

1 **Toward Fit-for-Purpose Evapotranspiration Observations**

2 Justin L Huntington^{1,†,*}, Yeonuk Kim^{1,†}, Todd Caldwell¹, Meetpal Kukal², Shawn Naylor³, Bruno
3 Comini de Andrade⁴, Christian Dunkerly¹, Christopher Pearson¹, Richard Jasoni⁵, John Volk¹,
4 Murphy Gardner¹, Maria Isabel Zamora Re⁶, Dragomira Zheleva⁶, Robert R. Lotspeich⁷

5 **Affiliations**

- 6 1. Division of Hydrologic Sciences, Desert Research Institute, Reno, Nevada, USA
- 7 2. College of Agricultural & Life Sciences, University of Idaho, Boise, Idaho, USA
- 8 3. U.S. Geological Survey, Ohio-Kentucky-Indiana Water Science Center, Indianapolis, IN, USA
- 9 4. Independent contractor, Porto Alegre, Rio Grande do Sul, Brazil
- 10 5. Division of Earth and Ecosystem Sciences, Desert Research Institute, Reno, Nevada, USA
- 11 6. Biological and Ecological Engineering, Oregon State University, Corvallis, Oregon, USA
- 12 7. U.S. Geological Survey, Water Resources Mission Area, Reston, VA, USA

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14 * Correspondence to: Justin L. Huntington (Justin.Huntington@dri.edu)

15 † These authors contributed equally: Justin L. Huntington and Yeonuk Kim

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18 19 **Abstract**

20 Evapotranspiration (ET) underpins water, energy, and carbon cycling, yet remains among the
21 least observed hydrologic fluxes, creating a persistent paradox: hydrology is advancing rapidly
22 through artificial intelligence and data-driven methods while its observational foundation
23 remains sparse and fragmented. Eddy covariance provides robust ET measurements, but high
24 cost and operational demands limit deployment. The scarcity of in situ ET observations for
25 model validation creates a persistent barrier to evaluating, interpreting, and adopting scalable
26 satellite-based ET products. Emerging low-cost sensors offer a pathway to expand observations,
27 but rely on simplifying assumptions, proprietary processing, and limited diagnostics, introducing
28 uncertainty and constraining process interpretation. We present an ET measurement ladder that
29 organizes approaches along levels of affordability, capturing trade-offs in reliability, physical
30 constraint, and analytical capability. A fit-for-purpose strategy is essential to expand ET
31 measurements, strengthen confidence in ET observations and products, and enable credible,
32 scalable monitoring of hydrometeorological processes under increasing resource constraints.

33 **Main**

34 Evapotranspiration (ET) links the terrestrial water, energy, and carbon cycles and plays a central
35 role in water use and availability, agricultural productivity, drought intensity, and land–
36 atmosphere feedbacks¹⁻⁷. Demand for accurate ET information is accelerating across scientific,
37 operational, and policy domains as water systems face compounding pressures, including climate
38 change-driven increases in atmospheric evaporative demand and drought⁸⁻¹⁰, expanding
39 irrigation and freshwater depletion¹¹⁻¹³, and intensifying competition for water rights across
40 farms, irrigation districts, sectors, states, and nations¹⁴⁻¹⁶. Yet direct in situ measurements of ET
41 remain far less extensive than those of precipitation, meteorological variables, streamflow, and
42 groundwater. Across the United States, for example, only on the order of 300–400 sites measure
43 ET directly, even when currently inactive sites are included¹⁷⁻¹⁹, compared to more than ten
44 thousand meteorological stations, streamflow gauges, and groundwater monitoring wells
45 nationwide²⁰⁻²². This disparity is glaring given that ET is the second largest hydrologic flux and
46 frequently exhibits greater spatial variability, particularly across heterogeneous landscapes and
47 land cover gradients spanning multiple spatial scales²³⁻²⁶.

48 Although satellite-based ET products, such as OpenET²⁷, now provide spatially explicit
49 estimates of ET from field to regional scales, their reliability and adoption hinge on ground
50 observations for evaluation and model advancement²⁸⁻³¹. The paucity of in situ measurements
51 remains a primary constraint on integrating satellite ET products into operational water resources
52 management and contributes to a well-documented confidence gap, as limited high-quality
53 observations reduce the robustness of accuracy assessments, undermine scientific credibility, and
54 delay adoption^{32,33}. More broadly, this reflects a persistent paradox: hydrology is advancing
55 rapidly through artificial intelligence and data-driven methods, yet its observational foundation
56 remains sparse, underutilized, and fragmented—systematically constraining both scientific
57 inference and operational adoption³⁴.

58 Historically, ET has been inferred through surrogate measurements, such as pan evaporation³⁵, or
59 empirical approaches using reference ET and crop coefficients^{36,37}. Although these approaches
60 may provide useful indicators of atmospheric evaporative demand, they do not directly represent
61 actual ET, particularly over dry and heterogeneous land surfaces³⁸.

62 Direct measurements of ET are primarily from weighing lysimeters³⁹ and micrometeorological
63 techniques⁴⁰, which quantify water loss through mass balance or turbulent fluxes, respectively.
64 Most notably, the eddy covariance (EC) technique provides direct turbulent flux measurements;
65 however, like all measurement approaches, EC relies on assumptions and corrections, and
66 typically requires extensive post-processing to ensure data quality and consistency⁴¹. Networks
67 such as AmeriFlux and FLUXNET now form the backbone of ecosystem flux observations^{17-19,42-}
68 ⁴⁴.

