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COMMENTARY

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Challenges and Future Directions in Quantifying Terrestrial Evapotranspiration

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Key Points:

- The main challenge in ET science is reconciling spatial data with point data from various sources across heterogeneous areas
- Each of the three general approaches to ET science (in situ measurements, partitioning, remote sensing) has strengths and weaknesses
- Communication and translation across these disciplines are key to closing the gaps

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Abstract Terrestrial evapotranspiration is the second-largest component of the land water cycle, linking the water, energy, and carbon cycles and influencing the productivity and health of ecosystems. The dynamics of ET across a spectrum of spatiotemporal scales and their controls remain an active focus of research across different science disciplines. Here, we provide an overview of the current state of ET science across in situ measurements, partitioning of ET, and remote sensing, and discuss how different approaches complement one another based on their advantages and shortcomings. We aim to facilitate collaboration among a cross-disciplinary group of ET scientists to overcome the challenges identified in this paper and ultimately advance our integrated understanding of ET.

1. Introduction

Terrestrial evapotranspiration (ET), which includes both plant transpiration (T) and soil and vegetation surface evaporation (E), is a crucial component of the land water cycle, comprising about 60% of land precipitation volume (Trenberth et al., 2007). ET also significantly influences ecosystem functioning and climate variables within the energy and carbon cycles due to the close link between carbon and water fluxes (Allen et al., 1998; Anderson et al., 2011, 2013; Baldocchi & Meyers, 1998; Fisher et al., 2011, 2017; Katul et al., 2012; Miralles et al., 2014; Otkin et al., 2016; Senay et al., 2020; Tanner & Sinclair, 1983; Yi et al., 2019, 2024). The importance of ET highlights the need for accurate monitoring and understanding of this essential component of the Earth's water cycle.

Despite its importance, global spatiotemporal ET dynamics and their controls remain debated (Jung et al., 2010; Mankin et al., 2019). ET estimates from various sources, such as upscaled observations, remote sensing (RS), land surface models (LSMs), and atmospheric re-analyses, often show significant disparities (Good et al., 2017; Hu et al., 2023; Mao et al., 2015; Pan et al., 2020; Vinukollu et al., 2011), highlighting gaps in our understanding of the terrestrial water cycle (Stoy et al., 2019). Robust integration of ET observations, models, meta-syntheses, and collaborative efforts is essential for addressing these challenges.

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In response to the need for deeper understanding of ET dynamics, AmeriFlux launched the Year of Water Fluxes in 2021 to facilitate data syntheses and new measurements related to the water cycle and foster robust collaborations across disciplines. An international workshop on ET, organized by the AmeriFlux Management Project (November 2021) and a subsequent working group meeting supported by the USGS Powell Center and Consortium of Universities for the Advancement of Hydrologic Science Inc. (January 2024), identified significant challenges in enhancing our understanding of ET dynamics. We concluded that synergies between three fields in ET science—in-situ measurements, ET partitioning, and remote sensing—hold promise for advancing ET science. Each field has unique perspectives on research questions, spatial and temporal resolutions, and assumptions (Figure 1). To enhance interconnections and progress in ET science, we need to identify cross-cutting approaches. This commentary summarizes the workshop outcomes, highlighting potential cross-disciplinary links and outlining research efforts for future collaboration to advance ET science.

2. Overview of Research Themes

2.1. In Situ Measurements of ET

In situ measurements of ET aim to improve mechanistic understanding at specific sites and validate data-driven and process-based models that estimate water fluxes (Fisher et al., 2011; Stoy et al., 2019). The eddy covariance technique is a valuable tool for monitoring long-term ET in terrestrial ecosystems, quantifying the carbon, water, and energy exchanges between the terrestrial biosphere and atmosphere on a sub-hourly basis (Baldocchi & Meyers, 1998). Furthermore, networks of flux measurement sites, such as FLUXNET (Baldocchi et al., 2001; Pastorello et al., 2020), AmeriFlux (Baldocchi et al., 2024; Chu et al., 2023; Novick et al., 2018), and NEON (Keller et al., 2008), enable the assessment of spatial differences in water vapor exchange rates within and across natural ecosystems and climatic gradients (Baldocchi et al., 2001, 2024). Other parallel field measurements, such as SAPFLUXNET (Poyatos et al., 2021) for T measurements of individual trees and lysimeters can serve as a baseline for validating eddy covariance or RS approaches for directly measuring actual evapotranspiration at high temporal resolution (Perez-Priego et al., 2017). Therefore, flux sites typically provide comprehensive field data, offering a more holistic understanding of ecosystem dynamics.

