

Dear Editors,

We are pleased to submit our revised manuscript “Reviews and syntheses: Eddy covariance–based evapotranspiration partitioning” (EGUSPHERE–2026–906) after addressing comments from the open discussion of the preprint on EGU sphere. We would like to thank both reviewers for providing constructive feedback which has helped to improve the quality of the manuscript.

We have considered each comment and incorporated as much we deemed appropriate into this revised manuscript. Below are the detailed responses to each comment. Our responses are colored in blue and the revised lines from the text are blue, italicized text. All line numbers referenced refer to the revised manuscript, although a tracked changes version is also provided.

In addition to the revisions recommended by the reviewers, we also reran the database search on May 22nd, and the manuscript has been updated to include all new, relevant studies to ensure the review is as up-to-date as possible.

Please feel free to contact me with any further comments or to seek additional information.

Regards,
Emma Cochran

Reviewer comments:

We would like to thank the reviewer for the time taken to review our manuscript and their insightful comments. We have carefully reviewed each one and taken them into account as we considered appropriate. We believe these comments and our responses have helped to strengthen the overall manuscript and hope that the updates made are to your satisfaction.

1. Clarify EC's unique role and motivation for an EC-centric review.

Please provide a more explicit introduction to EC and why it is unique relative to other ET estimation approaches. Many methods that separately estimate E and T rely heavily on modeling assumptions, whereas EC directly constrains total ET (the sum of E and T). Framing the motivation this way will help readers understand why an EC-based synthesis is needed as opposed to getting the values “cleanly” from LSM's or remote-sensing based algorithms.

We have revised the introduction to better emphasize EC's unique advantages over alternative ET partitioning approaches. The updated section now clarifies that eddy covariance provides direct, continuous measurement of total ET at the ecosystem level, avoiding the limitations of separate E and T estimation methods. Specifically, we explain that alternative approaches (isotopes, sap-flux, and soil evaporation methods) are labor-intensive and difficult to scale, and modeling approaches require extensive parameterization and validation data. EC-based methods offer an accessible pathway to study long-term E and T dynamics using readily available measurements. We then position our comprehensive review of EC partitioning methods as essential to address this gap, as existing reviews focus either on model-based approaches or non-EC data sources.

Lines 78–94

Eddy covariance (EC) is a technique used to measure ecosystem gas and heat exchange within the atmospheric boundary layer, including ET (Baldocchi, 2020). EC systems take above-canopy, high frequency (usually 10 Hz) measurements of water vapor mixing ratio and three-dimensional wind velocity in order to continuously measure ET, which is then aggregated to half-hour fluxes to study how an ecosystem's ET is continuously changing in response to environmental factors (Baldocchi, 2020; Kool et al., 2014; Stoy et al., 2019). Methods have been developed to then partition measured ET into its relative components rather than measuring each part individually. This allows for long-term studies of an ecosystem's T and E dynamics from easily available data in global biomes (Cao et al., 2022; Maes et al., 2020; Nelson et al., 2020; Xue et al., 2023). On the other hand, direct measurements of T or E by means of isotopic, sap-flux, or soil evaporation methods are time, money, and labor intensive and are associated with significant uncertainties when upscaling to the ecosystem level (Cammalleri et al., 2013; Griffis, 2013; Kool et al., 2014; Li et al., 2019; Oishi et al., 2008; Poyatos et al., 2016; Stoy et al., 2019; Wilson et al., 2001). Modeling methods often require complex parameterization and require validation data not easily accessible (Fatichi and Pappas, 2017; Kool et al., 2014; Sun et al., 2018). As such, using EC-measured ET data with an appropriate partitioning method positions researchers to study E and T dynamics even without extensive field campaigns. Previous reviews focused on deriving E and T through model-based approaches (i.e., Shuttleworth–Wallace, FAO–Dual KC, TSEB, and Priestley–Taylor) as well as non-EC data-based methods (i.e., solar induced fluorescence-based, carbonyl sulfide flux-based, and isotope-based) (Kool et al., 2014; Stoy et al., 2019) exist, however, there is a need for an updated, comprehensive review of EC-based partitioning methods.

2. Articulate direct and indirect climate effects on ET and T/ET.

Rising temperatures directly influence atmospheric demand and ET, but also indirectly through changes in LAI, plant functional type composition, and phenology.

We have revised this section to better present the pathways through which climate influences ET partitioning. The updated text now emphasizes that temperature exerts both direct effects on atmospheric demand and evaporative processes, as well as indirect effects operating through shifts in LAI, plant stand composition, and phenological timing. By highlighting these overlapping environmental drivers and their interconnected impacts on transpiration and

evaporation dynamics, we underscore the complexity inherent in predicting ET partitioning responses to climate change.

Lines 58–77

While both T and E have similar and even overlapping drivers, the rates at which they respond to these drivers are unequal in magnitude (Scott and Biederman, 2017). For example, the timescales on which E and T operate differ significantly, another factor impacting the hydrological cycle (Scott et al., 2006; Scott and Biederman, 2017). Rates of E will increase in response to any precipitation event that results in wet surfaces. On the other hand, T will only respond to rainfall when enough water has entered the root zone to allow for plant water uptake, a response that can lag up to 10 days after the precipitation event (Feldman et al., 2018; Kurc and Small, 2007; Scott et al., 2006). Beyond these direct effects, precipitation also indirectly modulates T and E by influencing their response to other environmental drivers (da Rocha et al., 2022). For example, rainfall promotes plant growth and increases leaf area index (LAI), which subsequently enhances T (Lowry et al., 2021; Wagle et al., 2020). Conversely, drought stress can cause quick increases in E (through elevated temperatures and vapor pressure deficits) but if prolonged, decreases in T (through LAI decline and reduced plant water uptake), creating opposing responses in the two fluxes (Nie et al., 2021; Restrepo-Coupe et al., 2023). The recovery from drought also illustrates their divergent timescales: E rebounds immediately upon rewetting, but T may remain suppressed for months or even a year as LAI recovers from stress, a response especially true in tall canopies with high correlations between T and LAI (Restrepo-Coupe et al., 2023; Sun et al., 2020). As such, perhaps the biggest difference in the drivers of T and E is that T is significantly affected by vegetation characteristics and plant water dynamics, while E is only dependent on environmental conditions (Wang et al., 2014; Zhou et al., 2016). This makes T an active, biotic process regulated by stomatal conductance, while E remains a passive, abiotic process (Nelson et al., 2018). The differentiation of the biotic and abiotic components of ET allows for the study of how the water cycle is impacted by changes in vegetation (Cao et al., 2010; Scott and Biederman, 2017; Wilcox et al., 2012). By quantifying the relative contributions of T and E, we can also study the influences of changing climatic and biological conditions on the spatial and temporal variability of ET (Gan and Liu, 2020; Reich et al., 2024).

3. Introduce LAI earlier and more prominently.

LAI is a primary explanatory variable for T/ET variability across many studies, yet it appears late in the manuscript. Consider integrating LAI into the background/motivation and method summaries, so ecological context and methodological choices are connected from the outset.

