

1 **Title**

2 Challenges and Future Directions in Quantifying Terrestrial Evapotranspiration

3

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44

45 **Abstract**

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

56

57 **Keywords**

58 Terrestrial evapotranspiration, in-situ measurements, evapotranspiration partitioning,
59 remote sensing, eddy covariance

60

61 **Highlights**

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

68

69 **1. Introduction**

70 Terrestrial evapotranspiration (ET), which includes both plant transpiration (T)
71 and soil and vegetation surface evaporation (E), is a crucial component of the land
72 water cycle, comprising about 60% of land precipitation volume (Trenberth et al., 2007).
73 ET also significantly influences ecosystem functioning and climate variables within the
74 energy and carbon cycles due to the close link between carbon and water fluxes (Allen
75 et al., 1998; Anderson et al., 2011, 2013; Baldocchi & Meyers, 1998; Fisher et al., 2011,
76 2017; Katul et al., 2012; Miralles et al., 2014; Otkin et al., 2016; Senay et al., 2020;
77 Tanner & Sinclair, 1983; Yi et al., 2019, 2024). The importance of ET highlights the
78 need for accurate monitoring and understanding of this essential component of the
79 Earth's water cycle.

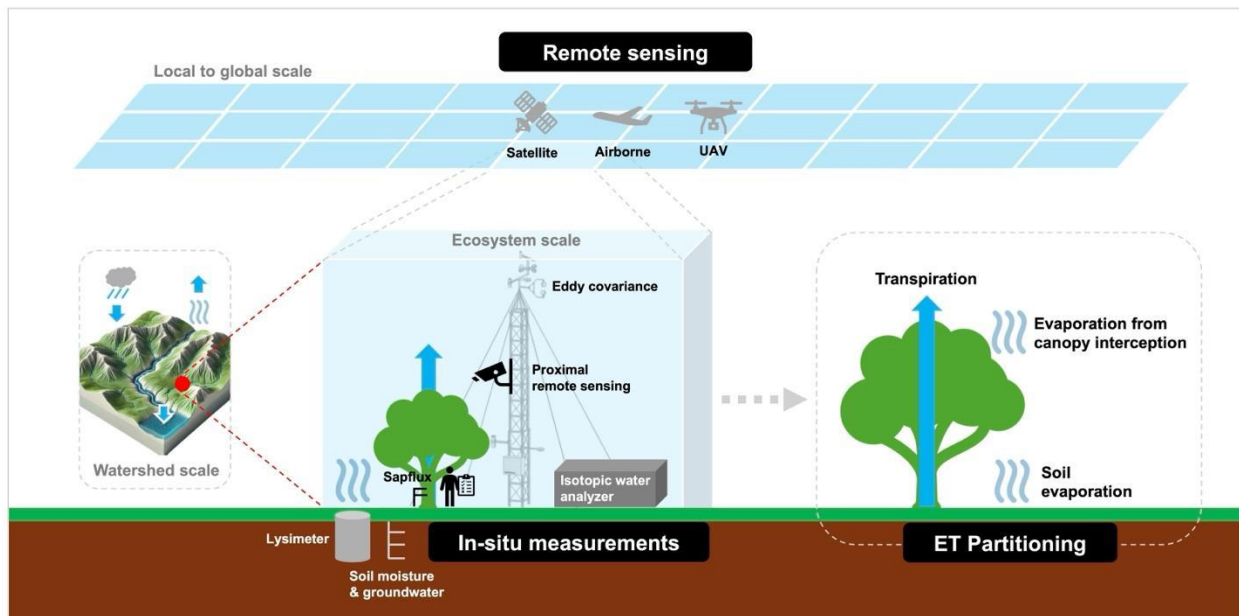
80 Despite its importance, global spatiotemporal ET dynamics and their controls
81 remain debated (Jung et al., 2010; Mankin et al., 2019). ET estimates from various
82 sources, such as upscaled observations, remote sensing (RS), land surface models
83 (LSMs), and atmospheric re-analyses, often show significant disparities (Good et al.,
84 2017; Hu et al., 2023; Mao et al., 2015; Pan et al., 2020; Vinukollu et al., 2011),
85 highlighting gaps in our understanding of the terrestrial water cycle (Stoy et al., 2019).
86 Robust integration of ET observations, models, meta-syntheses, and collaborative
87 efforts is essential for addressing these challenges.

