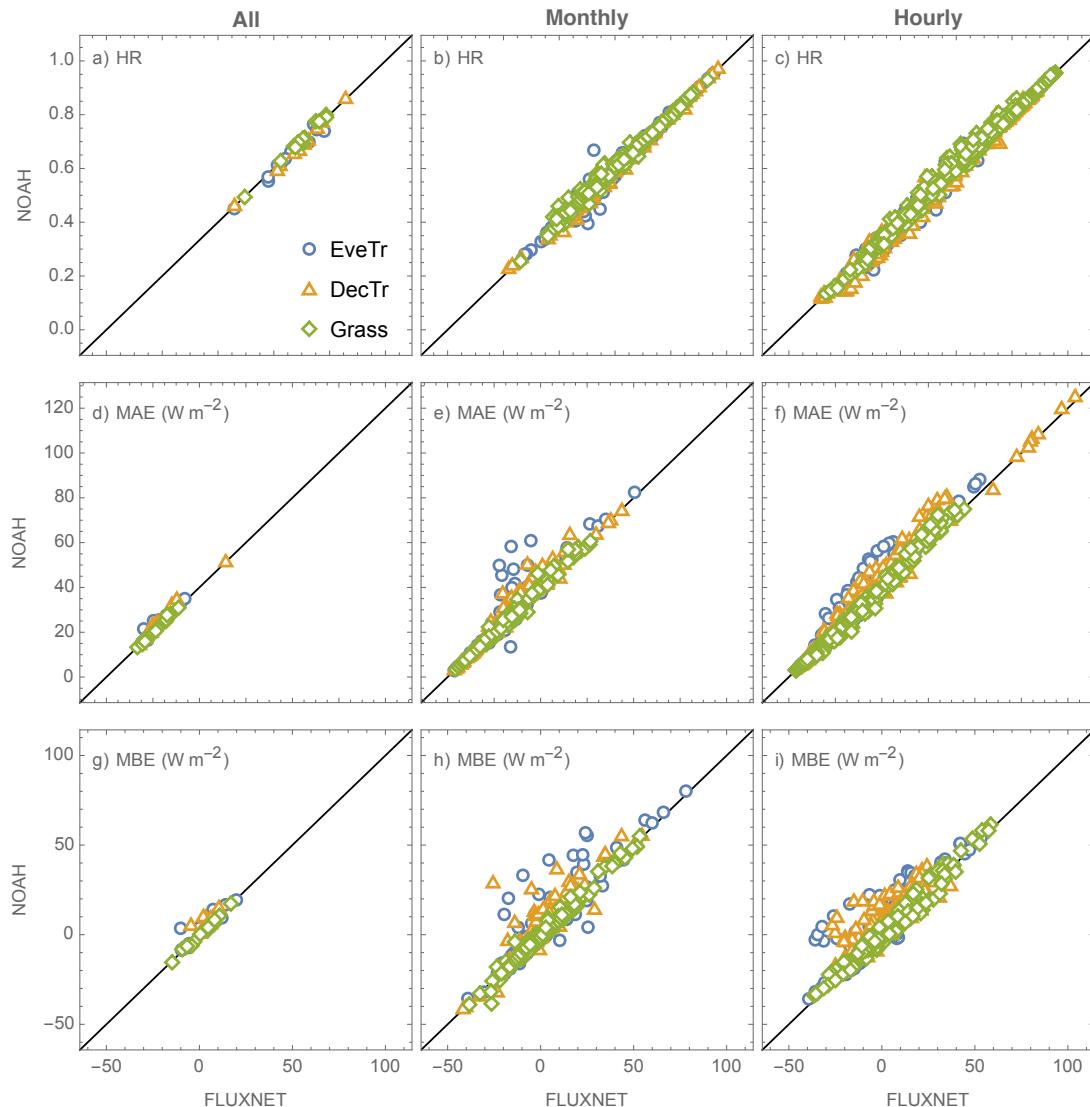


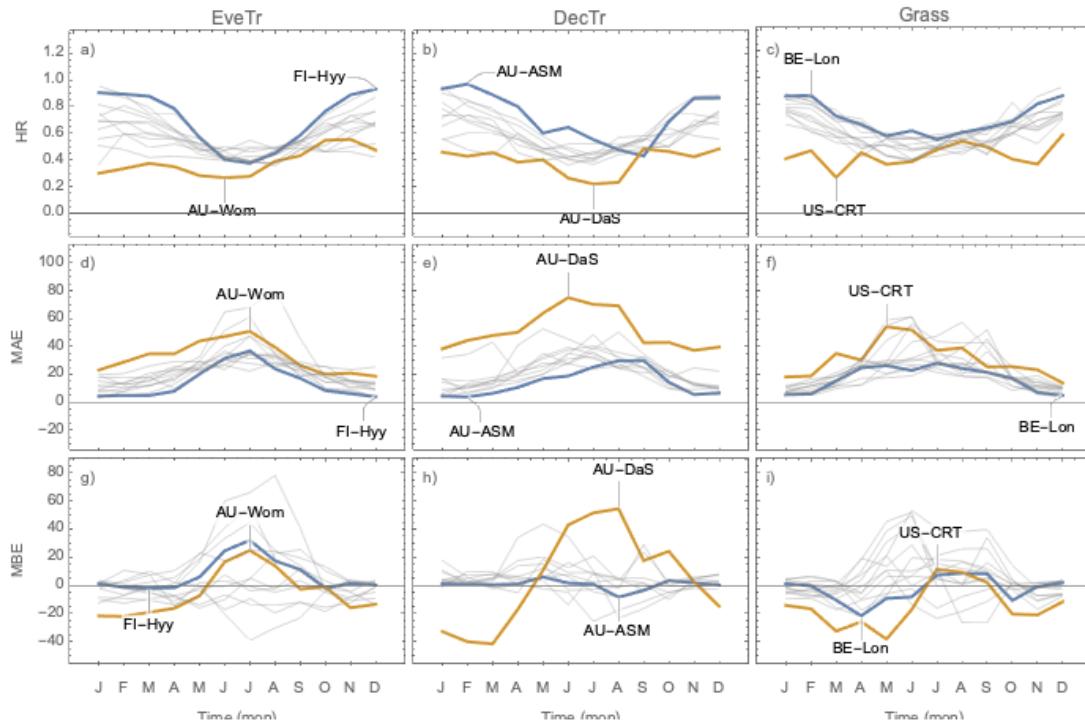
Figure 15 Relation between NOAH and FLUXNET of (rows) three evaluation metrics for (columns) three temporal scales (all, $n = 38$ sites but different number of samples per site, Table 3; monthly, $n = 456 = 38$ sites $\times 12$ months; and hourly, $n = 912 = 38$ sites $\times 24$ hours). Data points are colour coded by land cover class.

5.4 Evaluation of SUEWS simulated Q_E and key parameters at sites with contrasting model performance

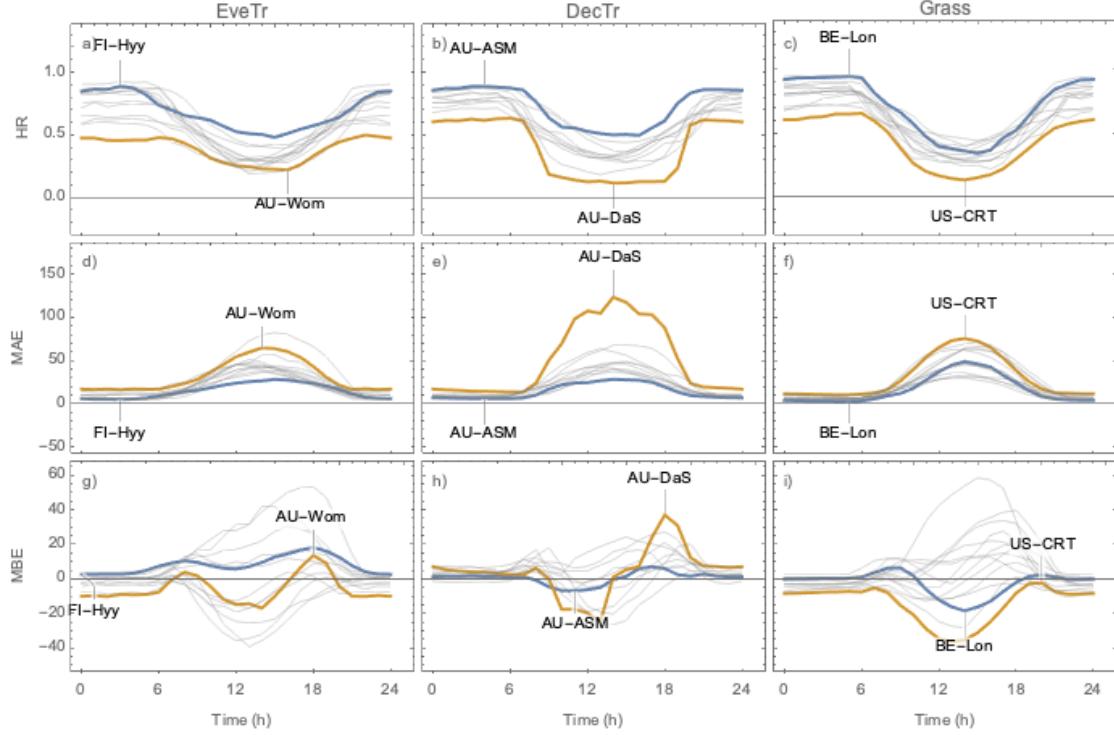
Given the results in Section 5.3, the performance of individual sites using the FLUXNET2015-derived parameters (Sect. 4) at monthly (Fig. 16) and hourly (Fig. 17) time scales are investigated.

As expected (Sect. 5.2), the HR values are consistently better at all sites during cooler (winter) than warmer (summer) seasons (Fig. 16a–c), and similarly for night rather midday time periods (Fig. 17a–c). Given the consistency in MAE and HR (Fig. 16, 17d–f) patterns, the sites identified to be simulated the ‘best’ (blue) and ‘poorest’ (orange) are the same (Section 5.1).

617 However, using the MBE different sites are selected. For example, monthly MBE at AU-ASM stays close
 618 to zero throughout the year while at AU-Das it varies between -40 W m^{-2} and 60 W m^{-2} (Fig 16h). The
 619 largest intra-month MBE range for an EveTr site is 87.1 W m^{-2} , which occurs at FR-Hyy. The equivalent
 620 range for DecTr sites is larger (96.1 W m^{-2} at AU-DaS) but smaller at Grass sites (69.6 W m^{-2} ; US-Ne3).
 621 The intra-hourly MBE ranges are smaller than intra-monthly values: with a DecTr and a Grass site having
 622 a large range than the largest EveTr site (AU-DaS (61.9 W m^{-2}), US-Goo (60.0 W m^{-2}), FR-LBr (53.1 W
 623 m^{-2}), respectively).



624
 625 **Figure 16** Variation in evaluation metrics (Section 5.2) based on 30/60-min Q_E data by month using
 626 the derived parameters based on FLUXNET2015 dataset (Tables C1–C3): (a–c) HR, (d–f) MAE,
 627 (g–l) MBE by sites grouped into three PFTs (a,d,g) EveTr, (b,e,h) DecTr and (c,f,i) Grass with
 628 sites of best (blue)/poorest (orange) performance highlighted while others in grey (indicated by
 629 PS: see text and Eqn. 35 for details). Note Southern Hemisphere sites are offset by 6 months
 630 (Sect. 5.1), so ‘general’ seasons are consistent across sites.

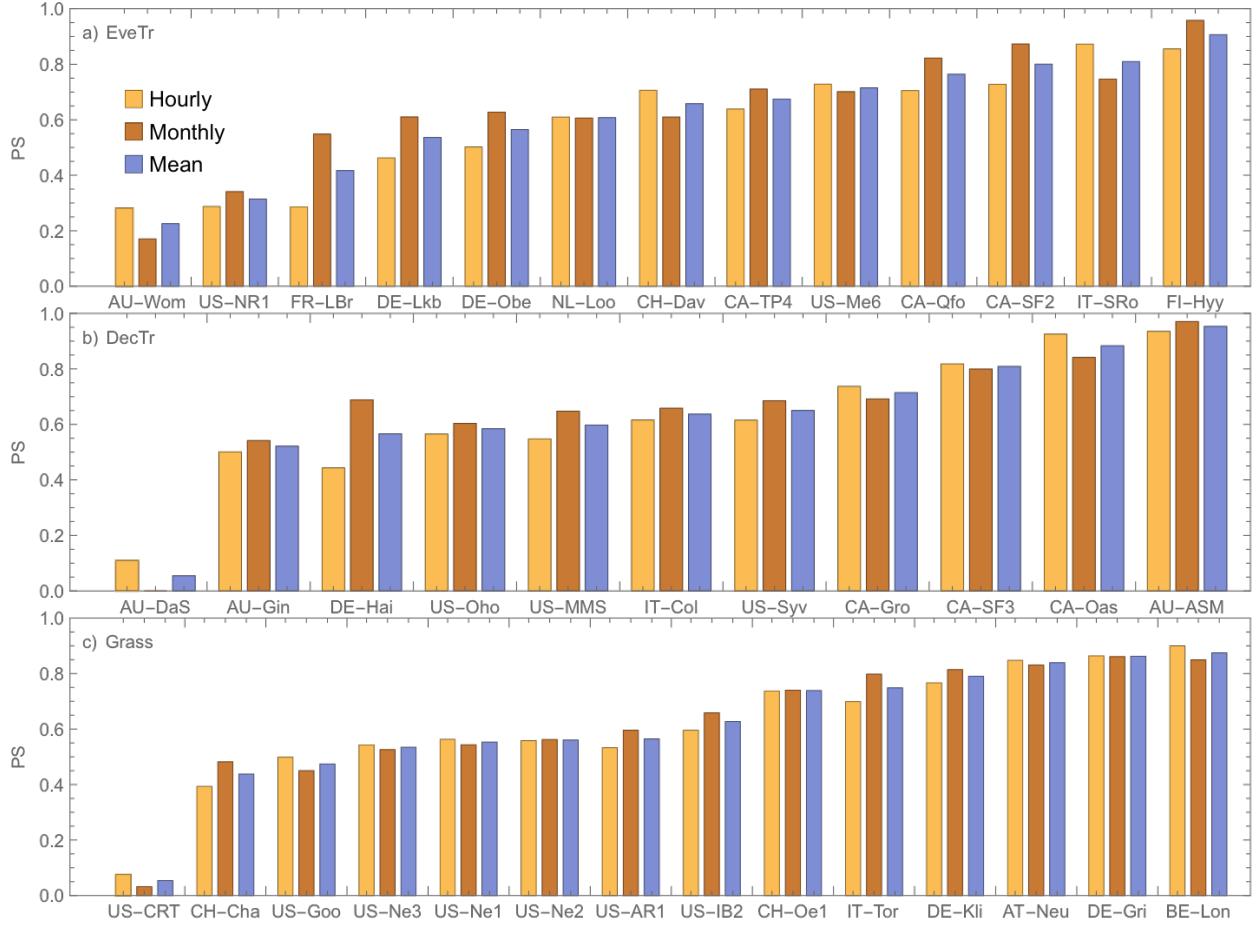


631

632 **Figure 17** As Fig. 16, but for diurnal cycles using local standard time.

633

634 To investigate Q_E performance relative to key parameters (LAI, r_a , and g_s) we select the sites with
 635 contrasting results from each PFT to understand the drivers. The hourly and monthly ranked performance
 636 (Eqn. 35) are broadly consistent within each PFT type (Fig. 18). Sites with higher hourly scores generally
 637 have better monthly scores, except for IT-SRo within the EveTr cohort. It has the highest hourly PS
 638 (0.86) but is ranked fourth based on PS_{monthly} (0.64), whereas the highest PS_{monthly} (0.91) is for FI-Hyy
 639 which also has the second rank PS_{hourly} (0.83). To select sites for further analysis we rank based on the
 640 mean of monthly and hourly PS results. The six sites chosen are the best and poorest sites for the three
 641 PFTs (i.e. extremes in Fig. 18, highlighted in Fig. 16 and 17).



