

1 Technical note: How well do evapotranspiration partitioning 2 approaches perform in moss-covered wetlands?

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8 **Abstract.** Evapotranspiration (ET) is the dominant hydrologic flux in wetlands, and partitioning into transpiration (T)
9 and evaporation (E) is essential for understanding water and carbon dynamics, guiding sustainable water management
10 practices, and predicting responses to climate change in these systems. However, the presence of moss layers and the
11 dynamic hydrological condition in many wetlands challenges the assumptions of commonly used partitioning
12 methods. This study evaluates ten eddy covariance (EC)-based ET partitioning approaches representing three
13 methodological groups, namely high-frequency EC-based, ecosystem carbon-water coupling, and machine learning
14 approaches, across four moss-covered wetlands in the boreal region and the Canadian Rocky Mountains.

15 Evapotranspiration, partitioning estimates were evaluated against independent measurement-based T:ET estimates
16 derived from flux chambers, micro-lysimeters, sap flow sensors, and EC measurements, and against the ensemble
17 mean of all ET partitioning approaches. Results showed that none of the evaluated approaches consistently
18 outperformed the others across sites or under both flooded and non-flooded conditions, and no methodological group
19 demonstrated a clear overall advantage. Evapotranspiration, partitioning performance is likely influenced by the
20 combined effects of multiple environmental and methodological factors, including moss cover, flooding conditions,
21 canopy structure, ecosystem heterogeneity, EC measurement configuration and data quality, and the assumptions
22 underlying each approach. In addition, the evaluation results are also influenced by the choice of reference dataset,
23 which highlights the uncertainty associated with benchmarking ET partitioning methods. These findings suggest that
24 applying multiple ET partitioning approaches concurrently, whenever possible, can help identify sources of
25 uncertainty and potential errors. The study also highlights the need to develop wetland-specific ET partitioning
26 approaches that better represent moss-mediated carbon uptake, dynamic carbon-water coupling, and transitions
27 between unsaturated and flooded conditions.

28 1. Introduction

29 Evapotranspiration (ET) represents the total water flux from terrestrial ecosystems to the atmosphere through
30 vegetation transpiration (T) and direct evaporation (E) from canopy and ground surfaces. Distinguishing the
31 contributions of T and E is important for understanding the terrestrial carbon cycle, as T is directly related to vegetation
32 carbon assimilation processes (Jarvis and Menaughton, 1986; Farquhar et al., 1980; Farquhar and Sharkey, 1982).
33 Despite its importance, there is a broad consensus within the biogeosciences community that accurately quantifying

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T and E, whether through direct measurements or computational methods, remains a challenge (Kool et al., 2014; Stoy et al., 2019; Nelson et al., 2020; Zahn et al., 2024). Briefly, directly quantifying T and E involves a combination of multiple field-based measurements, such as stable isotope analysis, lysimeters, porometers, flux chambers, sap flow measurements, and eddy covariance systems (Kool et al., 2014). These methods can be labor-intensive, require site-specific instrumentation, and are often constrained in both spatial (e.g., plot-scale) and temporal (e.g., depending on measurement frequency) resolutions (Albert-Saiz et al., 2025). In contrast, modelling approaches, especially the eddy covariance (EC)-based ET partitioning methods to partitioning ET into E and T at the ecosystem level, may be convenient and enable the exploration of temporal variability for estimating E and T at the ecosystem scale. However, they rely on assumptions that are ecosystem-dependent, require accurate parameterization, and model validation is not always available due to the lack of on-site measurements (Eichelmann et al., 2022; Zhou et al., 2016; Stoy et al., 2019). As reviewed by Stoy et al. (2019), these limitations highlight the need for ecosystem-scale experiments using multiple methods to measure E and T to understand their distinct responses to climate variability and change across diverse ecosystems and also to evaluate and refine the assumptions underlying ET partitioning approaches (Stoy et al., 2019).

Currently, research specifically addressing ET partitioning within wetland ecosystems remains notably scarce, even though wetlands, especially peatlands, are critical carbon sinks and play a critical role in regulating regional hydrology and global climate (Mitra et al., 2005; Leifeld and Menichetti, 2018; Strack et al., 2022; Frolking et al., 2006). Consequently, there is limited field data available to develop and evaluate reliable ET partitioning approaches for wetland ecosystems. Moreover, most of the existing studies have focused on hydroperiods where E mostly comes from standing water or saturated soils (Xu et al., 2011; Allen et al., 2017; Zhang et al., 2018; Hussey and Odum, 1992; Burba et al., 1999; Goulden et al., 2007; Kiniry et al., 2023; Bijoor et al., 2011; Eichelmann et al., 2022). However, it should be noted that many wetlands are not consistently in a saturated state (e.g., Jacobs et al. (2002), Wu et al. (2010), Kettridge et al. (2017), and Streich and Westbrook (2020)), which raises concerns about whether methods developed under flooded conditions can be applied reliably to non-flooded conditions or to estimate ET partitioning under changing environmental conditions. Furthermore, current studies report varying results regarding the dominance of T or E in wetland ET and their controlling environmental factors, which suggests that ET partitioning in wetland ecosystems is regulated by both structural properties including vegetation composition, density, and areas of open water, and environmental conditions such as climatic variables and water table (Goulden et al., 2007; Kiniry et al., 2023; Warren et al., 2018; Allen et al., 2017; Eichelmann et al., 2022; Admiral and Lafleur, 2007). Given that many ET partitioning approaches rely on assumptions about T dominance or dominant environmental controls, it remains uncertain if there is a universally reliable ET partitioning method for wetland ecosystems.

Despite the limited research focused specifically on wetlands, ET partitioning approaches are relatively abundant, particularly those based on EC data, as EC systems have been widely deployed across diverse ecosystems. Several of these EC-based methods have been tested across a range of ecosystems, including forests, grasslands, woody savannas, and croplands, and have shown broad applicability, not restricted to water-limited ecosystems (Yu et al., 2022; Nelson et al., 2020; Zhou et al., 2016; Li et al., 2019; Zahn et al., 2024). However, most of these methods have not been evaluated in wetlands. In fact, it cannot be guaranteed that these methods are suitable for wetlands, as the unique

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74 characteristics of wetlands, particularly moss-covered ground surfaces in many peatlands, may not only influence the
 75 evaporative response of the wetlands to environmental drivers (Speranskaya et al., 2024), but also violate key
 76 assumptions on which these ET partitioning approaches primarily rely. Specifically, mosses can photosynthesize and
 77 contribute to ecosystem carbon sequestration (Pacheco-Cancino et al., 2024; Street et al., 2013; Badorek et al., 2011;
 78 Kokkonen et al., 2022), but they do not contribute to T_v fluxes. This decoupling may violate the assumption in some
 79 methods that photosynthesis and T_v share identical sources and sinks. Moreover, most mosses cannot actively regulate
 80 water transport and water fluxes; instead, they rely on passive capillary rise to transport water (Proctor, 1982). When
 81 free capillary rise is limited by low soil-water pressures, the water potential of moss cells can rapidly equilibrate with
 82 the surrounding air, reducing both E_v and photosynthetic activity, even when atmospheric demand for evaporation
 83 remains high (Goetz and Price, 2015; Mccarter and Price, 2012; Proctor, 1982; Kettridge and Waddington, 2013;
 84 Ketcheson and Price, 2013). In addition, mosses can absorb water directly from their surroundings through their leaves
 85 and stems, and store water equivalent to 300 to 500% of their dry weight for extended periods (Rouse, 2000; Bayfield,
 86 1973). This remarkable water storage capacity, combined with their ability to rapidly equilibrate their water content
 87 with ambient humidity, helps conserve moisture in deeper soil layers during dry periods (Ketcheson and Price, 2013;
 88 Kettridge and Waddington, 2013), and cools the soil surface (Chen et al., 2019). These unique behaviors of mosses
 89 may therefore violate assumptions about key environmental controls on T or E fluxes, as well as the assumed
 90 relationships between carbon uptake and water exchange used by some methods to separate T and E fluxes.

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91 Although the presence of mosses may violate some of the assumptions used in EC-based ET partitioning approaches,
 92 it is uncertain whether these violations render the methods completely unsuitable for wetland research, or whether
 93 these methods can still offer insights into the dynamics of T and E fluxes. Intuitively, the extent to which these
 94 violations affect the accuracy of EC-based ET partitioning approaches depends on the relative contribution of mosses
 95 to wetland gross primary production (GPP) compared to vascular plants at a given site. Although multi-site analyses
 96 have shown a positive correlation between peatland carbon assimilation and moss cover percentage (Strack et al.,
 97 2016; Pacheco-Cancino et al., 2024), quantitative data on moss contributions to ecosystem-level GPP remains
 98 extremely scarce. Limited evidence suggests that mosses can play a considerable role: for instance, a field study in a
 99 raised mire complex in southern Finland reported moss contributions to cumulative community-level photosynthesis
 100 of about 1.5%, 35.2% and 41.2% in the undrained area in rich fen, poor fen, and bog, respectively (Kokkonen et al.,
 101 2022). Similarly, in a drained forested peatland dominated by moss on the forest floor, CO₂ assimilation by the forest
 102 floor represented 20 to 30% of the forest's total CO₂ uptake (Badorek et al., 2011). But these findings also indicate
 103 that while mosses can substantially contribute to ecosystem GPP, vascular plants generally dominate, accounting for
 104 over 50% of the ecosystem GPP. Consequently, the presence of mosses may not markedly compromise the
 105 performance of EC-based ET partitioning methods. Regardless of these considerations, there remains a need to
 106 evaluate the performance of ET partitioning approaches in moss-covered wetlands.

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107 The ET partitioning approaches discussed above, whose fundamental assumptions may be violated by the presence of
 108 moss cover, are all physically based methods. In contrast, machine learning (ML)-based ET partitioning methods have
 109 recently been developed for wetland ecosystems, and are based on assumptions that are, in principle, unaffected by

115 the presence of mosses. For example, the approach proposed by Eichelmann et al. (2022) and subsequently extended
116 by Stapleton et al. (2022) trained ML models to predict E using nighttime EC measurements under the assumption
117 that nighttime T is negligible. ~~Transpiration~~ is then estimated as the difference between measured ET and the predicted
118 E. These ML models performed well in four freshwater marshes in northern California. Their predicted ~~E_v~~ agreed
119 closely with EC-derived ET during flooding periods and winter, when T was also assumed to be negligible (Stapleton
120 et al., 2022; Eichelmann et al., 2022). In addition, Eichelmann et al. (2022) showed good agreement between model-
121 estimated T and leaf-level T measurements of the two dominant plant species, tule and cattail.

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122 Although the presence of mosses does not violate the assumption underlying these ML models, the assumption of
123 negligible nighttime T may not be universally applicable across wetland ecosystems with different vegetation
124 communities. Increasing evidence indicates that nighttime T occurs in a wide range of grasses, shrubs and trees (Daley
125 and Phillips, 2006; Caird et al., 2007; Fisher et al., 2007), where it typically accounts for 10–30% of the total daily ~~T_v~~
126 (Novick et al., 2009). Furthermore, nighttime EC measurements are generally subject to greater uncertainty because
127 of weak atmospheric turbulence and reduced mixing within the nocturnal boundary layer (Baldocchi, 2003; Aubinet
128 et al., 2012). Although nighttime T may indeed be small relative to E in many wetlands as suggested in Eichelmann
129 et al. (2022), this assumption has not been directly validated. Moreover, these ML approaches have so far been
130 evaluated only in four freshwater marshes, and their applicability to other wetland types remains uncertain. Despite
131 these limitations, ML approaches have emerged as powerful tools in Earth system science because of their ability to
132 identify complex, nonlinear relationships between environmental drivers and target variables without requiring
133 explicit process-based formulations (Reichstein et al., 2019). Therefore, although this study primarily focuses on ET
134 partitioning approaches whose underlying assumptions may be challenged by the presence of moss cover, ML-based
135 approaches are also included to assess their robustness and general applicability in wetland ecosystems.

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136 The overall objective of this study is to evaluate the performance of existing EC-based ET partitioning methods in
137 moss-covered wetlands. Specifically, we address the following research questions: (1) Is there any ET partitioning
138 approach that consistently outperforms the others across different wetland sites? (2) Do these approaches perform well
139 under both flooded and non-flooded conditions? (3) Do ML-based approaches outperform physically based
140 approaches? And (4) What factors influence the performance of ET partitioning approaches in the studied wetlands?

141 2. Methods

142 2.1 Overview of ~~eddy covariance~~-based ~~evapotranspiration~~ partitioning approaches considered

143 ~~Evapotranspiration~~ partitioning approaches selected for this study were chosen based on three criteria: (1) they rely
144 primarily on EC-based CO₂ and H₂O fluxes, (2) focus on the ecosystem level with daily or finer temporal resolution,
145 are not restricted to water-limited conditions, and (3) have publicly available formulations or programming codes.
146 Based on these criteria, ten methods were selected for evaluation (Table 1). Several existing approaches were excluded,
147 including the method of Wei et al. (2017), which was not developed for daily or finer temporal scales; the methods
148 of Scott and Biederman (2017) and Reich et al. (2024), which were developed for water-limited ecosystems; Rigden

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et al. (2018), which primarily relies on weather data rather than EC-based measurements; and Eichelmann et al. (2022), for which no source code is available.

To the best of the authors' knowledge, the ET partitioning methods evaluated in this study cover most of the existing EC-based approaches. Based on the type of EC data they utilize, either high-frequency measurements or fluxes aggregated to a half-hourly timestep, and the partitioning formulations they employed, either ecosystem carbon-water coupling or machine learning based, these approaches are grouped into three categories: (1) high-frequency EC data-based methods (Group 1), (2) ecosystem carbon-water coupling methods (Group 2), and (3) machine learning (ML) methods (Group 3). These approaches and their required data and limitations for application in moss-covered wetland ecosystems are summarized in Table 1. Note that the Transpiration Estimation Algorithm (TEA) is based on both the ecosystem carbon-water coupling and the Random Forest model which is an ML algorithm. Consequently, TEA is classified as both a Group 2 and Group 3 approach.

It should also be noted that Group 3 does not represent a collection of individual ET partitioning methods, but rather a framework developed by Stapleton et al. (2022) that comprises seven ML algorithms. The framework identifies the best performing machine learning algorithm from the candidate models, determines the optimal combination of predictor variables, and ranks these variables according to their importance to predictive accuracy. It extends the ET partitioning approach proposed by Eichelmann et al. (2022), who applied an artificial neural network (ANNs) to partition ET. Although the ANN model and its source code are not publicly available, the underlying assumptions governing ET partitioning are consistent between the two studies.