However, a major challenge for in situ measurements is insufficient spatial coverage, especially compared to RS-based approaches, which require further attention on underrepresented regions globally (Figure 2). Resource limitations, site accessibility, and complex terrain pose challenges to establishing more extensive ET measurements. Villarreal and Vargas (2021) assessed flux tower coverage across Latin America, finding that only 34% of ET patterns were represented by current tower sites.

Increased spatial coverage of in situ flux observations in agroecosystems is desirable for evaluating and improving ET models (Volk et al., 2023, 2024). While the Long-Term Agroecosystem Research (LTAR) network provides water budget component information at a watershed scale (Baffaut et al., 2020), relatively few AmeriFlux sites are in agricultural areas (22% as of July 2024; Figure 2). This gap is significant considering that agriculture uses about 70% of global freshwater resources (K. Zhang et al., 2022).

Another challenge is the energy balance closure issue for eddy covariance-based flux measurements (Wilson et al., 2002). Stoy et al. (2013) analyzed energy balance closure from 173 FLUXNET sites, finding an average closure of 0.84 per site, indicating a persistent imbalance. Moreover, different approaches to adjusting for energy imbalance can lead to significant uncertainties in daily ET estimates (Bambach et al., 2022). Improving energy balance closure requires regular calibration of eddy covariance components (e.g., net radiometers and infrared gas analyzers), appropriate spectral correction, incorporation of storage terms (e.g., soil heat storage), enhanced footprint analysis, accounting for advection, and making precise environmental and site-specific adjustments (Foken, 2008; Foken & Leclerc, 2004; Heusinkveld et al., 2004; Leuning et al., 2012; Meyers & Hollinger, 2004; Reed et al., 2018; Twine et al., 2000).

Fragmented observation protocols are another challenge with in situ measurements. While Individualized protocols allow flexibility, they can impede direct comparisons among sites and introduce biases and uncertainties (Novick et al., 2022). The ONEFlux processing effort by the AmeriFlux Management Project is currently working to harmonize multiple networks of flux data with standardized processing protocols, which will greatly increase data comparability between networks (Pastorello et al., 2020).