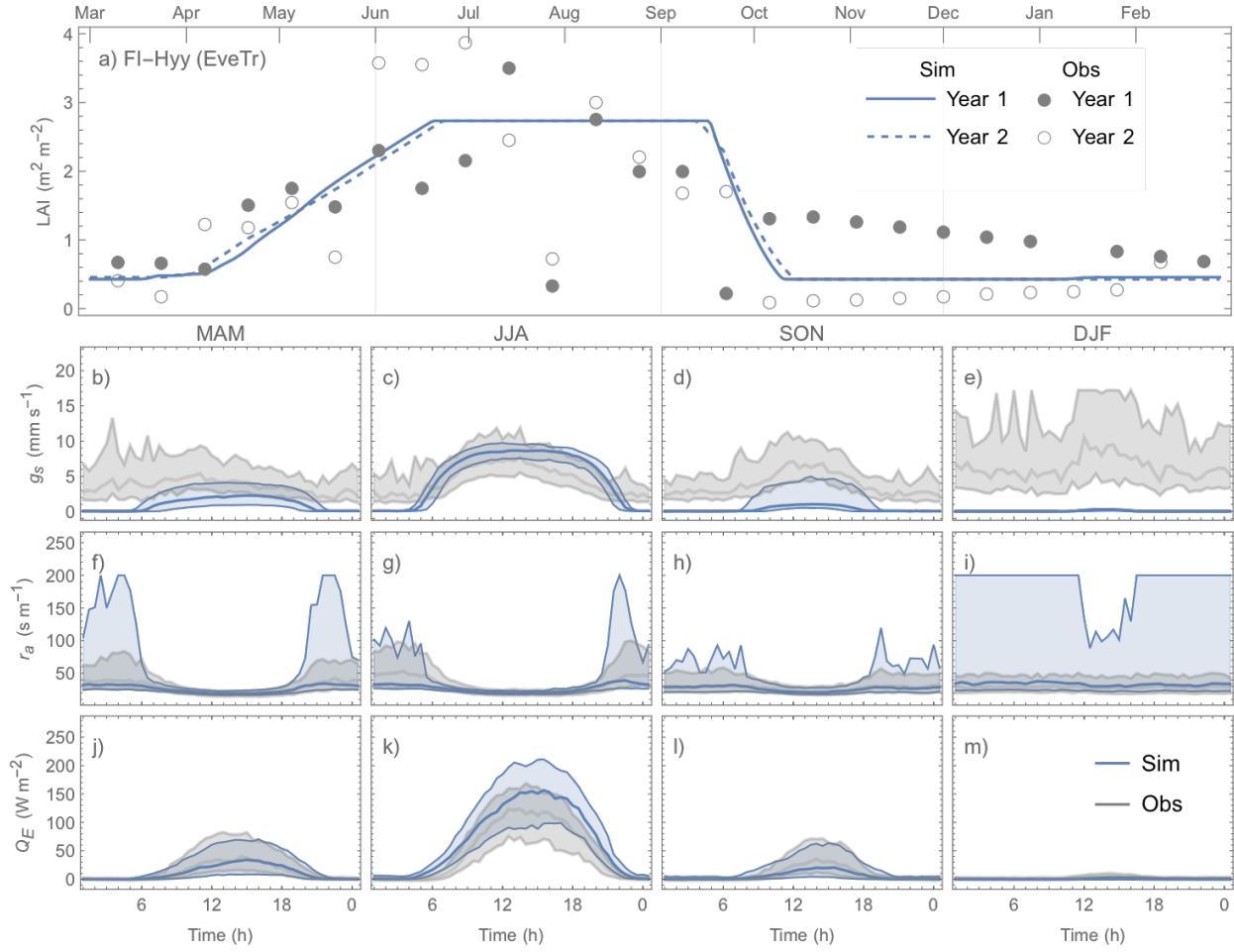
642

643 **Figure 18** Performance score (PS, Eqn. 35, higher value better) using FLUXNET2015 derived
 644 parameters for sites (Table 3) from three PFT: a) EveTr, b) DecTr and c) Grass.

645 Comparing the contrasting site Q_E performance (best cf. poorest) for the three PFTs (Fig. 19 cf. 20; 21 cf.
 646 22; 23 cf..24), we identify the skill of capturing the annual LAI dynamics is crucial to seasonal model
 647 performance (Fig. 19–24a). At the “best” sites but BE-Lon (a Grass site, whose performance is more
 648 controlled by surface conductance g_s skill and shall be discussed later) the phenology generally has the
 649 correct timing while at the poorest onsets of some stages are missed (e.g. Fig 22a). Timing appears to be
 650 more critical than magnitude, as although the LAI magnitude at AU-ASM has a large bias in year 2 (0.5
 651 $m^2 m^{-2}$, Fig. 21a) the phenology timing is well captured. This result for a first rank site (i.e. best
 652 performance) implies the rescaling nature of LAI in parameterisation of albedo (Eqn. 6) and surface
 653 conductance (Eqn. 14) plays an important role. This indicates the importance of assigning appropriate
 654 LAI parameters, notably those influencing the timing (i.e. temperature thresholds $T_{base,GDD}$ and $T_{base,SDD}$ in
 655 Eqn. 4), in SUEWS modelling Q_E at vegetated sites.

656 As expected (Sect 5.2), SUEWS performance is critically impacted by surface conductance g_s skill (Fig.
657 19–24b–e *cf.* j–m): sites and seasons with better model g_s skill (i.e. simulations and observations closer)
658 show overall better performance (e.g. for Grass sites, BE-Lon vs. US-CRT, *cf.* Fig. 23c and 24c). g_s is
659 better modelled in warmer (JJA and SON) than cooler seasons (MAM and DJF). At night, g_s is generally
660 underestimated, by a similarly order of magnitude as that in cooler seasons ($\sim 3 \text{ mm s}^{-1}$). These results,
661 consistent with SUEWS results for two UK urban sites (Ward et al 2016), suggest improvements are
662 needed in the Jarvis type g_s parameterisation during cooler periods. Given the method adopted here of
663 using summertime observations, as used by many other land surface models (e.g. NOAH - Chen and
664 Dudhia 2001; HTESSEL - Balsamo et al. 2009), it implies that the widely adopted Jarvis type g_s
665 parameterisations and/or related parameter values (*cf.* Sect. 4.3) maybe biased towards vegetation
666 canopies in warmer periods. The “cool” bias in modelled g_s found here, and in earlier SUEWS work (e.g.,
667 Ward et al. (2016)), should be considered a more common issue beyond the SUEWS model. Given the
668 needs in long-term climate modelling, systematic biases should be removed suggesting other land surface
669 models that adopt the Jarvis type g_s parameterisation might need revisions as well.

670 The aerodynamic resistance r_a is modelled well at all sites (Fig. 19–24f–i), with nocturnal biases larger
671 (e.g. underestimate of $\sim 50 \text{ s m}^{-1}$ at AT-Neu, Fig. 23f–i). This good performance may be largely attributed
672 to the use of local site - growth stage derived aerodynamic roughness parameters (Appendix B) rather
673 than estimated using a morphometric model (e.g. based on canopy height). To estimate z_{0m} and z_d using
674 Eqn. 9 and 10 the f_0 and f_d parameters can be derived using Sun et al. (2021) for different growing stages
675 with the FLUXNET2015 data when canopy heights are available. The largest intra-PFT variability,
676 occurs for ‘Grass’ sites (Fig. B1).

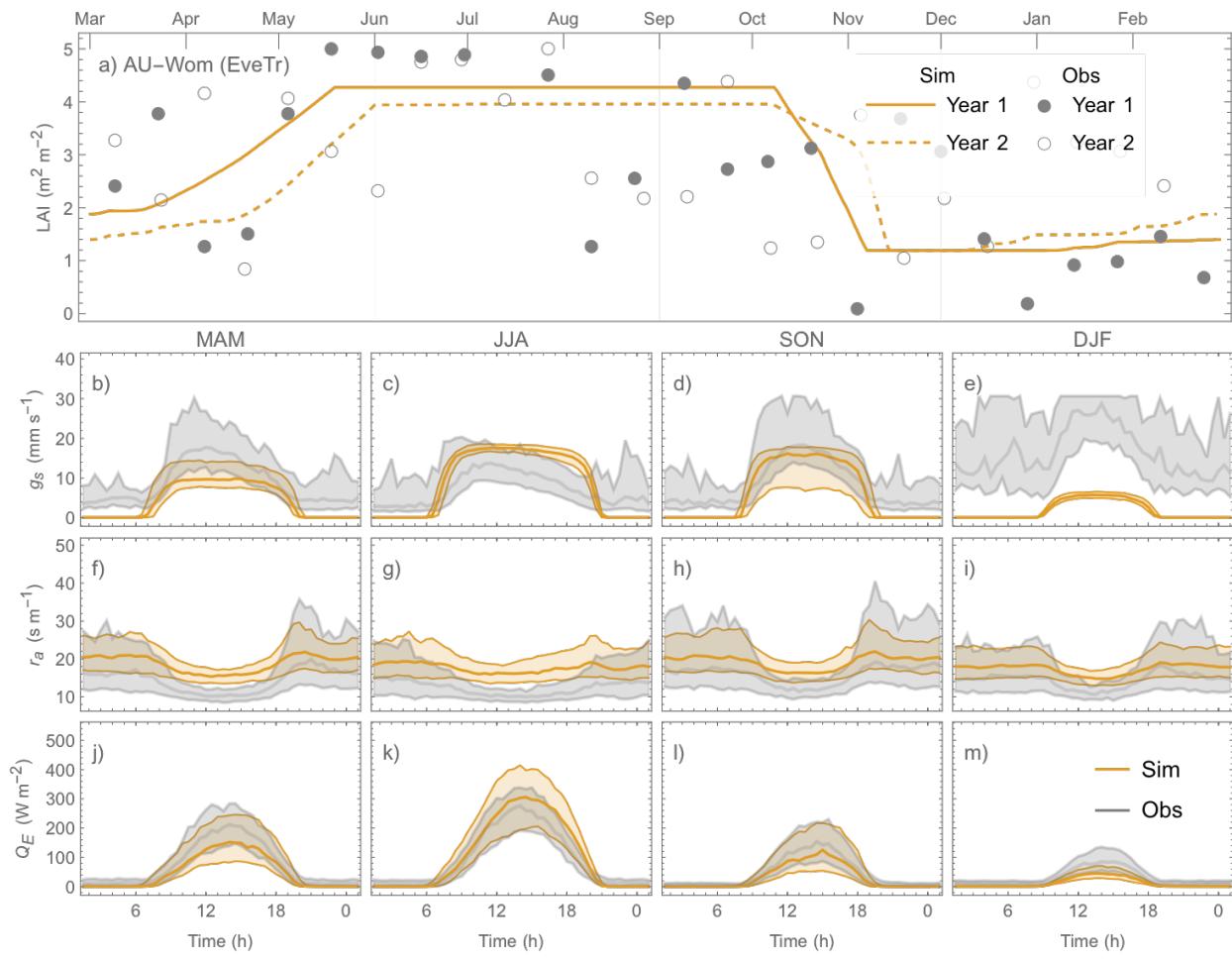


677

678 **Figure 19** FI-Hyy (EveTr, $PS=0.92$) performance (a) annual LAI. (b–e) g_s (in seasonal ensemble of
 679 diurnal cycles: median values in bold lines, while interquartile ranges in shadings), f–i) r_a ; and j–
 680 m) Q_E . Note the same colouring of simulations for sites with best/poorest model performance and
 681 six-month offset in annual cycles are applied for consistency with Fig. 16 and 17.

682

683

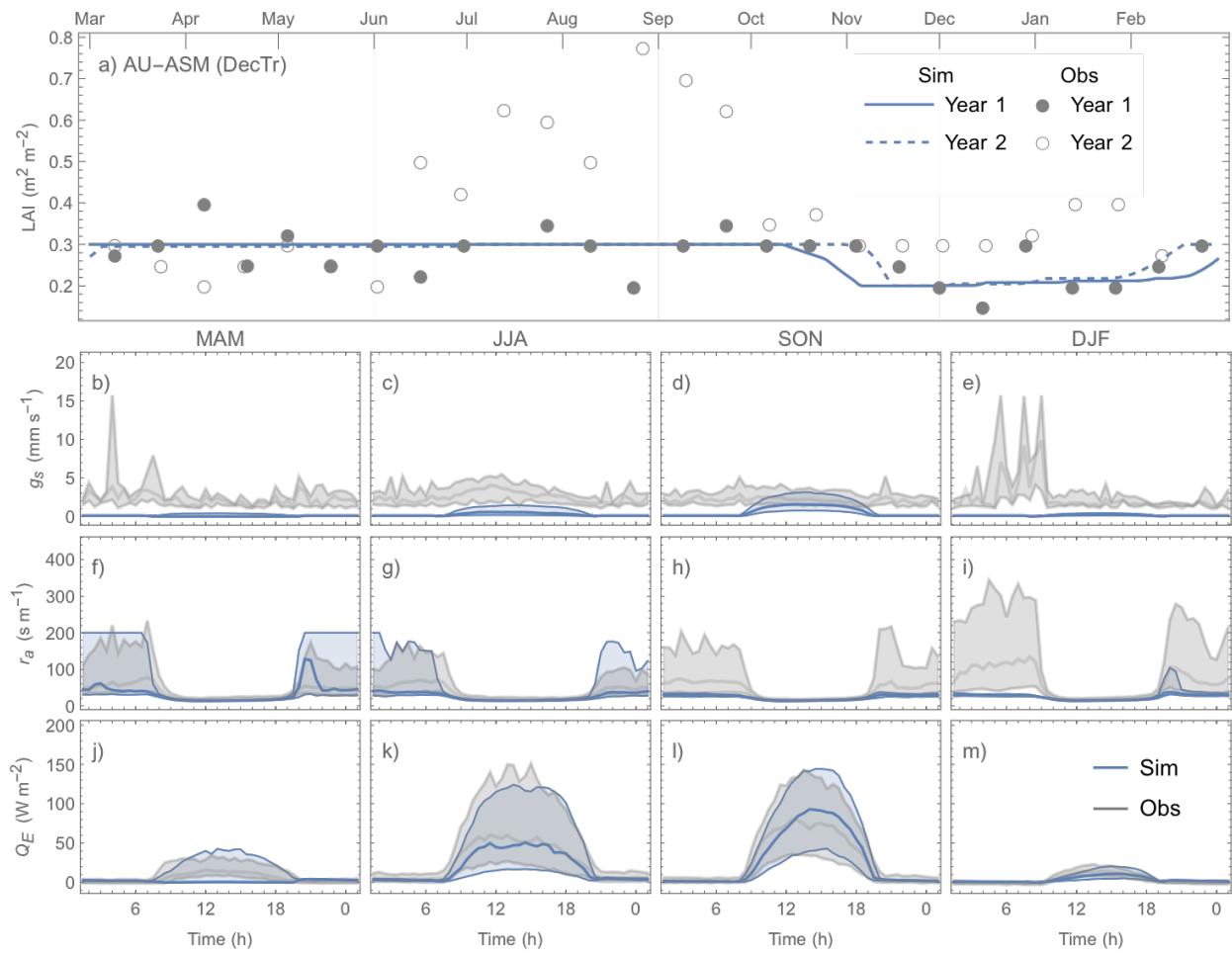


684

685 **Figure 20** As Fig. 19, but for AU-Wom (EveTr, PS=0.18).