69 The high hardware cost, technical complexity, and maintenance requirements of EC systems
70 continue to limit their spatial density^{23,45,46}, resulting in sparse observational coverage that limits

71 the scalability of ET science and broader operational application³³. These constraints also limit
72 spatial replication across representative areas of the same ecosystem, reducing the ability to
73 resolve spatial heterogeneity and increasing spatial sampling uncertainty²³. In arid and endorheic
74 environments, groundwater ET from phreatophyte shrubland and playa systems is commonly
75 estimated as the residual between total measured ET and precipitation⁴⁷, yet uncertainty in ET
76 can exceed the groundwater signal itself, rendering groundwater discharge, recharge, and basin-
77 scale water budgets poorly constrained^{48,49}, highlighting the need for physically constrained
78 measurements—particularly those that resolve the full surface energy balance—to improve
79 accuracy, diagnostic insight, and water balance closure.

80 A new generation of relatively inexpensive ET sensors is rapidly emerging, offering a pathway to
81 expand the spatial density of ET measurements^{23,50,51}. These sensors enable broader deployment
82 across landscapes and user communities not traditionally engaged in micrometeorology.
83 However, many rely on simplifying assumptions, limited diagnostics, and opaque data
84 processing, even though they may provide data of sufficient quality for management
85 applications. This evolving instrumentation landscape highlights a fundamental and unresolved
86 trade-off between the measurement reliability of research-grade EC systems and the spatial
87 coverage required for hydrology, water management, and model evaluation. As a result, a gap
88 remains between ET measurement methodologies that are both affordable and scientifically
89 robust.

90 In this Perspective, we contend that the central challenge is not identifying a single “best”
91 method but determining what hydrologic information each methodology provides, at what cost,
92 with what transparency, complexity, uncertainty, and physical constraint, and for which
93 applications it is fit for purpose. To help accomplish this goal, we introduce an ET measurement
94 ladder that organizes methods along levels of affordability, while recognizing that measurement
95 capability spans multiple, interrelated dimensions, including accuracy, physical constraint, and
96 analytical capability. We position this ladder as a tool for aligning measurement objectives with
97 resource constraints, enabling the selection of approaches that meet required levels of accuracy
98 and diagnostic capability.

99 Rather than prescribing a single solution, the ladder establishes a fit-for-purpose hierarchy of
100 observations, recognizing that different applications demand different levels of measurement
101 rigor. We show how this construct can guide the deployment, interpretation, and evaluation of ET
102 observations across research and operational contexts, diverse land covers, and user needs,
103 providing a basis for more defensible and scalable in situ ET observation strategies. By
104 comparing methodological trade-offs, observational constraints, and application needs, the
105 measurement ladder extends beyond prior method comparisons to help guide the selection,
106 interpretation, and deployment of ET measurement approaches across applications.

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109 **The ET measurement ladder**

110 Although multiple in situ approaches for quantifying ET exist (e.g., weighing lysimeters,
111 chambers, sap flow measurements, water balance methods, scintillometry), this Perspective
112 focuses on micrometeorological techniques that are most amenable to scalable deployment.
113 Other approaches are not considered here because their capacity for spatial replication remains
114 limited. Accordingly, our scope includes the research-grade benchmark EC approach, simplified
115 or attenuated EC configurations designed to reduce instrumentation costs, Bowen ratio-based
116 methods, surface renewal techniques, and indirect ET estimation models based on meteorological
117 observations.

118 Box 1 synthesizes the principal micrometeorological approaches and groups them by their
119 underlying principles, while Figure 1 presents the ET measurement ladder along with illustrative
120 site configurations. These methods differ in their instrumentation requirements, operational
121 complexity, diagnostic capability, and underlying assumptions. Even the benchmark EC method
122 relies on assumptions (e.g., stationarity and negligible advection), with uncertainties managed
123 through established corrections, quality control, and post-processing pipelines^{43,52-55}.

124 Instrumentation and cost ranges in Box 1 exclude net radiation and soil heat flux measurements.
125 While not required for EC-based methods in principle, these measurements are central to their
126 physical defensibility and are required for most other methods. They are not treated as primary
127 instrumentation here because some commercial systems estimate available energy (AE; net
128 radiation minus soil heat flux) from minimal inputs. However, available energy strongly
129 influences cost, operational complexity, and, critically, the reliability and physical constraint of
130 ET estimates¹. These distinctions are explored further in a dedicated section on the role of the
131 surface energy balance and are explicitly represented in Figures 2 and 3 through the separation of
132 methods with and without available energy measurements.

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134 **Box 1.** ET measurement capability ladder: principles, instrumentation, and assumptions.
135 Methods are organized by underlying physical principle and increasing abstraction from direct
136 flux measurement. Instrumentation for net radiation and soil heat flux used to calculate available
137 energy is excluded. (\$) represents ~2.5K USD)

Direct turbulent flux measurements

Benchmark eddy covariance (EC)⁴¹⁻⁴³: Measures turbulent water vapor flux via high-frequency (10–20 Hz) covariance between vertical wind velocity and water vapor density. Data require standard corrections (e.g., coordinate rotation, density, and spectral corrections)⁵²⁻⁵⁴. Resulting half-hourly fluxes are further subject to quality control (e.g., filtering under low-turbulence conditions), gap filling, and energy balance closure correction^{43,55}.
- Instrumentation: 3D sonic anemometer, infrared gas analyzer (>\$\$\$\$\$\$\$\$\$).
- Key assumptions: Steady-state conditions during the half-hourly block averaging period; negligible horizontal advection (homogeneous landscape and adequate fetch).