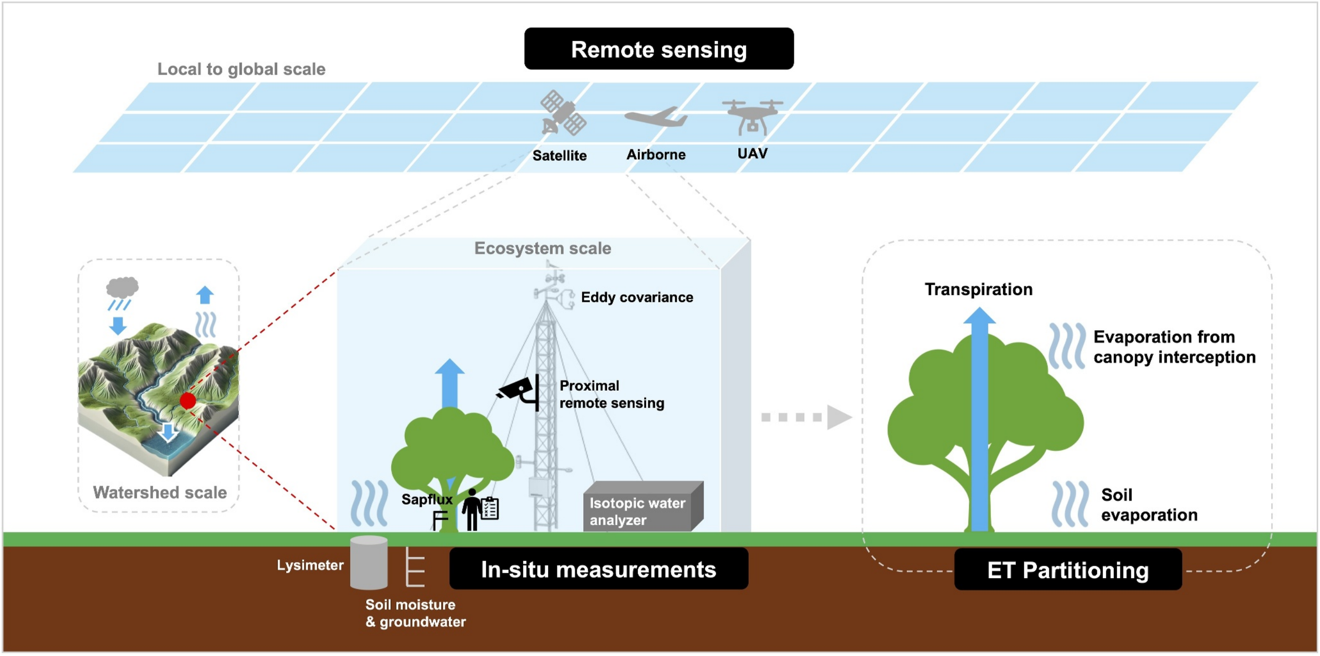

Figure 1. Enhanced integration of the areas of ET science—namely in situ measurements of ET, ET partitioning, and remote sensing of ET—will complement each other and help clarify long-term trends in ET by minimizing biases and uncertainties in ET estimation.

Other challenges include limited data on vegetation water content, matric potential, and flow. Within a site, plant species are often undersampled, with a focus on dominant species and frequent neglect of the understory. Certain in situ measurements are discontinuous annually, with few measurements outside the growing season, limiting the ability to accurately quantify ET components.

2.2. ET Partitioning

Partitioning ET into surface evaporation and transpiration is crucial for quantifying biological feedbacks on the hydrological cycle, improving hydrological models, understanding ecosystem resilience to climate change, and validating RS approaches and products (Baldocchi & Ryu, 2011; Nelson et al., 2020; Stoy et al., 2019; Yuan et al., 2022).

ET partitioning has been performed using various measurements and modeling methods, each with unique assumptions and limitations (Kool et al., 2014; W. Xiao et al., 2018), making it challenging to achieve absolute validation of partitioning methods and models. Methodological intercomparisons have been conducted using multiple approaches simultaneously; however, most meta-analyses integrate studies that employ different approaches at various sites and times (L. Wang et al., 2014).

Another critical challenge in ET partitioning is the independent estimation of E from T. While wet forest canopies significantly contribute to surface evaporation, there is a lack of research analyzing ET measurements using eddy covariance during wet conditions. Additionally, measuring the duration of wet canopy conditions is challenging and often neglected in studies or simply estimated as a constant period after rainfall ends (Aparecido et al., 2016; Fischer et al., 2023). In practice, canopy wetness or the duration of an entire interception event can be determined using leaf wetness sensors or models, which require analyzing evaporation conditions, vegetation properties, and rainfall characteristics (Muzylo et al., 2009; Wilson et al., 2001). Furthermore, the contribution of epiphytes to ET, such as precipitation interception and water storage until evaporation, is often overlooked despite reports of substantial variability (Hargis et al., 2019; Tobón et al., 2011).