686

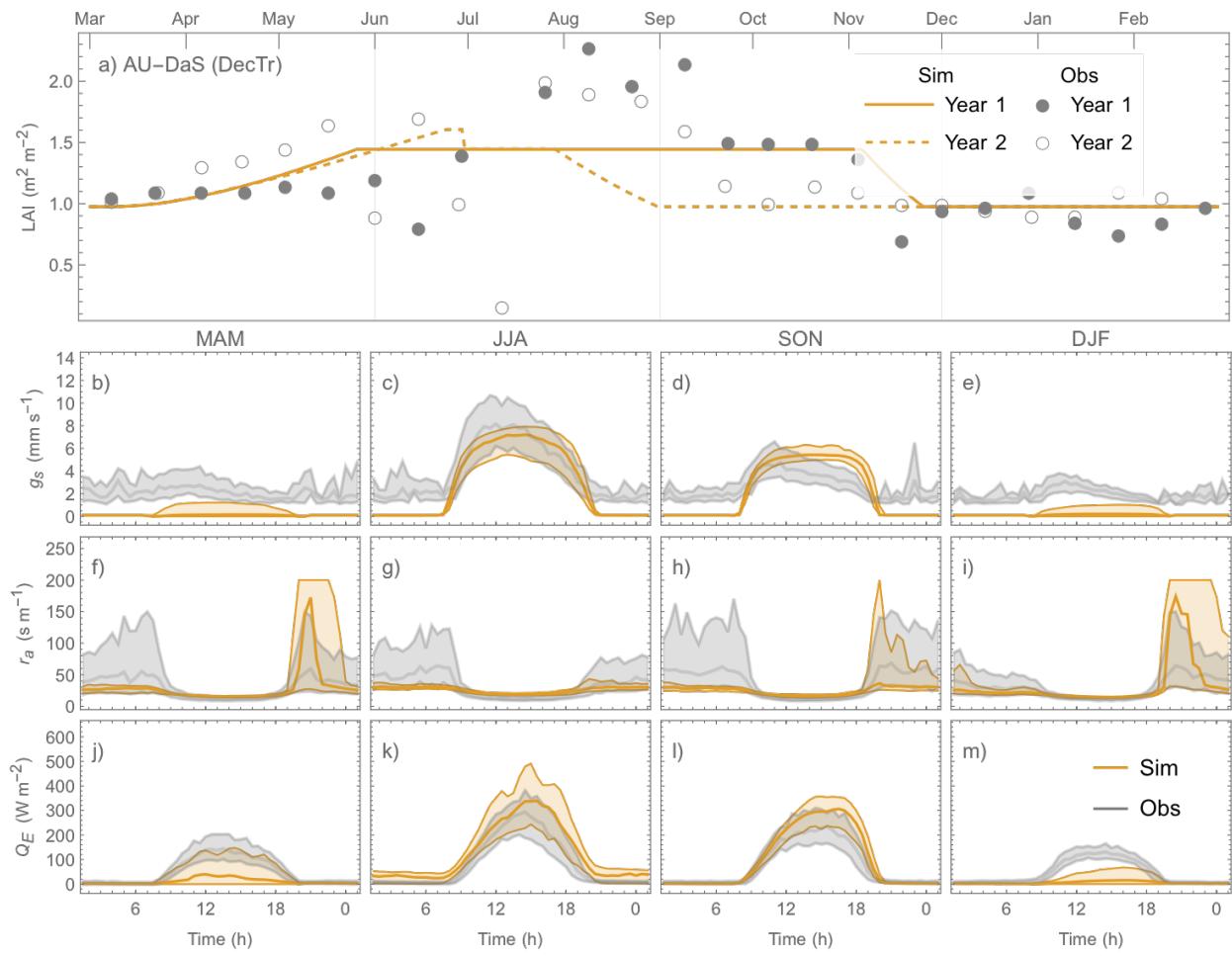
687



688

689 **Figure 21** As Fig. 19, but for AU-ASM (DecTr, PS=0.96).

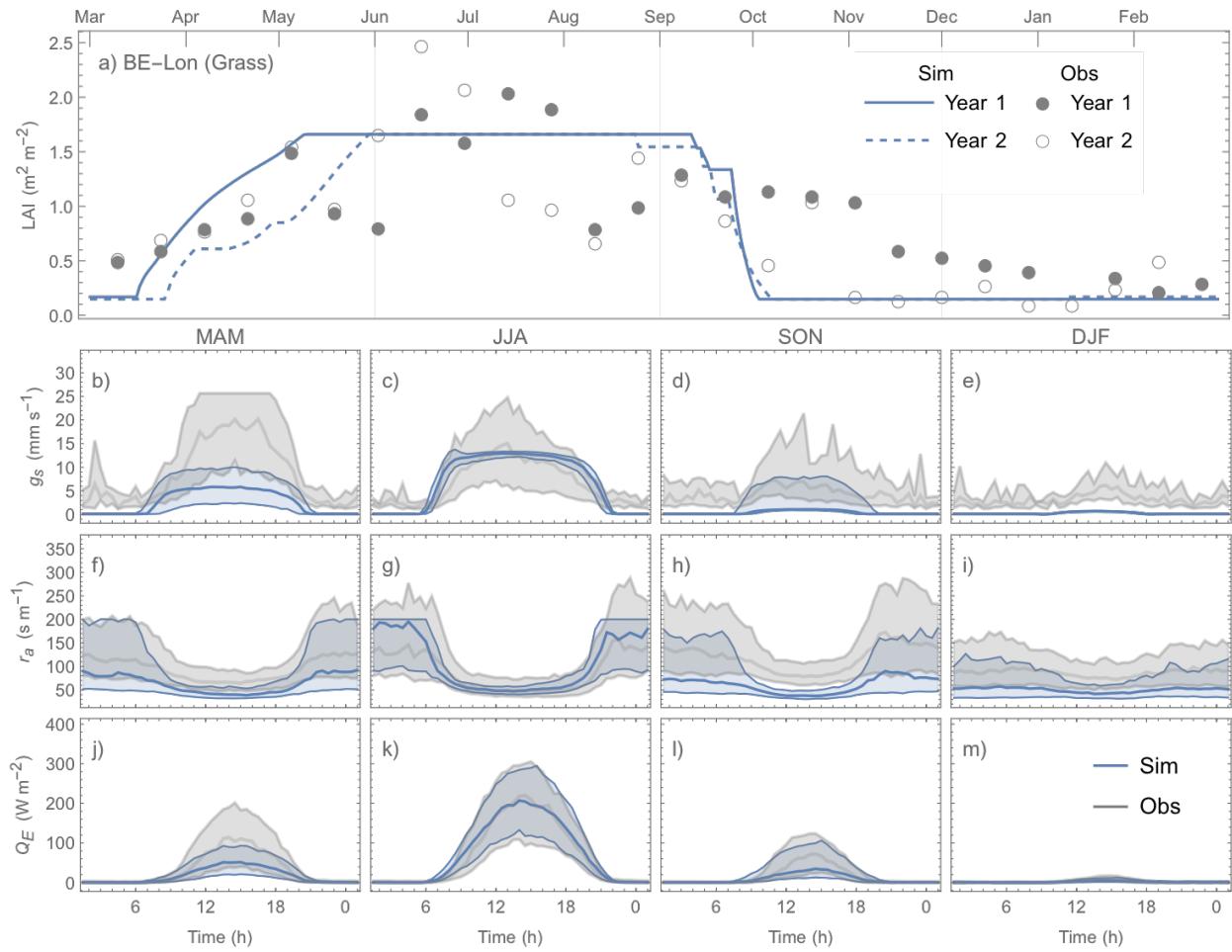
690

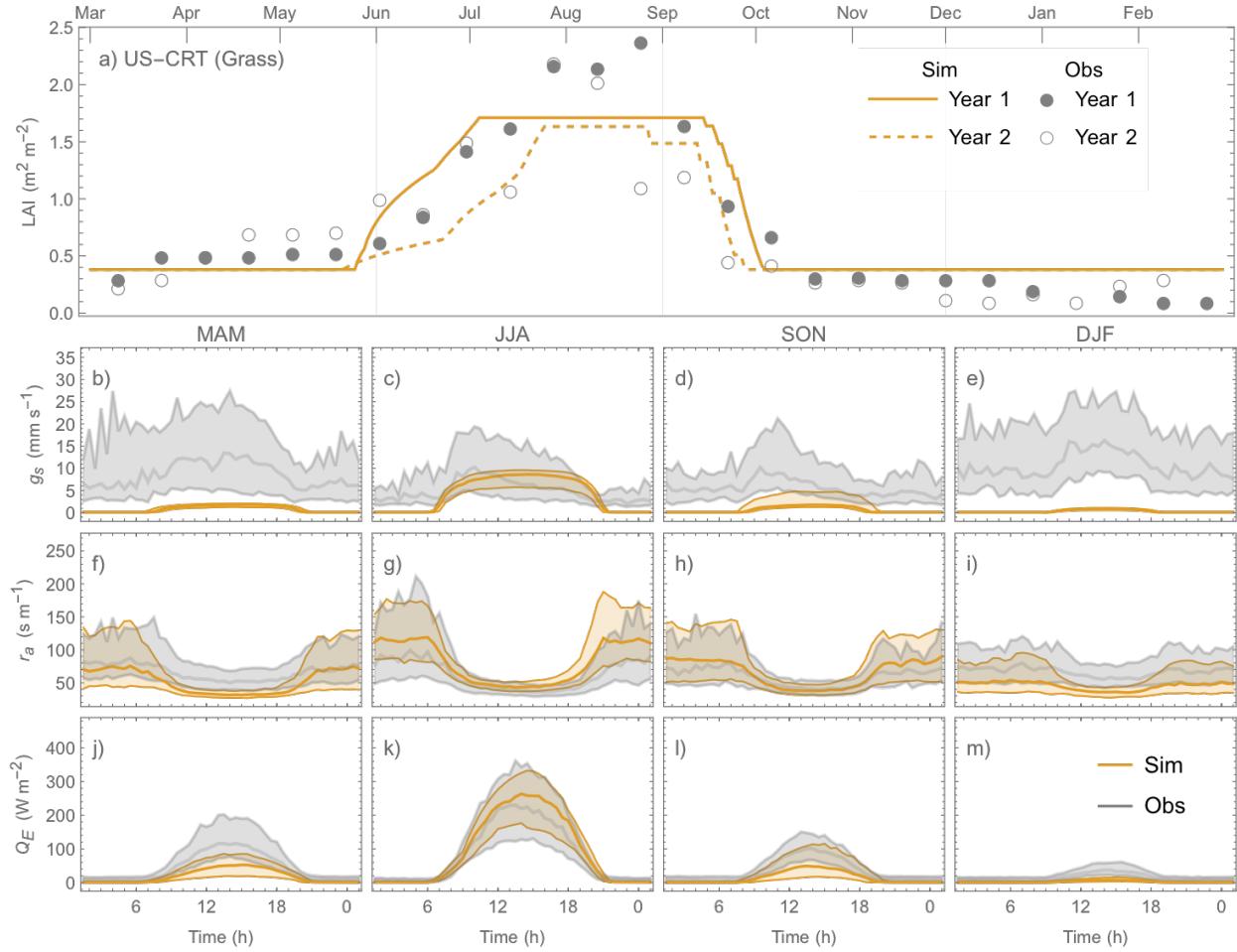


691

692 **Figure 22** As Fig. 19, but for AU-DaS (DecTr, PS=0.04).

693





698

699 **Figure 24** As Fig. 19, but for US-CRT (Grass, PS=0.04).700 **6 Concluding remarks**

701 In this work, we derive parameters for SUEWS for fully vegetated land covers that are commonly found
 702 in background ('rural') contexts of cities, where SUEWS has been widely used to model urban climates.
 703 To facilitate derivation of SUEWS parameters we provide workflows in Jupyter notebooks (Sun et al.
 704 2021) for leaf area index (LAI), albedo, Objective Hysteresis Model (OHM) coefficients, aerodynamic
 705 roughness parameters and surface conductance (g_s). We use these to determine parameters at 38 vegetated
 706 FLUXNET sites in North America, Europe and Australia. Using the derived parameters, we assess
 707 performance of SUEWS in predicting latent heat flux (Q_E) at different temporal scales (monthly and
 708 hourly).

709 It is concluded that:

- Where observations are available, we recommend determining local parameters, as derived parameters vary within PFT (Appendix C). The tools provided here are designed to facilitate this (Sect. 4).
- Given the global availability of MODIS LAI and reanalysis-based air temperature datasets (e.g., ERA5), it is feasible to derive site by site LAI parameters for SUEWS (Sect. 4.1).
- OHM coefficients for modelling storage heat flux derived here show clear seasonality: summertime (i.e., days warmer than annual median air temperature) a_1 and a_3 are smaller than their wintertime counterparts while the seasonal contrast in a_2 is smaller, suggesting seasonally varying values should be used for long-term (i.e. > one year) simulations.
- Surface conductance related parameters derived using summertime upper-boundary-based approach (Matsumoto et al. 2008), produce parameter related to solar radiation (G_K) and optimal air temperature (G_T) with some dependence on geographical locations, which could be used as a proxy to derive these two parameters.
- SUEWS modelled Q_E is particularly sensitive to surface conductance as informed by the attribution analysis using an analytical framework by McCuen (1974) and consistent with results of Beven (1975) that surface conductance plays a dominant role in moderating the bias in modelled Q_E .
- SUEWS configured with NOAH-based parameters has comparable prediction skill in Q_E compared to site-specific parameters when assessed by hit rate (HR) with medians being ~0.65. However, site-specific parameters improve SUEWS performance as shown by the mean absolute error (MAE) and mean bias error (MBE) metrics, becoming increasingly evident at finer temporal scales (monthly and hourly).
- SUEWS with site-specific parameters outperforms in cooler periods (i.e., winter and night) compared to warmer periods (i.e., summer and day): HR is consistently higher in the former periods than the latter (0.71 cf. 0.52 in median) while MAE (cooler vs. warmer seasons median: ~12 cf. ~31 W m⁻²).
- Correctly predicting LAI timing dynamics has a crucial influence on overall Q_E model performance, followed by surface conductance g_s that is generally underestimated during cooler periods (more pronounced at night by ~3 mm s⁻¹).

As the first comprehensive study of SUEWS at multiple vegetated sites, we also identify future development and application needs:

- None of the simple LAI schemes in SUEWS account for hydrological impacts on LAI. Vegetation with shallow roots (e.g. US-SRG in Arizona, US, categorised as GRA according to IGBP, Fig. D2) are not well modelled when air temperature if the only phenology forcing variable. Hydrological feedback should be considered in future development of the LAI scheme in SUEWS.

- 743 ▪ The specific humidity deficit surface conductance parameter relation needs improvement as a plateau-
 744 like trend is observed near the lower end (e.g., Fig. 9c).
- 745 ▪ A potential source of parameters values for PFT beyond those studied here (i.e. values provided
 746 Appendix C, Sun et al. 2021) could be NOAH-based parameters (Appendix A) but these should be
 747 used with caution, as demonstrated (Section 5).
- 748 ▪ More careful treatment of snow cover should be incorporated to enhance SUEWS capacity in high-
 749 latitude regions

750 **Appendix A: NOAH-based equivalent values for surface conductance related
 751 parameters for SUEWS**

752 The NOAH land surface scheme (Chen et al. 1996) uses a similar Jarvis-type parameterisation of surface
 753 conductance g_s as in SUEWS (i.e. Eqn. 13) but with different formulation of g_s sub-components from
 754 SUEWS (Eqn A1-A4 cf. Eqn. 15–18). The NOAH equations, using our notation are:

- 755 • Incoming solar radiation (K_{\downarrow}):

$$756 g_{NOAH}(K_{\downarrow}) = \frac{\frac{R_{cmin}}{5000} + f}{1 + f} \quad (A1)$$

757 where $f = 0.55 \frac{K_{\downarrow}}{R_{gl}} \frac{2}{LAI}$ with R_{gl} an adjustable parameter for K_{\downarrow} .

- 758 • Air specific humidity (q):

$$759 g_{NOAH}(q) = \frac{1}{1 + h_s(q_s - q)} \quad (A2)$$

760 where h_s is the adjustable parameter for specific humidity q and q_s the saturation specific humidity.

- 761 • Air temperature (T_a):

$$762 g_{NOAH}(T_a) = 1 - 0.0016(T_{ref} - T_a)^2 \quad (A3)$$

763 where T_{ref} is the adjustable parameter for air temperature T_a .

- 764 • Soil moisture (θ_{soil}):

$$765 g_{NOAH}(\theta_{soil}) = \frac{\theta_{soil} - \theta_{WP}}{\theta_{FC} - \theta_{WP}} \quad (A4)$$

766 where θ_{FC} and θ_{WP} are field capacity and wilting point (see Table A2 for values of different soil types).

767 To use the NOAH parameters (as given in Table 1 and 2 of Chen and Duhdia 2001), we convert the
 768 NOAH parameters (Eqn. A1- A4) to the SUEWS required parameters (i.e. for Eqn. 15-18). The resulting
 769 SUEWS parameters (Table A1) are used (Sect. 5) to produce results in Fig. 14 and 15 denoted by NOAH.