The seven candidate ML algorithms included in the Stapleton et al. (2022) framework are Linear Regression, Ridge Regression, K-nearest Neighbors, Decision Trees, Gradient Boosting Decision Trees, LightGBM and XGBoost (Stapleton et al., 2022). Following the procedure described by Stapleton et al. (2022), only the ET partitioning predictions generated by the best-performing model identified by this framework were retained for evaluation in this study. Details of the performance of each candidate ML model and the rankings of the importance of the predictor variables are provided in Section S1 of the Supplementary Material.

Table 1. Overview of data requirements and potential limitations of eddy covariance (EC)-based evapotranspiration (ET) partitioning methods in moss-covered wetlands. Group 1 includes methods using high-frequency EC data, Group 2 and Group 3 includes methods using EC data aggregated at specific timesteps.

Method	Group	Required Data	Examples of Potential Issues When Applied to Moss-covered Wetlands	References
Flux Variance Similarity (FVS)	1	High-frequency c, q, u, v, w, and WUE_{canopy}	The assumption of identical source/sink for transpiration (T) and photosynthesis is invalidated by moss photosynthesis.	Scanlon and Kustas (2010)
Conditional Eddy Accumulation method (CEA)	1	High-frequency c, q, u, v, and w	The uneven and open canopy often found in wetlands, together with moss photosynthesis, can blur ground and vegetation signals used for flux partitioning.	Businger and Oncley (1990) and Zahn et al. (2024)

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Modified Relaxed-Eddy Accumulation method (MREA)	1	High-frequency c, q, u, v, and w	The presence of short or multi-layered canopies, often found in wetlands, along with moss photosynthesis and respiration in the understory, may violate the similarity of turbulent transport of non-stomatal components from the soil.	Thomas et al. (2008) and Zahn et al. (2024)
Conditional Eddy Covariance method (CEC)	1	High-frequency c, q, u, v, and w	Same as CEA	Zahn et al. (2022)
Underlying water-use efficiency method (uWUE)	2	GPP, ET, and VPD	The assumption that T dominates ET during periods of high GPP/ET may not hold in <u>evaporation (E)</u> -dominated wetlands; and carbon assimilation is assumed to occur only from leaf-level photosynthesis.	Zhou et al. (2016)
Pérez-Priego method (PP)	2	GPP, C _a , P _a , T _{air} , VPD, LE, H, U _{star} , WS, R _g , Q, and Z	The big leaf representation used to estimate optimal stomatal conductance from EC- <u>inferred photosynthesis rate</u> does not account for moss photosynthesis; and the complexity of the optimization procedure can sometimes fail in reaching a numerical solution.	Pérez-Priego et al. (2018)
Transpiration Estimation Algorithm (TEA)	2 and 3	GPP, RH, R _g , R _{gpot} , T _{air} , VPD, Precip, WS, and year	The assumption that <u>transpiration-to-evapotranspiration ratios (T:ET) approach 1</u> during periods with minimal surface moisture conditions may not hold in E-dominated wetlands.	Nelson et al. (2018)
Conductance Partitioning method (CP)	2	GPP, ET, VPD, and θ	The assumption that surface conductance is not sensitive to VPD may be invalidated by moss responses to ambient humidity.	Li et al. (2019)
Carbon-water relationship and stomatal conductance model (CWSC)	2	GPP, ET, VPD, C _a , P _a and g _i	Carbon assimilation is assumed to occur only from leaf-level photosynthesis; and publicly available g _i dataset by plant functional types (PFTs) are lacking for wetland ecosystems.	Yu et al. (2022)
Machine Learning Algorithms (ML)	3	All EC, micrometeorological, and environmental data measured at the study sites	The assumption of negligible nighttime T may introduce prediction biases, and nighttime EC measurements are generally less reliable.	Stapleton et al. (2022)

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Note. c, high-frequency CO₂ concentration; q, high-frequency H₂O concentration; u, high-frequency streamwise wind speed; v, high frequency cross-stream wind speed; w, high frequency vertical wind speed; WUE_{canopy}, canopy-level water-use efficiency; GPP, ecosystem gross primary production; ET, ecosystem evapotranspiration; VPD, vapor pressure deficit; C_a: mean atmospheric CO₂ concentration; P_a, atmospheric pressure; T_{air}, air temperature; LE, latent heat flux; H, sensible heat flux; U_{star}, friction velocity; WS, mean wind speed; R_g, incoming shortwave radiation; Q, photosynthetic active radiation; Z, altitude; RH: relative humidity; R_{gpot}, daily potential radiation; Precip, precipitation; θ , soil moisture; g_i, a parameter in the optimal stomatal conductance model. Some required variables differ from those listed in the original publications and instead reflect the data inputs used in the publicly available codes provided by the authors of each method. Specifically, the FVS, CEA, MREA and CEC methods were applied using the ET partitioning code developed by Zahn (2024); the PP method by Pérez-Priego and Wutzler (2018); the uWUE and TEA methods by Nelson (2020); the CWSC method by Jiang and Yu (2021); and the ML method by Stapleton (2022). Please refer to the corresponding references for further details.

2.2 Study sites

The best way to evaluate the ET partitioning approaches is by comparing their outputs to direct field measurements. However, to the best of the authors' knowledge, no publicly available datasets exist for wetland ET and its components. Therefore, we compiled data from four sites where field measurements of ET and its components had previously been conducted.

The first three sites, Sibbald, Burstall, and Bonsai, are located in the Canadian Rocky Mountains, where field measurements were conducted during the 2021 growing season. The fourth site, Poplar, is situated in the western

boreal plain near Fort McMurray, Alberta, Canada, and its field measurements were conducted during the 2013 growing season. Among the four sites, only Sibbald and Poplar are peatlands. The study sites have been extensively described in detail in previous publications (Wang and Petrone, 2022; Wang et al., 2023; Wang, 2025; Gabrielli, 2016; Hathaway et al., 2022; Hrach et al., 2021; Streich and Westbrook, 2020; Morison et al., 2021); therefore, only the characteristics relevant to this study are briefly provided here. The geographic coordinates, wetland type, elevation, meteorological conditions during the study period, soil properties, water table depth, vegetation composition, and instrumentation used to measure evapotranspiration and its components are summarized in Table 2.

These sites are covered by mosses. At Sibbald, the moss layer is approximately 5 mm thick and includes species such as *Aulacomnium palustre* (Hedw.) Schwaegr., *Bryum pseudotriquetrum* (Hedw.) Gaertn. et. al., *Calliergon giganteum* (Schimp.) Kindb., *Calliergon richardsonii* (Mitt.) Kindb. in Warnst., *Campylium stellatum* (Hedw.) C. Jens., *Hypnum lindbergii* (Mitt.), *Plagiomnium ellipticum* (Brid.) T. Kop., *Pohlia nutans* (Hedw.) Lindb., and *Warnstorfia fluitans* (Hedw.) Loeske (Lei, 2021). At Burstall, the moss layer, about 1 cm thick, is dominated by peat moss (*Sphagnum* spp.) and feather moss (*Eurhynchium* spp.). At Bonsai, the moss cover consists primarily of brown moss (*Tetradontium* spp.) with a thickness of up to 5 mm. At Poplar, the moss layer is around 2.5 cm thick (Goetz and Price, 2015), dominated by *Tomenthypnum nitens* (Hedw.) Loeske and *Aulacomnium palustre* (Hedw.). It is important to clarify that the moss layer in this study refers mainly to the photosynthetically active (green) components of the mosses, including their shoots and capitula.

Although all sites are moss-covered wetlands, they differ considerably in meteorological conditions, water table levels, vegetation composition, and canopy structure (Table 2 and Fig. S3). During the study period, the growing season LAI was 4.56, 1.64, 1.33 and 2.82 for Sibbald, Burstall, Bonsai and Poplar, respectively, with the value at Poplar representing the tree canopy only. The average canopy height was 1.6 m for Sibbald and Burstall, 0.8 m for Bonsai and 4.2 m for Poplar. Notably, Sibbald and Bonsai remained under non-flooded conditions throughout the study period, whereas Burstall transitioned to flooded conditions after August 17, 2021. In contrast, Poplar remained flooded for almost entire study period. The water table dynamics and meteorological conditions for each study site during the respective study period are shown in Fig. S4.

Table 2. Summary of site characteristics, including geographic coordinates, wetland type, altitude, meteorological conditions during the study period, soil properties, water table depth, vegetation composition, instrumentation used for measuring evapotranspiration and its components, and the study period.

Site	Sibbald	Burstall	Bonsai	Poplar
Wetland Class	Fen	Marsh	Wet meadow	Fen
Latitude	51.06°N	50.78°N	50.82°N	56.56°N
Longitude	114.87°W	115.34°W	115.21°W	111.33°W
Elevation (m)	1,490	1,900	2,100	322
Temp.* (°C)	14.0	11.6	11.7	18.4
Precip.* (mm)	137.7	32.2	128.3	320.8

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Soil (0-15 cm)	Peat	Peat	Silt and clay	Peat
WT depth* (m)	-1.24 to -0.56	0.15 to 0.1	< -2	-0.13 to 0.16
Vascular vegetation	• Overstory: clusters of <i>Salix</i> spp. • Understory: dense <i>Carex</i> spp.	• Overstory: sparse <i>Salix</i> spp. • Understory: dense <i>Carex</i> spp.	• Overstory: sparsely distributed species <i>Salix</i> spp., <i>Larix</i> spp., and <i>Abies</i> spp. • Understory: dense <i>Erigeron</i> spp., <i>parnassia</i> spp., and <i>Equisetum</i> spp.	• Overstory: dense <i>Larix laricina</i> with sparse occurrences of <i>Picea mariana</i> . • Understory: dense shrub layer including <i>Betula pumila</i> , <i>Equisetum fluviatile</i> , <i>Smilacena trifolia</i> , <i>Carex prairea</i> , and <i>Carex diandra</i> .
Instruments	Micro-lysimeter, porometer and eddy covariance system	Micro-lysimeter, porometer and eddy covariance system	Micro-lysimeter, porometer and eddy covariance system	Flux chamber, sap flow system, and eddy covariance system
Study Period	July 1 to August 31, 2021	July 1 to August 31, 2021	July 27 to August 31, 2021	May 18 to August 21, 2013

Note. Elevation is the elevation above sea level (in meters). Temp* represents the mean air temperature during the measurement period, and Precip.* is total precipitation during the same period. Soil describes the dominant soil type within the top 15 cm where micro-lysimeters were installed. WT depth* represents the mean water table position relative to the ground surface during the study period, calculated from all available monitoring wells. Negative values indicate that the water table was below the ground surface, whereas positive values indicate flooded conditions (i.e., the water table was above the ground surface). Instruments summarize the main equipment used to measure or estimate E, T and ET at each site. The study period for Bonsai begins on 27 July because the EC system malfunctioned before that date.

2.3 Field measurements of evaporation, transpiration and evapotranspiration

Ecosystem-scale water and carbon fluxes at all sites were measured by EC systems operating throughout the respective measurement periods. The ratio of EC measurement height to canopy height (z/h) is 1.88 at Sibbald, 1.25 at Burstall, 3.75 at Bonsai, and 1.55 at Poplar. EC data processing followed common FLUXNET protocols (Kaimal and Finnigan, 1994; Foken and Leclerc, 2004; Aubinet et al., 2012; Burba et al., 2012; Leuning and Judd, 1996; Webb et al., 1980; Pastorello et al., 2020). Latent heat flux (LE) was gap-filled using the MDS method (LE_F_MDS). Note that GPP is a required input for many ET partitioning approaches. In this study, it was estimated from EC-measured net ecosystem exchange (NEE_VUT_USTAR50) using the nighttime flux partitioning method described by Reichstein et al. (2005).

In addition to EC measurements, E_a at Sibbald, Burstall and Bonsai was measured using micro-lysimeters on six separate occasions during July and August in 2021, with each measurement period lasting mostly 2 to 4 days (Wang et al., 2023; Wang and Petrone, 2022). Stomatal conductance of the dominant vascular vegetation (Table 2) at these three sites were measured by leaf porometer (Wang, 2025). At the Poplar site, transparent flux chambers and sap flow systems were used to measure ground E_a and canopy T during the 2013 growing season (Gabrielli, 2016). These measurements were conducted within the EC footprint of each site. Detailed descriptions of site characteristics, field measurements, instrumentation, and the upscaling of plot-level data to estimate ecosystem-level daily transpiration-to-evapotranspiration ratios (T:ET) are provided in Wang (2025) and Gabrielli (2016). The errors and uncertainties of the measurements of E, T and ET are summarized in Table S4.

2.4 Reconstruction of daily ecosystem-scale measurement-based evapotranspiration partitioning time series

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276 For the Sibbald, Burstall, and Bonsai sites, the measurement-based T:ET time series are derived from a site-calibrated
 277 and validated Shuttleworth–Wallace (S–W) model rather than direct averaging of ground E_g measurements. This
 278 approach was necessary because micro-lysimeters measure ground E_g over multi-day intervals, whereas EC
 279 measurements of ET at the study sites are subject to intermittent data gaps. Using calibrated S–W model enabled the
 280 reconstruction of a continuous daily T:ET time series and characterization of its temporal variation.

281 The detailed calibration of the S–W model for each study site, together with the development of a surface resistance
 282 formulation that explicitly accounts for the effects of moss and litter on ground E_g and its incorporation into the S–W
 283 model, are described in previous publications (Wang et al., 2023; Wang, 2025). The performance of the calibrated S–
 284 W model is further summarized in Section S3 of the Supplementary Material. Overall, the model accurately
 285 reproduced both latent heat flux (LE) and ground E_g across the study sites. Because the S–W model is based on the
 286 surface energy balance, its predicted LE was evaluated against the energy balance-corrected EC measurements
 287 (LE_CORR). Across all sites, the relationship between modelled and measured LE was given by $LE_{modelled} = 0.97$
 288 $\times LE_{CORR} + 2.23 \text{ W m}^{-2}$ ($R^2 = 0.83$). Agreement between modelled and measured ground E_g (W m^{-2} , expressed as
 289 λE) was similarly strong, with $\lambda E_{modelled} = 0.91 \times \lambda E_{measured} - 4.46 \text{ W m}^{-2}$ ($R^2 = 0.85$). These results support
 290 the use of the S–W model-reconstructed T:ET time series as the measurement-based, ecosystem-scale daily T:ET for
 291 the three study sites.