Quantifying soil evaporation requires detailed soil information and an improved understanding of resistances (Bittelli et al., 2008) and often relies on fully coupled numerical models accounting for heat flow, liquid water movement, and vapor movement at the soil-atmosphere interface and within the topsoil (Parlange et al., 1998; Rose, 1968a, 1968b; Saito et al., 2006). Accurate quantification of soil evaporation depends on correct soil

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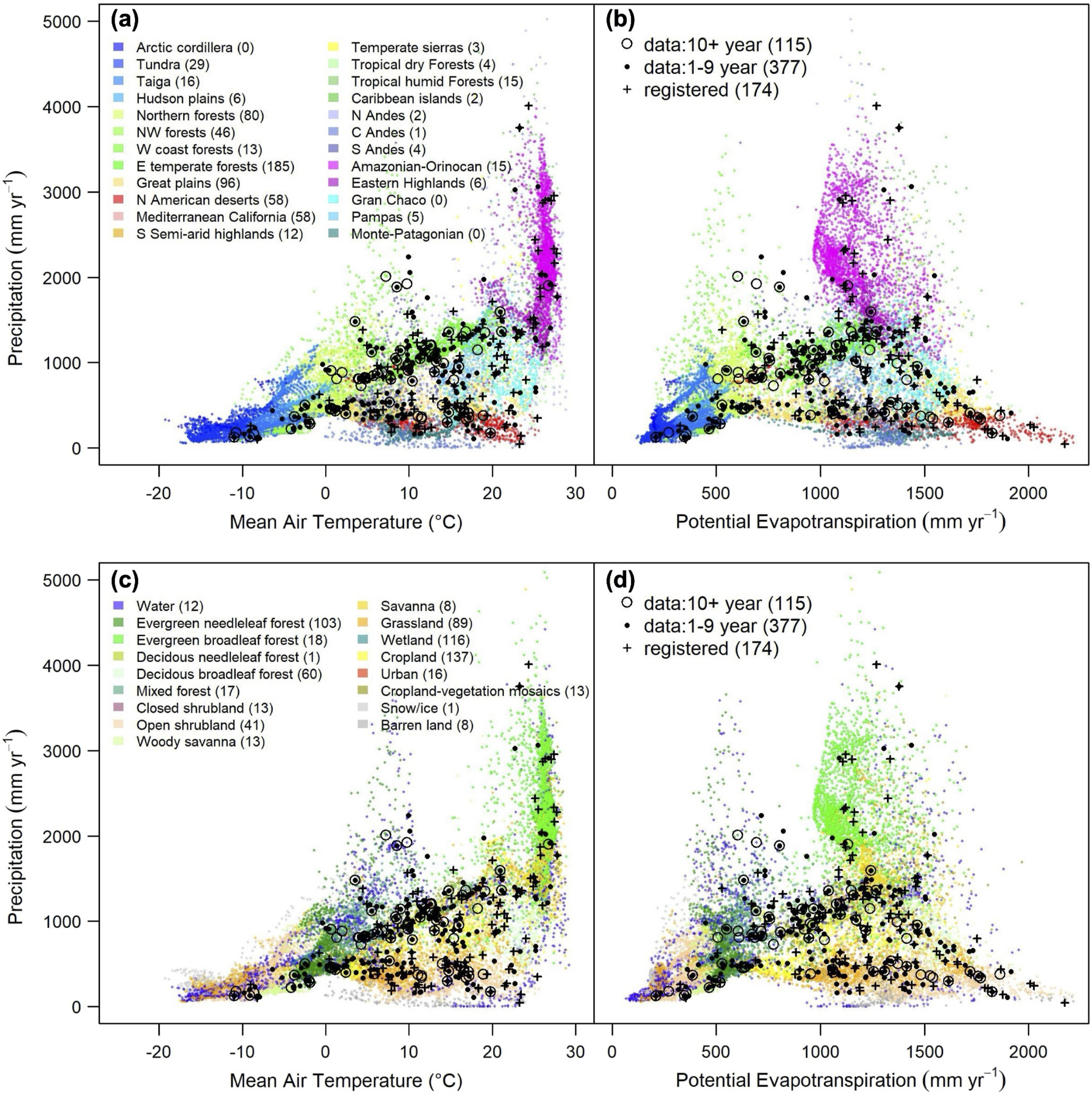