770 **Table A1** NOAH-derived (data: based on Table 1 and 2 of Chen and Duhdia 2001) surface
 771 conductance related parameters for SUEWS

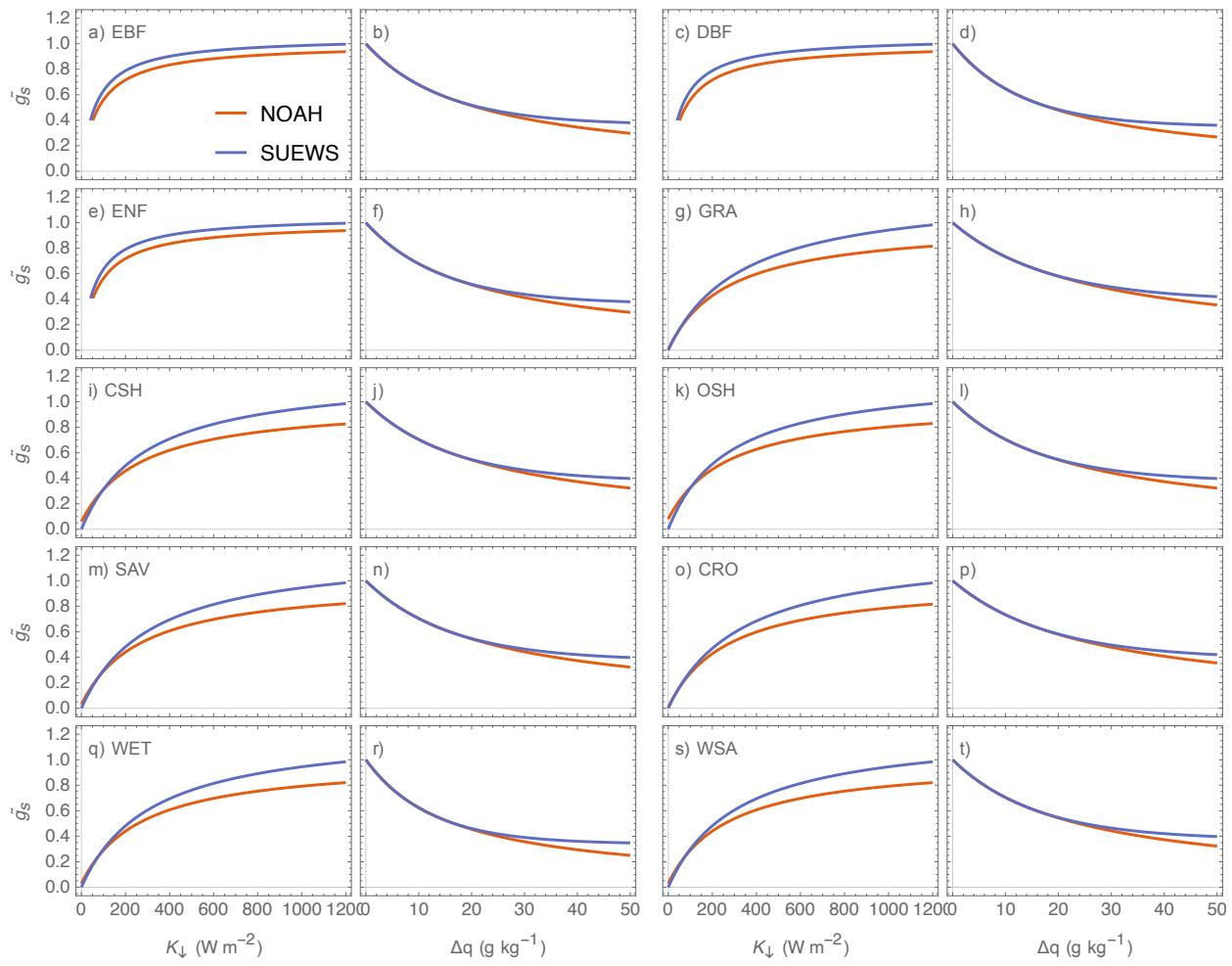
	g_{max} [mm s ⁻¹]	G_K [W m ⁻²]	G_T [°C]	T_L [°C]	T_H [°C]	$G_{q,base}$ [-]	$G_{q,shape}$ [-]	G_θ [-]
EBF	10.0	67	24.85	-0.15	49.85	0.361	0.932	0.002
DBF	10.0	67	24.85	-0.15	49.85	0.348	0.924	0.002
MF	10.0	66	24.85	-0.15	49.85	0.352	0.927	0.002
ENF	6.7	65	24.85	-0.15	49.85	0.361	0.932	0.002
GRA	25.0	336	24.85	-0.15	49.85	0.384	0.945	0.002
CSH	3.3	291	24.85	-0.15	49.85	0.372	0.938	0.002
OSH	2.5	275	24.85	-0.15	49.85	0.372	0.938	0.002
SAV	6.7	316	24.85	-0.15	49.85	0.372	0.938	0.002
CRO	25.0	336	24.85	-0.15	49.85	0.384	0.945	0.002
WET	6.7	316	24.85	-0.15	49.85	0.338	0.919	0.002
WSA	6.7	316	24.85	-0.15	49.85	0.372	0.938	0.002

772 **Table A2** Soil field capacity (θ_{FC}) and wilting point (θ_{WP}) used in NOAH (data: based on Table 2 of
 773 Chen and Duhdia 2001).

	θ_{FC} [m ³ m ⁻³]	θ_{WP} [m ³ m ⁻³]
Sand	0.236	0.01
Loamy sand	0.283	0.028
Sandy loam	0.312	0.047
Silt loam	0.36	0.084
Silt	0.36	0.084
Loam	0.329	0.066
Sandy clay loam	0.314	0.067
Silty clay loam	0.387	0.12
Clay loam	0.382	0.103
Sandy clay	0.338	0.1
Silty clay	0.404	0.126
Clay	0.412	0.138

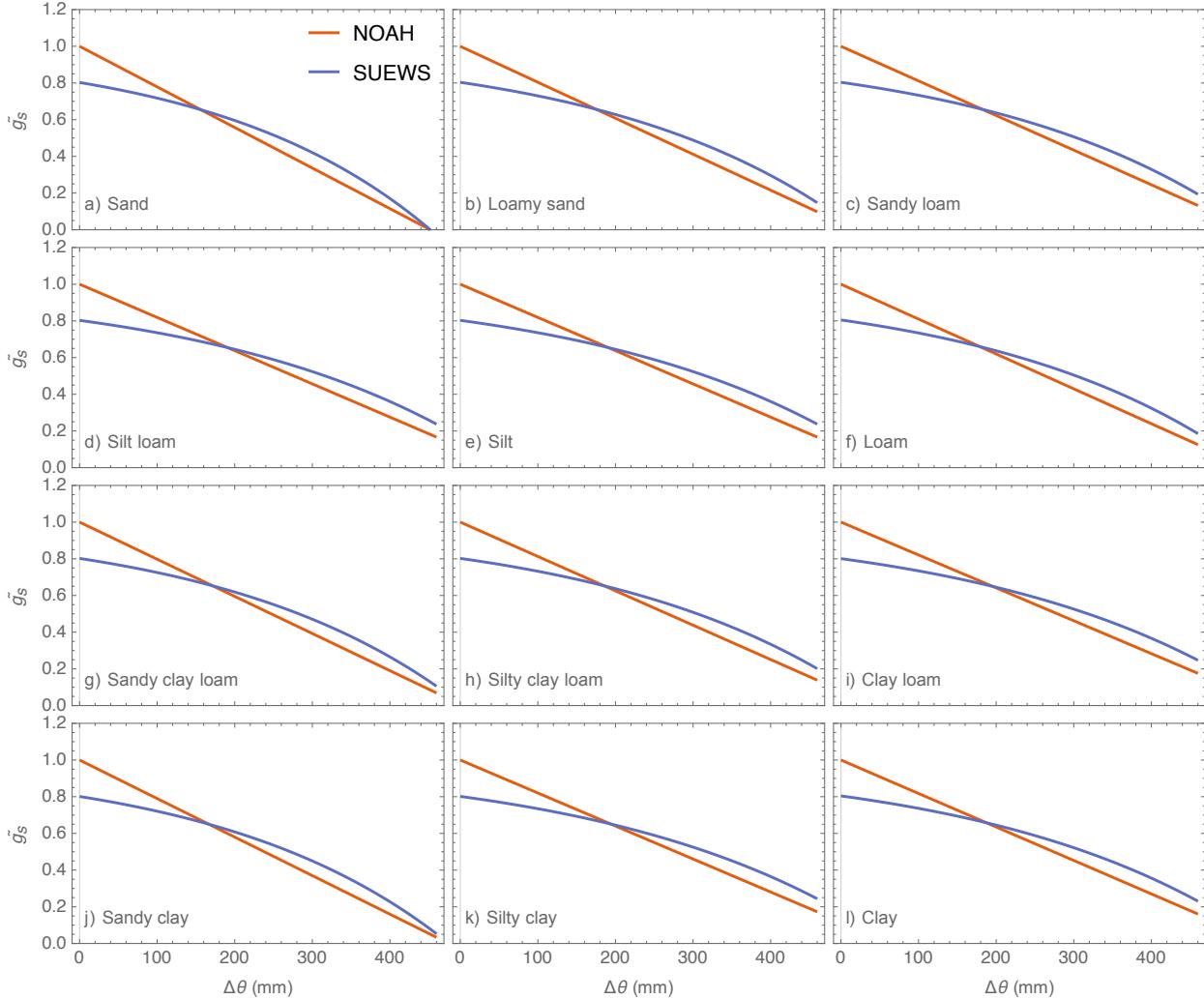
774 Except for the g_s function for air temperature – SUEWS and NOAH adopt the effectively same
 775 formulation – other g_s functions may produce different results even using the converted parameter values
 776 (Table A1). In particular, the shortwave radiation and specific humidity (Fig. A1), the SUEWS values
 777 (blue) are higher for all PFT types than NOAH (red). The role of soil type (Table A2) on the soil moisture
 778 deficit function (Fig. A2) results in larger differences at dry and mid-wet extremes.

779



780

781 **Figure A1** NOAH (red) and SUEWS (blue) surface conductance functions for incoming solar
 782 radiation (K_{\downarrow}) and specific humidity deficit (Δq) for different IGBP PFTs.



783

784 **Figure A2.** As Fig A1 but for soil moisture deficit ($\Delta\theta$) for different soil types with an assumed soil
 785 depth of 2000 mm. Soil hydraulic properties (field capacity θ_{FC} and wilting point θ_{WP}) are provided
 786 in Table A2.

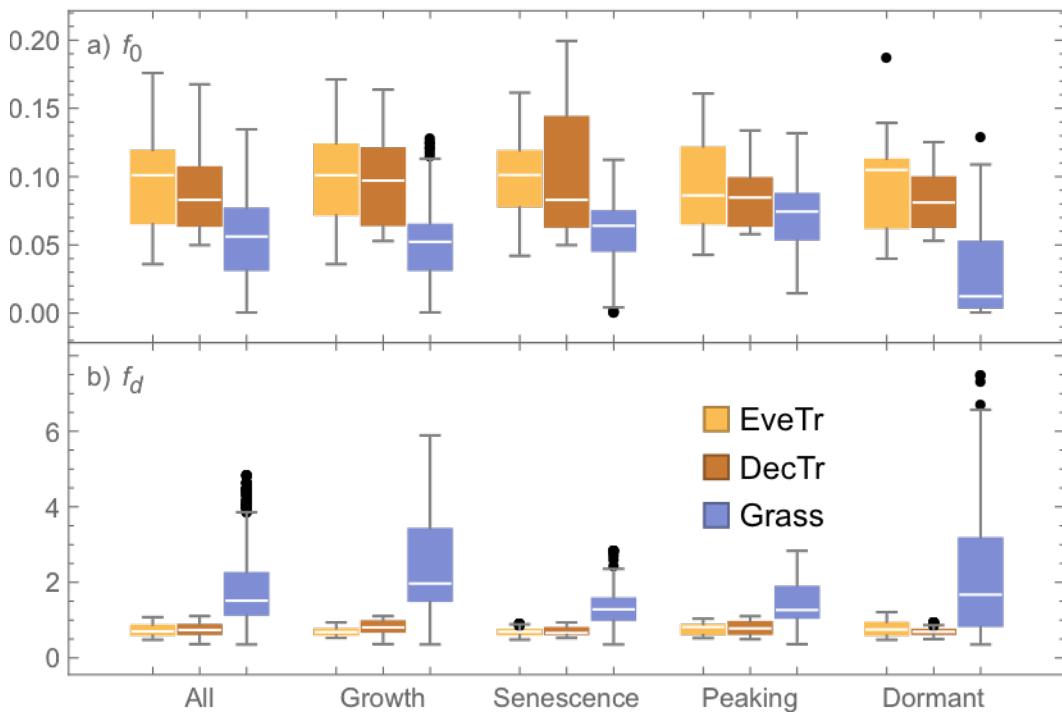
787 **Appendix B: Derivation of roughness length and zero-plane displacement height
 788 for momentum**

789 The aerodynamic roughness parameters for momentum (roughness length z_{0m} and zero-plane
 790 displacement height z_d) are derived using observed u_* and u under neutral conditions (i.e. $\left|\frac{z_m - z_d}{L}\right| < 0.01$
 791 with an initial estimate of $z_d = 0.7H_c$) of different vegetation stages based on LAI (see Sect. 4.1 for
 792 classification details) by the least-square method for the following relation (Monin and Obukhov, 1954):

$$793 u = \frac{u_*}{\kappa} \ln \left(\frac{z_m - z_d}{z_{0m}} \right) \quad (B1)$$

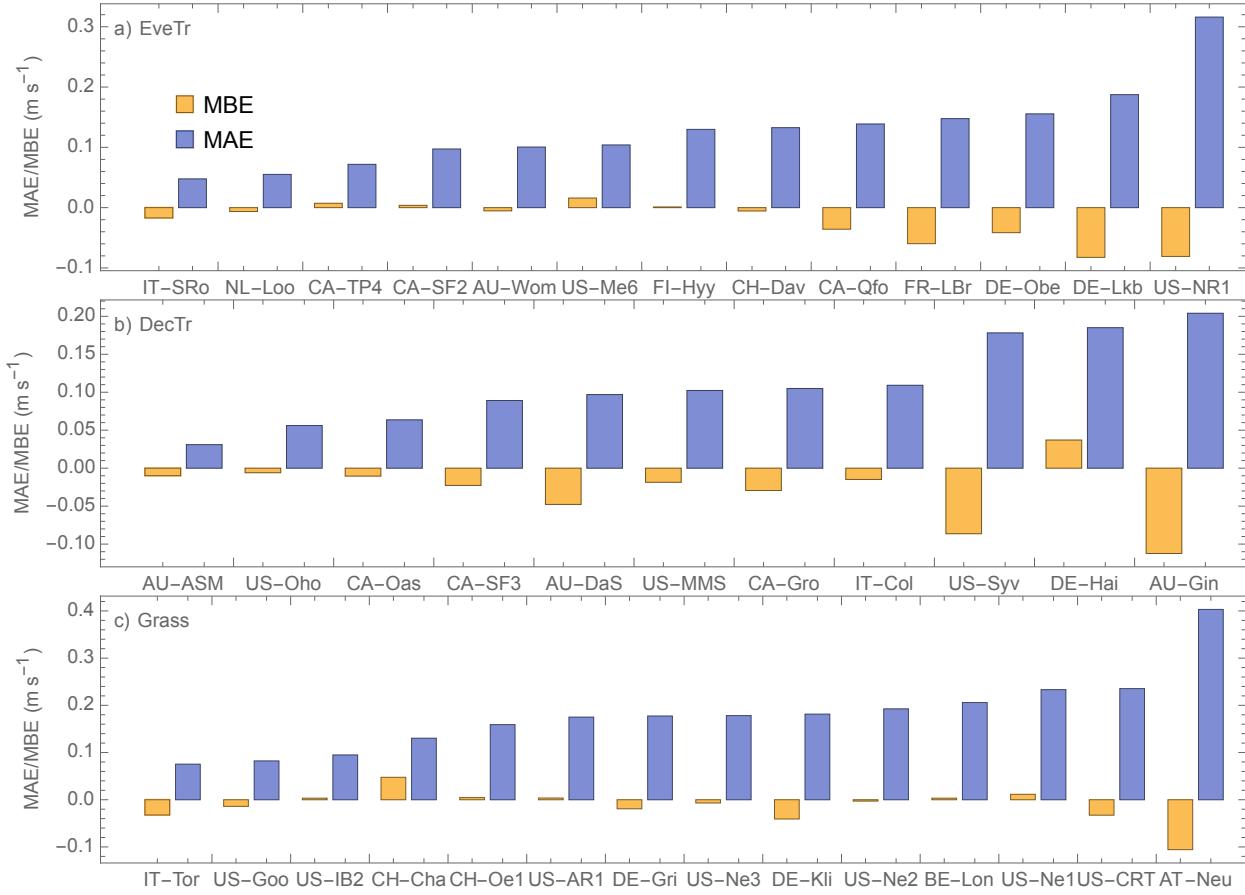
794 where κ is the von Kármán constant (0.4 is used here). In particular, for sites with varying canopy height
 795 H_c , z_{0m} and z_d are derived for each of the periods when H_c stayed unchanged and more than 20
 796 observational pairs of u_* and u are available.

