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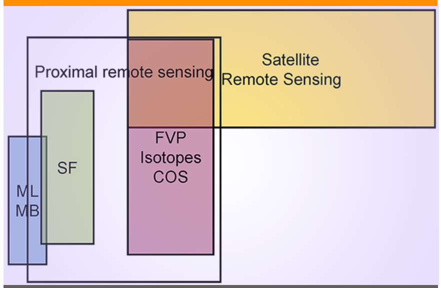

Measurement and Partitioning of Evapotranspiration for Application to Vadose Zone Studies

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Partitioning evapotranspiration (ET) into its constituent components, evaporation (*E*) and transpiration (*T*), is important for numerous hydrological purposes including assessing impacts of management practices on water use efficiency and improved validation of vadose zone models that parameterize *E* and *T* separately. However, most long-established observational techniques have short observational timescales and spatial footprints, raising questions about the representativeness of these measurements. In the past 15 yr, new approaches have allowed ET partitioning at spatial scales ranging from the pedon to the globe and at long timescales. In this update, we review some recent methodological developments for partitioning ET. These include micrometeorological approaches involving the flux variance partitioning of high-frequency eddy covariance observations and proxies for photosynthesis and transpiration such as measurements of isotopic fractionation and carbonyl sulfide uptake. We discuss advances in partitioning the energy balance between canopy and soil using remote sensing. We conclude that the flux variance partitioning with raw eddy covariance data and the two-source energy balance approaches with remote sensing platforms may have the greatest potential for partitioning ET, in part because large public repositories of eddy covariance and satellite data could be readily reprocessed to partition ET.

Abbreviations: COS, carbonyl sulfide; CRDS, cavity ring-down spectroscopy; ECV, eddy covariance; ET, evapotranspiration; FVP, flux variance partitioning; ICOS, integrated cavity output spectroscopy; TSEB, two-source energy balance; UAV, unmanned aerial vehicle; WUE, water use efficiency.

Core Ideas

- Partitioned evaporation and transpiration is important for validating vadose zone models.
- New partitioning approaches overcome spatiotemporal limitations of previous methods.
- Some techniques can be applied to existing data to increase *E* and *T* observations.
- Intercomparisons of approaches at a variety of field sites are needed to better assess each approach.

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Evapotranspiration (ET) is one of the largest hydrologic fluxes on Earth, accounting for approximately 60% of terrestrial precipitation globally (Haddeland et al., 2011) or about 6.5 to 6.8 × 10^4 km^3 water yr^{-1} (Oki and Kanae, 2006; Jung et al., 2010; Miralles et al., 2011). Evapotranspiration is clearly one of the most important boundary conditions for vadose zone studies, and it is well recognized that there are numerous controls on the amount of ET, including meteorological and vegetation conditions (Williams et al., 2012; Puma et al., 2013) and soil moisture (Seneviratne et al., 2010; Jung et al., 2010). Depending on the temporal and spatial scale, ET can be observed with a wide variety of techniques including lysimetry (Gee and Hillel, 1988; Poss et al., 2004; Johnson et al., 2005), micrometeorology (including eddy covariance) (Snyder et al., 1996; Todd et al., 2000; Hemakumara et al., 2003; Williams et al., 2004), satellite remote sensing (Bastiaanssen et al., 1998; Allen et al., 2007; Senay et al., 2013), water balance (Wilson et al., 2001; Zeng et al., 2014), or a combination approach (Nagler et al., 2005; Anderson and Goulden, 2009; Goulden et al., 2012; Zhang et al., 2015). Evapotranspiration can be modeled with a variety of models, ranging from complex, mechanistic equations (Monteith, 1965) to simple, empirical formulae (Makkink, 1957; Hargreaves and Samani, 1985) as well as intermediate approaches (Priestley and Taylor, 1972). In managed landscape settings, ET is commonly parameterized by using a reference ET to estimate meteorological demand and a crop or landscape coefficient to represent the ability of the land surface to evaporate and transpire (Hargreaves, 1994; Allen, 2000). The choice of a reference ET equation and crop coefficient is largely dependent on the quantity and quality of meteorological and phenological data available to parameterize the ET model (Droogers and Allen, 2002; Satti et al., 2004; Kamble et al., 2013). When sufficient data are available, the FAO-56 model (Allen et al., 1998) is a common standard, but simpler or alternative models should be used if the underlying reference surface meteorological data are not available.