292 At the Poplar site, the measurement-based T:ET time series was constructed differently from the other three sites, as
 293 this site includes direct EC-based ET measurements and upscaled sap flow measurements for dominant tree and
 294 understory species, informed by forest inventory data and LiDAR-based vegetation classification, as well as ground-
 295 based chamber flux measurements (Gabrielli, 2016). Ground E_g was calculated as the residual (ET minus upscaled site-
 296 level T) and evaluated against chamber measurements dominated by moss. This comparison yielded a regression slope
 297 of 0.96, an intercept of 0.08 mm h^{-1} , and an R^2 of 0.26 (Fig. S6). Because both T and ET were measured at the same
 298 timestep, whereas chamber measurements are instantaneous and inherently variable, we used the sap-flow-derived T
 299 together with EC-based ET to construct the Poplar T:ET time series. We acknowledge the relatively low R^2 , which
 300 reflects the high variability in the chamber measurements, but the near-unity slope and small intercept indicate good
 301 overall agreement. On this basis, we consider the reconstructed T:ET time series to be a reasonable representation for
 302 this study site.

303 2.5 Data quality control procedure

304 Given the measurement techniques described above, it is important to clarify that E_g in this study represent only ground
 305 evaporation. However, during rainy periods, E_g can occur from leaf surfaces. Excluding this canopy E_g may introduce
 306 bias in estimating ecosystem-scale ET partitioning into E and T. To minimize this potential bias, all methods except
 307 for the CP method exclude rainy days and 1 to 2 days afterward, following the precipitation and potential
 308 evapotranspiration (PET)-based criteria described in Zhou et al. (2015) and Yu et al. (2022). Specifically, if $PET <$
 309 $Precip < 2PET$, 1 day after a rainy day was excluded, if $Precip > 2PET$, 2 days were excluded. PET was estimated

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328 using the Priestley-Taylor equation (Priestley and Taylor, 1972). For the CP method, data screening follows its original
329 protocol, which removes data during rainy hours and the 6 hours following rainfall (Li et al., 2019).

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330 In addition to excluding rainy periods, all methods were prescreened to include only data from the growing season,
331 during daytime hours, and under conditions where net radiation, GPP, LE, H and VPD were greater than zero. Half-
332 hourly EC fluxes data with poor quality (i.e., the quality flag (QC) > 1) were removed. For the CP method, additional
333 filters were applied by excluding data with RH above 0.95, and by retaining only those periods where H exceeded 5
334 W m⁻² and Rg exceeded 50 W m⁻² (Li et al., 2019).

335 When aggregating half-hourly ET partitioning results to daily values, only days with more than 10 valid half-hourly
336 values were included, following the procedure in Yu et al. (2022). Additionally, any half-hourly T:ET values that were
337 negative or greater than 1 were excluded prior to daily aggregation.

338 2.6 Evaluation of evapotranspiration partitioning approaches

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339 Direct measurements of ET components offer an independent means to evaluate the performance of ET partitioning
340 approaches. However, this study does not focus on comparing exact magnitudes of T:ET between measurement-based
341 estimates and those derived from ET partitioning approaches. This is because most field measurements were conducted
342 at the plot level, and upscaling to the ecosystem level introduces uncertainties, as a wetland is a mosaic of diverse
343 habitats with varying extents of vegetation cover, open water, and exposed bare soil (Drexler et al., 2004), which
344 makes spatial upscaling very challenging. In peatlands, such complexity is further increased by micro-topographical
345 features, such as hummocks (local high points) and hollows (local low points), which have been shown to influence
346 ground E processes (Wang and Petrone, 2022).

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347 In addition, the temporal resolution of measurements varies across methods. For example, flux chamber and porometer
348 measurements provide instantaneous variables during daytime, whereas micro-lysimeters measurements in this study
349 operated over multiple days, which yields averaged daily values. Reconstructing daily T:ET at the ecosystem level
350 from these different measurements introduces additional biases. Moreover, all Group 2 ET partitioning approaches,
351 strictly speaking, fundamentally rely on the coupling between carbon and water fluxes during the daytime period when
352 photosynthesis takes place. Consequently, their ET partitioning results may not precisely align with measurements
353 that include the nighttime period.

354 Furthermore, some required input variables were not directly measured and had to be approximated, which also
355 introduces uncertainties. For example, the FVS method requires canopy-level water-use efficiency (WUE_{canopy}) as
356 input, and its outputs are sensitive to the estimates of this parameter (Sulman et al., 2016). However, direct
357 measurements of WUE_{canopy} and intercellular CO₂ concentration to estimate WUE_{canopy} were unavailable, as a result,
358 the optimization method proposed by Scanlon et al. (2019) was used to estimate WUE_{canopy} . But this method is more
359 appropriate for light-saturating conditions (Scanlon et al., 2019), which may not always occur. The FVS method that
360 uses estimated WUE_{canopy} from this optimized method is hereafter referred to as FVSopt. The CWSC method requires
361 the parameter g_l , which is not readily available for wetland ecosystems. Since most wetland plants are C3 species and

365 mosses also follow a photosynthesis pathway similar to C3 plants (Aro and Gerbaud, 1984), g_l values for each site
366 were derived from the reported values for C3 species based on a moisture index (MI) of each site, following Lin et al.
367 (2015). Specifically, Sibbald and Burstall have MIs of 0.77 and 0.72, respectively, and were therefore both given a g_l
368 value of $4.69 \text{ kPa}^{0.5}$. Bonsai, with an MI of 5.38, was assigned a g_l value of $4.02 \text{ kPa}^{0.5}$. Poplar, with an MI of 0.48,
369 was given a g_l value of $3.77 \text{ kPa}^{0.5}$. However, these estimates may not accurately represent the actual g_l at the site,
370 which potentially affects model performance.

371 Given those limitations, this study emphasizes evaluating whether T:ET values derived from partitioning approaches
372 are broadly consistent with measurement-based estimates and exhibit similar temporal dynamics. Therefore, the
373 coefficient of determination (R^2) was selected as the primary evaluation metric, following Eichelmann et al. (2022)
374 and Stapleton et al. (2022), to quantify how well the predicted T:ET follows the overall pattern of the measurement-
375 based estimates. Values of R^2 closer to 1 indicate better agreement in their temporal dynamics of T:ET. In addition,
376 the Nash–Sutcliffe model efficiency coefficient (NSE) was included to provide a complementary assessment of model
377 performance. An NSE value of 1 indicates perfect agreement between predictions and measurements, a value of 0
378 suggests the model performs no better than the observed mean, and negative values imply the observed mean is a
379 better predictor than the model.

380 Finally, because the measurement-based daily T:ET time series may be subject to measurement and upscaling
381 uncertainties, model performance was also evaluated against the ensemble mean of all ET partitioning approaches, as
382 ensemble averaging can reduce the influence of method-specific errors and thus provide a more stable and robust
383 reference than any individual approach (Dietterich, 2000). For each day, the ensemble mean was calculated as the
384 average of all available model predictions of T:ET and is hereafter referred to as the all-method ensemble. In addition,
385 ensemble means were calculated separately for each method group, referred to as the HF ensemble (Group 1 ensemble),
386 CW ensemble (Group 2 ensemble), and ML ensemble (Group 3 ensemble). These three group-specific ensembles were
387 evaluated against both the measurement-based T:ET time series and the all-method ensemble to assess whether any
388 group of ET partitioning approaches consistently outperformed the others.

389 It should be noted that E_s measured by the microlysimeters was not compared with E_s derived from the ensemble mean
390 because the ensemble mean was derived from model predictions after applying the rainy-day exclusion procedure,
391 whereas the microlysimeter measurements represented cumulative evaporation over multiple days, some of which
392 included rainfall events (Table S3 and Fig. S4). Consequently, ensemble mean estimates were unavailable for portions
393 of the microlysimeter observation periods. This mismatch in temporal coverage prevented a robust direct comparison.
394 Since the measurement-based T:ET was independently validated against site measurements (Sections S3 and S4 of
395 the Supplementary Material), comparing the ensemble mean with the measurement-based T:ET provides an indirect
396 assessment of how well the ensemble mean agrees with the observations.

397 3. Results and Discussions

398 3.1 Evaluation of the high-frequency eddy covariance-based methods (Group 1)

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408 The daily T:ET estimates derived from the Group 1 approaches, which are based on high-frequency EC measurements,
409 are presented in Fig. 1. The measurement-based daily T:ET time series and the ensemble mean of all ET partitioning
410 approaches are also shown for comparison. As shown in Fig. 1, the daily T:ET estimates produced by the Group 1
411 approaches do not always closely match either the measurement-based values or the overall ensemble mean. Likewise,
412 the measurement-based values and the overall ensemble mean do not always agree, which reflects the uncertainty
413 associated with both the reconstruction of the measurement-based T:ET time series and the ET partitioning approaches.
414 Across four sites, the mean T:ET of the overall ensemble exceeds the mean of the measurement-based T:ET by 10.4%.
415 The mean T:ET of the Group 1 ensemble is even higher, exceeding the mean measurement-based daily T:ET by 18.4%.
416 Relative to the mean of all method ensemble, the mean of Group 1 ensemble is 5.3% higher.

417 Among the Group 1 approaches, MREA and CEC generally produce the highest daily T:ET estimates, whereas CEA
418 consistently produce the lowest. Across four sites, the mean T:ET estimated by MREA exceeds the mean
419 measurement-based by 26.4%, followed by CEC (18.3%). In contrast, the mean T:ET estimated by CEA is only 0.17%
420 lower than the mean measurement-based values. FVSopt produces intermediate T:ET estimates among the four Group
421 1 approaches. The relatively lower T:ET estimates from FVSopt compared with MREA are consistent with the findings
422 of Klosterhalfen et al. (2019b), who compared the FVS and MREA approaches across multiple ecosystems. They
423 reported that FVS tends to overestimate the soil flux component (higher soil evaporation and thus lower T:ET),
424 whereas MREA tends to underestimate the soil flux component.

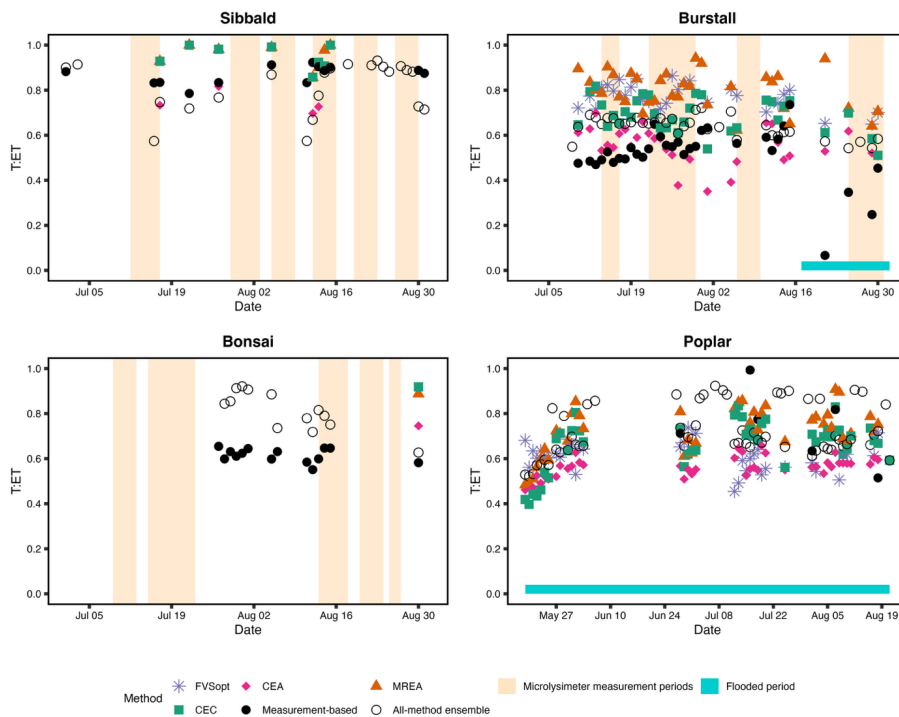
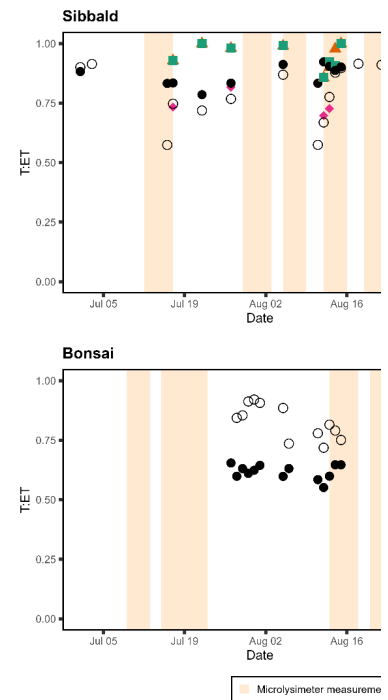


Figure 1: Comparison of transpiration-to-evapotranspiration ratio (T:ET) from the high-frequency eddy covariance-based methods (Group 1) with the measurement-based values (black circles) and the ensemble mean of all evapotranspiration partitioning approaches (open circles) for the four study sites. The light beige shading indicates periods during which ground evaporation was measured using micro-lysimeters at Sibbald, Burstall and Bonsai. The cyan bars at the bottom of the Burstall and Poplar panels indicate flooded periods. The FVSopt method was excluded from the Sibbald analysis because it did not produce realistic T:ET values. Although FVSopt generated realistic T:ET estimates at Bonsai, no data remained after the exclusion of rainy periods.

The R^2 and NSE values for the four Group 1 approaches are presented in Table 3. Regardless of whether the approaches are evaluated against the measurement-based T:ET or the ensemble mean of all ET partitioning approaches, no single Group 1 approach consistently outperforms the others across all four study sites. Furthermore, most approaches perform no better than using the observed mean as the predictor, as indicated by the predominantly negative or near zero NSE values (Table 3). In terms of capturing the temporal variability of T:ET, as indicated by R^2 , CEA performs best at Sibbald when evaluated against the measurement-based T:ET, whereas FVSopt performs best at both Burstall and Poplar, and MREA performs best at Bonsai. The Group 1 ensemble mean does not outperform the best individual approach at any of the study sites. When evaluated against the ensemble mean of all ET partitioning approaches, MREA remains the best-performing approach at Sibbald, FVSopt continues to perform best at Burstall, and CEC



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achieves the highest R^2 at Poplar. The Group 1 ensemble mean outperforms the individual Group 1 approaches only at Poplar.