797 Using the derived z_{0m} and z_d , f_0 and f_d parameters can be obtained (Eqn. 9 and 10). These is considerable
 798 intra-PFT variability of both f_0 and f_d (Fig. B1). There are also intra-site variations associated with varying
 799 H_c . Given the large variability in both f_0 and f_d , the rule-of-thumb approach would incur large bias in
 800 estimated aerodynamic and surface resistances and subsequently the modelled Q_E . To reduce such bias, in
 801 the evaluation of the other sub-models and parameter determinations in this paper, we use the derive z_{0m}
 802 and z_d determined for each vegetation stage and site.



803
 804 **Figure B1.** Relations between canopy height (H_c) and a) roughness length for momentum (z_{0m} , Eqn.
 805 B2) and b) displacement height (z_d , Eqn. B3) for different vegetation stages based on LAI (see
 806 Sect. 4.1 for classification details)

807 Modelled wind speed under neutral conditions matches well with observations at 38 study sites with
 808 MAE $< 0.3 \text{ m s}^{-1}$ and MBE close to zero (Fig. B2). Of the three SUEWS PFTs, ‘Grass’ sites have the
 809 poorer performance. This is probably because this PFT includes crops which will change frequently
 810 because of crop rotations: cereal, potato, sugar beet at BE-Lon (Moureaux et al., 2006); winter barley,
 811 rapeseed, winter wheat, maize and spring barley at DE-Kli (Prescher et al., 2010), maize and soybean at
 812 US-Ne2 and US-Ne3).



813
814
815

Figure B2 MAE (blue) and MBE (orange) for modelled wind speed under neutral conditions for three SUEWS PFTs: a) EveTr, b) DecTr and c) Grass.

816 Appendix C: SUEWS parameters derived at selected FLUXNET sites

817 **Table C1** LAI and albedo related parameters at 38 sites (Table 3 gives site information) derived
818 using FLUXNET2015 dataset (Sect. 4.1).

	α_{min} [-]	α_{max} [-]	LAI_{max} $[m^2 m^{-2}]$	LAI_{min} $[m^2 m^{-2}]$	GDD_{full} $^{\circ}C day$	SDD_{full} $^{\circ}C day$	$T_{base,GDD}$ $^{\circ}C$	$T_{base,SDD}$ $^{\circ}C$	$\omega_{1,GDD}$ [-]	$\omega_{1,SDD}$ [-]	$\omega_{2,GDD}$ [-]	$\omega_{2,SDD}$ [-]
AT-Neu	0.23	0.19	2.24	0.18	1200.58	-1015.40	-0.20	14.02	-2.00	-3.02E-03	5.35E-05	0.09
AU-ASM	0.12	0.09	0.30	0.20	93.17	-31.48	13.90	16.42	-1.32	-2.21E-03	1.43E-05	0.97
AU-DaS	0.14	0.12	1.86	0.97	350.98	-78.63	25.74	24.90	-2.00	-5.45E-03	5.29E-05	1.37
AU-Gin	0.13	0.11	1.09	0.60	239.14	-96.09	12.73	17.21	-2.00	-1.16E-03	7.87E-05	2.95
AU-Wom	0.10	0.09	4.51	1.19	404.14	-43.42	5.50	7.86	-2.00	-5.17E-03	2.10E-03	1.17
BE-Lon	0.17	0.14	1.66	0.15	264.31	-467.14	8.63	14.53	-2.00	-2.27E-03	4.64E-04	3.33
CA-Gro	0.09	0.08	2.97	0.65	1000.69	-300.71	-0.62	13.37	-2.00	-5.50E-04	2.88E-04	1.72
CA-Oas	0.12	0.11	3.87	0.56	252.15	-193.36	8.69	13.81	-1.71	-3.22E-03	3.81E-03	1.65
CA-Qfo	0.11	0.06	1.82	0.20	932.53	-675.56	-4.41	12.84	-1.26	-1.05E-03	6.79E-05	0.57
CA-SF2	0.12	0.11	2.74	0.50	781.58	-382.78	1.43	12.35	-2.00	-9.12E-04	2.08E-04	3.03
CA-SF3	0.10	0.09	2.22	0.45	724.36	-598.25	1.40	14.45	-2.00	-7.55E-03	1.24E-04	0.10
CA-TP4	0.09	0.08	2.57	0.43	1042.85	-599.76	4.54	18.51	-2.00	-3.77E-03	1.32E-04	0.14
CH-Cha	0.21	0.18	2.39	0.52	161.91	-369.59	2.69	9.41	-2.00	-6.79E-03	2.45E-03	1.04
CH-Dav	0.07	0.06	2.04	0.20	645.94	-380.00	1.95	9.97	-1.36	-3.69E-04	1.14E-04	2.83
CH-Oe1	0.22	0.18	1.98	0.31	399.90	-486.85	2.78	12.45	-2.00	-1.39E-03	4.58E-04	0.29
DE-Gri	0.21	0.19	2.52	0.69	369.12	-383.65	3.10	12.72	-2.00	-7.57E-03	6.59E-04	0.05
DE-Hai	0.13	0.09	3.82	0.98	101.43	-49.58	7.46	9.89	-0.09	-1.00E-02	3.49E-03	4.00
DE-Kli	0.19	0.14	2.24	0.30	371.62	-129.27	2.81	9.29	-2.00	-7.34E-03	4.20E-04	1.46
DE-Lkb	0.22	0.14	2.68	0.51	967.50	-293.93	-1.32	7.59	-2.00	-3.45E-03	1.45E-04	0.52
DE-Obe	0.07	0.06	2.84	0.59	349.45	-306.51	1.77	7.74	-2.00	-7.57E-03	1.05E-03	1.27

FI-Hyy	0.10	0.09	2.73	0.43	859.30	-512.51	0.08	14.97	-2.00	-3.98E-03	3.35E-04	0.10
FR-LBr	0.11	0.10	2.35	0.62	322.30	-263.61	11.58	17.10	-2.00	-2.58E-03	7.28E-04	2.51
IT-Col	0.13	0.11	3.12	0.54	390.41	-424.85	3.60	11.45	-2.00	-7.40E-04	1.22E-03	0.85
IT-SRo	0.09	0.07	2.73	0.92	481.73	-564.19	8.39	18.06	-2.00	-2.68E-03	6.75E-04	0.07
IT-Tor	0.23	0.18	2.08	0.20	625.92	-467.45	0.70	9.16	-2.00	-9.33E-04	1.58E-04	1.45
NL-Loo	0.10	0.09	2.01	0.49	676.48	-937.96	6.27	16.31	-2.00	-6.60E-03	9.67E-05	0.02
US-ARI	0.15	0.14	0.96	0.27	387.82	-929.25	10.88	22.53	-2.00	-2.31E-03	3.71E-05	0.06
US-CRT	0.12	0.11	2.53	0.38	23.74	-264.69	25.24	17.99	-2.00	-1.21E-03	4.49E-03	1.25
US-Goo	0.20	0.16	3.13	0.73	131.20	-276.51	16.85	19.13	-2.00	-5.99E-04	7.11E-03	2.09
US-IB2	0.15	0.13	1.94	0.21	1403.13	-940.31	1.12	19.90	-1.74	-7.04E-03	4.08E-05	0.06
US-Me6	0.15	0.11	1.46	0.61	22.89	-309.48	6.70	4.74	-2.00	-5.80E-04	2.91E-03	0.15
US-MMS	0.12	0.11	5.00	1.01	68.61	-50.83	13.97	15.79	-0.45	-7.11E-03	8.30E-03	2.22
US-Ne1	0.16	0.14	2.13	0.34	475.09	-321.98	14.84	22.34	-1.80	-7.23E-04	2.07E-04	1.62
US-Ne2	0.16	0.13	2.08	0.30	469.13	-380.78	14.65	22.42	-1.83	-2.03E-03	2.13E-04	0.41
US-Ne3	0.17	0.16	2.18	0.33	491.72	-317.46	14.89	22.64	-1.60	-5.25E-04	2.15E-04	1.47
US-NR1	0.14	0.14	1.53	0.51	640.96	-1239.29	-0.32	11.62	-2.00	-1.20E-03	9.67E-05	0.04
US-Oho	0.14	0.12	2.78	0.45	1540.19	-981.83	1.50	21.71	-1.65	-5.24E-03	9.67E-05	0.05
US-Syy	0.16	0.10	4.81	0.66	461.96	-202.37	4.30	15.08	-1.67	-3.25E-03	2.33E-03	1.12

819

Table C2 As Table C1 but for OHM related parameters (Sect. 4.2)

	a_1 [-]		a_2 [h]		a_3 [W m^{-2}]	
	summer	winter	summer	winter	summer	winter
AT-Neu	0.37	0.88	0.05	0.02	-12.12	11.15
AU-ASM	0.39	0.39	0.15	0.13	-26.44	-35.45
AU-DaS	0.31	0.30	0.05	0.06	-29.17	-21.82
AU-Gin	0.40	0.25	0.17	0.21	-11.35	-25.75
AU-Wom	0.29	0.29	0.10	0.08	3.54	-18.13
BE-Lon	0.32	0.82	0.18	0.04	-3.58	8.00
CA-Gro	0.31	0.51	0.15	0.19	-9.62	-8.94
CA-Oas	0.27	0.45	0.13	0.25	-6.84	-0.58
CA-Qfo	0.30	0.43	0.22	0.25	-10.70	-1.50
CA-SF2	0.16	0.46	0.15	0.09	-17.05	-3.39
CA-SF3	0.25	0.60	0.20	0.09	-22.22	-8.67
CA-TP4	0.28	0.42	0.17	0.13	-7.94	1.07
CH-Cha	0.25	0.67	0.05	0.00	-29.09	-8.37
CH-Dav	0.56	0.65	0.13	0.11	-29.23	-12.08
CH-0e1	0.34	0.67	0.08	0.12	-22.53	-6.21
DE-Gr1	0.44	0.76	0.04	0.02	-6.13	5.14
DE-Hai	0.15	0.21	-0.01	0.15	-1.31	9.81
DE-Kli	0.45	0.77	0.12	0.07	-11.62	4.91
DE-Lkb	0.23	0.84	0.09	-0.04	-31.59	-18.49
DE-0be	0.33	0.53	-0.06	0.02	-10.33	-8.95
FI-Hyy	0.23	0.68	0.17	0.09	-8.75	7.89
FR-LBr	0.27	0.43	0.19	0.17	-17.30	-8.04
IT-C01	0.36	0.43	0.14	0.22	-4.56	-10.00
IT-SRo	0.31	0.51	0.27	0.15	-5.40	13.57
IT-Tor	0.23	0.94	0.09	0.05	-18.92	4.31
NL-Loo	0.24	0.44	0.14	0.20	1.06	2.90
US-ARI	0.18	0.17	0.16	0.11	-26.72	-16.50
US-CRT	0.32	0.63	0.11	0.06	-11.14	-6.23
US-Goo	0.38	0.41	0.04	0.07	-16.06	-20.52
US-IB2	0.29	0.37	0.00	0.03	-4.97	-6.43
US-Me6	0.35	0.51	0.21	0.12	-24.00	-0.93
US-MMS	0.34	0.45	0.19	0.25	-7.46	-7.21
US-Ne1	0.30	0.56	0.09	0.03	-13.72	-9.05
US-Ne2	0.29	0.51	0.06	0.04	-14.54	-9.19
US-Ne3	0.29	0.55	0.04	-0.02	-17.87	-8.34
US-NRI	0.27	0.22	0.05	0.06	-7.97	-15.95
US-Oho	0.32	0.44	0.10	0.16	-13.31	-12.73
US-syy	0.33	0.33	0.06	0.13	-9.21	-0.93

820

Table C3 As Table C1, but for surface conductance related parameters (Sect. 4.3)

g_{max} [mm s ⁻¹]	G_K [W m ⁻²]	G_T [°C]	T_L [°C]	T_H [°C]	$G_{q,base}$ [-]	$G_{q,shape}$ [-]	G_θ [-]	$\Delta\theta_{WP}$ [mm]
------------------------------------	-------------------------------	---------------	---------------	---------------	---------------------	----------------------	-------------------	-----------------------------

AT-Neu	39.6193	50.00	23.67	-15.74	31.59	0.50	0.90	0.04	687.75
AU-ASM	15.73	288.38	26.77	8.00	34.39	0.40	0.90	0.01	409.50
AU-DaS	19.92	83.22	37.78	-30.00	38.00	0.50	0.90	0.02	414.75
AU-Gin	7.44	94.79	13.23	-14.59	41.54	0.41	0.90	0.06	446.25
AU-Wom	30.63	70.26	14.73	2.00	41.91	0.36	0.90	0.10	535.50
BE-Lon	25.64	74.21	23.22	5.31	36.41	0.50	0.90	0.01	430.50
CA-Gro	22.96	50.00	5.33	-30.00	36.00	0.40	0.90	0.01	876.75
CA-Oas	26.76	50.00	14.53	-30.00	30.89	0.50	0.90	0.01	603.75
CA-Qfo	15.56	50.00	11.62	-0.93	46.81	0.22	0.90	0.01	404.25
CA-SF2	23.59	91.88	12.21	-29.99	33.65	0.50	0.90	0.03	525.00
CA-SF3	23.95	50.00	-0.01	-30.00	38.43	0.36	0.90	0.07	514.50
CA-TP4	23.10	50.00	19.12	-9.57	50.00	0.50	0.90	0.03	446.25
CH-Cha	46.30	126.77	35.86	-30.00	50.00	0.50	0.90	0.10	173.25
CH-Dav	18.14	50.00	4.55	-15.93	49.96	0.50	0.90	0.07	141.75
CH-Oe1	41.74	77.78	16.52	-0.99	50.00	0.50	0.90	0.01	556.50
DE-Gri	25.43	142.40	20.71	-23.20	36.09	0.50	0.90	0.00	750.75
DE-Hai	22.45	69.16	5.61	-29.82	34.65	0.27	0.90	0.01	514.50
DE-Kli	24.50	51.37	19.63	-30.00	26.26	0.50	0.90	0.01	824.25
DE-Lkb	32.34	85.39	-0.12	-30.00	50.00	0.50	0.90	0.02	278.25
DE-Obe	14.76	50.01	4.44	-28.20	34.78	0.41	0.90	0.03	283.50
FI-Hyy	17.23	64.75	18.94	4.00	34.44	0.40	0.90	0.01	708.75
FR-LBr	24.48	50.00	14.03	-8.96	33.12	0.33	0.90	0.01	1065.75
IT-Col	14.66	50.00	13.96	-12.26	50.00	0.50	0.90	0.02	425.25
IT-SRo	20.57	50.00	7.66	-30.00	49.99	0.47	0.90	0.01	971.25
IT-Tor	42.23	73.54	23.20	-15.96	49.99	0.50	0.90	0.09	294.00
NL-Loo	16.53	50.00	17.70	6.00	37.06	0.35	0.90	0.10	252.00
US-AR1	27.51	181.15	16.31	6.00	34.00	0.03	0.90	0.01	315.00
US-CRT	27.43	50.00	30.54	-14.00	42.02	0.50	0.90	0.10	824.25
US-Goo	41.46	172.08	24.45	-10.87	50.00	0.50	0.90	0.03	404.25
US-IB2	48.78	50.00	29.19	-7.90	36.00	0.50	0.90	0.06	483.00
US-Me6	13.70	92.88	3.44	-10.00	42.71	0.11	0.90	0.01	525.00
US-MMS	22.54	182.23	27.06	-0.24	36.62	0.50	0.90	0.01	845.25
US-Ne1	52.14	50.00	29.84	-30.00	34.43	0.50	0.90	0.04	519.75
US-Ne2	53.45	59.97	32.04	-30.00	34.02	0.50	0.90	0.10	383.25
US-Ne3	44.55	53.41	30.84	-30.00	50.00	0.50	0.90	0.07	645.75
US-NRI	15.91	52.94	5.51	-11.90	33.80	0.43	0.90	0.02	509.25
US-Oho	40.01	56.33	31.08	-29.99	36.53	0.50	0.90	0.10	220.50
US-Syy	16.85	130.28	18.77	-4.00	40.65	0.50	0.90	0.01	456.75

822 **Appendix D: Typical Intra-annual LAI dynamics under contrasting meteorological**
823 **controls**

824 Given sufficient CO₂, vegetation phenology indicated by LAI dynamics, is predominantly controlled by
825 input energy and water (Fang et al. 2019). Two variables that capture this seasonal variability are air
826 temperature and precipitation. Different intra-annual LAI dynamics are evident between sites, with
827 contrasting meteorological controls:

- 828 a) Thermally dominant (US-MMS; Fig. D1): Intra-annual cumulative precipitation at US-MMS steadily
829 increases throughout the year (Fig. D1a), implying a fairly even distribution of water supply; while
830 air temperature gradually increases from the mid winter (beginning of a year), peaks in August and
831 decrease with the start of the next winter (Fig. D1b). The LAI pattern at US-MMS responds to the air
832 temperature, notably the growing degrees days (GDD) and then autumn senescence (SDD). This
833 inverse “U”-shape typifies sites with thermally-dominant LAI dynamics. These types of sites are well
834 parameterised by the current LAI scheme in SUEWS (Sect. 2.2.1).