88 In response to the need for deeper understanding of ET dynamics, AmeriFlux
89 launched the Year of Water Fluxes in 2021 to facilitate data syntheses and new
90 measurements related to the water cycle and foster robust collaborations across
91 disciplines. An international workshop on ET, organized by the AmeriFlux Management

92 Project (November 2021) and a subsequent working group meeting supported by the
93 USGS Powell Center and Consortium of Universities for the Advancement of Hydrologic
94 Science Inc. (January 2024), identified significant challenges in enhancing our
95 understanding of ET dynamics. We concluded that synergies between three fields in ET
96 science—in-situ measurements, ET partitioning, and remote sensing—hold promise for
97 advancing ET science. Each field has unique perspectives on research questions,
98 spatial and temporal resolutions, and assumptions (Figure 1). To enhance
99 interconnections and progress in ET science, we need to identify cross-cutting
100 approaches. This commentary summarizes the workshop outcomes, highlighting
101 potential cross-disciplinary links and outlining research efforts for future collaboration to
102 advance ET science.

103

104



105

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

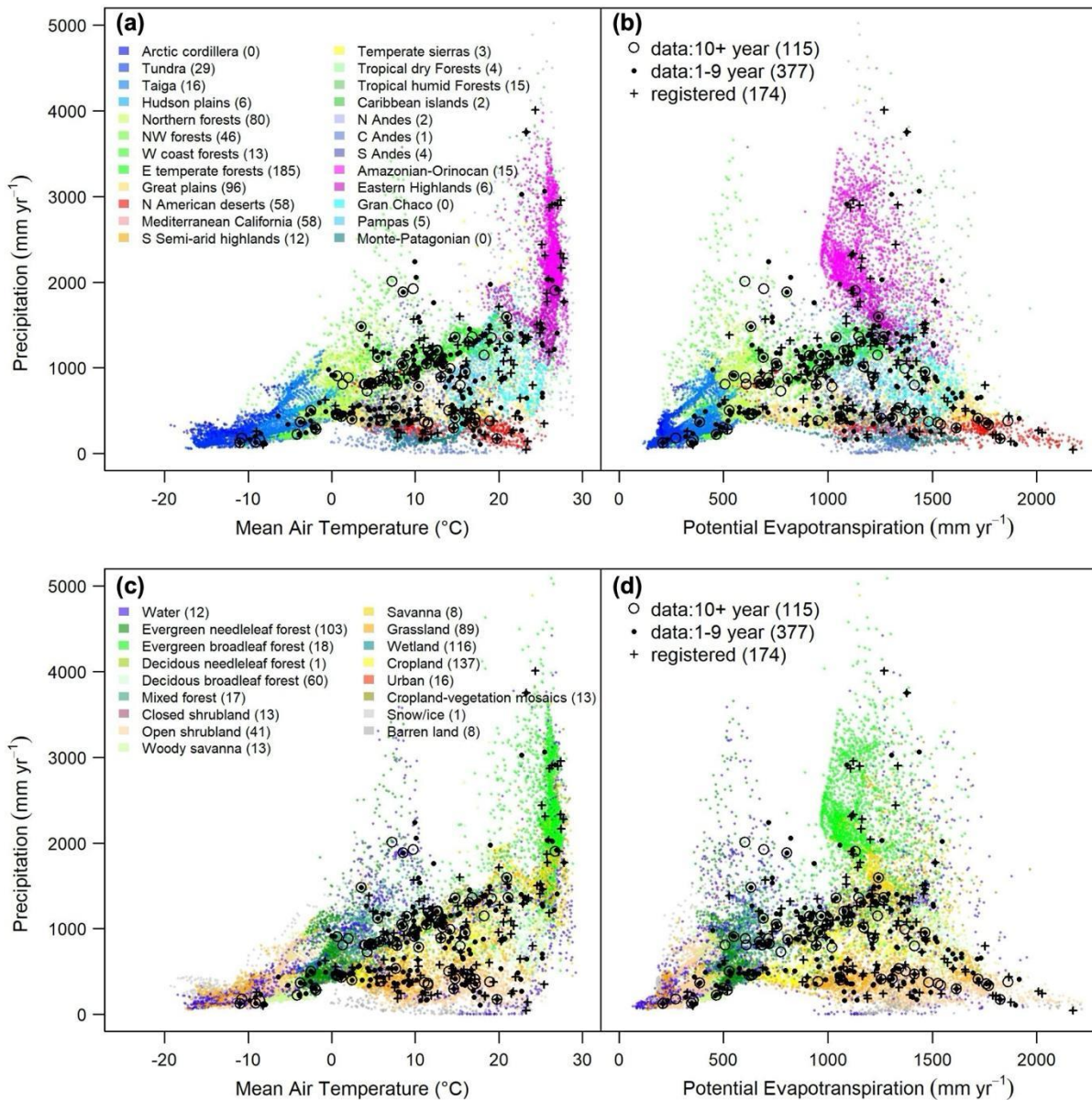
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111 **2. Overview of Research Themes**