Table 3. Comparison of coefficient of determination (R^2) and Nash-Sutcliffe efficiency (NSE) values for each Group 1 approach and the Group 1 ensemble mean (HF ensemble) relative to the measurement-based transpiration-to-evapotranspiration ratio (T:ET) and the ensemble mean of T:ET from all ET partitioning approaches.

Method	Sibbald		Burstall		Bonsai		Poplar		All sites	
	R^2	NSE	R^2	NSE	R^2	NSE	R^2	NSE	R^2	NSE
Comparison with the measurement-based T:ET:										
FVSopt	NA	NA	0.162	-4.101	NA	NA	0.336	-0.726	0.024	-2.200
MREA	0.174	-5.263	0.013	-6.366	NA	NA	0.031	-0.113	0.118	-1.383
CEA	0.552	-13.335	0.023	-0.727	NA	NA	0.039	-1.325	0.082	0.024
CEC	0.188	-4.836	0.062	-2.220	NA	NA	0.230	0.202	0.417	-0.151
HF ensemble	0.089	-4.469	0.025	-2.699	NA	NA	0.010	-0.162	0.289	-0.292
Comparison with the ensemble mean of all methods:										
FVSopt	NA	NA	0.234	-12.001	NA	NA	0.009	-1.591	0.002	-4.285
MREA	0.409	-4.098	0.270	-14.408	NA	NA	0.503	-2.678	0.437	-3.580
CEA	0.383	0.188	0.020	-7.532	NA	NA	0.465	-2.535	0.233	-3.083
CEC	0.189	-4.069	0.202	-2.421	NA	NA	0.550	-1.166	0.528	-1.111
HF ensemble	0.407	-2.587	0.450	-2.146	NA	NA	0.626	0.452	0.566	-0.274

Note. Any R^2 or NSE value greater than 0.5 is shown in bold.

The performance of the Group 1 approaches has previously been shown to depend on site characteristics. For example, Klosterhalfen et al. (2019b) found that the performance of FVS decreases with increasing measurement height to canopy height ratio (z/h) and leaf area index to canopy height ratio (LAI/h), but improves with increasing canopy height (h) and measurement height (z). This finding may partly explain the poor performance of FVSopt at Sibbald and Bonsai, where both z/h and LAI/h were substantially higher than at the other two sites and few physically realistic T:ET estimates were obtained. For MREA, Klosterhalfen et al. (2019b) reported that its performance is more strongly influenced by canopy structural characteristics, including h , LAI , and canopy gaps. More generally, they suggest that site characteristics increasing scalar dissimilarity, such as reduced turbulent mixing, greater source-sink separation, coherent turbulent structures, and ejection events, tend to improve the performance of both the FVS and MREA approaches (Klosterhalfen et al., 2019b).

To further examine how the performance of the Group 1 approaches is related to site characteristics, Spearman correlation analyses were conducted between site characteristics (canopy height, h ; measurement height, z ; LAI ; LAI/h ; z/h ; moss thickness; and mean water table depth, WTD) and the R^2 and NSE values of each Group 1 approach, as well as the Group 1 ensemble mean, relative to both the measurement-based T and the ensemble mean of all ET partitioning approaches. No significant correlations were identified between any site characteristic and the performance metrics.

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471 However, this result should be interpreted with caution because only three sites were available for the correlation
472 analysis (Table 3), which results in very limited statistical power.

473 Although no clear relationships between site characteristics and model performance were identified in this study, Zahn
474 et al. (2024) extended the work of Klosterhalfen et al. (2019b) by evaluating all the Group 1 methods and suggested
475 that the Group 1 methods tend to be more reliable under specific conditions: no strong vertical stratification or
476 convection, EC sampling height near the canopy top (i.e., $z/h \approx 1$), moderate or low LAI, and the canopy does not
477 have gaps that are too wide. Based on these criteria, the Group 1 methods would be expected to perform better at
478 Burstall and Poplar than Sibbald and Bonsai. Nevertheless, considerable disagreement among the four approaches
479 remains at both sites. At Burstall, the spread of daily T:ET estimates ranges from 0.10 to 0.42 across the study period,
480 and at Poplar it ranges from 0.09 to 0.39, indicating substantial uncertainty in the Group 1 predictions even under
481 conditions considered favorable for their application. Furthermore, Burstall transitions to flooded conditions after 17
482 August, during which the measurement-based T:ET exhibits a marked decline. In contrast, the T:ET estimates from
483 the Group 1 approaches show only a slight decrease, suggesting that their predictive performance deteriorates under
484 flooded conditions. However, a similar mismatch is not observed at Poplar, which remains flooded throughout the
485 entire study period. At Poplar, the four Group 1 approaches produce relatively consistent T:ET estimates despite the
486 persistent flooding. One possible explanation is the difference in vegetation structure between the two sites. Poplar is
487 a densely forested wetland, whereas Burstall is dominated by shrubs with a lower and more open canopy. This
488 observation suggests that the predictive performance of the Group 1 approaches may be more uncertain in waterlogged
489 wetlands with sparse vegetation cover than in densely forested wetlands. Further evaluation across a broader range of
490 wetland types is needed to confirm this hypothesis.

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491 3.2 Evaluation of the **ecosystem carbon-water coupling methods (Group 2)**

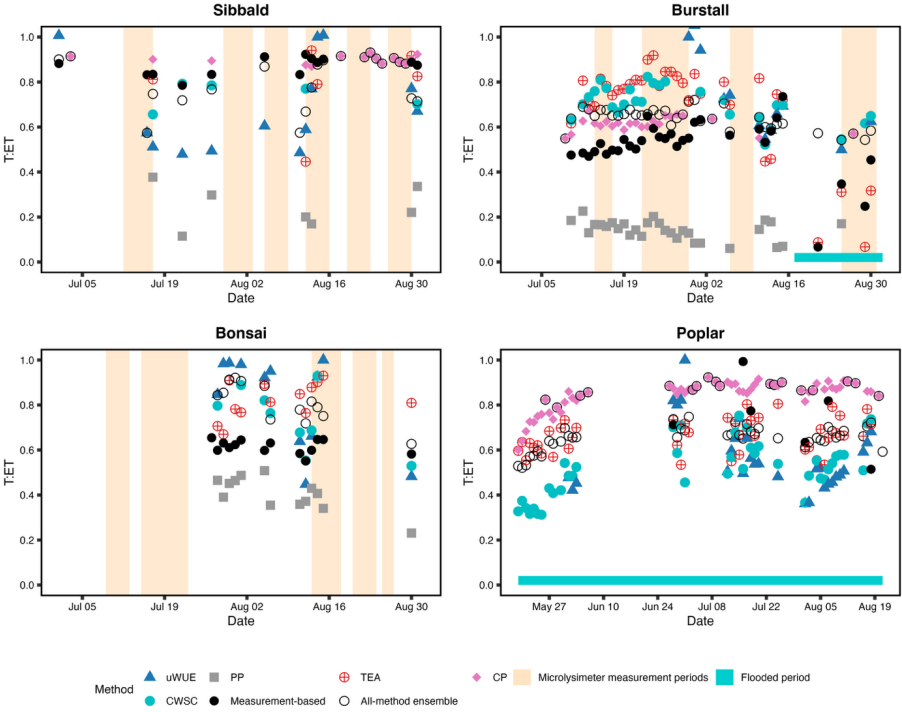
492 The daily T:ET estimates derived from the Group 2 approaches (uWUE, PP, TEA, CP, and CWSC) are presented in
493 Fig. 2. Compared with the measurement-based T:ET and the ensemble mean of all ET partitioning approaches, the
494 Group 2 approaches exhibit a considerably wider spread of daily T:ET estimates and generally larger temporal
495 fluctuations. Nevertheless, the Group 2 ensemble mean shows closer agreement with both reference datasets than the
496 Group 1 ensemble mean. Across all four sites, the mean T:ET of the Group 2 ensemble exceeds the mean measurement-
497 based T:ET by only 0.32% and is 5.01% lower than the overall ensemble mean.

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498 Although no single Group 2 approach consistently produces the highest or lowest T:ET across all four study sites,
499 several systematic patterns emerge. **The Perez-Priego (PP) method** consistently produces the lowest T:ET estimates,
500 whereas CP generally produces T:ET values that are comparable to or higher than the measurement-based values.
501 Among the five approaches, uWUE exhibits the largest temporal fluctuations, while TEA generally predicts higher
502 T:ET than CWSC. Relative to the measurement-based T:ET, TEA overestimates T:ET by 17.44% across four sites,
503 followed by CWSC (13.07%), CP (11.45%), and uWUE (0.43%), whereas PP underestimates T:ET by 167.84%.
504 Relative to the overall ensemble mean, CP overestimates T:ET by 10.39%, followed by TEA (3.84%), whereas uWUE,
505 CWSC, and PP underestimate T:ET by 7.31%, 7.65%, and 67.71%, respectively.

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509 Notably, TEA is the only method that captures the sharp decline in T:ET observed at Burstall after August 17, when
510 the site became flooded. In contrast, PP substantially underestimates T:ET and exhibits contrasting temporal trends
511 relative to the measurement-based values at Sibbald and Burstall. This observation is different from the findings in
512 Nelson et al. (2020) who reported similar results between the PP and uWUE methods. The exact cause of this bias
513 remains unclear. However, since other methods align more closely and PP is the only method in this group that requires
514 photosynthetically active radiation (Q) as an additional input, the discrepancy is likely related to this variable. It is
515 possible that Q measured at a single location may not adequately represent canopy-level conditions, potentially due
516 to the uneven and multi-layered canopy structures in these study sites (Fig. S3). Another potential explanation is that
517 the PP method's E_g component may include not only ground E_g but also canopy E_g (e.g., dewfall), as suggested by Pérez-
518 Priego et al. (2018). This inclusion of canopy E_g could result in lower T:ET. However, this hypothesis could not be
519 tested in the present study and requires further investigation.



520
521 **Figure 2: Comparison of transpiration-to-evapotranspiration ratio (T:ET) from the ecosystem carbon-water coupling**
522 **methods (Group 2) with the measurement-based values (black circles) and the ensemble mean of all ET partitioning**
523 **approaches (open circles) for the four study sites. Note that the CP method did not produce any realistic T:ET values at**
524 **Bonsai and thus was excluded. The PP method was not performed at Poplar due to missing photosynthetically active**

radiation data. The light beige shading indicates periods during which ground evaporation was measured using micro-lysimeters at Sibbald, Burstall and Bonsai. The cyan bars at the bottom of the Burstall and Poplar panels indicate flooded periods.

The performance statistics for the Group 2 approaches are summarized in Table 4. Similar to the Group 1 approaches, no single Group 2 approach consistently outperforms the others across all four study sites, and most approaches perform no better than using the observed mean as the predictor. However, in terms of capturing the temporal variability of T:ET, as measured by R², the Group 2 approaches generally perform better than the Group 1 approaches. For example, when evaluated against the measurement-based T:ET, TEA achieves the highest R² at Burstall, whereas uWUE and CWSC perform best at Bonsai. The Group 2 ensemble mean does not outperform the best individual approach at most sites, with the exception of Burstall. When evaluated against the overall ensemble mean, however, the Group 2 ensemble generally performs better than the individual Group 2 approaches at most sites. This result should be interpreted with caution because Group 2 contains more approaches than either Group 1 or Group 3 and therefore likely exerts a stronger influence on the overall ensemble mean.

Table 4. Comparison of coefficient of determination (R²) and Nash-Sutcliffe efficiency (NSE) values for each Group 2 approach and the Group 2 ensemble mean (CW ensemble) relative to the measurement-based transpiration-to-evapotranspiration ratio (T:ET) and the ensemble mean of T:ET from all ET partitioning approaches.

Method	Sibbald		Burstall		Bonsai		Poplar		All sites	
	R ²	NSE	R ²	NSE	R ²	NSE	R ²	NSE	R ²	NSE
Comparison with the measurement-based T:ET:										
uWUE	0.331	-41.666	0.147	-2.779	0.735	-85.989	0.079	-3.038	0.019	-2.043
TEA	0.178	-52.766	0.574	-2.608	0.020	-62.917	0.010	-0.311	0.228	-0.886
CWSC	0.016	-7.222	0.132	-3.581	0.732	-32.363	0.105	-2.490	0.000	-0.957
PP	0.000	-197.861	0.227	-32.868	0.049	-59.838	NA	NA	0.044	-10.179
CP	0.258	-1.121	0.044	-4.463	NA	NA	0.107	-0.589	0.711	0.450
CW ensemble	0.253	-36.742	0.664	0.636	0.141	-61.552	0.059	-0.783	0.192	-0.030
Comparison with the ensemble mean of all methods:										
uWUE	0.284	-1.977	0.420	-7.411	0.433	-2.651	0.317	-34.203	0.319	-2.686
TEA	0.192	-4.376	0.583	-16.882	0.005	-1.001	0.252	-0.575	0.286	-1.630
CWSC	0.031	-3.353	0.516	-3.033	0.581	-0.479	0.716	-8.217	0.387	-2.268
PP	0.032	-214.522	0.018	-176.717	0.830	-22.169	NA	NA	0.721	-27.959
CP	0.117	-0.446	0.258	-1.113	NA	NA	0.380	-0.787	0.376	-0.284
CW ensemble	0.760	0.234	0.428	-6.187	0.965	0.841	0.913	0.885	0.802	0.493

Note. Any R² or NSE value greater than 0.5 is shown in bold.

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Previous studies have shown that the performance of Group 2 approaches depends on both the quality of the input data, including EC-derived GPP and ET and environmental variables such as radiation, temperature, humidity, wind and precipitation, and the representation of ecosystem carbon-water coupling within each approach (Nelson et al., 2020; Li et al., 2019; Yu et al., 2022). Besides differences in the quality of the input variables used by the Group 2 approaches, differences in the formulation of ecosystem carbon-water coupling are likely to be a major source of

variation in the predicted T:ET among the approaches. All Group 2 methods are based, to varying extents, on the theory of optimal stomatal conductance. Among these, uWUE, CP, PP and CWSC are formulated using the unified stomatal conductance model proposed by Medlyn et al. (2011). The generally agreement between the measurement-based T:ET and the estimates from uWUE, CP, and CWSC (Fig. 3) supports previous conclusions that an optimal ecosystem response to VPD is a reasonable assumption (Stoy et al., 2019), even in some moss-covered wetlands such as those examined in this study.