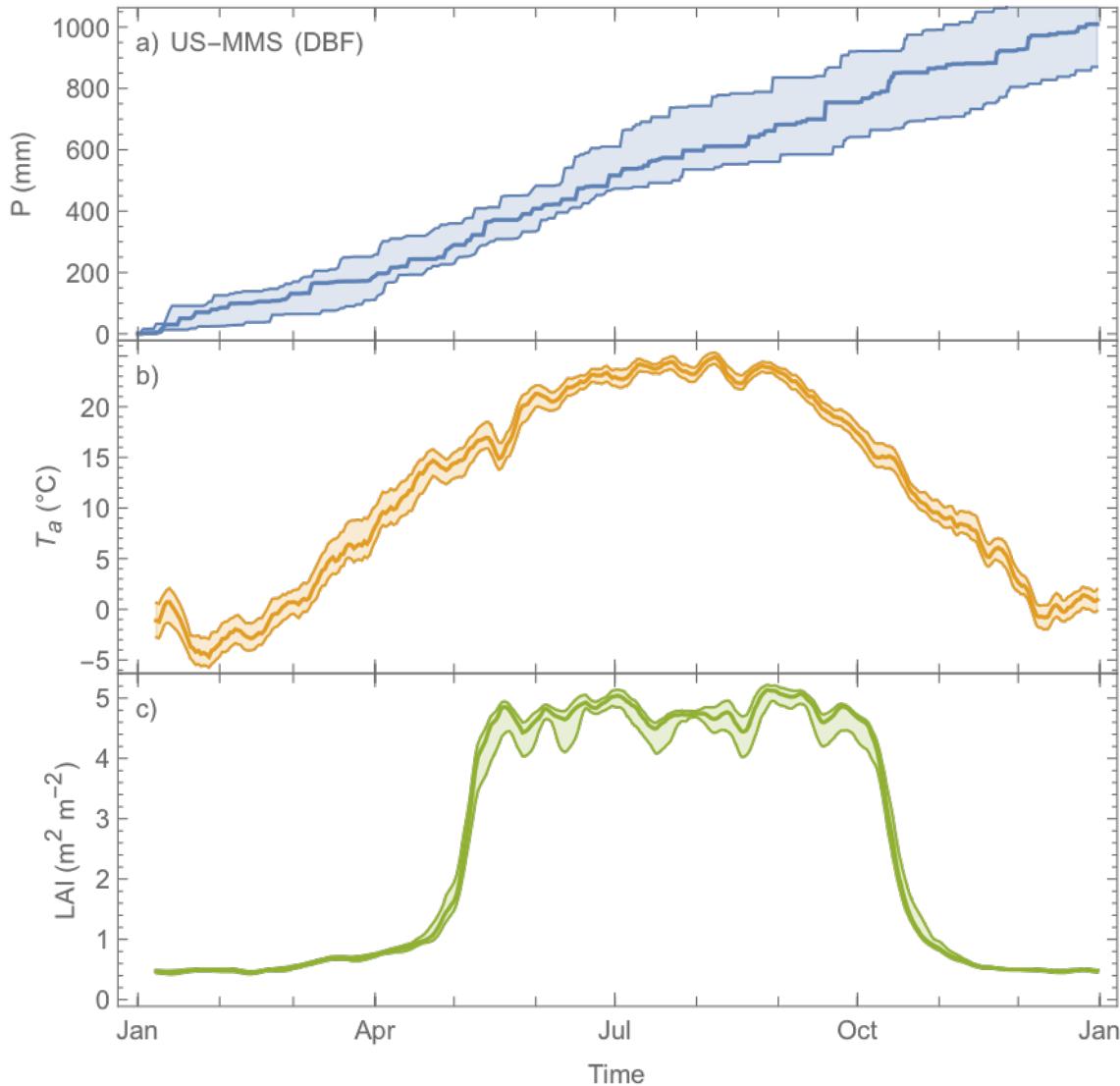
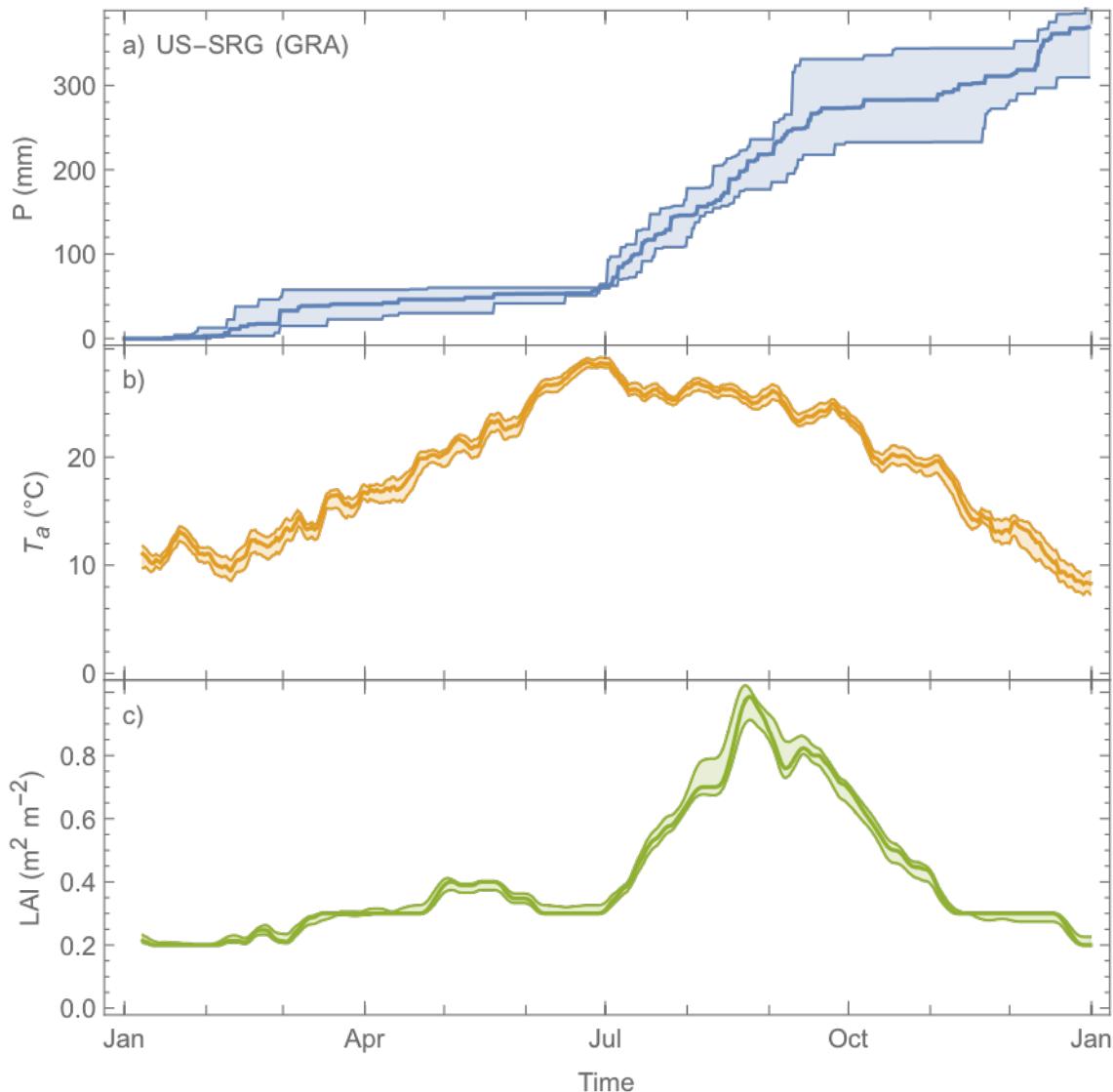


Figure D1 Median (line) and interquartile range (shading) daily variation at US-MMS a DBF site during the period 2002–2015 of (a) precipitation (cumulative), (b) air temperature (7-day moving average) and (c) LAI (7-day moving average).

b) Rainfall and thermal controls (US-SRG; Fig. D2): at this grassland site in Arizona, US the intra-annual precipitation has clear dry and wet seasons. The monsoon wet season after the peak air temperature in July through September (Fig. D2a), which has warmest air temperatures, Unlike US-MMS (Fig. D2b), the peak air temperature is more distinct (for a shorter period). A clear relation between the onset of rainfall and LAI enhancement can be seen but the GDD and SDD relation differs from US-MMS and it not captured by the current models in SUEWS. The rainfall and enhanced LAI and Q_E are associated with cooler daily air temperatures. Sites where the LAI dynamics are not captured are not explored further in this paper.



847
848
849

Figure D2 As Fig. D1, but for US-SRG (GRA according to IGBP; time span: 2008–2015; DOI: 10.18140/FLX/1440114)

850 **Code and data availability**

851 All source codes, input and output data are archived at Zenodo in Sun et al. (2021) which can be accessed
852 at: <https://zenodo.org/record/5519919>.

853 **Author contribution**

854 HO, TS and SG contributed to data preparation, parameter derivation, running simulations and writing the
855 paper. HO led the initial and TS the revised versions of this work. All other authors (DB, AB, JC, ZD, HI,

856 and JM) provided data for analysis of this work at different stages (some not used in this paper),
857 interpreted the results, and reviewed the manuscript.

858 **Competing interest**

859 The authors declare that they have no conflict of interest.

860 **Acknowledgments**

861 This work is funded by NERC-COSMA project (NE/S005889/1), Newton Fund Met Office CSSP-China
862 (SG), NERC Independent Research Fellowship (NE/P018637/1), and National Natural Science
863 Foundation of China (41875013; Zhiqiu Gao and Zexia Duan).

864 **References**

865 Anandakumar, K.: A study on the partition of net radiation into heat fluxes on a dry asphalt surface,
866 *Atmos Environ*, 33(24–25), 3911–3918, doi:10.1016/s1352-2310(99)00133-8, 1999.

867 André, J.-C., Goutorbe, J.-P. and Perrier, A.: HAPEX-MOBLIHY: A Hydrologic Atmospheric
868 Experiment for the Study of Water Budget and Evaporation Flux at the Climatic Scale, *B Am Meteorol
869 Soc*, 67(2), 138–144, doi:10.1175/1520-0477(1986)067<0138:hahaef>2.0.co;2, 1986.

870 Ao, X., Grimmond, C. S. B., Ward, H. C., Gabey, A. M., Tan, J., Yang, X.-Q., Liu, D., Zhi, X., Liu, H.
871 and Zhang, N.: Evaluation of the Surface Urban Energy and Water Balance Scheme (SUEWS) at a Dense
872 Urban Site in Shanghai: Sensitivity to Anthropogenic Heat and Irrigation, *J. Hydrometeorol.*, 19(12),
873 1983–2005, doi:10.1175/JHM-D-18-0057.1, 2018.

874 Asaadi, A., Arora, V. K., Melton, J. R. and Bartlett, P.: An improved parameterization of leaf area index
875 (LAI) seasonality in the Canadian Land Surface Scheme (CLASS) and Canadian Terrestrial Ecosystem
876 Model (CTEM) modelling framework, *Biogeosciences*, 15(22), 6885–6907, doi:10.5194/bg-15-6885-
877 2018, 2018.

878 Baldocchi, D., Falge, E., Gu, L., Olson, R., Hollinger, D., Running, S., Anthoni, P., Bernhofer, C., Davis,
879 K., Evans, R., Fuentes, J., Goldstein, A., Katul, G., Law, B., Lee, X., Malhi, Y., Meyers, T., Munger, W.,
880 Oechel, W., Paw, U. K. T., Pilegaard, K., Schmid, H. P., Valentini, R., Verma, S., Vesala, T., Wilson, K.
881 and Wofsy, S.: FLUXNET: A New Tool to Study the Temporal and Spatial Variability of Ecosystem-
882 Scale Carbon Dioxide, Water Vapor, and Energy Flux Densities, *Bull. Am. Meteorol. Soc.*, 82(11), 2415–
883 2434, doi:10.1175/1520-0477(2001)082<2415:FANTTS>2.3.CO;2, 2001.

884 Balsamo, G., Beljaars, A., Scipal, K., Viterbo, P., Hurk, B. van den, Hirschi, M., and Betts, A. K.: A
885 Revised Hydrology for the ECMWF Model: Verification from Field Site to Terrestrial Water Storage and
886 Impact in the Integrated Forecast System, 10, 623–643, <https://doi.org/10.1175/2008jhm1068.1>, 2009.