For vadose zone studies, partitioning ET into its respective plant and soil components, transpiration (T) and evaporation (E), is crucial for advancing process-based understanding of vadose zone fluxes in different environments. Most prominent vadose zone hydrologic models (e.g., HYDRUS, SWAP, Root Zone Water Quality Model) parameterize E and T separately. Transpiration is often parameterized using a distributed sink term that prescribes root water uptake at varying soil depths based on the root distribution (van Dam et al., 2008; Ma et al., 2012; Šimůnek et al., 2012). Transpiration may be reduced below potential rates by additionally parameterizing the sink as a function of soil water and salinity stress (Skaggs et al., 2006). Potential soil E is calculated for most models from atmospheric demand and the extent of the exposed soil surface. Actual E is then regulated by moisture conditions in the surface soil. Regulators can include the fraction of wet soil surface (Ahuja et al., 2000) or soil surface resistance (Tang and Riley, 2013; Decker et al., 2017). While modeled E and T can be combined and compared against measured ET, it is clearly superior to assess E and T individually to advance model parameterizations, particularly with large uncertainties in root depths (Wang-Erlandsson et al., 2016) and soil hydraulic properties (Baroni et al., 2010) across large spatial scales. The importance of accurate E and T in vadose zone modeling is crucial for applications such as predicting contaminant fate and transport, where the distribution of contaminants can be greatly affected by the partitioning of ET; a higher E can result in capillary action that can concentrate contaminants on the soil surface, whereas a higher T may result in higher contaminant concentrations in the root zone. Outside of the soil models mentioned above, E and T observations are useful for assessing plant growth models (Jones et al., 2003; Keating et al., 2003); for assessing irrigation practices, such as mulching (Li et al., 2013) and subsurface drip irrigation (Lamm and Trooien, 2003; Hanson and May, 2004), that are designed to improve crop water use efficiency by reducing soil E; and for evaluating linkages between plant physiology and water and C cycles (Dubbert et al., 2014).

Partitioning of ET into E and T has been of interest since the earliest stages of crop, soil, and forest modeling and observations (Ritchie, 1972; McNaughton and Black, 1973; Rosenthal et al., 1977). Since these early measurement and modeling studies, there have been numerous developments with partitioning ET. These include development of instruments to measure individual components of ET, including microlysimeters (Boast and Robertson, 1982; Shawcroft and Gardner, 1983; Evett et al., 1995), soil and plant chambers including using isotopic approaches (Stannard and Weltz, 2006; Rothfuss et al., 2010), micro-Bowen-ratio energy balance (Ashktorab et al., 1994; Holland et al., 2013), and sap flow sensors (Sakuratani, 1981; Granier, 1985; Burgess et al., 2001). An excellent review and synopsis of these approaches can be found in Kool et al. (2014). These methods have strong limitations in that (i) they all work on small spatial scales (<0.1 to $\sim$5 m^2) thus raising issues of spatial representativeness for larger areas, (ii) most can be used for a few hours to a few days at a time, and (iii) some of these approaches can significantly modify the volume that they observe, which reduces their usefulness for vadose zone observations and modeling at larger spatiotemporal scales. Other approaches exist to partition ET on longer time scales at field to global scales using leaf area index and/or gross primary productivity (Kemp et al., 1997; Zhou et al., 2016; Scott and Biederman, 2017), but these approaches assess only mean partitioning and can have significant difficulties where vegetation responds more slowly to hydrologic changes or where primary productivity has asynchrony with precipitation and peak ET.