Figure 2. Distribution of AmeriFlux sites by mean annual temperature, precipitation, and potential evapotranspiration (estimated using FAO Penman-Monteith; Harris et al., 2014) grouped by ecoregions (EPA; a and b) and land cover types (IGBP; c and d), as of July 2024. Tower locations are shown as crosses (registered sites) and circles (sites with data available, with size proportional to data record length). Background colored dots represent mean annual temperature and total precipitation across the Americas using the Climatic Research Unit (CRU) time series (TS) 4.05 gridded data set (0.5° × 0.5°, 1981–2020). Colors indicate the ecoregions or land cover types. Numbers in parentheses show the number of sites in each group.

surface resistance computation, which can be parameterized by measuring soil moisture and temperature at different soil depths near the surface (Bittelli et al., 2008; Camillo & Gurney, 1986; Idso et al., 1974; Kondo et al., 1990; van de Griend & Owe, 1994). Lysimeters, as point observations of ET or E, can also validate and improve ET partitioning (Perez-Priego et al., 2017). Measuring and modeling evaporation from open water, which is crucial for water resources management and aquatic ecology, remains a significant challenge due to the unique bathymetric and heat transfer controls distinct from those affecting vegetation ET (Fisher et al., 2023; Friedrich et al., 2018).

Given the close correlations between carbon and water fluxes and their simultaneous measurements by eddy covariance systems, ET partitioning using eddy covariance has become promising, either by concurrently measuring eddy fluxes below and above the canopy (e.g., Baldocchi & Vogel, 1996; Black et al., 1996; Paul-Limoges et al., 2020; Wilson & Meyers, 2001) or by using data-driven methods, such as machine learning models (Eichelmann et al., 2022; Nelson et al., 2018), optimization models (Perez-Priego et al., 2018), regression models (Reichstein et al., 2005; Scott & Biederman, 2017; Zhou et al., 2016), and simpler models requiring fewer input variables (Scanlon & Sahu, 2008; Thomas et al., 2008; Zahn et al., 2022). Efforts are also being made to compare different models to close knowledge gaps (e.g., Nelson et al., 2020; Zahn et al., 2022).

RS-based methods also show promise for ET partitioning. Thermal infrared partitioning has shown promising results in agricultural landscapes (Knipper et al., 2023). Satellite-based solar-induced fluorescence (SIF) observations constrain global transpiration values derived from land surface models (Jonard et al., 2020; Pagan et al., 2019; J. Yang et al., 2024). Efforts to address vegetation energy sources with more than two sources, such as a three-source energy balance model with an understory flux, aim to provide more robust simulations of latent heat flux and improved partitioning (Burchard-Levine, Nieto, Kustas, et al., 2022, Burchard-Levine, Nieto, Kustas, et al., 2022; Fisher et al., 2008).

2.3. ET Remote Sensing

Satellite-based RS provides extensive and consistent global spatial coverage for ET estimation. Major RS models include Surface Energy Balance (Allen et al., 2007; Anderson et al., 1997; Bastiaanssen et al., 1998; Kustas et al., 1990; Norman et al., 1995; Senay et al., 2013), Penman-Monteith (PM) (Cleugh et al., 2007; Leuning et al., 2008; Mallick et al., 2015, 2022; Mu et al., 2007, 2011; K. Zhang et al., 2009), Penman-Monteith-Leuning (PML) (Leuning et al., 2008; Y. Zhang, Peña-Arancibia, et al., 2016), Priestley-Taylor (PT) (Fisher et al., 2008; Miralles et al., 2011), and vegetation index-land surface temperature (VI-LST) space models (Carlson, 2007; Price, 1990). Advances in computational resources, data availability, and machine learning algorithms have enabled data-driven modeling for ET mapping (Alemohammad et al., 2017; Pan et al., 2020; Xu et al., 2019).

Despite the numerous methods, biases and uncertainties continue to affect the accuracy of ET estimation across various spatial variabilities, including climate, land cover, land use, topography, and cloud cover (Long et al., 2014; Melo et al., 2021). The lack of comprehensive in situ measurements complicates ground-truthing efforts (Farella et al., 2022). RS can partition ET into E and T by differentiating vegetation cover and density from the background soil (Talsma, Good, Jimenez, et al., 2018; Talsma, Good, Miralles, et al., 2018), but validation against in situ data has been limited (Stoy et al., 2019).