887 Bauerle, W. L., Oren, R., Way, D. A., Qian, S. S., Stoy, P. C., Thornton, P. E., Bowden, J. D., Hoffman,
888 F. M. and Reynolds, R. F.: Photoperiodic regulation of the seasonal pattern of photosynthetic capacity

- 889 and the implications for carbon cycling, Proc. Natl. Acad. Sci. U. S. A., 109(22), 8612–8617,
890 doi:10.1073/pnas.1119131109, 2012.
- 891 Bergeron, O., Margolis, H. A., Black, T. A., Coursolle, C., Dunn, A. L., Barr, A. G. and Wofsy, S. C.:
892 Comparison of carbon dioxide fluxes over three boreal black spruce forests in Canada, Glob. Chang.
893 Biol., 13(1), 89–107, doi:10.1111/j.1365-2486.2006.01281.x, 2007.
- 894 Beven, K.: A sensitivity analysis of the Penman-Monteith actual evapotranspiration estimates, J Hydrol,
895 44(3–4), 169–190, doi:10.1016/0022-1694(79)90130-6, 1979.
- 896 Billesbach, D., Bradford, J. and Torn, M.: AmeriFlux US-AR1 ARM USDA UNL OSU Woodward
897 Switchgrass 1, AmeriFlux Netw., doi:10.17190/AMF/1246137, 2009.
- 898 Bloomfield, P.: Fourier Analysis of Time Series: An Introduction. New York: Wiley-Interscience, 2000
- 899 Bobée, C., Ottlé, C., Maignan, F., De Noblet-Ducoudré, N., Maugis, P., Lézine, A. M. and Ndiaye, M.:
900 Analysis of vegetation seasonality in Sahelian environments using MODIS LAI, in association with land
901 cover and rainfall, J. Arid Environ., 84, 38–50, doi:10.1016/j.jaridenv.2012.03.005, 2012.
- 902 Bosveld, F. C. and Bouting, W.: Evaluation of transpiration models with observations over a Douglas-fir
903 forest, Agr Forest Meteorol, 108(4), 247–264, doi:10.1016/s0168-1923(01)00251-9, 2001.
- 904 Brutsaert, W.: Evaporation into the Atmosphere, Springer Netherlands, Dordrecht., 1982.
- 905 Campbell, G. S. and Norman, J. M.: An Introduction to Environmental Biophysics, in An Introduction to
906 Environmental Biophysics, pp. 1–13, Springer New York, New York, NY., 1998.
- 907 Cescatti, A., Marcolla, B., Vannan, S. K. S., Pan, J. Y., Román, M. O., Yang, X., Ciais, P., Cook, R. B.,
908 Law, B. E., Matteucci, G., Migliavacca, M., Moors, E., Richardson, A. D., Seufert, G. and Schaaf, C. B.:
909 Intercomparison of MODIS albedo retrievals and in situ measurements across the global FLUXNET
910 network, Remote Sens Environ, 121, 323–334, doi:10.1016/j.rse.2012.02.019, 2012.
- 911 Chen, F., Mitchell, K., Schaake, J., Xue, Y., Pan, H., Koren, V., Duan, Q. Y., Ek, M., and Betts, A.:
912 Modeling of land surface evaporation by four schemes and comparison with FIFE observations, J
913 Geophys Res Atmospheres, 101, 7251–7268, <https://doi.org/10.1029/95jd02165>, 1996.
- 914 Chen, F. and Dudhia, J.: Coupling an advanced land surface-hydrology model with the Penn State-NCAR
915 MM5 modeling system. Part I: Model implementation and sensitivity, Mon Weather Rev, 129(4), 569
916 585, doi:10.1175/1520-0493(2001)129<0569:caalsh>2.0.co;2, 2001.
- 917 Chu, H., Luo, X., Ouyang, Z., Chan, W. S., Dengel, S., Biraud, S. C., Torn, M. S., Metzger, S., Kumar, J.,
918 Arain, M. A., Arkebauer, T. J., Baldocchi, D., Bernacchi, C., Billesbach, D., Black, T. A., Blanken, P. D.,
919 Bohrer, G., Bracho, R., Brown, S., Brunsell, N. A., Chen, J., Chen, X., Clark, K., Desai, A. R., Duman,
920 T., Durden, D., Fares, S., Forbrich, I., Gamon, J. A., Gough, C. M., Griffis, T., Helbig, M., Hollinger, D.,
921 Humphreys, E., Ikawa, H., Iwata, H., Ju, Y., Knowles, J. F., Knox, S. H., Kobayashi, H., Kolb, T., Law,
922 B., Lee, X., Litvak, M., Liu, H., Munger, J. W., Noormets, A., Novick, K., Oberbauer, S. F., Oechel, W.,
923 Oikawa, P., Papuga, S. A., Pendall, E., Prajapati, P., Prueger, J., Quinton, W. L., Richardson, A. D.,
924 Russell, E. S., Scott, R. L., Starr, G., Staebler, R., Stoy, P. C., Stuart-Haëntjens, E., Sonnentag, O.,
925 Sullivan, R. C., Suyker, A., Ueyama, M., Vargas, R., Wood, J. D., and Zona, D.: Representativeness of
926 Eddy-Covariance flux footprints for areas surrounding AmeriFlux sites, Agricultural and Forest
927 Meteorology, 301–302, 108350, doi:10.1016/j.agrformet.2021.108350, 2021.

- 928 Curtis, P. S., Hanson, P. J., Bolstad, P., Barford, C., Randolph, J. C., Schmid, H. P. and Wilson, K. B.:
929 Biometric and eddy-covariance based estimates of annual carbon storage in five eastern North American
930 deciduous forests, *Agric. For. Meteorol.*, 113(1–4), 3–19, doi:10.1016/S0168-1923(02)00099-0, 2002.
- 931 Doll, D., Ching, J. K. S. and Kaneshiro, J.: Parameterization of subsurface heating for soil and concrete
932 using net radiation data, *Boundary-Layer Meteorol.*, 32(4), 351–372, doi:10.1007/BF00122000, 1985.
- 933 Ek, M. B., Mitchell, K. E., Lin, Y., Rogers, E., Grunmann, P., Koren, V., Gayno, G. and Tarpley, J. D.:
934 Implementation of Noah land surface model advances in the National Centers for Environmental
935 Prediction operational mesoscale Eta model, *J. Geophys. Res. Atmos.*, 108(D22), 2002JD003296,
936 doi:10.1029/2002JD003296, 2003.
- 937 Ershadi, A., McCabe, M. F., Evans, J. P., Chaney, N. W., and Wood, E. F.: Multi-site evaluation of
938 terrestrial evaporation models using FLUXNET data, *Agr Forest Meteorol*, 187, 46–61,
939 doi:10.1016/j.agrformet.2013.11.008, 2014.
- 940 Ester, M., Kriegel, H.-P., Sander, J., and Xu, X.: A density-based algorithm for discovering clusters in
941 large spatial databases with noise, in: *Proceedings of the Second International Conference on Knowledge
942 Discovery and Data Mining*, Portland, Oregon, 226–231, 1996.
- 943 Fang, H., Baret, F., Plummer, S., and Schaepman-Strub, G.: An Overview of Global Leaf Area Index
944 (LAI): Methods, Products, Validation, and Applications, 57, 739–799, doi:10.1029/2018RG000608,
945 2019.
- 946 Garratt, J.: Review: the atmospheric boundary layer, *Earth-Science Rev.*, 37(1–2), 89–134,
947 doi:10.1016/0012-8252(94)90026-4, 1994.
- 948 Garrigues, S., Lacaze, R., Baret, F., Morisette, J. T., Weiss, M., Nickeson, J. E., Fernandes, R., Plummer,
949 S., Shabanov, N. V., Myneni, R. B., Knyazikhin, Y. and Yang, W.: Validation and intercomparison of
950 global Leaf Area Index products derived from remote sensing data, *J Geophys Res Biogeosciences* 2005
951 2012, 113(G2), doi:10.1029/2007jg000635, 2008.
- 952 Gascoin, S., Ducharne, A., Ribstein, P., Perroy, E. and Wagnon, P.: Sensitivity of bare soil albedo to
953 surface soil moisture on the moraine of the Zongo glacier (Bolivia), *Geophys. Res. Lett.*, 36(2), n/a-n/a,
954 doi:10.1029/2008GL036377, 2009.
- 955 Gill, A. L., Gallinat, A. S., Sanders-DeMott, R., Rigden, A. J., Short Gianotti, D. J., Mantooth, J. A. and
956 Templer, P. H.: Changes in autumn senescence in northern hemisphere deciduous trees: a meta-analysis
957 of autumn phenology studies, *Ann. Bot.*, 116(6), 875–888, doi:10.1093/aob/mcv055, 2015.
- 958 Grimmond, C. S. B.: The suburban energy balance: Methodological considerations and results for a mid-
959 latitude west coast city under winter and spring conditions, *Int. J. Climatol.*, 12(5), 481–497,
960 doi:10.1002/joc.3370120506, 1992.
- 961 Grimmond, C. S. B. and Oke, T. R.: An evapotranspiration-interception model for urban areas, *Water
962 Resour. Res.*, 27(7), 1739–1755, doi:10.1029/91WR00557, 1991.
- 963 Grimmond, C. S. B. and Oke, T. R.: Aerodynamic Properties of Urban Areas Derived from Analysis of
964 Surface Form, *J. Appl. Meteorol.*, 38(9), 1262–1292, doi:10.1175/1520-
965 0450(1999)038<1262:APOUAD>2.0.CO;2, 1999.

- 966 Grimmond, C. S. B., Oke, T. R. and Steyn, D. G.: Urban Water Balance: 1. A Model for Daily Totals,
967 Water Resour. Res., 22(10), 1397–1403, doi:10.1029/WR022i010p01397, 1986.
- 968 Grimmond, C. S. B., Cleugh, H. A. and Oke, T. R.: An objective urban heat storage model and its
969 comparison with other schemes, Atmos. Environ. Part B. Urban Atmos., 25(3), 311–326,
970 doi:10.1016/0957-1272(91)90003-W, 1991.
- 971 Grimmond, C. S. B., King, T. S., Roth, M. and Oke, T. R.: Aerodynamic roughness of urban areas
972 derived from wind observations, Boundary-Layer Meteorol., 89(1), 1–24, doi:10.1023/A:1001525622213,
973 1998.
- 974 Grimmond, C. S. B., Blackett, M., Best, M. J., Barlow, J., Baik, J. J., Belcher, S. E., Bohnenstengel, S. I.,
975 Calmet, I., Chen, F., Dandou, A., Fortuniak, K., Gouvea, M. L., Hamdi, R., Hendry, M., Kawai, T.,
976 Kawamoto, Y., Kondo, H., Krayenhoff, E. S., Lee, S. H., Lorian, T., Martilli, A., Masson, V., Miao, S.,
977 Oleson, K., Pigeon, G., Porson, A., Ryu, Y. H., Salamanca, F., Shashua-Bar, L., Steeneveld, G. J.,
978 Tombrou, M., Voogt, J., Young, D. and Zhang, N.: The international urban energy balance models
979 comparison project: First results from phase 1, J. Appl. Meteorol. Climatol., 49(6), 1268–1292,
980 doi:10.1175/2010JAMC2354.1, 2010.
- 981 Harshan, S., Roth, M., Velasco, E. and Demuzere, M.: Evaluation of an urban land surface scheme over a
982 tropical suburban neighborhood, Theor. Appl. Climatol., 133(3–4), 867–886, doi:10.1007/s00704-017-
983 2221-7, 2018.
- 984 Heiskanen, J., Rautiainen, M., Stenberg, P., Möttus, M., Vesanto, V.-H., Korhonen, L. and Majasalmi, T.:
985 Seasonal variation in MODIS LAI for a boreal forest area in Finland, Remote Sens Environ, 126, 104–
986 115, doi:10.1016/j.rse.2012.08.001, 2012.
- 987 Hengl, T., Jesus, J. M. de, MacMillan, R. A., Batjes, N. H., Heuvelink, G. B. M., Ribeiro, E., Samuel-
988 Rosa, A., Kempen, B., Leenaars, J. G. B., Walsh, M. G. and Gonzalez, M. R.: SoilGrids1km — Global
989 Soil Information Based on Automated Mapping, Plos One, 9(8), e105992,
990 doi:10.1371/journal.pone.0105992, 2014.
- 991 Hengl, T., Jesus, J. M. de, Heuvelink, G. B. M., Gonzalez, M. R., Kilibarda, M., Blagotić, A., Shangguan,
992 W., Wright, M. N., Geng, X., Bauer-Marschallinger, B., Guevara, M. A., Vargas, R., MacMillan, R. A.,
993 Batjes, N. H., Leenaars, J. G. B., Ribeiro, E., Wheeler, I., Mantel, S. and Kempen, B.: SoilGrids250m:
994 Global gridded soil information based on machine learning, Plos One, 12(2), e0169748,
995 doi:10.1371/journal.pone.0169748, 2017.
- 996 Höglström, U.: Non-dimensional wind and temperature profiles in the atmospheric surface layer: A re-
997 evaluation, Boundary-Layer Meteorol., 42(1–2), 55–78, doi:10.1007/BF00119875, 1988.
- 998 Hoshika, Y., Osada, Y., Marco, A. de, Peñuelas, J. and Paoletti, E.: Global diurnal and nocturnal
999 parameters of stomatal conductance in woody plants and major crops, Global Ecol Biogeogr, 27(2), 257–
1000 275, doi:10.1111/geb.12681, 2018.
- 1001 Iwata, H., Hirata, R., Takahashi, Y., Miyabara, Y., Itoh, M. and Iizuka, K.: Partitioning Eddy-Covariance
1002 Methane Fluxes from a Shallow Lake into Diffusive and Ebullitive Fluxes, Boundary-Layer Meteorol.,
1003 169(3), 413–428, doi:10.1007/s10546-018-0383-1, 2018.

- 1004 Järvi, L., Grimmond, C. S. B. and Christen, A.: The Surface Urban Energy and Water Balance Scheme
 1005 (SUEWS): Evaluation in Los Angeles and Vancouver, *J. Hydrol.*, 411(3–4), 219–237,
 1006 doi:10.1016/j.jhydrol.2011.10.001, 2011.
- 1007 Järvi, L., Grimmond, C. S. B., Taka, M., Nordbo, A., Setälä, H. and Strachan, I. B.: Development of the
 1008 Surface Urban Energy and Water Balance Scheme (SUEWS) for cold climate cities, *Geosci. Model Dev.*,
 1009 7(4), 1691–1711, doi:10.5194/gmd-7-1691-2014, 2014.
- 1010 Järvi, L., Havu, M., Ward, H. C., Bellucco, V., McFadden, J. P., Toivonen, T., Heikinheimo, V., Kolari,
 1011 P., Riikinen, A. and Grimmond, C. S. B.: Spatial Modeling of Local-Scale Biogenic and Anthropogenic
 1012 Carbon Dioxide Emissions in Helsinki, *J. Geophys. Res. Atmos.*, 2018JD029576,
 1013 doi:10.1029/2018JD029576, 2019.
- 1014 Karsisto, P., Fortelius, C., Demuzere, M., Grimmond, C. S. B., Oleson, K. W., Kouznetsov, R., Masson,
 1015 V. and Järvi, L.: Seasonal surface urban energy balance and wintertime stability simulated using three
 1016 land-surface models in the high-latitude city Helsinki, *Q. J. R. Meteorol. Soc.*, 142(694), 401–417,
 1017 doi:10.1002/qj.2659, 2016.
- 1018 Kawai, T., Ridwan, M. K. and Kanda, M.: Evaluation of the simple urban energy balance model using
 1019 selected data from 1-yr flux observations at two cities, *J. Appl. Meteorol. Climatol.*, 48(4), 693–715,
 1020 doi:10.1175/2008JAMC1891.1, 2009.
- 1021 Kent, C. W., Grimmond, S. and Gatey, D.: Aerodynamic roughness parameters in cities: Inclusion of
 1022 vegetation, *J. Wind Eng. Ind. Aerodyn.*, 169, 168–176, doi:10.1016/j.jweia.2017.07.016, 2017a.
- 1023 Kent, C. W., Lee, K., Ward, H. C., Hong, J.-W., Hong, J., Gatey, D. and Grimmond, S.: Aerodynamic
 1024 roughness variation with vegetation: analysis in a suburban neighbourhood and a city park, *Urban*
 1025 *Ecosyst.*, doi:10.1007/s11252-017-0710-1, 2017b.
- 1026 Keyser, T. L., Lentile, L. B., Smith, F. W. and Shepperd, W. D.: Changes in Forest Structure After a
 1027 Large, Mixed-Severity Wildfire in Ponderosa Pine Forests of the Black Hills, South Dakota, USA., 2008.
- 1028 Kokkonen, T. V., Grimmond, C. S. B., Räty, O., Ward, H. C., Christen, A., Oke, T. R., Kotthaus, S. and
 1029 Järvi, L.: Sensitivity of Surface Urban Energy and Water Balance Scheme (SUEWS) to downscaling of
 1030 reanalysis forcing data, *Urban Clim.*, 23, 36–52, doi:10.1016/j.uclim.2017.05.001, 2018.
- 1031 Kowalczyk, E. A., Wang, Y. P. and Law, R. M.: The CSIRO Atmosphere Biosphere Land Exchange
 1032 (CABLE) model for use in climate models and as an offline model, *CSIRO Mar. Atmos. Res. Pap.*,
 1033 13(November 2015), 1–42, doi:<https://doi.org/10.4225/08/58615c6a9a51d>, 2006.
- 1034 Krinner, G., Viovy, N., de Noblet-Ducoudré, N., Ogée, J., Polcher, J., Friedlingstein, P., Ciais, P., Sitch,
 1035 S. and Prentice, I. C.: A dynamic global vegetation model for studies of the coupled atmosphere-
 1036 biosphere system, *Global Biogeochem. Cycles*, 19(1), doi:10.1029/2003GB002199, 2005.
- 1037 Kusaka, H., Kondo, H., Kikegawa, Y. and Kimura, F.: A Simple Single-Layer Urban Canopy Model For
 1038 Atmospheric Models: Comparison With Multi-Layer And Slab Models, *Boundary-Layer Meteorol.*,
 1039 101(3), 329–358, doi:10.1023/A:1019207923078, 2001.
- 1040 Levis, S., Bonan, G. B., Vertenstein, M. and Oleson, K. W.: Technical Documentation and User's Guide
 1041 to the Community Land Model's Dynamic Global Vegetation Model, , doi:10.5065/D6P26W36, 2004.