Simplified turbulent flux measurements

Attenuated eddy covariance (A-EC)^{23,24,56-58}: Applies EC principles using a lower-frequency humidity instrument. Requires correction for high-frequency attenuation, with reduced accuracy due to incomplete turbulence capture.

- Instrumentation: 3D sonic anemometer, low-frequency humidity sensor (\$\$\$\$)
- Key assumptions: EC assumptions + spectral correction for unresolved turbulence.

Limited-diagnostics eddy covariance (LD-EC)^{50,59}: Applies EC principles using simplified instrumentation (1D sonic anemometer and closed-path humidity sensor), with ET calculated on-board through proprietary processing. The absence of high-frequency raw data limits diagnostic capability and independent evaluation. Although operationally simplified, additional post-processing (e.g., quality control, gap filling, and energy balance diagnostics) is still required.

- Instrumentation: LI-COR LI-710 (\$\$)
- Key assumptions: Similar to EC, but with limited transparency for evaluating assumptions and validating flux estimates.

Surface energy balance approaches

Residual energy eddy covariance (RE-EC)⁶⁰: Measures sensible heat flux via EC, with ET derived as the residual of the surface energy balance. Differences between sonic and air temperature should be considered, as they can introduce bias in sensible heat flux estimates⁶¹.

- Instrumentation: 3D sonic anemometer (\$\$\$\$).
- Key assumptions: EC assumptions for sensible heat flux; surface energy balance closure.

Surface renewal (SR)^{62,63}: Estimates sensible heat flux from temperature ramp structures associated with turbulent surface renewal events, with ET derived as the residual of the surface energy balance. Calibration coefficients are required and may vary with site conditions. Some commercial implementations rely on proprietary algorithms for ramp calculation and available energy estimation, potentially limiting transparency and independent evaluation of the data processing workflow.

- Instrumentation: High-frequency air temperature sensor (\$).
- Key assumptions: Ramp-based heat flux estimation; surface energy balance closure.

Bowen Ratio Energy Balance (BREB)⁶⁴: Estimates the Bowen ratio from vertical gradients of temperature and humidity, assuming equal turbulent diffusivity for heat and water vapor—an assumption that may break down under advective conditions. ET is derived by combining the estimated Bowen ratio with measured available energy. Modified Bowen ratio approaches may instead use sensible heat flux in place of available energy⁶⁵.

- Instrumentation: Paired temperature and humidity sensors; the method can be implemented with inexpensive sensors, although commercially integrated systems include automatic exchange mechanisms or specialized vapor-gradient sampling, increasing total cost (\$\$).
- Key assumptions: Similar turbulent transport for heat and water vapor; surface energy balance closure.

Variance Bowen Ratio (VBR)^{61,66}: Estimates the Bowen ratio from the ratio of temperature variance to humidity variance, assuming similar correlation with vertical wind for heat and water vapor—an assumption that may degrade under advective or non-stationary conditions. ET is derived by combining the estimated Bowen ratio with measured available energy. High-frequency measurements (≥ 10 Hz) are typically required, although lower-frequency sensors are sometimes used⁶¹. Some commercial implementations estimate available energy from simplified radiation measurements to reduce instrumentation requirements.

- Instrumentation: Temperature and humidity sensors (high frequency) (<\$).
- Key assumptions: Similar turbulent transport for heat and water vapor; surface energy balance closure.

Meteorology-based ET estimation models

Crop coefficient-based model (EToKc)^{36,37}: Estimates ET by scaling reference ET—calculated from meteorological variables using the ASCE standardized Penman–Monteith equation—with crop coefficients.

- Instrumentation: Automatic weather station sited over a well-watered reference surface; nearby public weather networks may be used.
- Key assumptions: Well-watered, non-stressed, and well-characterized crop conditions, along with valid crop coefficient parameterization, which may not hold under heterogeneous or water-limited conditions.

Complementary relationship-based model (CR)^{67,68}: Estimates ET using the complementary relationship between actual ET and potential ET, typically implemented using Penman and Priestley–Taylor formulations to represent ambient potential and wet-environment conditions, respectively. Available energy may be measured or estimated from meteorological data. This category also includes equilibrium-based formulations (e.g., surface flux equilibrium)⁶⁹⁻⁷¹, which share similar assumptions but differ in their theoretical basis and implementation.

- Instrumentation: Standard meteorological data.
- Key assumptions: Strong land–atmosphere coupling; well-mixed boundary layer; and horizontally homogeneous surfaces.

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139 The ET measurement ladder provides a framework for evaluating the inherent trade-offs among
140 key attributes of ET measurement, including physical constraint, reliability, diagnostic capability,
141 maturity, affordability, and ease of use (Fig. 2). Attribute scores are qualitative but grounded in
142 widely recognized methodological characteristics and is intended to provide a consistent
143 comparative structure rather than a prescriptive ranking.