RS-based ET estimates and their uncertainties are influenced by various factors, highlighting the importance of understanding sensitivities and error propagation (Badgley et al., 2015; Polhamus et al., 2013; Trebs et al., 2021; K. Zhang, Kimball, & Running, 2016). Process-based models, such as PM models, are considered physically sound, but accurate ET estimation depends on precise surface conductance estimation, which introduces cumulative uncertainty if empirically estimated (Fisher et al., 2005; Mallick et al., 2018, 2022). Furthermore, variations in spatial resolutions of input data (e.g., 30 m Landsat vs. 1 km MODIS) affect the level of detail in gridded ET products.

RS is effective at monitoring spatial variation in ET but is challenged by short-term temporal variations due to substantial hourly to sub-weekly fluctuations in ET, which are shorter than the typical revisit periods of polar-orbiting satellites (Fisher et al., 2020; Gentine et al., 2007). This limitation motivates the need for complementary in situ measurements and modeling capabilities that are better suited for temporal characterization, such as geostationary satellites (Diak, 1990; Diak & Stewart, 1989; Khan et al., 2021), although these have coarse spatial resolution and inconsistent global coverage (J. Xiao et al., 2021; Yamamoto et al., 2022).

RS-based ET products are most effective on clear-sky days, which limits their temporal resolution in humid and tropical regions. Novel RS retrievals, such as cloud-tolerant microwave sensing, address persistent cloudiness but have coarse spatial resolution (Holmes et al., 2018; Z. Wang et al., 2021). The need for high-frequency (sub-daily) ET monitoring motivates the development of complementary instrumental and modeling capabilities, such as temporal upscaling (Ryu et al., 2011; Wandera et al., 2017), data fusion (Desai et al., 2021), and the use of

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geostationary satellites (Khan et al., 2021; J. Xiao et al., 2021; Yamamoto et al., 2022). Data fusion approaches that combine multiple sources, such as Landsat, ECOSTRESS, and VIIRS, are being developed to improve spatiotemporal resolution (Cammallari et al., 2014; Xue et al., 2022; Y. Yang et al., 2022; Yao et al., 2017). These advancements emphasize the importance of integrating process understanding with RS data to enhance ET estimates across diverse landscapes and climatic conditions.

3. Future Directions and Perspectives

Changes in the global hydrological cycle driven by ET variation significantly affect climate, ecosystem water availability, and biogeochemical processes. The grand challenge in ET science is to accurately quantify and partition ET everywhere, all the time, and to enhance forecasting capabilities. This challenge can be addressed by closing gaps between RS, in situ measurements, and modeling capabilities.

The primary limiting factors in quantifying ET trends are: (a) insufficient spatiotemporal data and (b) inadequate understanding of the key processes (e.g., CO_2 response, stomatal regulation, soil evaporation, and the relationships between temperature and heat fluxes) relevant to long-term ET changes. Extensive ET observations from eddy covariance networks are currently addressing the first challenge (Chu et al., 2023; Pastorello et al., 2020). However, ET estimates from eddy covariance may be inaccurate due to lack or energy balance closure, necessitating validation using other ET measurements (e.g., lysimeters) and accurate partitioning through robust partitioning methods and direct measurements of E and T separately, such as sap flux and soil surface evaporation.

To extrapolate ET estimation from in situ measurements to the global scale, enhancing data fusion techniques with RS and improving ET representation for various environmental conditions are necessary. Achieving this requires expanding the network of in situ measurements to cover underrepresented regions and increasing high-resolution thermal satellites. Mainstream ET models adopting key processes for accurate modeling show considerable disparity in simulation results due to different configurations. Accumulating information from in situ measurements, emerging field-based water flux networks (e.g., SAPFLUXNET and PSInet), and advanced ET partitioning techniques helps to better examine ET variations and constrain model simulations.