Within the past 15 yr, there have been significant advances in field-scale observational techniques to partition ET into its respective components, and these recent innovations are the focus of this update. These advances include new micrometeorological approaches as well as advances in proximal remote sensing technologies to differentiate energy exchange between canopy and soil. We focus first on methods that can use raw and processed observations from the widely used eddy covariance method because these methods could be applied to existing data for new analyses and insight. We then move on to recent instrumental developments with isotopic micrometeorological methods and field-scale remote sensing instruments. Finally, we discuss some key research needs for partitioning of ET and the next steps to better integrate partitioned ET observations into vadose zone studies.

Advances in Micrometeorological Flux Partitioning

Flux Variance Partitioning

One major recent advance in partitioning ET has been the development of an approach to directly parameterize E and T by analyzing the correlation structure of high-frequency eddy covariance (ECV) time series data (Scanlon and Sahu, 2008; Scanlon and Kustas, 2010). This approach, which we hereafter call flux variance partitioning (FVP), is a significant advance for directly partitioning ET (and C) fluxes at high temporal resolution with minimal additional information besides the high-frequency C, water, and temperature observations already measured as part of the ECV method. Flux variance partitioning works by decomposing the high-frequency CO_2 and H_2O observations into stomatal and non-stomatal components using a parameterized leaf-level water use efficiency (WUE) value. The complex system of equations and wavelet analysis approach for decomposing the CO_2 and H_2O scalars are well described elsewhere (Scanlon and Sahu, 2008; Scanlon and Kustas, 2010; Palatella et al., 2014) and are not reproduced here in the interest of brevity. Theoretically, in an atmospheric layer where the transfer of H_2O and CO_2 across leaf stomata during photosynthesis was the only source–sink for H_2O and CO_2, high-frequency ECV measurements of CO_2 and H_2O would be related linearly with a slope equivalent to the WUE. In the FVP method, correlation analysis is used to analyze the extent to which actual measured data deviate from this hypothesis and thereby provide an estimate of the fractional contribution of other sinks and sources (direct evaporation, non-stomatal respiration) to the total measured fluxes.

Leaf-level WUE has been extensively observed across a multitude of global ecosystems, with measurements often made with leaf chambers (Long et al., 1996; Wullschleger et al., 1998; Damour et al., 2010). Because it is the ratio of leaf-level transpiration to photosynthetic flux, WUE is controlled by the diffusion of CO_2 into and H_2O out of the leaf:

$$\mathrm{WUE} = 0.7\frac{\overline{c}_a - \overline{c}_i}{\overline{q}_a - \overline{q}_i} \qquad [1]$$

where c is the CO_2 concentration; q is H_2O as expressed in terms of specific humidity; a and i subscripts represent atmospheric and leaf intercellular concentrations, respectively; and 0.7 is the ratio of diffusion through stomata and near-leaf convection for CO_2 and H_2O (Campbell and Norman, 1998, p. 247–278). Because the air in leaf intercellular spaces is saturated with respect to humidity, q_i is parameterized as the saturation vapor pressure of the leaf temperature. Existing FVP approaches often effectively assume that leaf temperature equals air temperature, thus $q_a - q_i$ is equivalent to the vapor pressure deficit (Scanlon and Kustas, 2010; Sulman et al., 2016). With c_a and q_a being easily parameterized from the ECV tower measurements, this leaves intercellular CO_2 (c_i) as the main unknown.