We appreciate the reviewer's suggestion to emphasize LAI's importance earlier in the manuscript. We have integrated LAI more prominently into the background section, where it is now discussed as both a direct and indirect control on T and E (see our response to Comment 2). However, we have been selective about incorporating LAI into the methods summaries. For the ZH16 method (section 3.1.1), we retained the descriptor 'sparse vegetation' rather than explicitly referencing LAI thresholds, as studies do not consistently report minimum LAI values, and we wished to avoid introducing vagueness into the method description. For BH16, we have added a sentence clarifying that the threshold for defining minimum ET values depends on LAI (along with instrument biases and site-specific biome characteristics). Since LAI functions primarily as a post-hoc interpretation tool for understanding interannual and seasonal ET variability in the remaining methods, we believe embedding LAI throughout the methods sections would be misleading, as it is not a required a priori input for any partitioning approach. Our revised background section, however, now establishes LAI as a critical ecological context from the outset.

4. Use precise terminology for evaporation vs. interception.

The manuscript frequently uses "interception evaporation," which specifically refers to water evaporated from the wet canopy. In many contexts you likely mean evaporation more broadly (including wet leaves, rocks, and moist soil layers). Adopting the broader term where appropriate will reduce confusion.

We initially considered grouping all E (both soil E and intercepted E) together but as per the editor's suggestions, we have decided it was beneficial to discuss soil E separately. However, to address this comment we have cleared up the

language used when defining intercepted E as well as clarified throughout the manuscript which type of E is being discussed. We have made the choice to continue to use the term 'interception evaporation' to describe any wet surfaces after rainfall instead of opting for a more general 'wet surface evaporation' as we felt the latter introduces confusion when referring to ecosystems with standing water (such as wetlands). However, we have more clearly defined our intent behind the term when it is introduced (section 1) to avoid confusion.

Lines 42–44

Evaporation is a physical process by which water is lost from non-stomatal surfaces. This is most often from soil surfaces (bare soil evaporation) but can extend to a wet canopy (including leaves and moist ground surfaces) following a precipitation event (hereafter, interception evaporation will refer to any E from wet surfaces directly following rain).

5. Define “high-frequency” data and explain availability constraints.

Please define “high-frequency” early and clarify why such data are not frequently available. Noting that 10 Hz data represent ~18,000 samples per half hour will help readers understand storage/processing constraints and why FluxNet typically provides aggregated half-hourly records. Explain how one would obtain high-frequency data.

We thank the reviewer for this suggestion. Now, high frequency is first defined in the updated EC definition / introduction towards the start of the manuscript in section 1. Then, when the high frequency-based methods are introduced (section 3.1.4), a better overview has been included to explain more specific disadvantages.

Lines 276–281

Alternatively, instead of using EC data processed at a half-hourly resolution, several methods exist to partition ET directly from the high frequency data. This data, often collected at 10 Hz (18,000 measurements per half hour), is not publicly available and must be requested from EC tower operators. The data size and storage requirements often introduce issues when analyzing multiple sites across multiple years, however by keeping data representing individual air parcels, assumptions on their origin can be made as opposed to when using aggregated 30-min fluxes.

6. Distinguish “applied” vs. “tested.”

In many instances, methods are applied to estimate T/ET rather than tested against independent observations or via cross-method comparisons. Replacing “tested” with “applied” where appropriate would improve accuracy and avoid implying validation that may not have occurred.

We thank you for this comment. Before, ‘applied’ and ‘tested’ were used interchangeably, but this is a great point which in clarifying throughout the manuscript will also indirectly emphasize the need for further validation studies. The manuscript has been altered throughout to better reflect when a method has been applied to a site vs. when it has been tested against some independent source of T/ET data.

7. Draw out conceptual links among method families.

There are clear relationships among the regression-type, uWUE, and physically-based methods. For example, uWUE methods can be viewed as special cases of linear regression; TEA18 is physically based but follows the same core $T = GPP/WUE$ structure; many ML approaches embed VPD information and use similar screening/upper-envelope logic (e.g., 75th vs. 95th percentile). Making these connections explicit could help unify the review a bit.

The following has been added to the discussion (section 4.1) in order to better help connect the method types:

Lines 490–502

Our systematic literature review identified 11 independent ET partitioning methods applied across 129 studies spanning 11 plant functional types. Despite their diversity, these methods converge on a small set of core mechanistic principles. The most prevalent approach leverages optimality theory and WUE assumptions to estimate T/ET. Several methods

employ WUE-based frameworks: the uWUE methods (ZH16 and BH16) apply optimality assumptions directly, while PP18 (a stomatal conductance approach) embeds optimality into the broader model structure. Linear regression-based methods (SB17 and SB17b) and TEA18 also capitalize on the established ecosystem-scale relationship between GPP and ET to derive T estimates. As such, these approaches (ZH16, BH16, SB17, SB17b, TEA18) all isolate periods when GPP:ET relationships approximate GPP:T relationships (reflecting ecosystem WUE) by filtering data with percentile thresholds. SK10 and ZN22b also incorporate WUE, though high frequency data allows them to derive leaf-level WUE directly from CO₂ and H₂O mixing ratios as opposed to ecosystem WUE like the half-hourly methods. These ties of functionality between different method types draw attention to the prevalence of using known characteristics of stomatal function when considering ecosystem T dynamics. Moreover, the methods' common shared reliance on percentile filtering and straightforward statistical relationships demonstrate efficient strategies for processing large, multi-site, multi-year datasets.

8. Discuss ecosystem/regional suitability of methods.

A practical addition would be qualitative guidance on where each method family tends to perform best (e.g., forests vs. grasslands, humid vs. arid sites, seasonal snow, low-stature canopies). Even high-level recommendations would be valuable for practitioners.

We appreciate the reviewer's suggestion to provide guidance on method selection for future studies. Unfortunately, the methods reviewed are largely unvalidated against independent ground truth measurements, preventing definitive statements about which approaches 'perform best' in specific ecosystems. However, we recognize that researchers would benefit from guidance. Therefore, we have added recommendations to Section 4.1 (Discussion) that guide method selection based on method assumptions, data availability, and ecosystem characteristics. Rather than claiming superior performance, these recommendations direct researchers toward methods whose assumptions are most appropriate given their specific ecological context and data constraints.

Lines 555–569

Even so, these method assumptions and limitations still lend themselves to more reliable applications in some ecosystems over others, even without rounds of robust ground truth validations. Many method types (uWUE, stomatal conductance, high frequency, and linear regression) favor homogenous ecosystems, making TEA18 a better option when partitioning in forest ecosystems. EE22, the other machine learning-based method, may also be able to partition ET in forest ecosystems, but only at sites that can verify negligible nocturnal transpiration. EE22 is, however, the best suited for wetland ecosystems as it estimates T independently of ecosystem carbon dynamics and WUE. The linear regression-based methods, SB17 and SB17b, have assumptions well suited to dryland ecosystems, but should not be used in rotational croplands where annual trends of GEP and ET vary by year and by crop type. The high frequency methods have, however, been applied heavily in croplands as they assume all T comes from plant leaves and function well in homogenous environments. If a researcher does not have access to high frequency data or lacks the computational resources to complete the partitioning, TEA18, the stomatal conductance methods (LI19 and PP18), and the uWUE methods (ZH16 and BH16) can all be applied and compared in croplands as well. Grasslands also lend themselves to the assumptions of the uWUE and stomatal conductance methods although neither group of method types can handle ecosystems with sparse vegetation or extensive heterogenous ecosystems like drylands or forests. However, to confidently determine which methods should be used in which biomes, more studies that test 2 or more partitioning methods on the same dataset, especially studies that can compare those results to ground truth data, are necessary.

9. Strengthen conclusions with future directions.

Consider reframing the Conclusions as “Conclusions and Recommended Future Directions.” This review is well positioned to identify priorities (e.g., validation datasets, better access to high-frequency data, harmonized screening protocols, sensitivity to WUE assumptions), and to lay out what the community should do next.