112 **2.1. In-situ Measurements of ET**

113 In-situ measurements of ET aim to improve mechanistic understanding at
114 specific sites and validate data-driven and process-based models that estimate water
115 fluxes (Fisher et al., 2011; Stoy et al., 2019). The eddy covariance technique is a
116 valuable tool for monitoring long-term ET in terrestrial ecosystems, quantifying the
117 carbon, water, and energy exchanges between the terrestrial biosphere and
118 atmosphere on a sub-hourly basis (Baldocchi & Meyers 1998). Furthermore, networks
119 of flux measurement sites, such as FLUXNET (Baldocchi et al., 2001; Pastorello et al.,
120 2020), AmeriFlux (Baldocchi et al., 2024; Chu et al., 2023; Novick et al., 2018), and
121 NEON (Keller et al., 2008), enable the assessment of spatial differences in water vapor
122 exchange rates within and across natural ecosystems and climatic gradients (Baldocchi
123 et al., 2001, 2024). Other parallel field measurements, such as SAPFLUXNET (Poyatos
124 et al., 2021) for T measurements of individual trees and lysimeters can serve as a
125 baseline for validating eddy covariance or RS approaches for directly measuring actual
126 evapotranspiration at high temporal resolution (Perez-Priego et al., 2017). Therefore,
127 flux sites typically provide comprehensive field data, offering a more holistic
128 understanding of ecosystem dynamics.

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



135

136 *Figure 2. Distribution of AmeriFlux sites by mean annual temperature, precipitation, and*
137 *potential evapotranspiration (estimated using FAO Penman-Monteith; Harris et al.,*
138 *2014) grouped by ecoregions (EPA; a & b) and land cover types (IGBP; c & d), as of*
139 *July 2024. Tower locations are shown as crosses (registered sites) and circles (sites*
140 *with data available, with size proportional to data record length). Background colored*
141 *dots represent mean annual temperature and total precipitation across the Americas*
142 *using the Climatic Research Unit (CRU) time series (TS) 4.05 gridded dataset*
143 *(0.5°×0.5°, 1981-2020). Colors indicate the ecoregions or land cover types. Numbers in*
144 *parentheses show the number of sites in each group.*

145

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

153 Another challenge is the energy balance closure issue for eddy covariance-
154 based flux measurements (Wilson et al., 2002). Stoy et al. (2013) analyzed energy
155 balance closure from 173 FLUXNET sites, finding an average closure of 0.84 per site,
156 indicating a persistent imbalance. Moreover, different approaches to adjusting for
157 energy imbalance can lead to significant uncertainties in daily ET estimates (Bambach
158 et al., 2022). Improving energy balance closure requires regular calibration of eddy

159 covariance components (e.g., net radiometers and infrared gas analyzers), appropriate
160 spectral correction, incorporation of storage terms (e.g., soil heat storage), enhanced
161 footprint analysis, accounting for advection, and making precise environmental and site-
162 specific adjustments (Foken, 2008; Foken et al., 2004; Heusinkveld et al., 2004;
163 Leuning et al., 2012; Meyers & Hollinger, 2004; Reed et al., 2018; Twine et al., 2020).