However, as noted by Stoy et al. (2019) and Nelson et al. (2020), the way in which optimality is conceptualized and implemented in these models may need to be refined. Improvements could include incorporating effects of plant hydraulic architecture, soil moisture, temperature, atmospheric CO₂ concentration (Bernacchi et al., 2004; Medlyn et al., 2011; Lin et al., 2015; Nardini and Salleo, 2000), as well as considering the timescales over which assumptions about constant parameters in the unified stomatal conductance model can hold (Mäkelä et al., 1996), could improve model performance. This is illustrated by the comparison of results from uWUE, CP and CWSC in Fig. 3. Both CP and CWSC, which account for soil moisture and atmospheric CO₂ concentration effects respectively, produced a narrower spread of T:ET estimates than uWUE, which suggests that including these additional constraints improves model performance at sub-daily and daily scales.

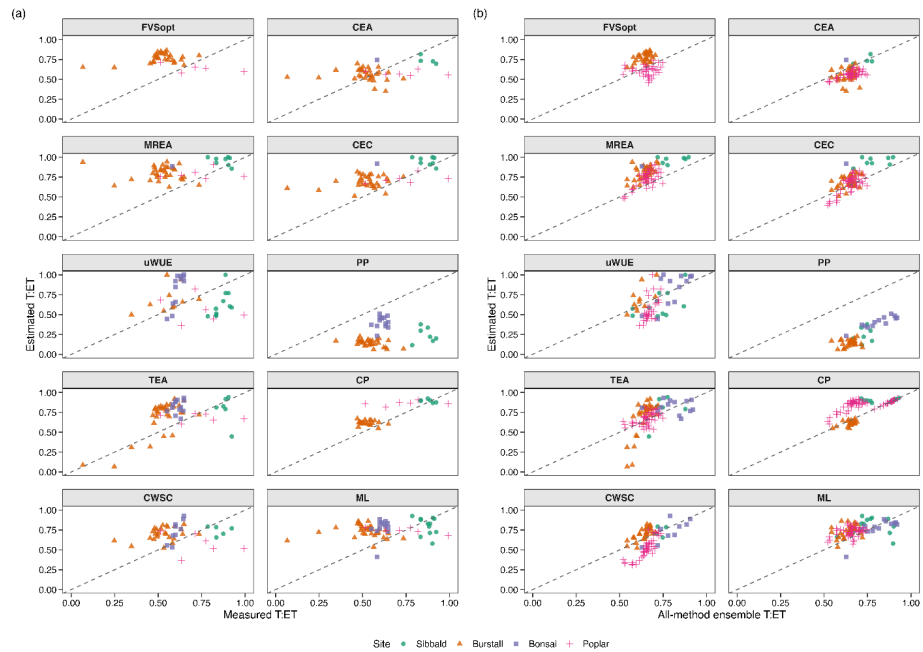


Figure 3: Transpiration-to-evapotranspiration ratio (T:ET) estimates from each ET partitioning approach, pooled across the four study sites, with the measurement-based T:ET values (left two columns) and the ensemble mean of T:ET from all ET partitioning approaches (right two columns).

3.3 Evaluation of the machine learning-based methods (Group 3)

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The best-performing ML models were identified using the adjusted R^2 criterion defined by Stapleton et al. (2022), based on their performance on the night-time validation dataset. The flooding validation dataset was not used for model selection because all candidate models produced negative adjusted R^2 values under flooded conditions (Fig. S1). The best-performing ML algorithms are the LightGBM for Sibbald and Poplar and the XGBoost for Burstall and Bonsai, each with a different optimal predictor sets (Tables S1 and S2). This finding is consistent with Stapleton et al. (2022), who reported that no single ML algorithm or predictor set consistently performs best across all study sites. Instead, each site has its own best-performing algorithm, predictor combination, and variable importance ranking. Across the four study sites, sensible heat flux, air temperature, and net radiation consistently ranked among the five most important predictors of evaporation (Table S1).

The daily T:ET estimates produced by the best-performing ML model for each study site are presented in Fig. 4, and their performance statistics are summarized in Table 5. Similar to Groups 1 and 2 approaches, the ML models do not consistently outperform the other ET partitioning approaches across all four study sites and, in most cases, perform no better than using the observed mean as the predictor. In terms of reproducing the temporal variability of T:ET, as indicated by R^2 , the best-performing ML model achieves its highest agreement with the measurement-based T:ET at Poplar. When the overall ensemble mean is used as the reference, however, the highest R^2 is obtained at Bonsai. Additionally, the Group 3 ensemble is defined as the average of the predictions from the best-performing ML model identified for each study site and the TEA approach, calculated from all available predictions on each day. Across four sites, the mean T:ET of the Group 3 ensemble exceeds the mean measurement-based T:ET by 16.09% and is 6.14% higher than the overall ensemble mean.

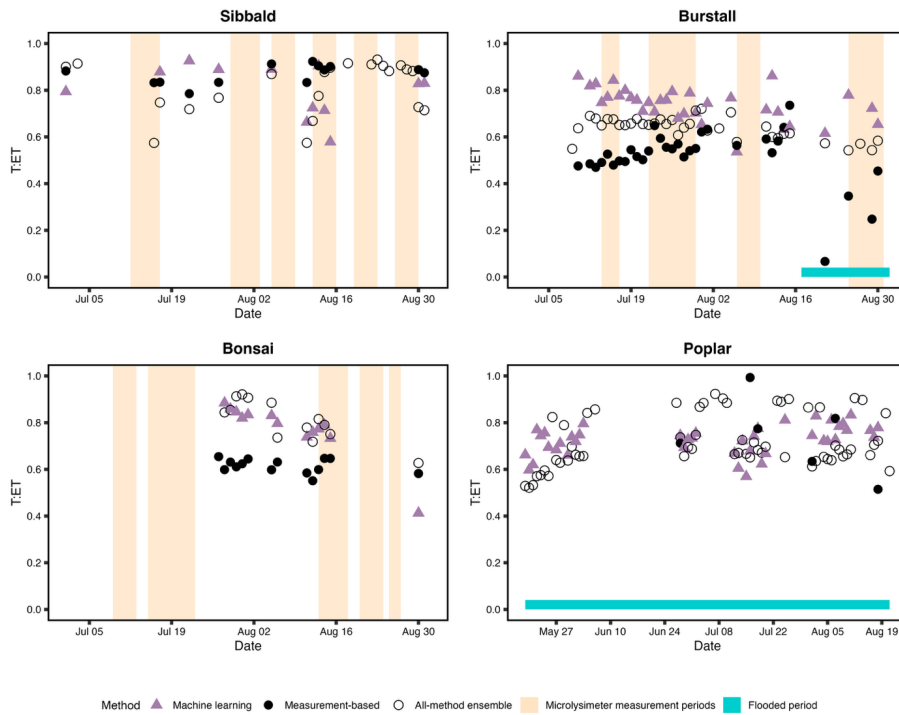


Figure 4: Comparison of transpiration-to-evapotranspiration ratio (T:ET) estimates from the machine learning methods (Group 3) with the measurement-based values (black circles) and the ensemble mean of T:ET from all evapotranspiration partitioning approaches (open circles) for the four study sites. The light beige shading indicates periods during which ground evaporation was measured using micro-lysimeters at Sibbald, Burstall and Bonsai. The cyan bars at the bottom of the Burstall and Poplar panels indicate flooded periods.

Table 5. Comparison of coefficient of determination (R^2) and Nash-Sutcliffe efficiency (NSE) values for the Group 3 approach and the Group 3 ensemble mean (ML ensemble) relative to the measurement-based transpiration-to-evapotranspiration ratio (T:ET) and the ensemble mean of T:ET from all ET partitioning approaches.

Method	Sibbald		Burstall		Bonsai		Poplar		All sites	
	R^2	NSE	R^2	NSE	R^2	NSE	R^2	NSE	R^2	NSE
Comparison with the measurement-based T:ET:										
ML	0.107	-11.960	0.003	-3.884	0.115	-47.647	0.680	-0.417	0.023	-0.736
ML ensemble	0.128	-15.081	0.449	-2.368	0.153	-47.613	0.222	-0.304	0.181	-0.381
Comparison with the ensemble mean of all methods:										
ML	0.002	-1.393	0.116	-6.261	0.627	0.144	0.084	-2.446	0.179	-0.564

ML ensemble	0.007	-1.396	0.634	-5.488	0.442	0.412	0.253	-0.594	0.332	-0.187
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Note. Any R² or NSE value greater than 0.5 is shown in bold. The ML ensemble includes the best-performing machine learning model identified using the framework of Stapleton et al. (2022) and the TEA approach, which is also classified as a machine learning-based ET partitioning approach.

Unlike the results reported by Eichelmann et al. (2022) and Stapleton et al. (2022), the ML models developed under their framework fail to reproduce the sharp decline in the measurement-based T:ET when Burstall transitions from unsaturated to flooded conditions. Assuming that the measurement-based T:ET reasonably represents the actual temporal dynamics of the site, one possible explanation is that the dominant environmental controls governing ground E_g and ET partitioning change substantially following flooding. Consequently, these ML models, which are trained under non-flooded conditions, rely on environmental relationships that are no longer representative once the site becomes inundated. In particular, the factors influencing WUE (i.e., the relationship between GPP and T) may change markedly following flooding. This interpretation is supported by the performance of the TEA approach, which is the only method that reproduces the observed decline in T:ET. Unlike the other carbon-water coupling approaches, TEA employs a random forest model to estimate a temporally varying WUE, which allows it to better adapt to changing environmental conditions. In contrast, the other carbon-water coupling approaches rely on presumed relationships between carbon and water fluxes and likewise fail to capture the transition in WUE following flooding. Although TEA demonstrates superior performance under these conditions, this does not necessarily imply that it is generally suitable for E_g-dominated ecosystems, as Nelson et al. (2018) reported that TEA tends to overestimate T_g at sites with a relatively constant E_g component. Therefore, the improved performance of TEA at Burstall is more likely attributable to its ability to accommodate temporal changes in WUE during the transition from unsaturated to flooded conditions than to a general advantage in E_g-dominated ecosystems. Together, these findings suggest that changes in WUE following inundation play an important role in determining ET partitioning.

Another important consideration is that, in both Eichelmann et al. (2022) and Stapleton et al. (2022), the ML models were validated by comparing predicted E_g with EC-measured ET during flooded periods when vegetation within the flux footprint had not yet become established. Under these conditions, T_g can reasonably be assumed to be negligible, such that nearly all measured ET originates from E_g. In contrast, this study evaluated the ML models under a different flooding scenario. At our sites, flooding occurred after vegetation was already well established and T_g remained an important component of ET. Consequently, these ML models may not perform equally well under all flooding scenarios, which may explain the negative adjusted R² values obtained when they were evaluated using the flooding validation dataset (Fig. S1). However, unlike at Burstall, the best-performing ML model at Poplar does not deviate substantially from the reference estimates (Fig. 4), suggesting that the framework may remain applicable to wetlands that are continuously flooded throughout the study period. Together, these findings suggest that, although the framework may perform well under conditions of initial flooding or persistent flooding, further evaluation is needed to determine its applicability to wetlands that transition between unsaturated and flooded conditions.

The performance of these ML models depends on several factors, including the validity of the assumption that nighttime T is negligible, the quality of the nighttime EC data and associated gap-filling procedures, as well as the

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657 choice of ML architecture and its hyperparameters (Stapleton et al., 2022). Among these factors, the influence of data
658 gaps and gap-filling procedures appears to be limited in the present study. Poplar and Sibbald have substantially larger
659 proportions of missing EC data (approximately 60%) than Burstall and Bonsai (approximately 20%). Nevertheless,
660 the best-performing ML model achieves its highest agreement with the measurement-based T:ET at Poplar, which
661 indicates that the extent of data gaps and the associated gap-filling procedures are unlikely to be the primary factors
662 controlling model performance in this study. The magnitude of nighttime transpiration at each study site and the choice
663 of machine learning architecture and hyperparameter settings may also contribute to differences in model performance.
664 However, evaluating these factors is beyond the scope of the present study. Overall, the results suggest that the
665 performance of the ML models is likely governed by the combined effects of data quality, machine learning
666 architecture, site-specific environmental conditions, and the validity of the underlying ET partitioning assumptions.

667 **3.4 Agreement among ~~evapotranspiration,~~ partitioning approaches**

668 The Spearman correlation analysis of the predicted T:ET among the ET partitioning methods evaluated in this study
669 (Fig. 5) provides an additional perspective on the agreement among methods. Spearman correlation was preferred
670 over Pearson correlation because it evaluates the monotonic relationship between methods without assuming a linear
671 relationship or normally distributed data (Weaver et al., 2017). It is therefore more robust to outliers and better suited
672 for comparing the temporal consistency of daily T:ET estimates produced by different ET partitioning approaches.
673 Overall, the strength, direction, and statistical significance of the correlations vary considerably across the four study
674 sites.

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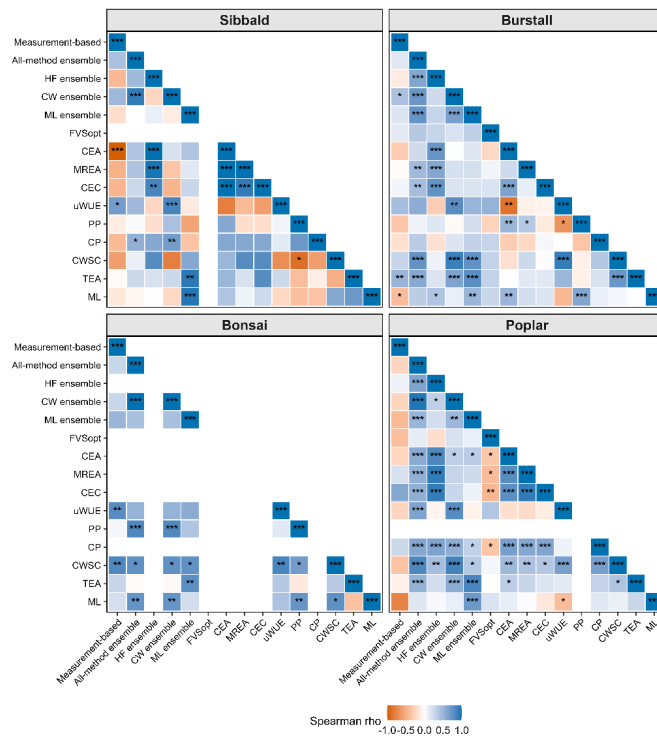


Figure 5: Spearman correlation matrix of the predicted **transpiration-to-evapotranspiration ratio (T:ET)** among the **evapotranspiration** partitioning methods evaluated in this study. Blue indicates positive correlations, whereas orange indicates negative correlations. Statistical significance is denoted by * ($P < 0.05$), ** ($P < 0.01$), and *** ($P < 0.001$).