We have added the following to the conclusions:

[Lines 638–651](#)

Currently, only 3 methods have been included in more than 10 studies and while North America, Europe, and Asia are well represented in the datasets, Africa and Oceania have been included in very few partitioning studies. Evergreen broadleaf forests and mixed forests also have limited testing; however, croplands and grasslands are well represented. To improve our understanding of ecosystem T dynamics and clearly define when and where each method should be applied, researchers would benefit from more publicly available validation datasets. Whether from lysimeters, sap flow measurements, or other ground truth data sources of E and/or T, all will help to constrain the magnitudes of T/ET estimates across methods and increase confidence in ET partitioning. Additionally, more studies focused on the relationship between water loss and carbon uptake from the stomatal-to leaf-to ecosystem level are needed to verify or adapt our current understanding of when and where the optimal WUE assumption holds. More accessible, high frequency data and more open-source code will allow for easier applications of methods and more studies comparing several partitioning methods against the same datasets will also help to better define a protocol for choosing a method for future partitioning studies. Further testing of all methods, especially newly established methods and additional studies in underrepresented regions and ecosystem types will give improved insights into how assumptions for each method hold in various ecosystems and provide information into changes of T and E under a warming climate.

10. Figure order and clarity.

Moving Figure 2 earlier may make the manuscript more compelling. In Figure 1 (which is overall quite nice), please clarify “records excluded” (row 2) and “reports not retrieved” (row 3).

We have changed the figure caption for Figure 1 to better illustrate the difference between records excluded (ones that didn't meet the inclusion criteria) and records not retrieved (any that wouldn't have been accessible online). The figure has also been altered so that all instances of ‘reports’ has been changed to ‘records’ because in this case they were used interchangeably.

We have elected not to move the location of Figure 2. We believe it is important to introduce and explain all 10 methods before presenting information about where and how they have been applied across different ecosystems. This order allows readers to first understand the methods themselves before reading about their spatial and ecosystem-specific applications. We have moved the figure above Table 2, but not to an earlier section.

11. Robustness to GPP bias (Lines 452–457).

The point that systematic GPP bias may not strongly affect T/ET in some methods is excellent.

Thank you for this comment, we also found this point to be relevant to the understanding of how GPP is a disadvantage to specific methods in specific ways. This is now at [Lines 526–531](#)

12. Terminology and definitions.

Define “domain knowledge” where used (especially in ML contexts), and ensure consistency across the manuscript. Is this ML jargon or an ecological category?

Domain knowledge in this context meant that the partitioner would need to know characteristics of the specific site they are applying the EE22 method to before application to ensure the input variables to the model are appropriately describing the ecosystem and driving its behavior. To avoid any future confusion, ‘domain knowledge’ has been changed throughout to instead say ‘site-specific knowledge’.

13. Line 24: This raises expectations about comparisons with independent partitioning methods, but the manuscript provides limited coverage of such comparisons. Consider clarifying what comparisons are feasible and expanding this discussion.

This comment was in reference to information that is found in the appendix tables. It has been expanded upon in the discussion section to better draw attention to the few partitioning studies where an EC-based method was compared to

a non-EC-based method as well as again underline the importance of collecting ground truth data for validation as there is little agreement between non-EC-based methods as well. The following has been added to the discussion:

[Lines 511–522](#)

While the uWUE methods predicted the lowest T/ET estimates among EC-based methods, when compared to independent methods, values were similar to many modelled values from LSMs, mechanistic, and hydrological models (Bai et al., 2019; Bu et al., 2024; Cao et al., 2022; Jin et al., 2022; MacBean et al., 2020; Song et al., 2021; Wu and Wang, 2025; Xu et al., 2024; Yu et al., 2022). Regardless of their general agreement with models built on similar underlying assumptions, predicted values from ZH16 were underestimated when compared to remote sensing-based products as well as when validated against the isotope method (Bai et al., 2019; Bu et al., 2021; Liu et al., 2022a; Song et al., 2022, 2023; Tong et al., 2019; Xue et al., 2023). TEA18 estimates on the other hand agreed well with most ecosystem models, remote sensing-based models, and sap flow measurements though had higher values than an isotope study and an LAI-based model (Bastos Campos et al., 2025; Hu and Lei, 2021; Liu et al., 2022a, 2025; Nelson et al., 2018; Xue et al., 2023; Yang et al., 2025). This variety of agreement against non-EC-based methods underscores the importance of collecting more robust ground truth validation to resolve T/ET and determine which ET partitioning methods, both EC-based and otherwise, are producing reliable T estimates.

14. Line 29: Agreed. Please expand or reinforce this point in the Discussion/Conclusions.

This comment has been addressed in the conclusions as apart of comments 8 and 9

15. Line 42: Snow sublimation may warrant brief mention for completeness, especially at high-latitude/high-elevation sites.

This has been added, thank you for the suggestion. Now at [Line 45](#)

16. Line 48: See W.K. Smith et al. (2019, Remote Sensing of Environment) for challenges in dryland ecosystems especially related to plant heterogeneity.

This was a very informative paper, thank you for the recommendation. We have, however, decided not to incorporate it into this section as it is heavily focused on ET as a total flux and only refers to transpiration outside the scope of eddy covariance. Because line 48 is just a brief introduction to T to become later relevant to EC measurements, we feel Smith et al. doesn't need to be included here, but again, it was a nice paper to read regardless.

17. Line 59: Suggest deleting "ecosystem and" for concision.

We have taken this suggestion. Now [Line 62](#)

18. Line 60: See also VOD-based studies by A. Feldman (e.g., Water Resources Research) relevant to ET partitioning.

Feldman et al., 2018: Moisture pulse-reserve in the soil-plant continuum observed across biomes, was of particular interest and has been added as a citation to further support the claim that transpiration rates respond to rainfall due to the relationship between plant hydraulics and soil moisture. Now [Line 63](#)

19. Line 71: "Above-canopy, ecosystem-scale integrated flux" could be more specific: How large is the typical flux footprint? How many plants/PFTs contribute?

The introduction of eddy covariance as a measurement technique was modified as per comment 1 to now mention that the systems measure above-canopy fluxes. In regard to flux footprints, the size is entirely site-dependent and based on the prevailing wind direction, topography of ecosystem, as well as general weather conditions and the type of

vegetation upwind of the system. As such, the locations of eddy systems are chosen with this in mind and all analyses based on the measurements are only representative of the area within the footprint. While it is common to place a tower within one PFT, it is possible to position a tower to represent a transitional zone between biomes and therefore there is no set standard of how many plant species or ecosystem types are required or even a typical size of the footprint. We believe providing an average value would undermine all the nuances of flux footprints and have decided not to include the information in this section.

20. Line 99: Please distinguish clearly between applying and testing a method.

The language used to describe the application/testing of methods has been changed as with comment 6. Additionally, we have added explicit information regarding the difference.

Lines 118–120

Hereafter, a method application would be any instance of partitioning applied to a flux dataset while method testing would refer to instances where partitioning estimates are compared against ground truth data or an independent, non-EC-based partitioning method.

21. Line 110: Clarify whether this refers to measurements independent of EC (separate instruments/approaches) or EC-derived estimates.

This has been accounted for, thank you for the suggestion. Now Line 129

22. Line 118: Address applicability to low-stature vegetation (e.g., savannas, shrublands) which can provide T.

Above- and below- concurrent EC measurements are typically only deployed in forests and savannas as the assumptions underpinning EC theory are not met in other ecosystems. The manuscript does state that this can be used for forests and savannas, but now also includes a bit more information on the method itself as well as this information.