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

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

176

177 **2.2. ET Partitioning**

178 Partitioning ET into surface evaporation and transpiration is crucial for quantifying
179 biological feedbacks on the hydrological cycle, improving hydrological models,
180 understanding ecosystem resilience to climate change, and validating RS approaches

181 and products (Baldocchi & Ryu, 2011; Nelson et al., 2020; Stoy et al., 2019; Yuan et al.,
182 2022).

183 ET partitioning has been performed using various measurements and modeling
184 methods, each with unique assumptions and limitations (Kool et al., 2014; Xiao et al.,
185 2018), making it challenging to achieve absolute validation of partitioning methods and
186 models. Methodological intercomparisons have been conducted using multiple
187 approaches simultaneously; however, most meta-analyses integrate studies that
188 employ different approaches at various sites and times (Wang et al., 2014).

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

201 Quantifying soil evaporation requires detailed soil information and an improved
202 understanding of resistances (Bittelli et al., 2008) and often relies on fully coupled
203 numerical models accounting for heat flow, liquid water movement, and vapor

204 movement at the soil-atmosphere interface and within the topsoil (Parlange et al., 1998;
205 Rose 1968a, 1968b; Saito et al., 2006). Accurate quantification of soil evaporation
206 depends on correct soil surface resistance computation, which can be parameterized by
207 measuring soil moisture and temperature at different soil depths near the surface
208 (Bittelli et al., 2008; Camillo & Gurney, 1986; Idso et al., 1974; Kondo et al., 1990; van
209 de Griend & Owe, 1994). Lysimeters, as point observations of ET or E, can also validate
210 and improve ET partitioning (Perez-Priego et al., 2017). Measuring and modeling
211 evaporation from open water, which is crucial for water resources management and
212 aquatic ecology, remains a significant challenge due to the unique bathymetric and heat
213 transfer controls distinct from those affecting vegetation ET (Fisher et al., 2023;
214 Friedrich et al., 2018).

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

226 RS-based methods also show promise for ET partitioning. Thermal infrared
227 partitioning has shown promising results in agricultural landscapes (Knipper et al.,
228 2023). Satellite-based solar-induced fluorescence (SIF) observations constrain global
229 transpiration values derived from land surface models (Jonard et al., 2020; Pagan et al.,
230 2019; Yang et al., 2024). Efforts to address vegetation energy sources with more than
231 two sources, such as a three-source energy balance model with an understory flux, aim
232 to provide more robust simulations of latent heat flux and improved partitioning
233 (Buchard-Levine et al., 2022a, 2022b; Fisher et al., 2008).

234

235 **2.3. ET Remote Sensing**

236 Satellite-based RS provides extensive and consistent global spatial coverage for
237 ET estimation. Major RS models include Surface Energy Balance (Allen et al., 1997;
238 Anderson et al., 1997; Bastiaanssen et al., 1998; Kustas et al., 1990; Norman et al.,
239 1995; Senay et al., 2013), Penman-Monteith (PM) (Cleugh et al., 2007; Leuning et al.,
240 2008; Mallick et al., 2015, 2022; Mu et al., 2007, 2011; Zhang et al., 2009), Penman-
241 Monteith-Leuning (PML) (Leuning et al., 2008; Zhang et al., 2016b), Priestley-Taylor
242 (PT) (Fisher et al., 2008; Miralles et al., 2011), and vegetation index-land surface
243 temperature (VI-LST) space models (Price, 1990; Carlson, 2007). Advances in
244 computational resources, data availability, and machine learning algorithms have
245 enabled data-driven modeling for ET mapping (Alemohammad et al., 2017; Pan et al.,
246 2020; Xu et al., 2019).

247 Despite the numerous methods, biases and uncertainties continue to affect the
248 accuracy of ET estimation across various spatial variabilities, including climate, land

249 cover, land use, topography, and cloud cover (Long et al., 2014; Melo et al., 2021). The
250 lack of comprehensive in-situ measurements complicates ground-truthing efforts
251 (Farella et al., 2022). RS can partition ET into E and T by differentiating vegetation
252 cover and density from the background soil (Talsma et al., 2018a, 2018b), but validation
253 against in-situ data has been limited (Stoy et al., 2019).