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Notably, the measurement-based T:ET is not significantly correlated with the all-method ensemble at any of the study sites, and the correlation is negative at Poplar. Likewise, the measurement-based T:ET shows no significant correlation with any of the group ensemble means, except at Burstall, where it is positively correlated the Group 2 ensemble. In contrast, all-method ensemble exhibits positive and significant correlations with almost all three groups. These contrasting correlation patterns indicate that the assessment of ET partitioning performance depends strongly on the choice of reference dataset. Although the present study does not provide sufficient evidence to determine whether the measurement-based T:ET or the all-method ensemble better represents the true site-scale T:ET dynamics, the discrepancy between these two references highlights the uncertainty associated with defining a benchmark for ET partitioning evaluation. Consequently, the choice of reference dataset should be carefully considered when comparing and interpreting the performance of different ET partitioning approaches.

Among the three methodological groups, the Group 1 ensemble is positively correlated with the Group 3 ensemble at all four study sites, although none of these correlations is statistically significant. In contrast, the correlation between

the Group 1 and Group 2 ensembles is site dependent, with a significant positive correlation observed only at Poplar. The Group 2 ensemble is positively correlated with the Group 3 ensemble at all sites except Sibbald, and these correlations are significant at Burstall and Poplar. Overall, the Group 3 ensemble exhibits stronger and more consistent agreement with both the Group 1 and Group 2 ensembles than the agreement observed between Groups 1 and 2. This pattern suggests that the ML models capture temporal variability that is shared by both the high-frequency EC-based and the carbon-water coupling approaches, likely because the predictor variables used in the machine learning framework capture information related to both turbulence transport and ecosystem carbon-water coupling.

Regarding the individual methods, approaches within the same methodological group generally exhibit stronger positive correlations than approaches from different groups. For example, MREA agrees more with CEA and CEC than with uWUE, which reflects their shared theoretical assumptions and common input variables. However, notable contrasts from the within-group correlation patterns are observed for FVSopt at Burstall and Poplar, and for CWSC and PP at Sibbald, where these methods exhibit substantially weaker agreement with the other approaches in their respective groups. This may reflect the uncertainty associated with estimating leaf-level WUE, as FVSopt, CWSC, and PP all rely on prescribed relationships to estimate leaf-level WUE, and these relationships may not adequately represent the responses of leaf-level WUE to the highly dynamic environmental conditions in wetlands. For example, Klosterhalfen et al. (2019a) demonstrated that the FVS is vulnerable to errors in water use efficiency estimates and atmospheric conditions that violate the variance similarity assumption, like under conditions of weak turbulence, canopy heterogeneity, and poorly separated soil and canopy source-sink distributions.

The degree of agreement among approaches also differs across the four study sites. Poplar exhibits the strongest agreement among methods, whereas Sibbald shows the weakest. This difference may be related to the greater ecosystem heterogeneity at Sibbald. Compared with the relatively homogeneous canopy of the dense forested Poplar peatland, Sibbald is characterized by a multi-layered shrub canopy, large canopy gaps, and pronounced hummock-hollow microtopography (Fig. S3). Such structural heterogeneity is likely to increase the spatial variability of carbon and water fluxes within the EC footprint, and thereby introduces greater uncertainty into EC measurements and reduces the applicability of both scalar transport assumptions and carbon-water relationships used by the EC-based ET partitioning approaches examined in this study.

3.5 Effects of moss cover and flooding on the performance of ~~evapotranspiration~~, partitioning

The primary objective of this study is to evaluate the performance of existing ET partitioning approaches in moss-covered wetlands. As discussed in Section 1 and 2.1, moss cover has the potential to violate several of the fundamental assumptions underlying these approaches. For the **Group 1 approaches**, strong moss photosynthesis can produce a net negative surface CO₂ signal, thereby violating the assumption that the surface acts as a net CO₂ source. Evidence for this behavior was reported by Walker et al. (2017), whose chamber measurements on Sphagnum-peat columns showed frequent transitions between positive and negative hourly CO₂ fluxes (their Fig. 4), together with sustained daily net CO₂ uptake from mid-June to mid-July. These observations suggest that a moss layer has the potential to compromise the applicability of **Group 1** approaches that rely on a persistent positive surface CO₂ signal.

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In terms of our study sites, direct measurements of surface CO₂ exchange were unfortunately not available during the study period. Nevertheless, existing evidence indicates that negative surface CO₂ fluxes are plausible, particularly at Poplar. Following the 2016 wildfire, chamber measurements conducted in 2017 over moss-dominated plots at Poplar showed that the unburned forest floor remained a net CO₂ sink until early August (Van Beest (2019); Fig. 3-1). Although these measurements were not collected during the same study period, they provide independent evidence that strong moss photosynthesis can occur at this site and may influence the assumptions underlying Group 1 approaches.

As for the ecosystem carbon-water coupling approaches (Group 2), moss cover introduces a different source of uncertainty. These approaches estimate WUE under the assumption that GPP originates exclusively from vascular vegetation that also contributes to T . However, mosses contribute to ecosystem GPP while making no contribution to T . Consequently, moss photosynthesis may bias WUE estimates and propagate errors into ET partitioning. The methods that are more sensitive to GPP errors, such as PP and uWUE, as diagnosed in Nelson et al. (2020), are expected to exhibit greater uncertainty. The magnitude of this effect depends on the contribution of mosses to ecosystem GPP, which has been reported to account for approximately 20% to 30% of total forest CO₂ uptake in a drained forested peatland (Badorek et al., 2011). Therefore, this source of uncertainty may not be trivial.

Another potential source of uncertainty affecting ET partitioning performance is flooding. Under flooded conditions, EC measurements may become less reliable because of weak turbulence and enhanced advection effects (Dai et al., 2026). For the Group 1 approaches, flooding may also weaken or obscure surface CO₂ signals, further challenging the assumptions underlying these methods. To evaluate the influence of flooding, we recalculated the R² and NSE values for Burstall after excluding the flooded period (Table 6) and compared the resulting performance statistics with those obtained using the complete dataset (Tables 3, 4 and 5). When evaluated against the measurement-based T:ET, the R² values of CEA, MREA, PP, the best-performing ML model, and the Group 1 ensemble increased slightly after the flooded period was excluded. When the overall ensemble mean was used as the reference, only CEA, MREA and PP showed slight improvements in R². However, despite these modest increases in R², the NSE values decreased for all approaches except TEA, and all NSE values remained negative. These results suggest that the factors affecting ET partitioning performance are more complex and cannot be explained by flooding alone.

Table 6. Comparison of coefficient of determination (R²) and Nash-Sutcliffe efficiency (NSE) values relative to the measurement-based transpiration-to-evapotranspiration ratio (T:ET) and the ensemble mean of T:ET from all ET partitioning approaches for Burstall after excluding the flooding period.

Methods	Comparison with the measurement-based T:ET		Comparison with the ensemble mean of all methods	
	R ²	NSE	R ²	NSE
FVSopt	0.050	-13.991	0.017	-21.977
CEA	0.204 (+)	-2.835	0.040 (+)	-16.612
MREA	0.104 (+)	-19.574	0.310 (+)	-23.020
CEC	0.019	-7.533	0.095	-4.611

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uWUE	0.000	-10.159	0.286	-11.256
PP	0.236 (+)	-45.558	0.055 (+)	-237.481
TEA	0.015	-13.755	0.262	-15.987 (+)
CP	0.044	-4.463	0.193	-1.843
CWSC	0.005	-7.338	0.396	-6.875
ML	0.385 (+)	-12.533	0.110	-10.169
HF Ensemble	0.087 (+)	-8.624	0.381	-4.037
CW Ensemble	0.040	-0.383	0.399	-4.716
ML Ensemble	0.074	-11.887	0.436	-9.104

Note. (+) indicates that the corresponding performance metric improved after excluding the flooding period.

Overall, regardless of whether the measurement-based T:ET or the overall ensemble mean was used as the reference, none of the evaluated approaches consistently outperformed the observed mean as the predictor. This was true even for the ML approaches, whose underlying assumptions are not fundamentally violated by moss cover. Together, these findings suggest that the performance of ET partitioning approaches in wetlands is influenced by the combined effects of multiple factors, including moss cover, flooding conditions, canopy structure, canopy density, canopy openness, site heterogeneity, the measurement height relative to canopy height, the quality of EC and environmental measurements, and the validity of the assumptions underlying each ET partitioning approach.

4. Summary and Closing Thoughts

This study provides first comprehensive evaluations of ET partitioning approaches in moss-covered wetlands across contrasting vegetation structures and hydrological conditions. Overall, no single ET partitioning approach consistently outperformed the others across the four study sites or under both flooded and non-flooded conditions. Likewise, no methodological group, including the high-frequency EC-based approaches, ecosystem carbon-water coupling approaches, or machine learning approaches, demonstrated a clear overall advantage. The performance of ET partitioning approaches in wetlands is likely governed by the combined effects of multiple environmental and methodological factors. In addition to the assumptions underlying each approach, performance is influenced by EC measurement configuration, site characteristics such as canopy height and leaf area index, ecosystem heterogeneity, moss cover, and flooding conditions. These factors interact to influence both the quality of EC and environmental observations and the validity of the assumptions on which current ET partitioning approaches are based.

An important finding of this study is that the evaluation results depend strongly on the choice of reference dataset. The measurement-based T:ET and the ensemble mean of all ET partitioning approaches exhibit markedly different correlation patterns with the evaluated methods, highlighting the uncertainty associated with defining a reference for ET partitioning evaluation. This finding suggests that greater attention should be given to reference dataset selection and uncertainty quantification in future benchmarking studies.

Although several approaches perform reasonably well under specific site conditions, none adequately captures the full range of environmental conditions encountered in wetlands, particularly transitions between unsaturated and flooded

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793 states. Future work should therefore focus on developing wetland-specific ET partitioning approaches that explicitly
794 account for dynamic hydrological conditions, improve the representation of carbon-water coupling, and incorporate
795 the influence of mosses on ecosystem carbon exchange. Such developments will improve the reliability of ET
796 partitioning in wetlands and advance our understanding of water and carbon cycling in these globally important
797 ecosystems.

798 Since the purpose of this study is to provide supporting evidence and recommendation for future research that plan to
799 apply EC-based ET partitioning approaches in moss-covered wetlands, particularly in cases where direct validation
800 through field measurements is not available. several practical recommendations can be made. Based on our study, the
801 ensemble of the high-frequency EC-based approaches and the machine learning approaches produced T:ET estimates
802 of similar magnitude, and both tended to overestimate T:ET relative to both the measurement-based estimates and the
803 overall ensemble mean. In contrast, the ensemble of the ecosystem carbon-water coupling approaches produced lower
804 mean T:ET values but generally exhibited larger temporal fluctuations. Rather than relying on a single ET partitioning
805 group, we recommend applying multiple approaches from all three methodological groups whenever possible.
806 Comparing predictions across different approaches provides a more comprehensive assessment of uncertainty and
807 helps identify potential sources of disagreement among methods. For example, our analysis suggests that the
808 parameterization of WUE is one of the major factors contributing to disagreement among methods. This finding
809 implies that the response of WUE to changing environmental conditions in wetland ecosystems may not yet be fully
810 represented in current formulations. However, it should be noted that this recommendation does not imply that the
811 ensemble mean or any single approach is consistently better than the others. Our results showed that the relative
812 performance of individual approaches, as well as the ensemble mean, depended on the reference dataset used for
813 evaluation.

814 Finally, several caveats must be considered when interpreting the results of this study. First, the study did not examine
815 the mechanisms by which mosses influence the results of ET partitioning approaches. This remains an important topic
816 for future research. Secondly, the ET partitioning results presented here were filtered based on the data quality controls
817 described in the Methods section. It is important to emphasize that rainy periods were excluded; if included, most
818 Group 2 methods produced unrealistic T:ET values exceeding 1. Third, the evaporation component considered in this
819 study refers exclusively to ground ~~E_g~~. Whether the findings can be extended to include canopy ~~E_c~~ remains an open
820 question. Lastly, the conclusions are most likely valid for sites with moss thickness similar to or less than that of those
821 studied here. Uncertainty remains regarding their applicability to ecosystems with thicker moss layers and fewer
822 vascular plants. Nonetheless, the study sites represent common wetlands and are expected to reflect a broad range of
823 wetland ecosystems. Therefore, the conclusions are highly likely applicable to many wetland ecosystems.

824 **Data Availability Statement**

825 The measurement-based T:ET estimates were previous published in Gabrielli (2016) and Wang (2025). ~~The raw EC~~
826 measurement data ~~are currently involved in an ongoing research project and are therefore not yet publicly available.~~

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833 ~~The raw EC data can be made available by the corresponding author upon reasonable request.~~ The FVS, CEA, MREA
834 and CEC methods were applied using the ET partitioning code developed by Zahn (2024); the PP method by Pérez-
835 Priego and Wutzler (2018); the uWUE and TEA methods by Nelson (2020); the CWSC method by Jiang and Yu (2021);
836 and the machine learning framework by Stapleton (2022). We sincerely thank these authors for generously sharing
837 their codes.

838 **Author contribution**

839 YW and RP jointly developed the research concept. YW carried out data compilation, data analysis, and manuscript
840 drafting. RP supervised the project, secured funding, and contributed to manuscript writing. LZ assisted with code
841 adaptation, development, and manuscript editing. All authors approved the final manuscript.

842 **Competing interests**

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

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853 **Declaration of Generative AI and AI-assisted technologies in the writing process**

854 During the preparation of this work the first author used ChatGPT-4.0 only for grammar checking and language
855 polishing. ChatGPT-4.0 was not used for content generation. After using this tool, the first author reviewed and edited
856 the content as needed and takes full responsibility for the content of the publication.