144 **Affordability**: Cost and practical feasibility of deploying and maintaining the measurement
145 system, including instrumentation, operation, calibration, and data processing requirements.

146 **Reliability**: Accuracy, consistency, and robustness of ET estimates across conditions,
147 including sensitivity to measurement error and violations of underlying assumptions.

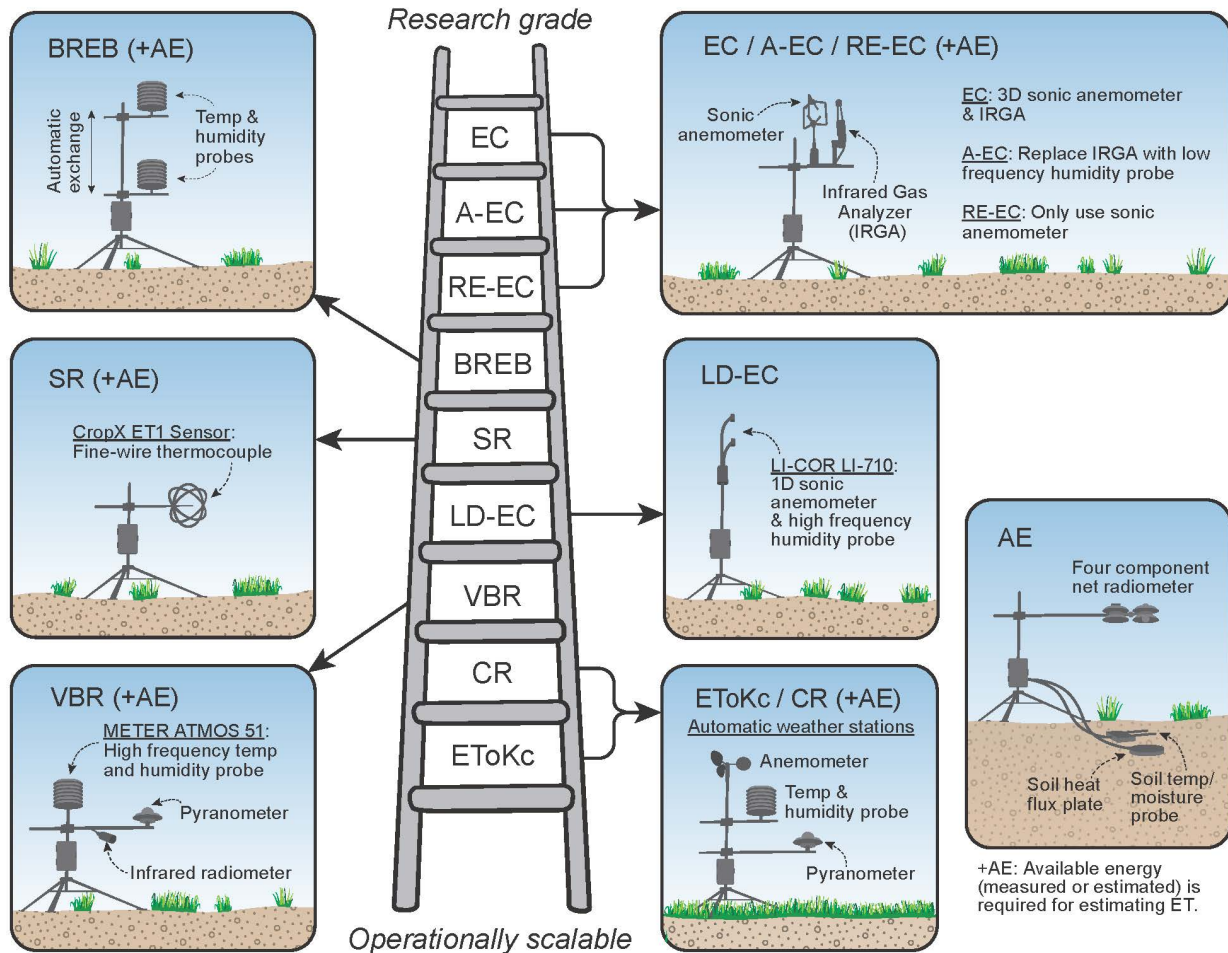
148 **Physical constraint**: Degree to which a method is grounded in first-principles relationships,
149 with minimal reliance on empirical assumptions.

150 **Diagnostic capability:** Availability of intermediate variables and raw measurements needed
151 to evaluate data quality, identify errors, and independently assess underlying assumptions.

152 **Maturity:** Level of methodological development, testing, and validation.

153 **Ease of use:** Simplicity of installation, operation, and data processing, including the level of
154 expertise required for deployment, post-processing, and interpretation.