Lines 136–142

Above- and below-canopy concurrent EC measurements can be used to partition ET in forests and savannas by assuming the below-canopy system measures only soil E which is then subtracted from the above-canopy ET measurements to find overstory T (Ma et al., 2020; Paul-Limoges et al., 2020; Sulman et al., 2016; Wilson et al., 2001). However, this method requires dual EC systems across a vertical profile and therefore was excluded from the identified methods as below canopy measurements are not routinely collected. Additionally, some of the underlying assumptions of EC theory, such as low wind speeds, constant turbulence, and heterogeneity, are not met under the canopy of many ecosystem types, again limiting the applicability of this method (Misson et al., 2007).

23. Line 139: Consider “substantially unique” instead of “independent,” which has other interpretations.

We have elected to continue using ‘independent’ as a way to refer to the partitioning methods. We believe the manuscript is clear in all instances of when “independent” is referring to the novel partitioning methods vs when it is referring to non-EC-based methods. We also think “substantially unique” may lead to discourse from the method establishers over the novelty of their respective methods, which we would like to avoid. All the methods have their own associated publications, and we are not trying to discount some methods over others but instead draw attention to differences in how T/ET is calculated. We have, however, added a definition to be explicit.

Lines 158–162

Eleven independent partitioning methods were identified, each built from a range of ecosystem assumptions. Methods were deemed as independent if the theory on which they are based or process of T/ET calculation are substantially

different to all of the other methods. Methods based on the concept of underlying water use efficiency (uWUE) were compared to ecosystem conductance-based methods, machine learning methods, methods requiring high frequency data, and linear regression-based methods (Table 1).

24. Table 1 (PP18): “Fails to produce reliable T estimates” reads as more than a limitation. Also, define what “reliable” means absent direct T observations; specify criteria (e.g., internal consistency, cross-method agreement, physical plausibility checks).

The language used to describe this has been changed to increase clarity. PP18 often fails to produce physically realistic T estimates (often in the case of negative values or values greater than that of ET).

25. Table 1 (EE22): Clarify “domain knowledge for feature selection.” Is this ML terminology (expert-guided predictor selection) or ecological knowledge (process-based variable choice)?

This was addressed with comment 12.

26. Line 154: You may find of interest Beer et al. (2009) Global Biogeochemical Cycles on inherent water-use efficiency and its spatial/temporal variability.

The references listed here are the most relevant papers in terms of establishing the original optimality theory and the method introduced by Zhou et al. (2016). Beer et al. (2009) has been included as a reference when introducing that T is dependent on soil water and VPD, it is just not included in this method summary.

27. Line 165: Explain why spatial heterogeneity in vegetation types within the flux footprint can lead to temporal variability in WUE estimates. This challenges single-uWUE assumptions (e.g., ZH16), though weekly/monthly approaches (SB17/SB17b) may be less sensitive.

We have addressed this in the text by explicitly stating that ZH16 assumptions break down in heterogeneous ecosystems, where spatial variation in vegetation type and structure produces variable transpiration across the ecosystem. Importantly though, this limitation extends beyond ZH16 as SB17b is also problematic in heterogeneous settings as its evaporation parameterization equations are not suited to spatially variable conditions. Further explanations of heterogeneity violating the constant WUE assumption have been added to this section for clarity.

Lines 191–195

The heavy reliance on GPP estimates from EC measurements mean that any uncertainties in GPP are amplified when predicting T using this method and the assumption of a constant $uWUE_p$ is violated in sites with a wide variety of vegetation types as spatial variations in plant heights and structures result in subsequent seasonal variations in CO_2 concentrations (Hu & Lei, 2021; Nelson et al., 2020; Reich et al., 2024; Stoy et al., 2019; Zhou et al., 2016).

28. Line 180: Describe physical conditions under which T/ET approaches 1 (long dry-down after precipitation, absence of wet surfaces, depleted near-surface soil moisture).

At this specific point in the manuscript, we are mentioning that this method (LI19) does not rely on the assumption that ecosystem $ET = T$, however, we have added in descriptions of the environmental conditions required for this assumption when it is introduced in the ZH16 method summary (Section 3.1.1).

Lines 177–181

This method assumes that at sub-daily time scales, periods occur when soil and interception evaporation are negligible and T/ET approaches 1. These conditions, often periods experiencing limited water availability, maintained vegetation cover, and depleted subsurface soil moisture following dry-down periods, are then used to define the potential uWUE

($uWUE_p$), a value assumed to be constant over long time periods and calculated using a 95th percentile regression on the assumed linear relationship between ET and GPP $\times$ VPD^{0.5}.

Ecosystems that consistently violate this assumption are also listed in this section:

[Lines 196–196](#)

Additionally, the assumption that $T=ET$ does not hold true throughout the day in ecosystems with sparse vegetation or where evaporation is never negligible such as in wetland ecosystems

29. Line 201: Citations needed.

Citations for the original optimality theory (Cowan and Farquhar, 1977) as well as the specific application for this method (Wang et al., 2017) have been added. Now [Line 231](#)

30. Line 229: Adjusting nighttime transpiration for daytime meteorology is sound in principle, but nighttime fluxes are often very small; clarify the magnitude of extrapolation and implications.

This method (EE22) predicts daytime E values from nighttime E values. T is then calculated from estimated E and measured ET. So, while nighttime T isn't being adjusted for daytime meteorology, there are still differing factors driving daytime E compared to nighttime E. However, this is addressed in the paper from Eichelmann et al. (2022) where they mention the capabilities of artificial neural networks in extrapolating to datasets larger / more diverse than the training data. They also include graphs as a part of the supplemental (Fig. S2 from Eichelmann et al. (2022)) regarding the probability density functions of the most important input features for both daytime and nighttime conditions to support the use of the method.

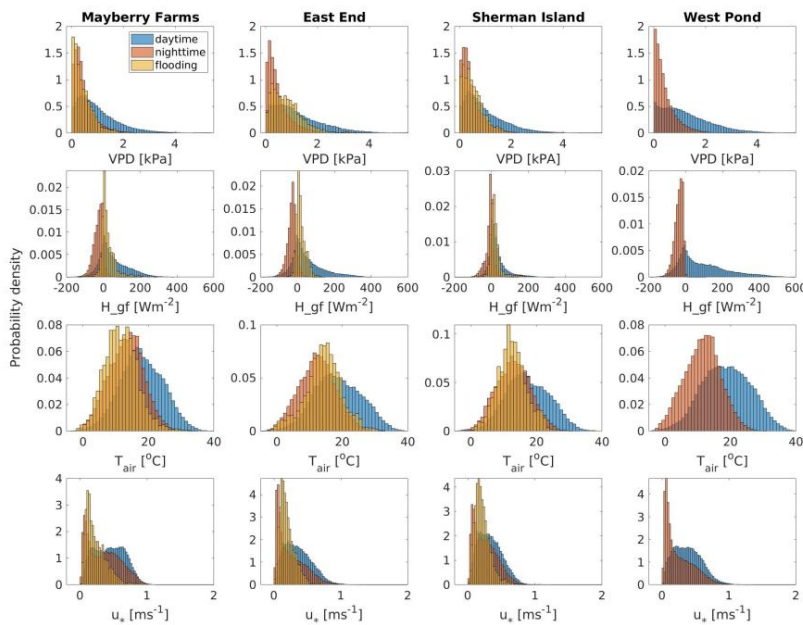


Figure S2 was used in the original manuscript to justify the input variables are adequately represented in the training (nighttime) data to then be used for daytime predictions. To further clarify this in the present manuscript, we have added the following to the EE22 method description:

[Lines 259–263](#)

Daytime E is then predicted using measured nighttime ET values, similar to established methods of partitioning NEE into GPP and respiration based on nighttime NEE values (Reichstein et al., 2005). While daytime drivers of E may differ from nighttime E, neural networks have been shown to capture non-linear relationships of biological data, even when extrapolated beyond the subsets used for model training (Papale and Valentini, 2003). This was supported in the method establishment study when the model performed well when validated against daytime data collected after flooding periods (Eichelmann et al., 2022).