Given its importance to the FVP algorithm, having robust WUE estimates are crucial for improving algorithm convergence and accuracy. One possible improvement in WUE is to use measured leaf temperature to parameterize q_i as opposed to parameterizing leaf temperature based on air temperature. This can be done with many existing ECV towers due to the use of infrared sensors to measure canopy temperature. A second approach would be to improve c_i parameterization. There is widespread evidence of c_i/c_a variability with the vapor pressure deficit across both C_3 and C_4 photosynthetic pathways (Morison and Gifford, 1983; Katul et al., 2009). This provides a convenient way to parameterize c_i using meteorological observations from the tower and to integrate leaf-level observations from chamber and cuvette approaches. Better constraints on the c_i/c_a relationship could help improve FVP performance, especially in environments where plants have substantial stress. To illustrate the potential impact of WUE on FVP performance, we partitioned fluxes from a peach [*Prunus persica* (L.) Batsch] orchard in California using different c_i and q_i parameterizations (Table 1). Information about the site and flux data were reported by Anderson et al. (2017). Parameterizing c_i/c_a as a linear or square root function of the vapor pressure deficit consistently increased the E/ET ratio for this site and season compared with a constant c_i/c_a ratio or holding c_i constant (Table 1). Using measured leaf temperature to parameterize q_i showed a differential seasonal effect on fluxes; early season (March and April) E/ET ratios were lower with measured leaf temperatures than with air temperatures, but they became higher later in the season (Table 1).

Along with work on improving WUE estimation, future work on FVP should also focus on improving the computational efficiency of the algorithm and the user friendliness of the tool. Skaggs et al. (unpublished data, 2017) recently developed the open source Fluxpart code, which features a more efficient implementation of the FVP algorithm. Computational limitations have reduced the use of the tool for ECV analysis despite the great potential for using FVP for analyzing the large number of existing ECV datasets (nearly 1000 sites and >7000 site-years) currently stored by international flux networks (Chu et al., 2017). Furthermore, ECV stations are increasingly user friendly and lower cost, thus

Table 1. Mean monthly fraction of evaporation as a percentage of total evapotranspiration for the 2014 peach data (Anderson et al., 2017) with flux variance partitioning run with different leaf intercellular CO_2 concentration (c_i) and specific humidity (q_i) parameterizations.†

Month	CPPM	CPPM_IR	CR	CR_IR	linear	linear_IR	SQ	SQ_IR	SQC	SQC_IR
	%									
3	42	33	42	33	29	21	36	26	36	26
4	38	34	39	36	32	29	36	33	36	33
5	31	31	35	35	33	34	35	35	35	35
6	28	31	33	36	44	46	40	43	40	43
7	26	33	32	40	42	49	39	46	39	46
8	16	20	27	31	31	37	31	36	31	36
9	22	27	29	34	35	40	33	39	33	39
10	34	41	45	52	36	45	43	51	43	51

† CPPM, constant c_i (in ppm); CR, constant ratio of c_i to atmospheric CO_2 concentration (c_a); linear, c_i/c_a ratio based on linear relationship with generic C_3 coefficient with vapor pressure deficit (VPD); SQ, c_i/c_a ratio based on square root relationship with VPD and generic C_3 coefficient; SQC, c_i/c_a ratio based on square root relationship with VPD and species-specific coefficient based on leaf gas exchange observations; IR, q_i parameterized from measured leaf temperatures, while other columns had q_i parameterized from air temperatures.

increasing their prevalence. Many research grants involving ECV observations require that data be publicly archived, but the requirement often applies only to processed fluxes and not to the much larger high-frequency time series observations that are often stored only locally by researchers. Techniques to partition ET with processed fluxes have been developed using mean leaf-level WUE (Zhou et al., 2016), but these partition ET only at longer time scales, thus missing changes in *E* and *T* due to wetting and drying events. Some networks (such as Ameriflux, http://ameriflux.lbl.gov/) have the ability to store and disseminate the high-frequency observations. More effort should be made to encourage project investigators to upload high-frequency data to these networks to enable reprocessing with methods such as FVP.