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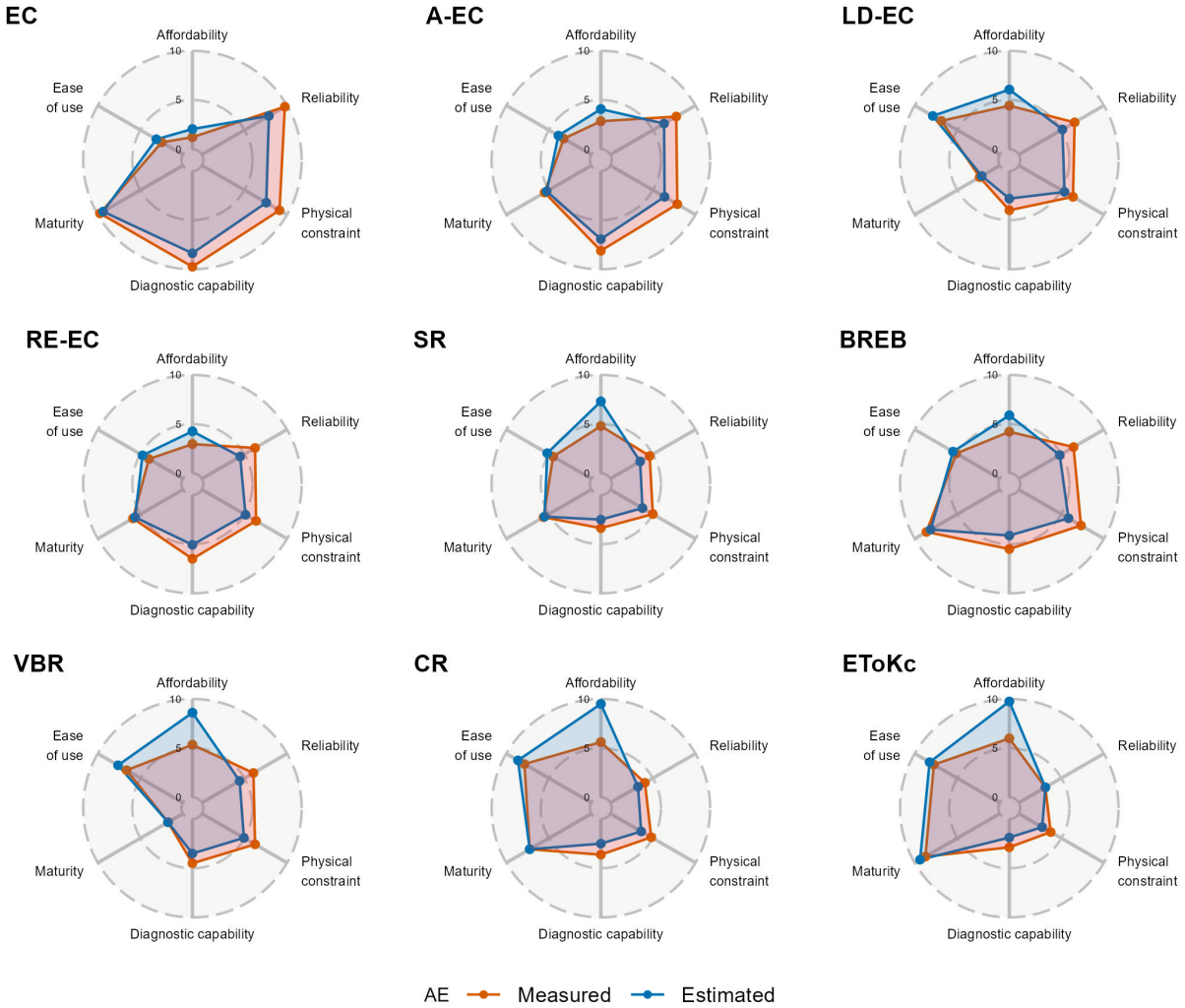


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157 **Fig. 1. ET measurement ladder and method profiles.** Methods are organized along levels of
158 affordability, from research-grade to operationally scalable approaches. Representative site
159 configurations illustrate the typical instrumentation used for each method.

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Fig. 2. Radar plots for ET measurement methods. Radar plots show relative capability across affordability, reliability, physical constraint, diagnostic capability, maturity, and ease of use for benchmark eddy covariance (EC), attenuated eddy covariance (A-EC), limited-diagnostics eddy covariance (LD-EC), residual energy eddy covariance (RE-EC), surface renewal (SR), Bowen Ratio Energy Balance (BREB), Variance Bowen Ratio (VBR), crop coefficient-based models (EToKc), and complementary relationship-based models (CR). Blue and orange lines denote configurations with and without available energy (AE) measurements, respectively. Scores are relative and represent consistent trade-offs among attributes rather than absolute performance. Affordability scores were based on approximate instrumentation costs evaluated on a logarithmic scale, together with practical considerations beyond equipment cost alone. For EToKc, measured AE is not used directly in the ET calculation but is retained as a diagnostic constraint for evaluating standardized ETo-based ET estimates relative to measured AE.

177 Higher-end systems maximize physical constraint, reliability, and diagnostic capability, whereas
178 more affordable approaches prioritize ease of use and scalability, enabling broader adoption
179 across user communities, often with reduced robustness and transparency. The appropriate
180 position on the ladder is therefore application-dependent: precision may be sufficient for
181 irrigation scheduling, whereas water balance closure demands higher accuracy and physical
182 constraint—thereby narrowing the viable set of approaches and establishing a fit-for-purpose
183 basis for selection. In practice, this framework enables users to match required accuracy,
184 temporal resolution, and diagnostic needs to an appropriate class of measurement approaches.