31. Line 238: Please define “domain knowledge” here.

This was adjusted for with comment 12.

32. Line 251: Differentiate leaf-level vs. ecosystem-scale WUE clearly. Some methods hinge on GPP:T, others on GPP:ET—these are fundamentally different constructs and should be contrasted.

On line 251 (now line 289), we are discussing leaf-level WUE used in the SK10 method. Here, in the absence of leaf-level measurements, WUE can be estimated from flux variables. However, this is then multiplied by a constant observed from leaf-level measurements in maize and therefore still represent leaf-level WUE as opposed to ecosystem WUE. This has been described more clearly in the manuscript to help understanding.

Lines 289–291

However, if leaf-level measurements are not available, WUE can be estimated from flux measurements, the ratio of molecular diffusivities for carbon dioxide and water vapor, and constants representing established leaf-level relationships of gas exchange.

Additionally, we agree there is a fundamental difference between the methods using leaf-level WUE in their estimates (and therefore T:GPP) and the methods using only ecosystem scale variables (and therefore ET:GPP). As such, we have added information regarding this difference in the discussion method as outlined with comment 7.

33. Line 262: For readers less familiar with field measurements, explain why spatial heterogeneity within the footprint translates into temporal heterogeneity in observed WUE.

This comment was addressed earlier to explain this concept, see comment 27.

34. Line 302: Consider noting that this condition applies to any ecosystem when it is not water-limited.

We are not entirely sure we understand this comment from the reviewer. The SB17 method described in the Line 302 of the original manuscript actually works best in water limited environments and does not work well in ecosystems with high water availability as outlined in lines 310–312 of the original manuscript, now lines 356–358.

35. Line 309: is 5–7 years a minimum requirement? It reads as though this is an optimal range, but presumably more years would be even better for regression methods?

The minimum requirement is 3 years (line 309 of the original manuscript and line 346 of the revised manuscript) but we have slightly adjusted the wording to improve clarity on the 5–7 year message, it now reads as follows:

Lines 354–355

While this method is more accessible as it does not require high frequency data or a priori plant WUE information, it does require a minimum of 3 years of data, with ideal data sets of at least 5–7 years in length to produce reliable results.

36. Line 376 (Section 3.3): The section is sound but could be revised to emphasize a smaller, more focused set of themes/take-home messages.

We have reworked the beginning of this section to more concisely summarize the trends between methods. We believe it is now easier to discern the take-away messages.

Lines 427–444

ZH16 and PP18 consistently produced the lowest T/ET values when compared to other EC-based partitioning methods (Figs. 3, 4; Tables 2, A1, A3). While ZH16 was applied in significantly more studies, both were compared on a global scale (Nelson et al., 2020) so low estimates can be concluded to be produced on a systemic basis from both methods. In regionalized studies, ZH16 predicted lower estimates across croplands, evergreen needleleaf forests, and woody savannas than PP18 although this comparison is pulled from several studies across several sites as opposed to direct comparisons of methods on the same dataset (Fig. 3).

On the other hand, TEA18 estimates consistently had either the highest or comparable T/ET value estimates when directly compared to other EC-based methods in 17 of 17 studies (Table A4, Figs. 3, 4). These high estimates agreed well with many non-EC based partitioning methods (i.e., sap flow, two-stage theory of bare soil evaporation, TSEB-SM, and LSMs). High frequency methods estimated high T/ET values as well, although still lower than when compared to TEA18, with common summer trends showing $ZN22 > TH08 > SK10$ (Fig. 3; Table A5, A7). Linear regression-based methods (SB17 and SB17b) had limited testing, which is in part due to the hefty requirement of ideal datasets having at least 5–7 years of data. However, from the 7 studies they have been applied collectively, SB17 produced mid-range and SB17b produced high T/ET estimates when compared to other method types (Tables A6, A7). LI19, a stomatal conductance method, also produced mid-range T/ET values compared to other methods (Table A2) while BH16, the other uWUE-based method, had no discernible trends regarding magnitudes of estimates across 5 studies.

37. Line 405 (Figure 3): Consider denoting the class of methods represented to aid readability.

The figure has been changed so that the method class is included in the legend and then described in the caption.

38. Line 432: Explain the physical reasoning for why this pattern is plausible/expected.

This suggestion has been included.

Lines 480–483

A tall grass prairie study found that T/ET was strongly positively correlated with sub surface SWC, as roots were able to access underground water sources, and slightly negatively correlated with upper layer SWC as surface water tended to be dedicated to soil evaporation, agreeing with results from GRA and DBF studies

39. Line 446: Do any of the 50+ ZH16 applications test sensitivity to the percentile used in the screening (e.g., 75th vs. 95th)?

Yes, one study tested an 80th percentile regression next to the 95th percentile. That study has now been highlighted in this section.

Lines 509–510

One study tested ZH16 using an 80th percentile alongside the more common 95th percentile, and while T/ET estimates were higher with the 80th (0.65 vs 0.47 in a grassland), both regressions still produced estimates lower than SB17 (Ma et al., 2020)

40. Line 497: Confirm that “juxtaposed” is the intended term here.

Yes, we did mean juxtaposed in this context, but we have changed the word to ‘contradicted’ to add clarity. Now [Line 601](#)

41. Line 507: Please elaborate on the implied mechanisms.

This has been done.

[Lines 610–611](#)

Another study found that the presence of drought increased global T/ET due to decreased soil evaporation from limited water availability

42. The article "Reviews and syntheses: eddy covariance–based evapotranspiration partitioning" provides an in depth review of evapotranspiration partitioning, including cataloguing the numerous methods available and a literature review of studies which use these methods. The study is highly relevant both as an analysis of the advantages and disadvantages of different partitioning methods from a practical stand point, as well as an assessment of how they correspond to global T/ET estimates and key apparent drivers of T/ET. Overall, I found the meta–analysis and method overview to be particularly strong and welcome addition to the current literature, as well as using the T/ET metric as a universal evaluation to put each method into context. I found the discussion overall to be very balanced, though the discussion of limitations across and between the methods should be expanded as it is a key component of the manuscript.

Thank you for your kind comments. In regard to the discussion, we have reworked this section to better highlight the limitations and connections between the methods. The section now starts with drawing conceptual links between the method groups (as with comment 7) which better ties together the process of ET partitioning in the eddy covariance field.