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

262 RS is effective at monitoring spatial variation in ET but is challenged by short-
263 term temporal variations due to substantial hourly to sub-weekly fluctuations in ET,
264 which are shorter than the typical revisit periods of polar-orbiting satellites (Fisher et al.,
265 2020; Gentine et al., 2007). This limitation motivates the need for complementary in-situ
266 measurements and modeling capabilities that are better suited for temporal
267 characterization, such as geostationary satellites (Diak, 1990; Diak & Stewart, 1989;
268 Khan et al., 2021), although these have coarse spatial resolution and inconsistent global
269 coverage (Xiao et al., 2021; Yamamoto et al., 2022).

270 RS-based ET products are most effective on clear-sky days, which limits their
271 temporal resolution in humid and tropical regions. Novel RS retrievals, such as cloud-

272 tolerant microwave sensing, address persistent cloudiness but have coarse spatial
273 resolution (Holmes et al., 2018; Wang et al., 2021). The need for high-frequency (sub-
274 daily) ET monitoring motivates the development of complementary instrumental and
275 modeling capabilities, such as temporal upscaling (Ryu et al., 2011; Wandera et al.,
276 2017), data fusion (Desai et al., 2021), and the use of geostationary satellites (Khan et
277 al., 2021; Xiao et al., 2021; Yamamoto et al., 2022). Data fusion approaches that
278 combine multiple sources, such as Landsat, ECOSTRESS, and VIIRS, are being
279 developed to improve spatiotemporal resolution (Cammallari et al., 2014; Yang et al.,
280 2022; Xue et al., 2022; Yao et al., 2017). These advancements emphasize the
281 importance of integrating process understanding with RS data to enhance ET estimates
282 across diverse landscapes and climatic conditions.

283

284 **3. Future Directions and Perspectives**

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

290 The primary limiting factors in quantifying ET trends are: 1) insufficient
291 spatiotemporal data and 2) inadequate understanding of the key processes (e.g., CO₂
292 response, stomatal regulation, soil evaporation, and the relationships between
293 temperature and heat fluxes) relevant to long-term ET changes. Extensive ET
294 observations from eddy covariance networks are currently addressing the first challenge

295 (Chu et al., 2023; Pastorello et al., 2020). However, ET estimates from eddy covariance
296 may be inaccurate due to lack of energy balance closure, necessitating validation using
297 other ET measurements (e.g., lysimeters) and accurate partitioning through robust
298 partitioning methods and direct measurements of E and T separately, such as sap flux
299 and soil surface evaporation.

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

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

317 sites, recruit non-affiliated sites, and continuously support affiliated sites for reliable
318 instrumentation management and long-term record collection.

319 RS observations are improving in spatial and temporal resolutions, enabling
320 differentiation of landscape heterogeneity (Doughty et al., 2023). Proximal RS
321 techniques, such as ground-based high-frequency monitoring systems (Shan et al.,
322 2021; Still et al., 2019; Yi et al., 2020) and repeated measurements from unmanned
323 aircraft systems (UAS) equipped with thermal, optical, and LiDAR sensors (Acharya et
324 al., 2021), provide data to estimate ET from individual trees. Simultaneously, ensemble
325 RS approaches combined with high-quality, footprint-aware eddy flux measurements
326 ensure robust applications (Melton et al., 2022; Volk et al., 2023, 2024). The Hydrosat
327 constellation of thermal satellites promises daily high-resolution ET globally (Fisher et
328 al., 2022).

329 Existing efforts using UAS in hydrology and agriculture highlight the need for
330 increased support in this area. Interdisciplinary field studies like FIFE (Sellers et al.,
331 1988), BOREAS (Sellers et al., 1997), CHEESEHEAD (Butterworth et al., 2021),
332 GRAPEX (Kustas et al., 2018), and T-REX (Bambach et al., 2024) demonstrate the
333 value of long-term investment in capturing weather and climate variations. Expanding
334 these studies to include more diverse ecosystems and climatic conditions is essential.

335 Integrating prognostic and diagnostic ET modeling approaches is another
336 promising avenue. The independence of energy flux errors in prognostic land surface
337 models from comparable diagnostic RS-based errors (Crow et al., 2005) provides a
338 basis for assimilating remotely sensed energy flux and ET products into prognostic

339 models, thereby improving the frequency of ET and soil moisture estimation (Lei et al.,
340 2020).

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

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

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

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

366

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382

383 **Data Availability Statement**

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