185 **Fit-for-purpose observations**

186 ET observations serve diverse users with varying data requirements and resource constraints. For
187 example, farmers and irrigation districts may prioritize lower cost and operational simplicity,
188 accepting higher uncertainty, whereas researchers may require higher accuracy and robustness at
189 greater cost. Water regulatory bodies and the scientific community share a common reliance on
190 ET observations; however, their priorities diverge in terms of the precision, accuracy, and
191 confidence required to support operational decisions versus scientific inquiry. A key need is
192 spatial replication across land covers and watersheds to support water resources management²³.
193 In research settings, affordable sensors are often deployed alongside EC systems for validation,
194 redundancy, and to enable spatial replication under both homogeneous and heterogeneous land-
195 cover conditions^{23,24,26}. In other cases, independent, high-accuracy measurements with well-
196 characterized uncertainty are required (e.g., satellite validation and phreatophyte groundwater ET
197 estimation)^{17,28,47,48}. Conversely, applications such as irrigation scheduling may prioritize
198 temporal variability and relative changes over absolute ET accuracy⁷².

199 These differing objectives imply that no single method is universally optimal. Where
200 affordability and reliability are both critical (e.g., watershed-scale water balance studies), optimal
201 solutions lie along the Pareto front (Fig. 3a). The Pareto front represents a boundary of non-
202 dominated solutions, where improving one attribute requires accepting lower performance in
203 another. Methods such as LD-EC lie on the front, reflecting a balance between cost and
204 reliability. When affordable sensors complement EC systems, diagnostic capability may
205 outweigh marginal gains in reliability. The trade-off therefore shifts (Fig. 3b) with LD-EC
206 becoming suboptimal due to limited diagnostic transparency. Thus, optimal solutions depend on
207 which attributes are prioritized, reinforcing the need for application-aligned ET measurement
208 strategies.

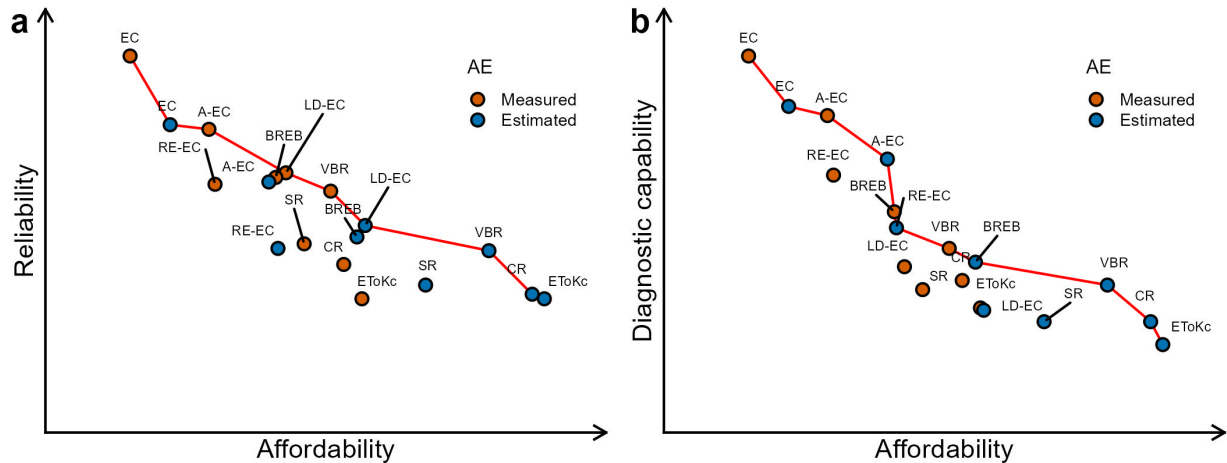
209 The scores used in Figures 2 and 3 are qualitative and represent general tendencies rather than
210 definitive rankings. Reliability, in particular, varies with temporal scale and site conditions (Fig.
211 4). For example, Bowen ratio methods may perform poorly at sub-daily time scales but improve
212 when aggregated to daily or longer periods⁷¹; similar scale dependencies exist for model-based
213 approaches⁷¹. Thus, required temporal resolution strongly influences method selection (Fig. 4a).

214 Method performance also depends on environmental conditions (Fig. 4b). In irrigated
215 agriculture, EToKc can provide useful field-scale estimates when crop coefficients and water-
216 stress conditions are well characterized, whereas CR methods may be better suited to rain-fed
217 and natural ecosystems where regional-scale land–atmosphere coupling assumptions are more
218 defensible^{36,67,68,73}. Bowen ratio approaches rely on similarity assumptions that can break down
219 under strong advection or stable atmospheric conditions, leading to degraded performance^{45,74,75}.
220 Specifically, VBR can underestimate ET under conditions with downward sensible heat flux, as
221 temperature variance alone cannot capture the direction of the turbulent flux^{45,61,76}. The energy
222 balance residual methods (RE-EC, SR) tend to perform best in well-watered systems, where ET
223 is relatively large⁶³, but they may be less reliable under low-ET conditions because uncertainty in
224 measured energy balance components can represent a larger fraction of the energy balance
225 residual. In addition, these surface energy balance–based methods may perform poorly in
226 environments where AE cannot be well constrained, such as wetlands or open water systems,
227 where heat storage and horizontal heat transport in water can be substantial but difficult to
228 measure or estimate⁴⁵.