[Lines 490–503](#)

Our systematic literature review identified 11 independent ET partitioning methods applied across 129 studies spanning 11 plant functional types. Despite their diversity, these methods converge on a small set of core mechanistic principles. The most prevalent approach leverages optimality theory and WUE assumptions to estimate T/ET. Several methods employ WUE–based frameworks: the uWUE methods (ZH16 and BH16) apply optimality assumptions directly, while PP18 (a stomatal conductance approach) embeds optimality into the broader model structure. Linear regression–based methods (SB17 and SB17b) and TEA18 also capitalize on the established ecosystem–scale relationship between GPP and ET to derive T estimates. As such, these approaches (ZH16, BH16, SB17, SB17b, TEA18) all isolate periods when GPP:ET relationships approximate GPP:T relationships (reflecting ecosystem WUE) by filtering data with percentile thresholds. SK10 and ZN22b also incorporate WUE, though high frequency data allows them to derive leaf–level WUE directly from CO₂ and H₂O mixing ratios as opposed to ecosystem WUE like the half–hourly methods. These ties of functionality between different method types draw attention to the prevalence of using known characteristics of stomatal function when considering ecosystem T dynamics. Moreover, the methods' common shared reliance on percentile filtering and straightforward statistical relationships demonstrate efficient strategies for processing large, multi–site, multi–year datasets.

Section 4.1: Identified partitioning methods and common uncertainties, now includes more information regarding common limitations mentioned from the method summaries and ends with a recommendation of which methods to use for which ecosystems, which we feel also highlights the strengths (and inherent weaknesses) of the methods.

Lines 535–569

Many of the methods are not suited for heterogenous ecosystems. Any method that assumes an optimal relationship between carbon gain and water loss at the leaf level (ZH16, BH16, PP18) oversimplifies the dynamicity of WUE with seasonal variations in CO₂, a property most apparent among varying vegetation types (Zhou et al., 2016). The high frequency methods assume all transpiration is coming exclusively from plant leaves, another assumption with the potential to be violated in heterogenous ecosystems (Reich et al., 2024; Scanlon and Kustas, 2010). Ecosystems with sparse vegetation also need to be wary of applying any method that assumes ET approaches T (ZH16, BH16, TEA18) as soil evaporation can never be ignored in ecosystems with low leaf area (Nelson et al., 2018; Zhou et al., 2016). Another source of large uncertainties is the handling of interception evaporation between the methods. The stomatal conductance-based methods ignore this process completely even with studies reporting that 8.5–10% of annual rainfall is intercepted by plant surfaces globally with some regional estimates reaching up to 50% depending on ecosystem type (Fischer et al., 2026; Lian et al., 2022; Zhong et al., 2022). EE22 does not remove wet periods from the training data like TEA18, however it still neglects to account for daytime interception rates that differ from their nocturnal counterparts (Czikowsky and Fitzjarrald, 2009). In high frequency methods, the inattention to rainfall often results in interception evaporation being incorrectly partitioned into T which may be in part responsible for this method type's high T/ET estimates (Fig. 4). The methods which do appropriately attribute interception to E, whether directly or by means of using GPP to estimate T, still face uncertainties as EC systems often underestimate the water flux of an ecosystem during precipitation (Van Dijk et al., 2015; Fischer et al., 2026). ET measurements from EC during rain are inherently biased adding additional uncertainties to ET partitioning estimates and correcting ET measurements to account for this leads to contradicting changes in T/ET depending on which method was applied (Zhang et al., 2023). This again emphasizes the importance of applying multiple partitioning methods for comparisons in studies to see where T/ET estimates are most uncertain.

Even so, these method assumptions and limitations still lend themselves to more reliable applications in some ecosystems over others, even without rounds of robust ground truth validations. Many method types (uWUE, stomatal conductance, high frequency, and linear regression) favor homogenous ecosystems, making TEA18 a better option when partitioning in forest ecosystems. EE22, the other machine learning-based method, may also be able to partition ET in forest ecosystems, but only at sites that can verify negligible nocturnal transpiration. EE22 is, however, the best suited for wetland ecosystems as it estimates T independently of ecosystem carbon dynamics and WUE. The linear regression-based methods, SB17 and SB17b, have assumptions well suited to dryland ecosystems, but should not be used in rotational croplands where annual trends of GEP and ET vary by year and by crop type. The high frequency methods have, however, been applied heavily in croplands as they assume all T comes from plant leaves and function well in homogenous environments. If a researcher does not have access to high frequency data or lacks the computational resources to complete the partitioning, TEA18, the stomatal conductance methods (LI19 and PP18), and the uWUE methods (ZH16 and BH16) can all be applied and compared in croplands as well. Grasslands also lend themselves to the assumptions of the uWUE and stomatal conductance methods although neither group of method types can handle ecosystems with sparse vegetation or extensive heterogenous ecosystems like drylands or forests. However, to confidently determine which methods should be used in which biomes, more studies that test 2 or more partitioning methods on the same dataset, especially studies that can compare those results to ground truth data, are necessary.

Then to further highlight limitations, we have added a paragraph in the conclusions regarding recommendations for future work which also emphasizes the gaps in current partitioning methods

Lines 638–651

Currently, only 3 methods have been included in more than 10 studies and while North America, Europe, and Asia are well represented in the datasets, Africa and Oceania have been included in very few partitioning studies. Evergreen broadleaf forests and mixed forests also have limited testing; however, croplands and grasslands are well represented. To improve our understanding of ecosystem T dynamics and clearly define when and where each method should be applied, researchers would benefit from more publicly available validation datasets. Whether from lysimeters, sap flow

measurements, or other ground truth data sources of E and/or T, all will help to constrain the magnitudes of T/ET estimates across methods and put more confidence in ET partitioning studies as a whole. Additionally, more studies focused on the relationship between water loss and carbon uptake from the stomatal-to leaf-to ecosystem level are needed to verify or adapt our current understanding of when and where the optimal WUE assumption holds. Easier, more accessible, high frequency data and more open-source code will allow for easier applications of methods and more studies comparing several partitioning methods against the same datasets will also help us to better define a protocol for choosing a method for future partitioning studies. Further testing of all methods, especially newly established methods and additional studies in underrepresented regions and ecosystem types will give way for better insights into how the methods assumptions hold in various ecosystems and will provide more information into the changing trends and values of T and E under a warming climate.

43. Furthermore, the study could improve on cross comparing sites where multiple methods have been used (even if in different studies), particularly in the case of methods with fewer reported examples (i.e. if a method has few studies, but is used at a common site with other methods, do the T/ET values match across studies for that site).

There are surprisingly few sites that have had several methods tested across 2 or more studies as any instances in which multiple methods are applied in the *same* study are expressed in the notes sections of the appendix tables with reference to how the method estimates compared. There is also a summary of how the methods directly compared to each other within studies at the start of section 3.3 which was adjusted: see comment 36. In many cases where a site's dataset has been applied in 2 or more studies, often the value reported in one of the studies would be an average of several datasets across 1 biome, so we found little value in, for instance, directly comparing a T/ET value for 1 site against an average T/ET value for 5 sites (which at that point is very similar to the comparisons occurring in Table 2). Also in many instances, one dataset would be used in 2 studies, and one would report a T/ET value and the other would only comment on annual trends, giving no quantitative metric for comparisons between studies/methods. This was the case for a cropland site in Weishan, North China where several methods are tested in Hu & Lei (2021) where comparisons between methods within that study are listed in the tables, and then the same site was used for the TEA18 method again in Yang et al. (2025) but in the second instance, only growing season trends were described with no T/ET values to then compare to the Hu & Lei study. There were also instances where the same method would be applied on a single dataset several times, as was the case with ZH16's prevalence in the Heihe River Basin sites, but again, this does not give way to an inter-method comparison.

From all the identified studies, there were only 3 sites that had reported T/ET values from 2 methods across 2 or more studies.

US-SRM, a woody savanna, applied both SB17 (MacBean et al., 2020; Scott and Biederman, 2017) and TEA18 (Kibler et al., 2023) and found higher T/ET estimates from TEA18.