Approaches Based on Stable Isotopes

It has long been recognized that ET fractionates surface and soil water by preferentially removing lighter stable isotopologues (e.g., ^{1}H instead of ^{2}H and ^{16}O instead of ^{18}O) of water (Craig and Gordon, 1965; Wang and Yakir, 2000). Partitioning of ET using the isotopic composition of atmospheric water vapor relies on the differential isotopic fractionation of transpiration compared with evaporation due to isotopic enrichment of water within the leaf (Moreira et al., 1997). Until recently, isotopic observations were primarily performed with field traps to collect sufficient water vapor (e.g., Yakir and Wang, 1996) or with flasks to capture atmospheric air samples for laboratory analysis, most frequently with isotope ratio mass spectrometry (Ehleringer et al., 2000). This past reliance on laboratory analysis limited the number of samples, resulting in studies of shorter duration or with more discrete analysis that were less easily compared with potentially rapid vadose zone changes.

Analytical approaches to interpreting isotopic data have previously focused on mixing model type approaches (Williams et al., 2004), with many studies using a Keeling Plot (Keeling, 1958), where the isotopic value of each water sample is plotted against the inverse of water vapor concentration. The *y* intercept of the Keeling Plot represents the mean isotopic signature of ET (δET). The isotopic signature of the *E* and *T* components can be measured at a small scale in the field to provide all the parameters in the mixing model for estimating the fraction of ET in *E* and *T* (Yakir and Sternberg, 2000). Measuring δET and mixing models have been shown to work well for partitioning ET during drier periods where the isotopic signature of the soil water is not rapidly changing. However, the mixing model approach has substantially more difficulty when recent precipitation or irrigation rapidly changes the isotopic soil water signature (Phillips and Gregg, 2003; Williams et al., 2004).

Starting in the 2000s, rapid advances in analytical instrumentation enabled rapid observation of atmospheric H_2O isotopologues without the need for collecting samples for laboratory analysis, allowing rapid and more frequent and continuous application of the analytical and mixing model approaches discussed above. Tunable diode laser absorption spectroscopy (TDLAS), originally applied to isotopologues of CO_2 for C flux partitioning (Bowling et al., 2003), originally relied on a temperature-controlled lead salt laser to observe both $^{18}O/^{16}O$ and $^{2}H/^{1}H$ absorption lines near 1500 cm^{-1} (Lee et al., 2005) and required active temperature control due to the temperature dependence of absorbance and frequent calibrations against known gas standards, which limited its utility. Newer versions can use a thermoelectrically cooled interband cascade laser that overcomes the temperature drawbacks (Brown et al., unpublished data). Tunable diode laser absorption spectroscopy has been successfully used for both continuous observation of atmospheric water vapor isotopic composition (Wen et al., 2008) and for ECV isoflux observations due to its higher temporal sampling capability compared with flask sampling (Griffis et al., 2010). Another major advancement has been the development of low-power laser cavity spectroscopic sensors, including integrated cavity output spectroscopy (ICOS) and cavity ring-down spectroscopy (CRDS), which can be deployed to field sites for extended, high-precision observations (Wang et al., 2009; Iannone et al., 2010; Richardson et al., 2012). Both ICOS and CRDS have been successfully used to partition ET across a variety of ecosystems and climates (Dubbert et al., 2013; Good et al., 2014; Wen et al., 2016; Lu et al., 2017). However, the current sampling frequency for H_2O isotopologues (1–2 Hz) is too slow for ECV, especially over short canopy landscapes. One possible future solution may be quantum cascade laser spectroscopy (Wang et al., 2014), which has already been used to partition CO_2 fluxes measured with ECV (Sturm et al., 2012). Along with atmospheric isotopic analyses, recent advances in high-frequency, in situ observations of soil water isotopic composition (Gaj et al., 2016) enable the integration of atmospheric and soil water isotopic signatures to assess differential fractionation from *E* and *T*. Improvements in ICOS and CRDS that enable higher frequency ($\sim$10 Hz) sampling would also be useful for partitioning fluxes using ECV. Finally, because all commercially available isotopic analyzers are closed path instruments, tubing considerations, such as tube length, tube material composition, flow rate, filtering, and potential heating requirements, must be accounted for to avoid measurement errors due to the interaction between H_2O vapor and tube walls (Ibrom et al., 2007; Mammarella et al., 2009).