229 Simplified turbulent flux approaches (A-EC and LD-EC) are also subject to greater uncertainty
230 under certain environmental conditions. These methods use lower-cost humidity sensors rather
231 than conventional infrared gas analyzers, which may face greater challenges in capturing high-
232 frequency water vapor fluctuations under humid conditions (e.g., the LI-710 is specified for
233 operation only up to ~85% relative humidity⁷⁷). LD-EC relies on one-dimensional sonic
234 anemometers, limiting the application of coordinate rotation corrections and making
235 measurements more vulnerable to errors in sloped terrain. In addition, the absence of full wind
236 vector measurements limits flux footprint characterization, making LD-EC better suited for
237 spatially homogeneous environments. These considerations underscore that method performance
238 is inherently context-dependent, with temporal scale and site characteristics jointly governing the
239 choice of ET measurement approaches.

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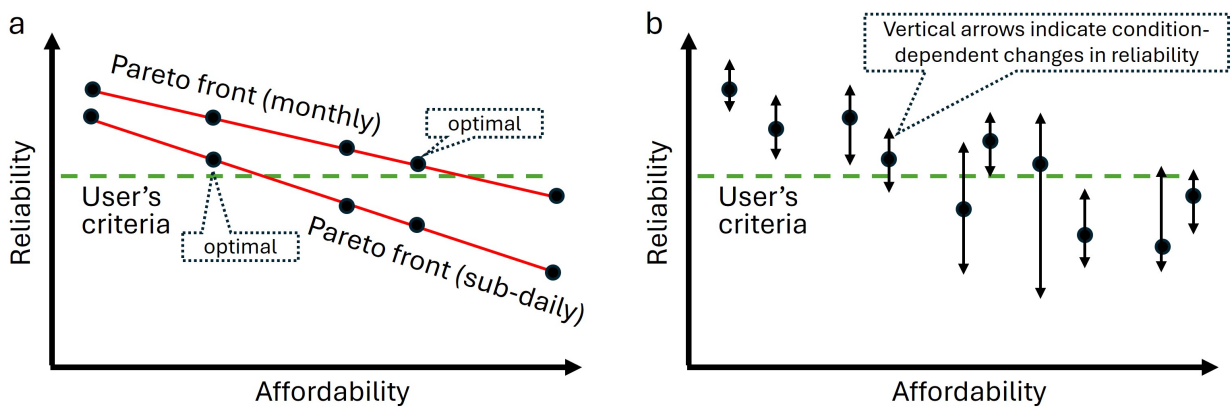
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243 **Fig. 3. Trade-offs among affordability, reliability, and diagnostic capability across ET**
 244 **measurement approaches.** Points represent ET methods evaluated against reliability (a) and
 245 diagnostic capability (b). Red lines denote the Pareto front. The fronts shift with the performance
 246 metric considered, indicating that optimal methods vary with application needs (e.g., reliability
 247 versus diagnostic capability). Measured and estimated AE configurations are shown separately
 248 where applicable.

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251 **Fig. 4. Conceptual illustration showing that optimal ET measurement solutions depend on**
 252 **user-defined performance requirements and trade-offs among methods.** Green dashed lines
 253 indicate user-defined performance requirements. (a) Shifts in the Pareto front across temporal
 254 scales. (b) Changes in individual method reliability under different observation conditions.

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256 **Beyond ET sensing: the role of surface energy balance**

257 While not required for all methods, AE measurements provide a critical benchmark for
 258 evaluating closure of the surface energy balance. Figures 2 and 3 contrast ET methods with and
 259 without AE, highlighting the central role of AE in reliability and diagnostic capability. Surface

260 energy balance methods (RE-EC, SR, BREB, VBR) are directly sensitive to AE, a dominant
261 source of uncertainty in ET estimation^{1,78}. While AE is often estimated rather than directly
262 measured in CR-style ET models, these approaches still depend on AE inputs, and direct
263 measurements of the net radiation and soil heat flux components of AE can provide additional
264 physical constraints⁷⁹. In contrast, EToKc does not directly use measured AE because the
265 standardized ASCE ETo formulation is defined for reference grass or alfalfa surfaces with
266 specified surface characteristics and radiation assumptions, and crop coefficients are specific to
267 their respective reference ETo calculations.

268 Although EC-based methods do not require AE to compute fluxes, concurrent AE measurements
269 remain critical for evaluation. Under ideal conditions (e.g., negligible advection, storage, and
270 other minor energy terms), AE equals the sum of sensible and latent heat fluxes⁸⁰. Deviations
271 from this balance, widely known as the energy balance closure problem, are routinely used to
272 assess EC data quality⁸⁰⁻⁸⁴. This issue also has important implications for method comparisons:
273 eddy covariance-based methods (EC, A-EC, LD-EC) generally produce lower ET estimates than
274 Bowen ratio-based methods (BREB, VBR), while energy balance residual approaches (RE-EC,
275 SR) produce higher estimates. Accordingly, EC measurements without AE are often excluded
276 from satellite validation, and closure-based corrections are commonly applied^{17,43,85},
277 underscoring the importance of AE measurements for high-reliability applications.

278 A key limitation is that measuring net radiation and soil heat flux adds cost and operational
279 complexity. Incorporating net radiometers and soil heat flux measurements can increase costs by
280 ~\$10,000, often exceeding the cost of simplified ET measurement systems. As a result, many
281 commercial systems estimate AE using simplified measurements and empirical approaches⁷⁸.
282 While potentially suitable for some operational applications (e.g., irrigation scheduling), such
283 simplified AE estimates are generally not recommended when high reliability is required.