The Daman site in the Heihe River Basin applied ZH16 (Bai et al., 2019; Zhou et al., 2018) and TEA18 (Liu et al., 2022a) both when the cropland was growing maize and found higher T/ET estimates from TEA18.

ES-LMA, a savanna, applied PP18 (Perez-Priego et al., 2018) and TEA18 (El-Madany et al., 2021) and again found higher T/ET estimates from TEA18.

From these identified flux sites, the general behavior of the methods established from direct comparisons (within one study) are the same. TEA18 continues to predict higher estimates when compared to other EC-based partitioning methods. Because of this, we feel as though describing these cases in the results section is a bit repetitive, although the instance where TEA18 is compared to other methods has been changed to better reflect this information:

Lines 433–438

On the other hand, TEA18 estimates consistently had either the highest or comparable T/ET value estimates when directly compared to other EC-based methods in 18 of 18 studies (Table A4, Figs. 3, 4). These high estimates agreed well with many non-EC based partitioning methods (i.e., sap flow, two-stage theory of bare soil evaporation, TSEB-SM, and LSMs).

Originally, it stated 14 of 14 studies, which has now been adjusted to account for the 3 additional cases listed above as well as an additional study found upon re-searching the databases for an updated record.

44. Additionally, the focus on number of studies does not help distinguish the quality of the assessment in each study, as some methods have been simply applied many times while others have been subject to more thorough inter-comparison and sensitivity analyses, a point which should be at least discussed.

We agree that there could be more emphasis on the depth of each study over the number of studies. Table 2 contains averages dependent on the number of data records each method was applied on. The N_R values included on this table better show the quantity of flux sites each method has been applied to; however, global studies are not included in this table as N_R as the T/ET values in the table were calculated from individual reported values for one data record, data which was not provided in the global studies. So, then the emphasis needs to be put on the global studies and how they applied different partitioning methods. To better emphasize the depth of these studies, explicit mention of every global study each method has been applied in has been added to section 3.2.

Lines 407–425

*ZH16 has been studied in all major biome types across all continents (excluding Antarctica) across 53 studies (Tables 2, A1; Fig. 2). The majority of reported results (N_R) were in croplands (30) representing a variety of annual and perennial crops (e.g. soybeans, rice, cotton, wheat, maize, etc.). Grasslands (22) and forests (32 across all forest types) were also frequently reported on. ZH16 was applied the most in Asian (30) and North American (18) sites (Fig. 2) and **was included in three global studies** (Cao et al., 2022; Nelson et al., 2020; Xue et al., 2023). SK10 usage was reported in 40 studies, mostly in croplands (29) with an emphasis in wheat (8), maize (6), and various orchards (6). SK10 was also heavily applied across different forest types (11) and in North America (20) however several continents and biomes have been neglected (Tables 2, A5; Fig. 2). TEA18 was the next most frequently applied method, appearing in 21 studies, **including 2 global studies** (Table A4) (Nelson et al., 2020; Xue et al., 2023). Like SK10 and ZH16, TEA18 was applied the most in forests (16) and croplands (12) and across Asia (8) and North America (7; Fig 2).*

*The remaining methods had a considerable drop in number of studies with the next highest applied method being SB17 featured in 7 papers where 6 were in North America (Table A6; Fig. 2). **PP18 and LI19 were each used in 6 and 7 studies, respectively, however both methods were included in global studies** (Tables A2, A3; (Maes et al., 2020; Nelson et al., 2020). The BH16 method was used in 5 studies, predominately in North America (3; Table A7, Fig. 2), 3 of which were in evergreen forests (mean = 0.66). The high frequency methods from ZN22 and TH08 were used in 5 and 3 identified studies, respectively (Table A7) and while they often agreed with each other, both tended to be higher than SK10 estimates. EE22 has been applied in 3 studies, 2 in North America and 1 in Asia (Table A7, Fig. 2). SB17b was only applied once in North America, and a combined method of ZH16 and SB17 was used once in a GRA / WSA ecosystem in North America (Table A7; Yuan et al., 2021).*

Then, in section 3.3, additional mentions of the global studies have been added to again emphasize the depth of each study.

Lines 427–444

*ZH16 and PP18 consistently produced the lowest T/ET values when compared to other EC-based partitioning methods (Figs. 3, 4; Tables 2, A1, A3). **While ZH16 was applied in significantly more studies, both were compared on a global scale** (Nelson et al., 2020) **so low estimates can be concluded to be produced on a systemic basis from both methods.** In regionalized studies, ZH16 predicted lower estimates across croplands, evergreen needleleaf forests, and woody*

savannas than PP18 although this comparison is pulled from several studies across several sites as opposed to direct comparisons of methods on the same dataset (Fig. 3).

On the other hand, TEA18 estimates consistently had either the highest or comparable T/ET value estimates when directly compared to other EC-based methods in 17 of 17 studies (Table A4, Figs. 3, 4). **Within this pool of studies was two global analyses where TEA18 was applied to FLUXNET sites across diverse ecosystems and produced higher T/ET estimates than ZH16 and PP18 in every biome with reported values across both studies (Nelson et al., 2020; Xue et al., 2023).** These high estimates agreed well with many non-EC based partitioning methods (i.e., sap flow, two-stage theory of bare soil evaporation, TSEB-SM, and LSMs). High frequency methods estimated high T/ET values as well, although still lower than when compared to TEA18, with common summer trends showing $ZN22 > TH08 > SK10$ (Fig. 3; Table A5, A7). Linear regression-based methods (SB17 and SB17b) had limited testing, which is in part due to the hefty requirement of ideal datasets have 5–7 years of data. However, from the 7 studies they have been applied collectively, SB17 produced mid-range and SB17b produced high T/ET estimates when compared to other method types (Tables A6, A7). LI19, a stomatal conductance method, also produced mid-range T/ET values compared to other methods (Table A2) while BH16, the other uWUE-based method, had no discernible trends regarding magnitudes of estimates across 5 studies.

We also feel that even with the discussion of the depth of research from the global studies, there is still a need for more method applications across diverse ecosystems. And while global studies are invaluable in understanding global ET partitioning, the level of analysis is different to that of a regionalized study which can focus more on individual datasets and ecosystems. Therefore, the recommendation for more research has not been adjusted although the language used to describe it now also mentions the robust studies.

Lines 571–578

ZH16, SK10, and TEA18 have been utilized to partition ET in many studies ($N_s = 58, 40, \text{ and } 22$, respectively) across even more datasets. However, while 15 LI19 T/ET estimates have been reported across 8 studies, every other method has reported less than 10 studies. Even though LI19 and PP18 were applied in global studies and therefore have been utilized in diverse biomes, this limited range of experiments, especially rare instances where several methods have been applied to the same data record for comparison or validated against independent observations, emphasizes the need for further testing of all methods across all PFTs in order to pair T/ET estimates, fully evaluate the performance of each method, and reliably track global T trends (Fig. S2).

45. In the end, I found the paper to be quite relevant and should be accepted for publication with some refinement. See below for more detailed points.

Thank you both for your time to review this manuscript and your comments which we feel have helped to improve the overall quality of the study.

46. Fig. 2: How does this map handle when multiple studies are carried out at the same site?

Originally, all site markers were equal in transparency and the cases where multiple studies used the same site's dataset were indistinguishable from others. That has now been changed so that each site marker is slightly transparent in color and the more opaque a star is, the more times that site has been used in different studies. This has now been added to the figure caption as well for the reader.