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Contents:

S1. Performance of the Candidate Machine Learning Models and Predictor Variable Importance Rankings

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S4. Validation of Measurement-based Transpiration-to-Evapotranspiration Ratio (T:ET) at Poplar

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S1. Performance of the Candidate Machine Learning Models and Predictor Variable Importance Rankings

The machine learning framework developed by Stapleton et al. (2022) was adopted with only minor modifications. The original workflow, data imputation, feature selection procedure, predictor variable importance ranking, and model ranking were retained to ensure consistency with the published framework. Only two minor modifications were made to accommodate differences in the available datasets. First, because winter observations were unavailable, the winter validation step described by Stapleton et al. (2022) was omitted. Second, the F25 predictor set was identical to that of Stapleton et al. (2022), except that the vegetation greenness index (GCC), mean water temperature (TW_mean), ecosystem respiration derived from the linear method (er_linear), speed of sound (sos), degree of instationarity for mean methane concentration (stat_m), and methane flux (wm_gf) were excluded because these variables were unavailable for the present study. All other predictor variables, machine learning algorithms, training, calibration, validation procedures, and model selection criteria were identical to those described by Stapleton et al. (2022). The results of the model comparison, recursive feature elimination (RFE) for predictor selection, feature importance rankings, and the best-performing machine learning model for each study site are presented in Figs. S1 and S2 and Tables S1 and S2.

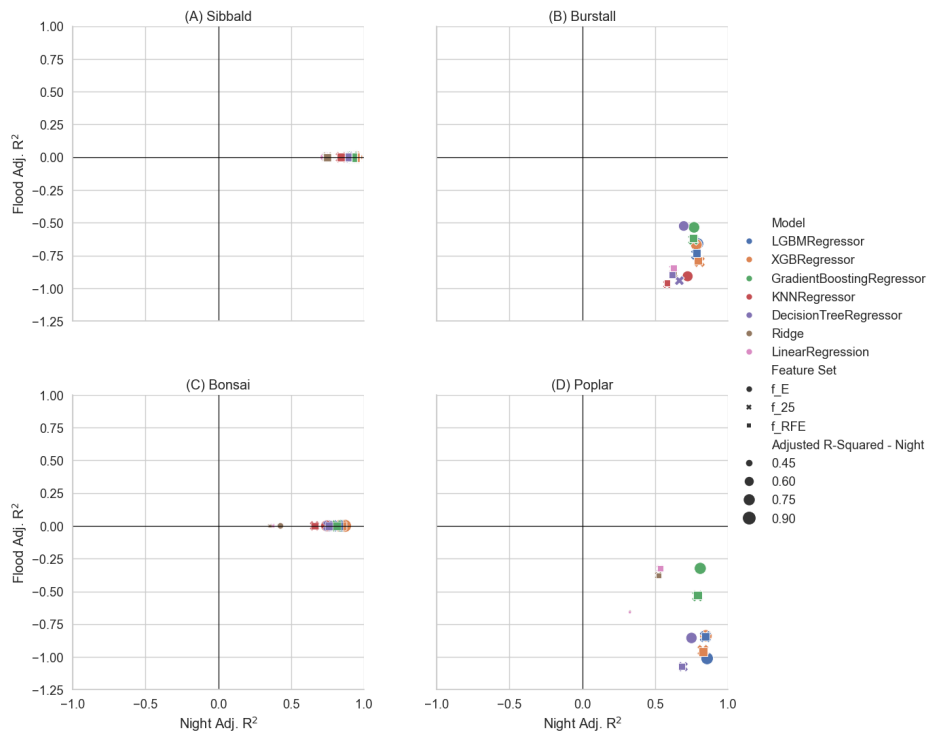
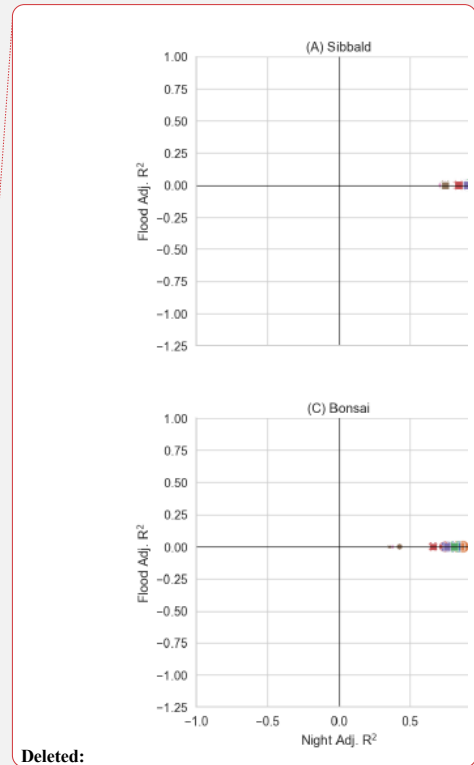


Figure S1: Results of model comparison using the adjusted R^2 defined in Stapleton et al. (2022). The x-axis shows the adjusted R^2 (Adj. R^2) for predictions under non-flooded (night-time validation) conditions, while the y-axis shows the adjusted R^2 for predictions during flooded conditions. Because flooding did not occur at Sibbald and Bonsai during the study period, their candidate models are plotted along the x-axis only. Marker colour indicates the machine learning algorithm, whereas marker shape denotes the predictor variable set used for model training. Models located farther to the right and higher on the plot exhibit better predictive performance. Negative adjusted R^2 values indicate poor generalization of the candidate models to the flooding validation dataset.



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Table S1. Feature importance ranked in order of importance for each site where the features obtained by the Recursive Feature Elimination process are denoted by F followed by the site label and the relative importance of that feature at that site is given by I followed by the site label. The notation for the predictor variables follows Stapleton et al. (2022). Detailed definitions of the predictor variables can be found therein.

Rank	F (Sibbald)	I (Sibbald)	F (Burstall)	I (Burstall)	F (Bonsai)	I (Bonsai)	F (Poplar)	I (Poplar)
1	H_gf	0.629	H_gf	0.555	DOY	0.514	RH	0.295
2	TA	0.132	VPD	0.103	H_gf	0.295	ww	0.116
3	DOY	0.084	RH	0.042	TA	0.038	RNET	0.092
4	RNET	0.078	RNET	0.039	RNET	0.036	H_gf	0.089
5	TS_mean	0.026	TA	0.038	RH	0.030	TA	0.082
6	er_Reichstein	0.018	PA_Met	0.033	VPD	0.021	vv	0.041
7	RH	0.017	ustar	0.026	TS_mean	0.018	DOY	0.041
8	VPD	0.004	ze	0.024	er_Reichstein	0.015	VPD	0.034
9	ze	0.003	rho_mol_Met	0.018	time	0.009	tsbar	0.032
10	uu	0.002	WD	0.018	ze	0.009	tbar	0.030
11	stat_wt	0.002	uu	0.014	ustar	0.004	er_Reichstein	0.028
12	uw	0.002	ubar	0.013	WD	0.003	ustar	0.020
13	stat_wm	0.001	TS_mean	0.012	cbar	0.002	TS_mean	0.015
14	tbar	0.001	er_Reichstein	0.011	PA_Met	0.002	ze	0.013
15	ustar	0.001	tbar	0.011	uw	0.002	cbar	0.012
16	time	0.001	stat_wc	0.006			WD	0.010
17			DOY	0.006			rho_mol_Met	0.009
18			cbar	0.004			uu	0.009
19			vv	0.004			PA_Met	0.009
20			stat_wt	0.004			ubar	0.007
21			time	0.003			stat_q	0.004
22			uw	0.003			stat_wm	0.004
23			stat_q	0.003			time	0.003
24			tsbar	0.003			stat_wc	0.001
25			WT	0.002				
26			ww	0.002				

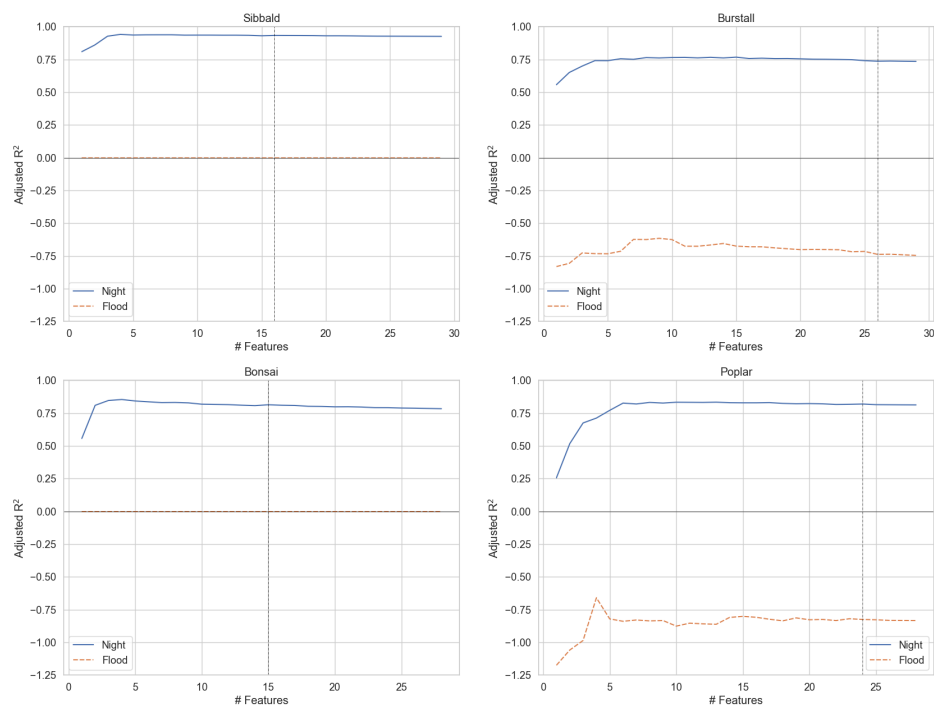
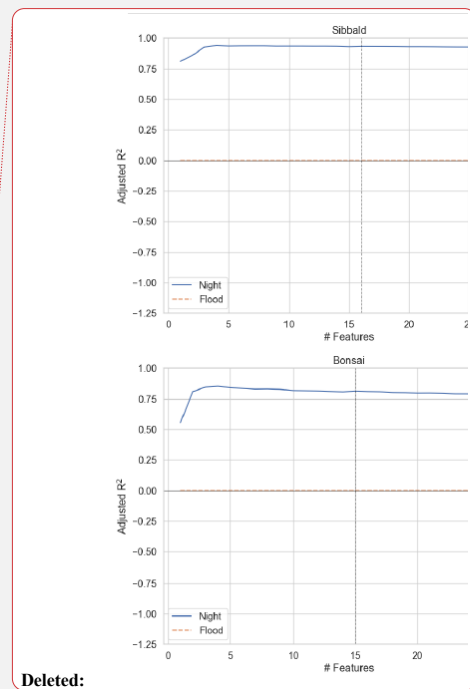


Figure S2: Results of the Recursive Feature Elimination process for each of the 4 sites tested with number of features on the x-axis and adjusted R^2 results on the y-axis. The iterations start on the right and move towards 0 as Recursive Feature Elimination iteratively decreases the number of features until only 1 feature remains for each of the sites and each of the test sets; Night and Flood. A vertical line on each graph indicates the number of features selected, where the optimal feature set is determined to be the last feature set preceding a 0.1% reduction in adjusted R^2 .



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Table S2. Best-performing machine learning algorithm based on adjusted R² from the nighttime dataset, corresponding predictor feature set, and performance metrics for each of the four study sites

Site	Best ML Model Structure	Best Feature Set	R ²	Adjusted R ²	RMSE	Slope	Number of Features
Sibbald	LightGBM	F_e	0.94638	0.94590	0.00356	0.94304	10
Burstall	XGBoost	F_25	0.81000	0.80446	0.00609	0.81747	29
Bonsai	XGBoost	F_e	0.87160	0.86993	0.00529	0.87158	9
Poplar	LightGBM	F_e	0.85791	0.85689	0.00407	0.85206	10

Note. The F_e feature set includes 10 variables: VPD, ustar, TA, WT, RNET, H_gf, er_Reichstein, year, DOY, time. Bonsai has 9 features because WT is not available for this site. The F_25 set includes 29 variables, and they are: DOY, H_gf, PA_Met, RH, RNET, TA, TA_Met, TS_mean, VPD, WD, WT, cbar, er_Reichstein, rho_mol_Met, stat_q, stat_wc, stat_wm, stat_wt, tbar, tie, tsbar, ubar, ustar, uu, uw, vv, ww, year, and ze. The predictor variable symbols are identical to those used by Stapleton et al. (2022); readers are referred to that study for their definitions. The RMSE is the mean test-set root mean squared error of the selected best model across the cross-validation folds. Specifically, using 10-fold cross-validation, the nighttime data were randomly divided into ten subsets. In each iteration, the model was trained on nine folds and evaluated on the remaining held-out fold. The root mean squared error was calculated for each held-out fold, and the reported RMSE is the mean across all 10 folds. Following Stapleton et al. (2022), RMSE was used for feature selection, but not for selecting the best model. The best model was selected based on the highest adjusted R², as formulated in Stapleton et al. (2022).

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S2. Site Characteristics and Meteorological Conditions During the Study Period

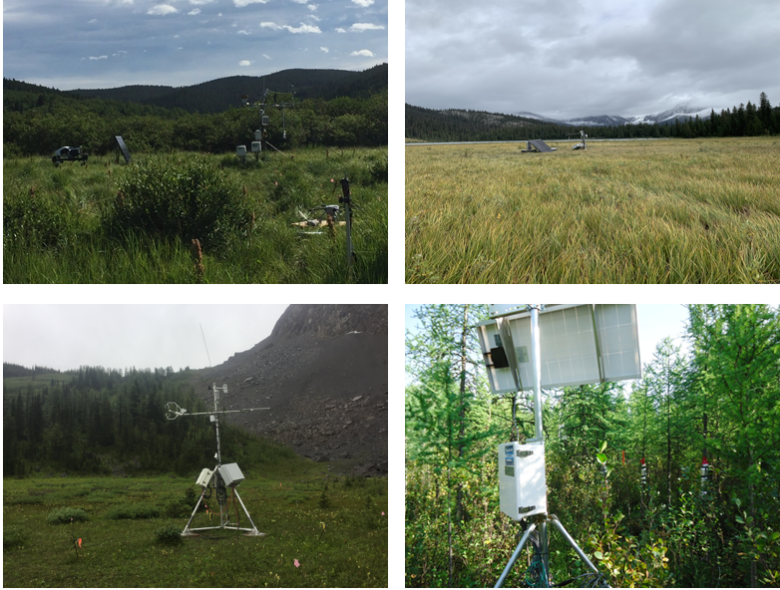


Figure S3: Photographs showing canopy conditions at the four study sites. The upper left image shows Sibbald, characterized by layered canopy with scattered shrubs and dense sedges. The upper right is Burstall, featuring very sparse shrubs and dense sedges. The bottom left is Bonsai, presenting clusters of trees and mixed understory vegetation. The bottom right is Poplar, which has a denser, more closed canopy formed by coniferous trees.