284 Net radiation, the dominant energy input to the land surface, is most reliably measured using
285 four-component radiometers, which are more costly than single- or two-component
286 alternatives^{86,87}. Four-component measurements are preferred, as they enable detailed quality
287 control⁸⁸, including comparison of incoming shortwave radiation to clear-sky conditions⁸⁸. When
288 cost constraints limit instrumentation, measurements can be prioritized as follows: (1) incoming
289 shortwave radiation, (2) outgoing longwave radiation (or surface temperature with assumed
290 emissivity), (3) incoming longwave radiation, and (4) outgoing shortwave radiation. Incoming
291 shortwave radiation is the primary driver of surface energy input and therefore highest priority.
292 Outgoing longwave radiation is second, but difficult to estimate without surface temperature¹. In
293 its absence, near-surface air temperature may be used under an isothermal assumption³⁷, though
294 bias may be substantial under dry conditions. Incoming longwave radiation can be estimated
295 from air temperature and humidity and is a lower priority^{37,89}. Outgoing shortwave radiation can
296 be approximated from albedo and incoming shortwave radiation and is least critical.

297 Surface soil heat flux (G_0) is often a relevant component of AE at sub-daily time scales and in
298 moist soils⁹⁰. However, affordable methods frequently rely on empirical approximations or
299 assume G_0 is negligible at daily time scales⁵⁸. Soil heat flux plates measure flux at depth,
300 requiring correction for heat storage above the plate to estimate surface flux (G_0). Standard
301 corrections (e.g., calorimetric approaches) require additional soil temperature and moisture
302 sensors, along with soil properties, increasing cost and operational complexity⁹⁰. A simplified
303 harmonic correction, based on the harmonic framework of Leuning, et al. ⁸⁰, or variant where
304 peak surface heat flux is assumed to occur near solar noon, could reduce instrumentation and
305 data-processing burden. Although this approach may underestimate peak daytime and
306 overestimate nighttime fluxes due to neglected higher-order harmonics⁹⁰, it provides a more
307 physically consistent alternative to simple approximations or neglecting G_0 , improving reliability
308 while maintaining affordability.

309 **Toward fit-for-purpose ET observations: needs and opportunities**

310 Affordable ET sensors are emerging rapidly, but many remain at early stages of maturity,
311 creating both challenges and opportunities. Advancing these approaches requires coordinated
312 progress from method development to integrated, multi-tier observation strategies. Methods such
313 as A-EC, LD-EC, and VBR occupy favorable positions in the trade-off space (Fig. 3), but their
314 reliability remains insufficiently characterized. Systematic intercomparison across diverse land
315 covers and climates is essential to establish confidence and identify context-dependent
316 limitations in ET estimates ^{45,59,91}. This is critical because these approaches may represent
317 optimal solutions under resource constraints despite lower maturity.

318 Improving transparency and diagnostic capability is essential for building confidence in ET
319 estimates, particularly for LD-EC and some commercial SR implementations. Proprietary
320 processing pipelines often limit access to intermediate variables and raw data, constraining
321 independent evaluation and reducing scientific interpretability. Providing access to key
322 diagnostics, processing assumptions, and quality indicators would substantially enhance
323 scientific and operational value.

324 Method-specific advances are also needed. For A-EC, improving spectral corrections and
325 developing standardized, user-friendly workflows are key priorities for broader adoption. For
326 VBR, limitations under strong advection highlight the need for additional diagnostics⁶¹. For
327 example, deviations from expected temperature–humidity correlations may indicate advection,
328 high atmospheric stability, or violation of underlying similarity assumptions and support quality
329 control^{76,92}. Further evaluation is needed to formalize these approaches.

330 Benchmark measurements have long played a central role in improving more scalable ET
331 estimation approaches. For example, crop coefficient approaches have been refined using EC
332 flux observations to improve Kc parameterization across crops, climates, and management
333 conditions⁹³, while CR models have likewise been evaluated and calibrated against EC
334 measurements⁶⁸. The same iterative logic is now needed for emerging intermediate-tier methods.

335 Continued side-by-side evaluation of A-EC, LD-EC, and VBR against research-grade EC
336 systems can identify systematic biases, refine correction procedures, and define the conditions
337 under which lower-cost methods provide reliable, fit-for-purpose ET estimates.

338 A central opportunity lies in integrating measurements across multiple tiers. Rather than
339 replacing research-grade systems, affordable sensors can complement EC observations by
340 enabling spatial replication. In such systems, EC measurements serve as benchmarks for
341 calibration, validation, and process interpretation, while lower-cost sensors provide spatial
342 coverage^{23,24,26}. This integration enables applications such as watershed-scale water balance
343 assessment and satellite ET evaluation, where both accuracy and spatial representativeness are
344 required.

345 Advancing affordable ET observations therefore requires coordinated progress in evaluation,
346 transparency, and system integration. Aligning measurement strategies with application needs
347 and leveraging complementary strengths will enable a more distributed and scalable observation
348 system. Moving beyond ad hoc adoption toward a coordinated, application-aligned observation
349 paradigm is essential to deliver credible, scalable monitoring and management of water and
350 climate processes in an increasingly resource-constrained and variable world.

351

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