Figure 2: Geographical locations of data records found in literature search. Stars are opaquer in cases where multiple studies have been carried out on the same site while a site with a single study would have a slightly transparent star.

47. Fig. 3: From which study does the global T/ET number come from? I would guess that all global estimates should have some associated uncertainty. Are the global and the average T/ET values comparable?

While this is not explained in the figure, it is explained in the body in section 3.3 however we have now added the standard deviations for ZH16 and TEA18 (the two methods used in more than 1 global study) for added context for the reader.

Lines 445–444

When focusing on global T/ET estimates, five studies presented a mean annual T/ET estimate across at least four biomes using at least 50 sites. ZH16 presented an average global annual T/ET of 0.50 ± 0.06 (NS=4; Cao et al., 2022; Chang et al., 2025; Nelson et al., 2020; Xue et al., 2023), TEA18 with 0.67 ± 0.07 (Ns=3; Chang et al., 2025; Nelson et al., 2020; Xue et al., 2023), PP18 with 0.45 (Ns=1; Nelson et al., 2020), and LI19 with 0.64 ± 0.03 (Ns=2; Chang et al., 2025; Maes et al., 2020). These global estimates agreed with the trends of magnitudes produced from each method in regional studies with low estimates from ZH16 and PP18, moderate estimates from LI19, and the highest T/ET estimates from TEA18. The global, annual mean of T/ET across the 4 methods in 5 studies was 0.573 ± 0.10 (Fig. 3). This is comparable to the average T/ET value (0.581 ± 0.14) found from all records regardless of partitioning method or ecosystem (Fig. 3).

And in the discussion section 4.2 refers to the comparability between the two values

Lines 581–584

*From these 5 studies presenting 10 estimates, an average annual T/ET value of 0.573 ± 0.10 was determined (Fig. 3). This value was comparable to the average T/ET value calculated from every identified record in the literature search ($T/ET = 0.581 \pm 0.14$; Fig. 3). **While these averages were calculated independently, their correlation suggests an even representation of PFTs in accordance with their abundance were identified in the search.***

48. Fig. 4: This figure is a bit subjective, as the number of studies does not necessarily correspond to level of testing. For instance, some methods have comparisons to independent estimates or sensitivity studies which likely provides more rigorous testing than just being used in many studies.

We admit that the figure is subjective, however, we also feel that by trying to reconfigure it to better represent the thoroughness of testing also leads to subjectivity. If we base the x-axis on number of records instead of number of studies, we feel as though that starts to misrepresent the applicability of each method. For instance, PP18 was only applied in 6 studies but within those, over 255 flux sites. If we were to alter the figure so that PP18 is then represented as one of the most frequently applied methods, it doesn't capture the real applicability of the method which is quite limited as the model often fails to estimate realistic T/ET values and the assumptions are not met in every ecosystem. PP18 and TEA18 were both published in 2018 and yet TEA18 has been applied in considerably more studies than PP18 because of the versatility of the method and we feel as though this figure set-up is able to represent that. Then, if we gauged the depth of study based on comparisons to independent estimates, the story does not change much. ZH16, the most applied method, has been validated against independent estimates more than any other methods. Then, SK10 and TEA18 have been validated in over 5 studies each and all the other methods have been compared to non-EC-based estimates in 3 or less studies. Because this trend follows how the methods are already depicted on the graph, we also believe then that this representation is an adequate overview. Of course, by summarizing this many studies, it is hard to avoid any subjectivity as always some nuance will be lost if you view the figure in isolation without the supporting text. However, we do believe that this figure is sending the intended message. With all that being said, we have changed the wording to describe the x-axis. It now reads as 'high frequency of application / testing' as opposed to 'high level of testing' as this hopefully better represented what is being displayed. We have also altered the caption to reflect this as well.

Figure 4: Summarized results of relative T/ET output from the 11 independent methods identified in this review and the frequency of their application and validation against non-EC-based estimates. Methods were placed on the x-axis according to number of studies with methods left of the origin appearing in less than 10 studies and compared to independent measurements in 3 or less instances.

49. Section 3.3.1: Clarify the distinction between the temporal and spatial variability. There is some discussion about the distinction, but the section is titled "Regional drivers of T/ET", but most of the reporting is a mix of both spatial and temporal.

We have added more specific references to the variability we are discussing

[Lines 474–480](#)

LAI and similar vegetation indices were found to be the most common identified driver of T/ET from the regionalized studies included in this review (Li et al., 2024; Lowry et al., 2021; Restrepo-Coupe et al., 2023; Sun et al., 2020; Waggle et al., 2020; Wang et al., 2016; Zahn et al., 2022; Zhou et al., 2016). While LAI influenced the temporal variability of T/ET within a site/ecosystem, the spatial variability of T/ET presented that a higher LAI did not always indicate higher transpiration rates across sites/ecosystems, as the highest T values were found in SAV ecosystems and relatively low T was estimated for MF (Fig. S1). SWC, especially during dry conditions, was also found to be one of the most important temporal drivers of T/ET in several studies across global biomes (Liu et al., 2022b; Nie et al., 2021; da Rocha et al., 2022)...

We have also renamed the section to "Spatial and temporal drivers of T/ET"

50. Section 4.1: The discussion on the effects of interception could be expanded, as this has come up a number of times in the discussion of ET partitioning methods. On the one hand, removing rain periods and tying transpiration to GPP would result in interception being included in the residual, which in this case is attributed to non-transpiration evaporation, thus interception would be implicitly attributed to the correct box. However, there may also be systematic biases in the measurement of latent energy during rain even (e.g. <https://doi.org/10.1016/j.agrformet.2022.109305>) so the underlying eddy covariance measurements may underestimate interception, particularly for open path sensors. I'm not sure if there is a conclusion in the end, but likely it is a point of uncertainty and would further highlight the need to apply different methods to identify conditions with high uncertainties.

More information regarding interception evaporation and its associated uncertainties has been added to the discussion

[Lines 541–554](#)

Another source of large uncertainties is the handling of interception evaporation between the methods. The stomatal conductance-based methods ignore this process completely even with studies reporting that 8.5–10% of annual rainfall is intercepted by plant surfaces globally with some regional estimates reaching up to 50% depending on ecosystem type (Fischer et al., 2026; Lian et al., 2022; Zhong et al., 2022). EE22 does not remove wet periods from the training data like TEA18, however it still neglects to account for daytime interception rates that differ from their nocturnal counterparts (Czikowsky and Fitzjarrald, 2009). In high frequency methods, the inattention to rainfall often results in interception evaporation being incorrectly partitioned into T which may be in part responsible for this method's high T/ET estimates (Fig. 4). The methods which do appropriately attribute interception to E, whether directly or by means of using GPP to estimate T, still face uncertainties as EC systems often underestimate the water flux of an ecosystem during precipitation (Van Dijk et al., 2015; Fischer et al., 2026). ET measurements from EC during rain are inherently biased adding additional uncertainties to ET partitioning estimates and correcting ET measurements to account for this leads to contradicting changes in T/ET depending on which method was applied (Zhang et al., 2023). This again emphasizes the importance of applying multiple partitioning methods for comparisons in studies to see where T/ET estimates are most uncertain.

51. L379: While PP18 was only used in 6 studies, there was a comprehensive comparison in Nelson et al. 2020 which I would say shows that the predictions are systematically lower.

This was addressed with comment 44

52.

Additionally, the database search was run again on May 22nd, and the manuscript has been updated to include all new, relevant studies to ensure the review is as up-to-date as possible.

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