Other Tracers

Along with isotopes, other atmospheric trace gases could be used to partition ET. One potential tracer for ET partitioning could be carbonyl sulfide (COS). One major atmospheric sink of COS is photosynthesis, as it has similar pre-photosynthesis pathways as CO_2, and COS is not emitted during respiration. Thus, COS has been used to partition CO_2 fluxes into photosynthetic and respiratory fluxes (Stimler et al., 2010; Asaf et al., 2013; Billesbach et al., 2014). Given the strong relationship between photosynthesis and *T* and extensive work on parameterizing leaf-level WUE, photosynthesis observations using COS could be used to partition ET (Seibt et al., 2010). However, substantial work is needed on understanding the leaf-level conductance of COS as well as improved understanding of the atmospheric budget and fluxes of COS, including soil sources and sinks (Bunk et al., 2017), to make this partitioning robust (Wohlfahrt et al., 2012).

Advances in Remote Sensing of Partitioned Fluxes

Satellite remote sensing has been extensively used to observe ET globally (Kustas and Norman, 1996; Li et al., 2009), with most approaches using thermal bands to observe ET as a residual from the energy balance, multispectral bands to observe vegetation health in conjunction with evaporative demand, or some combination thereof. While the majority of satellite remote sensing studies do not partition ET, several approaches can separate E and T. One is the two-source energy balance (TSEB) approach. Originally proposed by Norman et al. (1995), the TSEB relies on solving the surface energy budget separately for the plant canopy and soil, with the assumption that the residual energy terms represent T and E, respectively. The TSEB, including its successor algorithms Atmosphere Land EXchange Inverse (ALEXI) and disaggregated ALEXI, has been applied with a variety of satellite platforms, spatial and temporal scales (Fig. 1), and study regions (Anderson et al., 2011; Choi et al., 2011; French et al., 2015). The TSEB has been incorporated into observational ET systems (Otkin et al., 2014). Along with the TSEB, other modeling approaches have used satellite inputs to parameterize E and T using a variety of models, including Penman–Monteith (Cleugh et al., 2007; Mu et al., 2011) and the Soil–Water–Atmosphere–Plant model (Kroes et al., 2000).

Disaggregation approaches involve using higher spatial resolution multispectral imagery to estimate subpixel temperature variations in thermal pixels with relatively coarse (>1 km) spatial resolution (Gao et al., 2006; Anderson et al., 2011; Bisquert et al., 2016). Disaggregation has been shown to be a good way to integrate coarse-spatial-resolution thermal imagery that has higher temporal resolution with higher spatial resolution imagery with less frequent revisit intervals. With the highest resolution multispectral platforms (e.g., SPOT and Sentinel 2A/2B), ET could be partitioned at up to 10-m spatial resolution. Near-surface proximal remote sensing from ground-based and aerial sensors use many of the same principles as satellite remote sensing, but they can take advantage of improvements in capabilities and reduced costs from newer sensors and platforms such as unmanned aerial vehicles (UAVs). The TSEB methodology, for example, has been applied to both ground-based point infrared sensors (Sánchez et al., 2008; Colaizzi et al., 2012) and to UAV thermal imagery (Morillas et al., 2013; Hoffmann et al., 2016). With proximal remote sensing, ET can be partitioned at the submeter scale.