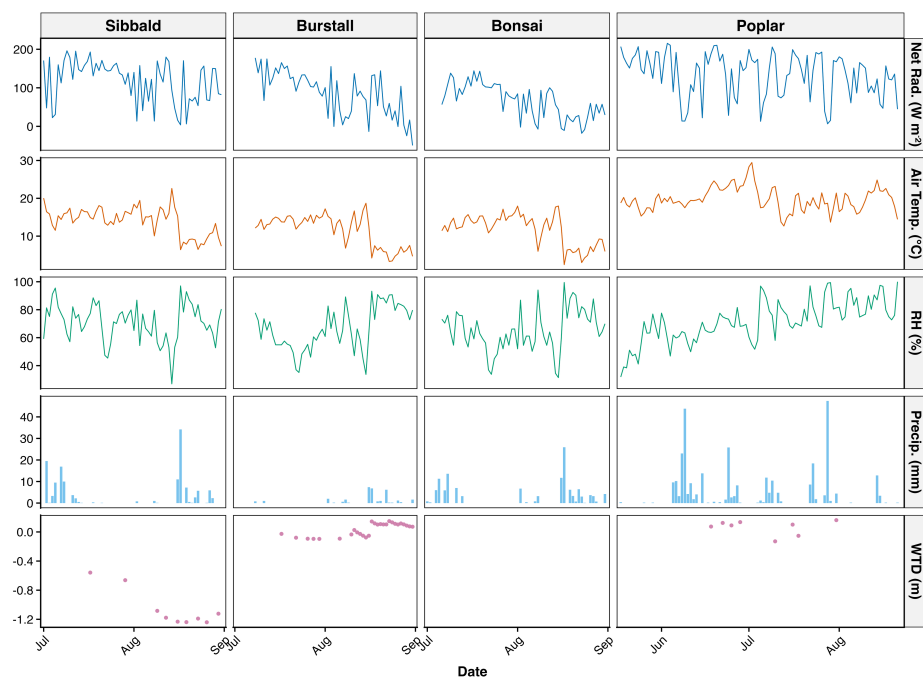


Figure S4: Meteorological conditions, including net radiation (**Net Rad.**), air temperature (**Air Temp.**), relative humidity (**RH**), precipitation (**Precip.**), and water table depth (**WTD**), at the four study sites. Water table depth at Bonsai exceeded 2 m below the ground surface throughout the study period and therefore could not be measured. Positive water table depths indicate flooded conditions (i.e., the water table was above the ground surface).



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S3. Validation of Measurement-based Transpiration-to-Evapotranspiration Ratio (T:ET), at Sibbald, Burstall and Bonsai

Detailed description of the design of the controlled evaporation experiments and supplementary microclimatic measurements has been provided elsewhere (Wang et al., 2023). Briefly, the controlled evaporation experiments involved various ground cover combinations, such as bare soil (S), bryophyte-covered soil (BS), litter and bryophytes covered soil (LBS), and soil covered by ground vascular vegetation, litter, and bryophytes (PLBS). The PLBS treatment was applied only at Bonsai, where the ground vascular vegetation was the understory short vascular plants. Additionally, two levels of canopy treatment were applied: no canopy (NC) and below the canopy of willow trees (BC). The experiments were carried out during July and August of 2021, during which each site underwent 6 measurement rounds, with each round lasting 2 to 4 days (Table S3). Within each round, there were three replicates for every treatment level. At each site, one of the six rounds is unique because ground evaporation was measured both in the middle and at the end of that round. As a result, this round contains two evaporation measurements. Specifically, these measurements are labeled as round 1.1 and 1.2 at Sibbald, and round 3.1 and 3.2 at both Burstall and Bonsai.

The detailed calibration of the S-W model for each study site, together with the development of a surface resistance formulation that explicitly accounts for the effects of moss and litter on ground evaporation and its incorporation into the S-W model, are described in previous publications (Wang et al., 2023; Wang, 2025). The errors and uncertainties of the measurements of evaporation (E), transpiration (T) and evapotranspiration (ET) are summarized in Table S4.

Partitioning results were validated by comparing latent heat (λET) from the modified S-W model with eddy covariance measurements at the daily scale and by comparing modelled λE (modelled evaporation converted to its energy equivalent) with microlysimeter measurements across all 6 rounds of evaporation experiments. As shown in Fig. S5, the modelled λET agrees well with the measured λET , especially with the energy balance-corrected λET , as the slopes of fitted linear regressions range from 0.87 to 1.16, intercepts range from -18.50 to 3.78 W m⁻², and R² values are all greater than 0.78. Better agreement with the energy balance corrected fluxes is anticipated, as the S-W model is based on the energy balance closure.

In Fig. S5, the purple lines linking modelled ground E (purple triangles) in the right panel illustrate the temporal variation of the modelled E across 6 rounds of experiments. In these plots, the range and the magnitude of measured E under various ground covers and overstory canopy conditions for each round of evaporation experiment are represented by the black range bars and the colorful dots. Clearly, the modelled ground E at the three sites is slightly lower than the lysimeter-based measurements but it is considered a reasonable representation of actual ground E. This is because the three wetlands had sedges and other tall vascular plants present, which might exert shading effects that led to lower ground E. However, these plants were removed in the controlled evaporation experiments; therefore, the lysimeter-based ground E would have been greater than the actual ground E. Notably, Sibbald has noticeably denser growth of sedges, as shown in the field photo (Fig. S3). This could explain the larger intercept of the fitted linear regression between modelled and measured λET , as the actual light availability below the hypothetical canopy at Sibbald may be less than that in the S-W model's parameterization.

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Overall, the modelled results show satisfactory consistency with the measurements in terms of both magnitude and temporal dynamics, which substantiates the appropriateness of the modified S_W model for accounting for the impact of bryophytes and litter on ground E and ET partitioning.

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Table S3. The date and duration of evaporation experiments at the three sites.

Site	Round	Start Date	Duration (days)
Sibbald	1-1*	7/12/2021	2
	1-2*	7/14/2021	3
	2	7/29/2021	5
	3	8/5/2021	4
	4	8/12/2021	4
	5	8/19/2021	4
Burstall	6	8/26/2021	4
	1	7/14/2021	3
	2	7/22/2021	4
	3-1*	7/26/2021	2
	3-2*	7/28/2021	2
	4	8/6/2021	4
Bonsai	5	8/25/2021	2
	6	8/27/2021	4
	1	7/9/2021	4
	2	7/15/2021	4
	3-1*	7/19/2021	2
	3-2*	7/21/2021	2
	4	8/13/2021	5
	5	8/20/2021	4
	6	8/25/2021	2

Note. The symbol * indicates the round of the evaporation experiments during which the microlysimeters were weighed midway through the experimental period, but no bryophyte or litter biomass was harvested.

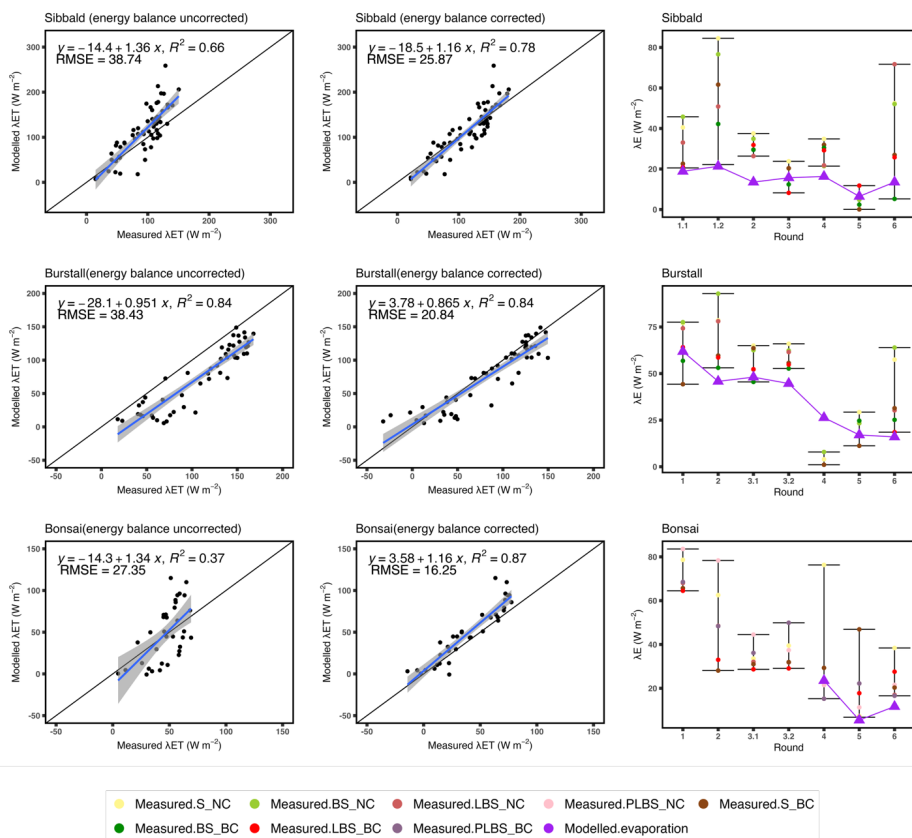
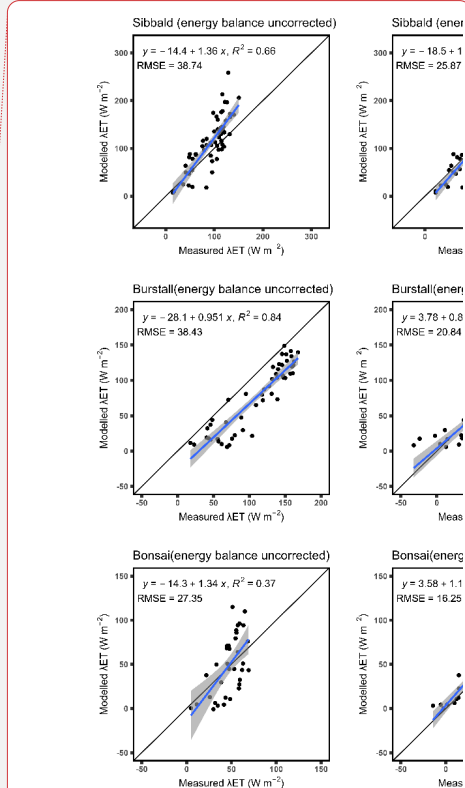


Figure S5: Comparisons between the modelled and measured latent heat (λET) during the study period (left and middle panels), and between the modelled and measured ground evaporation (λE) across all 6 rounds of evaporation experiments (right panel).



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Table S4. Examples of Errors and Uncertainties of Flux Measurements

Flux contributions	Method	Source of errors	Normalized Root Mean Square Error (%)	Reference
Evapotranspiration (ET)↓	EC	One-point Uncertainty	8.3	Kroon et al. 210
Transpiration↓	Sap flow system (stem heat balance method)	System measurement resolution, Steady-state assumption, Heat-storage error	15.0	Groot and King, 1992 Shackel et al., 1992 Grime et al., 1995 Perämäki et al., 2001
ET (ground)	Chamber	Lower net radiation↓ Altered Microclimate	6.6	Reicosky et al., 1983 McLeod et al., 2004 Hamel et al., 2015
Evaporation↓	Micro-lysimeter	Soil disturbances, Handling and weighing	17.8	Calculated using micro-lysimeter measurements from this study

(Note: Table adapted from Gabrielli 2016).

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S4. Validation of Measurement-based Transpiration-to-Evapotranspiration Ratio (T:ET) at Poplar

At the Poplar site, direct eddy covariance (EC)-based evapotranspiration (ET) measurements and upscaled sap flow-derived transpiration (T) estimates were available for the dominant tree and understory species. The transpiration estimates were informed by forest inventory data, LiDAR-derived vegetation classification, and ground-based chamber measurements (Gabrielli, 2016). Because both T and ET were measured at the same temporal resolution, whereas chamber measurements represent instantaneous fluxes and are inherently more variable, the sap flow-derived T and eddy covariance-based ET were used to construct the Poplar Transpiration-to-Evapotranspiration Ratio (T:ET) time series.

The validity of the reconstructed T:ET time series was evaluated by comparing estimated evaporation (E), calculated as the difference between EC-based ET and sap flow-derived ecosystem T, with chamber-based E measurements. The comparison and fitted linear regression are presented in Fig. S6. We acknowledge that the comparison between the estimated ground E and chamber-measured E yielded a relatively low R^2 , which is likely attributable to the high variability of chamber measurements, as they represent instantaneous fluxes. However, the regression slope closes to unity, and the small intercept indicate good overall agreement with little systematic bias between the two estimates. Therefore, we consider the reconstructed T:ET time series to provide a reasonable representation of ET partitioning at this study site.

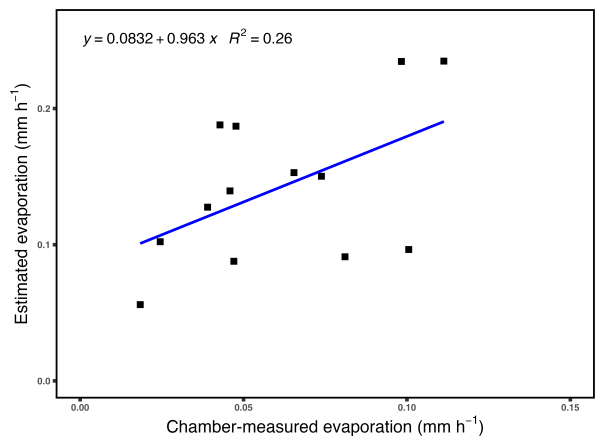


Figure S6: Comparison between estimated evaporation (E), calculated as the difference between eddy covariance (EC)-based evapotranspiration (ET) and sap flow-derived ecosystem transpiration (T), and chamber-based E measurements at the Poplar site. The solid blue line represents the fitted linear regression.

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