- 1042 Liu, Y., Xie, R., Hou, P., Li, S., Zhang, H., Ming, B., Long, H. and Liang, S.: Phenological responses of
1043 maize to changes in environment when grown at different latitudes in China, *F. Crop. Res.*, 144, 192–199,
1044 doi:10.1016/j.fcr.2013.01.003, 2013.
- 1045 Loridan, T., Grimmond, C. S. B., Offerle, B. D., Young, D. T., Smith, T. E. L., Järvi, L. and Lindberg, F.:
1046 Local-Scale Urban Meteorological Parameterization Scheme (LUMPS): Longwave Radiation
1047 Parameterization and Seasonality-Related Developments, *J. Appl. Meteorol. Climatol.*, 50(1), 185–202,
1048 doi:10.1175/2010JAMC2474.1, 2011.
- 1049 Margolis, H. A.: AmeriFlux CA-Qcu Quebec - Eastern Boreal, Black Spruce/Jack Pine Cutover,
1050 doi:10.17190/AMF/1246828, 2001.
- 1051 Martilli, A., Clappier, A. and Rotach, M. W.: An Urban Surface Exchange Parameterisation for
1052 Mesoscale Models, *Boundary-Layer Meteorol.*, 104(2), 261–304, doi:10.1023/A:1016099921195, 2002.
- 1053 Masson, V.: A physically-based scheme for the urban energy budget in atmospheric models, *Boundary-*
1054 *Layer Meteorol.*, 94(3), 357–397, doi:10.1023/A:1002463829265, 2000.
- 1055 Matsumoto, K., Ohta, T., Nakai, T., Kuwada, T., Daikoku, K., Iida, S., Yabuki, H., Kononov, A. V.,
1056 Molen, M. K. van der, Kodama, Y., Maximov, T. C., Dolman, A. J. and Hattori, S.: Responses of surface
1057 conductance to forest environments in the Far East, *Agr Forest Meteorol*, 148(12), 1926–1940,
1058 doi:10.1016/j.agrformet.2008.09.009, 2008.
- 1059 McCaughey, J. H.: Energy balance storage terms in a mature mixed forest at Petawawa, Ontario - A case
1060 study, *Boundary-Layer Meteorol.*, 31(1), 89–101, doi:10.1007/BF00120036, 1985.
- 1061 McCuen, R. H.: A Sensitivity and Error Analysis of Procedures Used for Estimating Evaporation, *Jawra J*
1062 *Am Water Resour Assoc*, 10, 486–497, <https://doi.org/10.1111/j.1752-1688.1974.tb00590.x>, 1974.
- 1063 Moene, A. F. and van Dam, J. C.: *Transport in the Atmosphere-Vegetation-Soil Continuum*, Cambridge
1064 University Press., 2013.
- 1065 Monin, A. S. and Obukhov, A. M.: Basic laws of turbulent mixing in the surface layer of the atmosphere,
1066 *Contrib. Geophys. Inst. Acad. Sci. USSR*, 24(151), 163–187, 1954.
- 1067 Moureaux, C., Debacq, A., Bodson, B., Heinesch, B., and Aubinet, M.: Annual net ecosystem carbon
1068 exchange by a sugar beet crop, *Agr Forest Meteorol*, 139, 25–39,
1069 <https://doi.org/10.1016/j.agrformet.2006.05.009>, 2006.
- 1070 Monteith, J. L.: Evaporation and environment., *Symp. Soc. Exp. Biol.*, 19(19), 205–34, 1965.
- 1071 Myneni, R., Knyazikhin, Y. and Park, T.: MCD15A3H MODIS/Terra+Aqua Leaf Area Index/FPAR 4-
1072 day L4 Global 500m SIN Grid V006. NASA EOSDIS Land Processes DAAC, 2015.
- 1073 Nash, J. E. and Sutcliffe, J. V.: River flow forecasting through conceptual models part I — A discussion
1074 of principles, *J Hydrol*, 10, 282–290, [https://doi.org/10.1016/0022-1694\(70\)90255-6](https://doi.org/10.1016/0022-1694(70)90255-6), 1970.
- 1075 Noilhan, J. and Planton, S.: A Simple Parameterization of Land Surface Processes for Meteorological
1076 Models, *Mon Weather Rev*, 117(3), 536–549, doi:10.1175/1520-0493(1989)117<0536:aspols>2.0.co;2,
1077 1989.

- 1078 United Nations: 2018 revision of world urbanization prospects, 2018.
- 1079 Nishihama, M., Wolfe, R., Solomon, D., Patt, F., Blanchette, J., Fleig, A. and Masuoka, E.: MODIS Level
1080 1A Earth Location: Algorithm Theoretical Basis Document By the MODIS Science Data Support Team,
1081 Greenbelt, Md., 1997.
- 1082 Noormets, A., McNulty, S. G., DeForest, J. L., Sun, G., Li, Q. and Chen, J.: Drought during canopy
1083 development has lasting effect on annual carbon balance in a deciduous temperate forest, *New Phytol.*,
1084 179(3), 818–828, doi:10.1111/j.1469-8137.2008.02501.x, 2008.
- 1085 Nunez, M., Davies, J. A. and Robinson, P. J.: Surface albedo at a tower site in Lake Ontario, *Boundary-*
1086 *Layer Meteorol.*, 3(1), 77–86, doi:10.1007/BF00769108, 1972.
- 1087 Offerle, B., Grimmond, C. S. B. and Oke, T. R.: Parameterization of Net All-Wave Radiation for Urban
1088 Areas, *J. Appl. Meteorol.*, 42(8), 1157–1173, doi:10.1175/1520-
1089 0450(2003)042<1157:PONARF>2.0.CO;2, 2003.
- 1090 Ogink-Hendriks, M. J.: Modelling surface conductance and transpiration of an oak forest in The
1091 Netherlands, *Agr Forest Meteorol.*, 74(1–2), 99–118, doi:10.1016/0168-1923(94)02180-r, 1995.
- 1092 Oke, T. R.: City size and the urban heat island, *Atmospheric Environ.* 1967, 7(8), 769–779,
1093 doi:10.1016/0004-6981(73)90140-6, 1973.
- 1094 Oke, T. R.: The energetic basis of the urban heat island, *Q J Roy Meteor Soc.*, 108(455), 1–24,
1095 doi:10.1002/qj.49710845502, 1982.
- 1096 OpenStreetMap contributors: OpenStreetMap, <https://www.openstreetmap.org> (Accessed 30 July 2021),
1097 2017
- 1098 Pastorello, G., Trotta, C., Canfora, E., Chu, H., Christianson, D., Cheah, Y.-W., Poindexter, C., Chen, J.,
1099 Elbashandy, A., Humphrey, M., Isaac, P., Polidori, D., Reichstein, M., Ribeca, A., Ingen, C. van,
1100 Vuichard, N., Zhang, L., Amiro, B., Ammann, C., Arain, M. A., Ardö, J., Arkebauer, T., Arndt, S. K.,
1101 Arriga, N., Aubinet, M., Aurela, M., Baldocchi, D., Barr, A., Beamesderfer, E., Marchesini, L. B.,
1102 Bergeron, O., Beringer, J., Bernhofer, C., Berveiller, D., Billesbach, D., Black, T. A., Blanken, P. D.,
1103 Bohrer, G., Boike, J., Bolstad, P. V., Bonal, D., Bonnefond, J.-M., Bowling, D. R., Bracho, R., Brodeur,
1104 J., Brümmer, C., Buchmann, N., Burban, B., Burns, S. P., Buysse, P., Cale, P., Cavagna, M., Cellier, P.,
1105 Chen, S., Chini, I., Christensen, T. R., Cleverly, J., Collalti, A., Consalvo, C., Cook, B. D., Cook, D.,
1106 Coursolle, C., Cremonese, E., Curtis, P. S., D'Andrea, E., Rocha, H. da, Dai, X., Davis, K. J., Cinti, B.
1107 D., Grandcourt, A. de, Ligne, A. D., Oliveira, R. C. D., Delpierre, N., Desai, A. R., Bella, C. M. D.,
1108 Tommasi, P. di, Dolman, H., Domingo, F., Dong, G., Dore, S., Duce, P., Dufrêne, E., Dunn, A., Dušek,
1109 J., Eamus, D., Eichelmann, U., ElKhidir, H. A. M., Eugster, W., Ewenz, C. M., Ewers, B., Famulari, D.,
1110 Fares, S., Feigenwinter, I., Feitz, A., Fensholt, R., Filippa, G., Fischer, M., Frank, J., Galvagno, M., et al.:
1111 The FLUXNET2015 dataset and the ONEFlux processing pipeline for eddy covariance data, *Sci Data*,
1112 7(1), 225, doi:10.1038/s41597-020-0534-3, 2020.
- 1113 Penman, H. L.: Natural evaporation from open water, bare soil and grass, *Proc. R. Soc. Lond. A. Math.*
1114 *Phys. Sci.*, 193(1032), 120–145, doi:10.1098/rspa.1948.0037, 1948.
- 1115 Peters, E. B., Hiller, R. V. and McFadden, J. P.: Seasonal contributions of vegetation types to suburban
1116 evapotranspiration, *J. Geophys. Res. Biogeosciences*, 116(1), G01003, doi:10.1029/2010JG001463, 2011.

- 1117 Philip Bloomington, R. and Novick Bloomington, K.: AmeriFlux US-MMS Morgan Monroe State Forest,
1118 doi:10.17190/AMF/1246080, 2016.
- 1119 Porter, C. L.: An Analysis of Variation Between Upland and Lowland Switchgrass, *Panicum Virgatum*
1120 L., in Central Oklahoma, *Ecology*, 47(6), 980–992, doi:10.2307/1935646, 1966.
- 1121 Prescher, A.-K., Grünwald, T., and Bernhofer, C.: Land use regulates carbon budgets in eastern Germany:
1122 From NEE to NBP, *Agr Forest Meteorol*, 150, 1016–1025,
1123 https://doi.org/10.1016/j.agrformet.2010.03.008, 2010.
- 1124 Saxton, K. E. and Rawls, W. J.: Soil Water Characteristic Estimates by Texture and Organic Matter for
1125 Hydrologic Solutions, *Soil Sci. Soc. Am. J.*, 70, 1569–1578, 2006.
- 1126 Schmid, H. P., Grimmond, C. S. B., Cropley, F., Offerle, B. and Su, H. B.: Measurements of CO₂ and
1127 energy fluxes over a mixed hardwood forest in the mid-western United States, *Agric. For. Meteorol.*,
1128 103(4), 357–374, doi:10.1016/S0168-1923(00)00140-4, 2000.
- 1129 Shuttleworth, W. J.: A simplified one-dimensional theoretical description of the vegetation-atmosphere
1130 interaction, *Boundary-Layer Meteorol.*, 14(1), 3–27, doi:10.1007/BF00123986, 1978.
- 1131 Shuttleworth, W. J.: Evaporation models in the global water budget., *Var. Glob. water Budg.*, 147–171,
1132 doi:10.1007/978-94-009-6954-4_11, 1983.
- 1133 Skamarock, W. C. and Klemp, J. B.: A time-split nonhydrostatic atmospheric model for weather research
1134 and forecasting applications, *Journal of Computational Physics*, 227, 3465–3485,
1135 doi:10.1016/j.jcp.2007.01.037, 2008.
- 1136 Spronken-Smith, R. A., Oke, T. R. and Lowry, W. P.: Advection and the surface energy balance across an
1137 irrigated urban park, *Int. J. Climatol.*, 20(9), 1033–1047, doi:10.1002/1097-
1138 0088(200007)20:9<1033::AID-JOC508>3.0.CO;2-U, 2000.
- 1139 Stewart, J. B.: Modelling surface conductance of pine forest, *Agr Forest Meteorol*, 43(1), 19–35,
1140 doi:10.1016/0168-1923(88)90003-2, 1988.
- 1141 Stoy, P. C., Mauder, M., Foken, T., Marcolla, B., Boegh, E., Ibrom, A., Arain, M. A., Arneth, A., Aurela,
1142 M., Bernhofer, C., Cescatti, A., Dellwik, E., Duce, P., Gianelle, D., Gorsel, E. van, Kiely, G., Knohl, A.,
1143 Margolis, H., McCaughey, H., Merbold, L., Montagnani, L., Papale, D., Reichstein, M., Saunders, M.,
1144 Serrano-Ortiz, P., Sottocornola, M., Spano, D., Vaccari, F., and Varlagin, A.: A data-driven analysis of
1145 energy balance closure across FLUXNET research sites: The role of landscape scale heterogeneity, *Agr
1146 Forest Meteorol*, 171, 137–152, doi:10.1016/j.agrformet.2012.11.004, 2013.
- 1147 Stöckli, R., Lawrence, D. M., Niu, G. -Y., Oleson, K. W., Thornton, P. E., Yang, Z. -L., Bonan, G. B.,
1148 Denning, A. S. and Running, S. W.: Use of FLUXNET in the Community Land Model development, *J
1149 Geophys Res Biogeosciences*, 113, G01025, doi:10.1029/2007jg000562, 2008.
- 1150 Sun, T. and Grimmond, S.: A Python-enhanced urban land surface model SuPy (SUEWS in Python,
1151 v2019.2): development, deployment and demonstration, *Geosci. Model Dev*, 12, 2781–2795,
1152 doi:10.5194/gmd-12-2781-2019, 2019.
- 1153 Sun, T., Järvi, L., Omidvar, H., Theeuwes, N., Lindberg, F., Li, Z. and Grimmond, S.: Urban-
1154 Meteorology-Reading/SUEWS: 2020a Release, doi:10.5281/zenodo.3828525, 2020.

- 1155 Sun, T., Omidvar, H. and Grimmond, S.: Workflow notebooks and FLUXNET2015 data for deriving
1156 parameter of SUEWS v2020 based FLUXNET2015 dataset, doi:10.5281/zenodo.5519919, 2021.
- 1157 van Ulden, A. P. and Holtslag, A. A. M.: Estimation of atmospheric boundary layer parameters for
1158 diffusion applications., J. Clim. Appl. Meteorol., 24(11), 1196–1207, doi:10.1175/1520-
1159 0450(1985)024<1196:EOABLP>2.0.CO;2, 1985.
- 1160 Wang, Y., Broxton, P., Fang, Y., Behrangi, A., Barlage, M., Zeng, X., and Niu, G.: A Wet-Bulb
1161 Temperature-Based Rain-Snow Partitioning Scheme Improves Snowpack Prediction Over the Drier
1162 Western United States, Geophys Res Lett, 46, 13825–13835, doi:10.1029/2019gl085722, 2019.
- 1163 Ward, H. C., Kotthaus, S., Järvi, L. and Grimmond, C. S. B.: Surface Urban Energy and Water Balance
1164 Scheme (SUEWS): Development and evaluation at two UK sites, Urban Clim., 18, 1–32,
1165 doi:10.1016/j.uclim.2016.05.001, 2016.
- 1166 Wolfram Research, NonlinearModelFit, Wolfram Language function,
1167 <https://reference.wolfram.com/language/ref/NonlinearModelFit.html> (accessed on 03 Aug 2021). 2008.
- 1168 Wolfram Research, ClusterClassify, Wolfram Language function,
1169 <https://reference.wolfram.com/language/ref/ClusterClassify.html> (accessed on 03 Aug 2021). 2020.
- 1170 Wright, I. R., Manzi, A. O. and Rocha, H. R. da: Surface conductance of Amazonian pasture: model
1171 application and calibration for canopy climate, Agr Forest Meteorol, 75(1–3), 51–70, doi:10.1016/0168-
1172 1923(94)02203-v, 1995.