Satellite and proximal remote sensing have multiple advantages including (i) the ability to sample a wide variety of spatial scales from the pedon to the globe, (ii) the ability to partition ET with minimal measurement interference (similar to micrometeorology and substantially less than sap flow or micro-lysimetry), (iii) the potential ability to partition E and T in a routine, observational manner with relatively low expense per area to the end user, and (iv) the ability to relate remotely sensed variables such as canopy cover to other observations of E and T partitioning (Anderson et al., 2017). One of the main disadvantages of remote sensing partitioning is the temporal discontinuity of most remote sensing platforms. With the exception of ground-based sensors continuously operating in the field, remote sensing approaches offer only an instantaneous partitioning of E and T; additional methods or assumptions are needed to interpolate E and T between sampling times. For observation of the overall ET, many algorithms assume that the ratio of latent heat to available energy or actual ET to potential ET remains constant between images (Bastiaanssen et al., 1998; Allen et al., 2007). This assumption has been shown to be valid across a variety of land surfaces (Cragoa and Brutsaert, 1996; Anderson and Goulden, 2009; Liang et al., 2017). However, it is clear that the ratio of E and T varies diurnally relative to the available energy and potential ET. Transpiration is negligible at nighttime while E, while reduced, can still occur due to soil heat storage. During the day, the phase shift between ground heat flux and net radiation (Leuning et al., 2012) can make scaling E and T maps challenging, particularly if the image comes from a time of day when E and T differ from the daily average. More work is needed on assessing the diurnal variation of E and T to enable better scaling of partitioned fluxes from remote sensing.

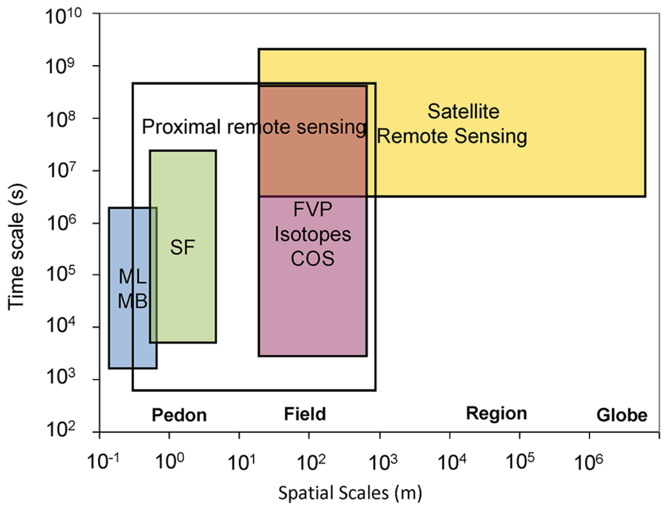

Fig. 1. Spatial and temporal scales of different evapotranspiration partitioning approaches: microlysimeter (ML), micro-Bowen ratio (MB), sap flow (SF), flux variance partitioning (SVP), isotopes, and carbonyl sulfide (COS). All three of the atmospheric methods have approximately the same temporal and spatial scales.

Integrating Differing Approaches to Constrain Partitioning of Evaporation and Transpiration

Recently developed ET partitioning methods have contrasting spatiotemporal scales of observation, although generally they can operate at longer and larger scales than previously established methods such as micro-lysimetry and sap flow. Figure 1 shows the observational scales of different methods to determine *E* and *T*. Combined with the different strengths and weaknesses of each method, integrating multiple approaches can provide a more robust partitioning of ET by complementing each other's strengths while mitigating weaknesses, particularly when the methods have independent physical bases. For example, micrometeorological approaches can help interpolate satellite remote sensing between images, while satellite remote sensing can help scale tower observations to larger scales. At the subfield-scale level, integrating proximal remote sensing (particularly from UAVs) with more established techniques including micro-lysimetry, micro-Bowen ratio, and sap flow can help assess pedon-scale variation in *E* and *T* and can also assist in interpolating between UAV images to help develop a more complete understanding of *E* and *T* variation. This methods integration approach is already being applied at larger hydrologic scales for multiple applications including predicting stream flow (Velázquez et al., 2011), observing terrestrial water balances (Pan et al., 2012), and monitoring soil moisture (Reichle et al., 2016).