Community actions through scientific networks are crucial for enhancing data coverage and developing standardized ET estimation and partitioning protocols. Understanding ecological processes in underrepresented regions will reduce biases and uncertainties in ET estimation. For example, the AmeriFlux network has grown rapidly, with over 650 registered sites and more than 3,000 site-years of data available as of July 2024; however, 75% of the sites are in the conterminous United States (Figure 2). Expanding flux networks requires top-down support, including efforts to establish new sites, recruit non-affiliated sites, and continuously support affiliated sites for reliable instrumentation management and long-term record collection.

RS observations are improving in spatial and temporal resolutions, enabling differentiation of landscape heterogeneity (Doughty et al., 2023). Proximal RS techniques, such as ground-based high-frequency monitoring systems (Shan et al., 2021; Still et al., 2019; Yi et al., 2020) and repeated measurements from unmanned aircraft systems (UAS) equipped with thermal, optical, and LiDAR sensors (Acharya et al., 2021), provide data to estimate ET from individual trees. Simultaneously, ensemble RS approaches combined with high-quality, footprint-aware eddy flux measurements ensure robust applications (Melton et al., 2022; Volk et al., 2023, 2024). The Hydrosat constellation of thermal satellites promises daily high-resolution ET globally (Fisher et al., 2022).

Existing efforts using UAS in hydrology and agriculture highlight the need for increased support in this area. Interdisciplinary field studies like FIFE (Sellers et al., 1988), BOREAS (Sellers et al., 1997), CHEESEHEAD (Butterworth et al., 2021), GRAPEX (Kustas et al., 2018), and T-REX (Bambach et al., 2024) demonstrate the value of long-term investment in capturing weather and climate variations. Expanding these studies to include more diverse ecosystems and climatic conditions is essential.

Integrating prognostic and diagnostic ET modeling approaches is another promising avenue. The independence of energy flux errors in prognostic land surface models from comparable diagnostic RS-based errors (Crow et al., 2005) provides a basis for assimilating remotely sensed energy flux and ET products into prognostic models, thereby improving the frequency of ET and soil moisture estimation (Lei et al., 2020).

Lastly, despite their distinct advancements, there is a close interdependence among in situ measurements, ET partitioning, and RS communities. Breakthroughs in scientific disciplines often emerge from interdisciplinary intersections, and the resulting synergy plays a vital role in addressing challenges and advancing the field of ET science. The first two steps, which are often overlooked and underrated, are communication and translation. Without these essential first steps, interdisciplinary advances are limited.

We call for a combination of systems engineering analysis to match the requirements and uncertainties of remotely sensed ET with the capabilities of in situ and modeling approaches, supported by a foundation of integrative analysis to advance our understanding of ET. For example, a possible step to close gaps between the disciplines is to design in situ studies with other approaches in mind (i.e., using in situ ET studies as ground truth to validate and calibrate RS-based ET estimation and ET partitioning). This will require close interdisciplinary communication discussing advantages and disadvantages of approaches, their limitations and opportunities, and creative ways to overcome shortcomings.

Another potential lies in integrating physical knowledge and process-based background with the wealth of in situ and satellite data in physics-informed machine learning frameworks for more reliable ET estimation. These hybrid models can leverage the unprecedented availability of measured data in a bottom-up approach to reduce the uncertainties of RS-based ET estimations.

In conclusion, synthesizing across the disciplines of ET science will provide the state of the knowledge on remotely sensed ET accuracy, clarity on limits and strengths for applications, and identify traceable research and development needs to continue closing key knowledge gaps.

Data Availability Statement

Flux data are available at the following websites: AmeriFlux Data Portal (https://ameriflux.lbl.gov/sites/site-search/), FLUXNET2015 Data set (https://fluxnet.org/data/fluxnet2015-dataset/), NEON data portal (https://data.neonscience.org/), and SAPFLUXNET (https://sapfluxnet.creaf.cat/). NASA remote sensing data are available from various sources, including NASA Earthdata (https://www.earthdata.nasa.gov/), Land Processes Distributed Active Archive Center (LP DAAC; https://lpdaac.usgs.gov/) Oak Ridge National Laboratory DAAC (ORNL DAAC; https://daac.ornl.gov/), and USGS EarthExplorer (https://earthexplorer.usgs.gov/).

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