Along with obvious factors such as available resources (e.g., financial, personnel–technical, and infrastructure), the choice of methods to partition ET needs to be guided by how *E* and *T* will be used to calibrate and/or validate vadose zone models. For studies focusing on process validation and refinement, higher temporal scale observations would be more useful to assess how well the model predicts *E*, *T*, and other values such as drainage across a wide variety of land surfaces and irrigation and precipitation conditions. For other, more operational models, assessing longer term performance is needed to evaluate how models predict critical parameters such as recharge and discharge. At the spatial scale, higher resolution methods are clearly needed for highly heterogeneous landscapes, whereas scale mismatch may not be as significant for model evaluation in homogeneous landscapes such as agroecosystems.

Concluding Remarks

There have been substantial advances in the past 15 yr in partitioning ET at field and regional scales into *E* and *T*. New techniques include (i) micrometeorological techniques using the variance between CO_2 and H_2O (the FVP method) as well as the simultaneous uptake of COS and CO_2 during photosynthesis, (ii) in situ, near-real-time, atmospheric isotopic techniques that allow long-term and continuous partitioning of ET, and (iii) improvements in satellite and proximal remote sensing that allow partitioning of the energy balance and latent heat flux between the soil and the plant canopy at field to global scales (the TSEB). These methods have contrasting strengths, limitations, and spatiotemporal observational scales (Fig. 1; Table 2), thus combining methods can result in a more robust ET partitioning. Intercomparisons of multiple partitioning approaches across a variety of sites are needed to further assess the advantages and disadvantages as well as the accuracy of these approaches.

Two of the recently develop methods, FVP and the TSEB, can be applied to archived eddy covariance and satellite data. National and international data archives for eddy covariance and satellite imagery could reprocess these data to create an archive of partitioned ET data. Large data repositories have experience with automated, large-scale data processing and could accomplish this task more efficiently than individual investigators. This would be especially useful for vadose zone modelers who may not have the expertise and/or resources to collect additional *E* and *T* data for model calibration and validation and would benefit an archive by integrating the vadose zone community among its users. In the

Table 2. Summary of major partitioning approaches reviewed here. Advantages and disadvantages of chambers, sap flow, microlysimeter, and micro-Bowen ratio methods are only briefly discussed due to focus elsewhere.

Method	Main advantages	Major disadvantages	Selected references
Flux variance partitioning	no additional instrumentation above standard eddy covariance; potential reanalysis of network data set	multiple sources of uncertainty in water use efficiency parameterization	Scanlon and Sahu (2008), Scanlon and Kustas (2010), Palatella et al. (2014)
Isotopic methods	direct mixing model separation of evaporation (*E*) and transpiration (*T*) with distinct isotopic signatures	cost of instrumentation; uncertainty in isotopic fractionation with *E* and *T*	Griffis et al. (2010), Richardson et al. (2012), Good et al. (2014), Gaj et al. (2016)
Carbonyl sulfide (COS)	strong relationship between COS and photosynthesis can provide independent estimate of *T*	cost of additional instrumentation; COS budget not well constrained	Seibt et al. (2010), Wohlfahrt et al. (2012), Billesbach et al. (2014)
Two-source energy balance	can be implemented across proximal and satellite sensing platforms; potential reanalysis of satellite data repositories	partitioning energy components between soil and vegetation components; coarser resolution of satellite infrared data	Kustas and Norman (1996), Anderson et al. (2011), Mu et al. (2011), Colaizzi et al. (2012), French et al. (2015)
Plant and soil chambers	well established approaches; sap flow and microlysimeter used extensively globally; lower instrumentation costs than micrometeorological approaches (particularly microlysimeter)	scaling measurements from single sensor or network of sensors to larger area; technique alters observational environment (microlysimeters and chambers)	Stannard and Weltz (2006), Rothfuss et al. (2010)
Sap flow			Granier (1985), Burgess et al. (2001)
Microlysimeter			Boast and Robertson (1982), Evett et al. (1995)
Micro-Bowen ratio			Ashktorab et al. (1994)

absence of a community effort, modelers and researchers who can use E and T data should collaborate with ECV users and remote sensing specialists to partition ET where needed by maximizing the analysis of already collected data.

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