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Research papers

Comparative analysis of water budgets across the U.S. long-term agroecosystem research network

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ABSTRACT

Understanding the movement and storage of water within agricultural landscapes as functions of management and climate is essential for more efficient and sustainable water use. However, knowledge of water storage and fluxes on U.S. agricultural lands is largely incomplete. The Long-Term Agroecosystem Research (LTAR) network

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provides a unique and geographically diverse set of agricultural study sites in the United States. The objectives of this study were to: 1) characterize the hydrologic variability across the LTAR network; 2) identify data gaps in the water budgets across the LTAR network; and 3) identify opportunities to leverage the LTAR network to improve understanding of water budgets across agricultural landscapes. For each of the 18 LTAR sites, we developed water budgets on an average annual basis. Uncertainty propagation methods combined individual component uncertainties to calculate an overall water budget uncertainty. Datasets length ranged from three to 50 years. The network covers a range of precipitation from 240 to 1400 mm yr^{-1}, evapotranspiration from 228 to 1080 mm yr^{-1}, and surface runoff and subsurface flow from negligible to 560 mm yr^{-1}. However, uncertainties of where all the water is going remained high, in part because soil water storage and downward movement of water were often neglected or measured for very short periods, resulting in average water budget uncertainty of 25% of the water inputs. More accurate measurement of the major inputs and outputs, and direct measurement of water content and percolation are key to understanding how agricultural lands affect terrestrial water budgets.

1. Introduction

Intensification of agriculture can affect water availability by increasing land under crop and forage production (Raymond et al., 2008; Schilling et al., 2008; Tomer and Schilling, 2009) or by increasing land productivity (Zeri et al., 2013). Simultaneously, climatic changes in temperature and precipitation can alter available water resources in several ways by: 1) increasing the rate and timing of evapotranspiration through elevated temperatures (Flerchinger et al., 2019; Kingston et al., 2009) and changes in crop planting times (Gautam et al., 2018), 2) altering the amount, timing, and form of seasonal or annual precipitation (i.e., rain or snow [US Global Change Research Program, 2017]), and 3) altering precipitation intensity, which could lead to greater runoff and reduced percolation (Gautam et al., 2018; Groisman et al., 2001).

Key to the adaptation of agriculture across varying climates is the management of water, the natural availability of which ranges from deficit to excess for crops and rangelands. In water-limited environments, agriculture competes with other water users. Conversely, water-replete environments may be challenging because of poorly drained soils. Extreme precipitation events are challenging everywhere because of erosion and loss of water to runoff. Agricultural activities can affect the availability and quality of surface and ground waters, making careful management a fundamental requirement for sustainability.

Conflicts arising from agricultural water management such as water availability for municipal, industrial, or recreational uses (e.g., water shortages in Brazil in 2017, South Africa in 2018, and in India in 2019), and contamination of water bodies from agricultural pollution are becoming more frequent and threaten the well-being of future generations and the environment (United Nations Convention to Combat Desertification, 2017). In the United States, recent droughts (e.g., 2016 in Georgia or 2011–2017 in California) and floods (2008 in Iowa, 2011 and 2019 along the Mississippi and Missouri Rivers) have significantly impacted agricultural production, as well as water quality of receiving water bodies. Understanding the balance between precipitation, evapotranspiration, runoff, and groundwater recharge is critical to evaluating local, regional and global water resources (Healy et al., 2007).

A balanced water budget accounts for all of the major water inputs and outputs over an annual cycle in a defined area. Water budgets depend on topography, climate, soils, land use, and land management. In small catchments, a water budget provides an overview of the fate of water inputs. Evapotranspiration is commonly the main output, with the remaining balance going to groundwater recharge or streamflow generation. Water budgets describe the water pathways through the farm and rangeland management systems. Accurate water budgets for small catchments can also inform integrated land and water management in larger catchments and contribute to the analysis of potential trade-offs between water allocations for agriculture and other uses. Understanding how each budget component may shift as a function of management informs the optimal use of available water resources under varying climate, land use, and agricultural production. Optimization of water resources at the watershed or regional scale may in turn result in specific recommendations for the management of agricultural land in those regions.

Our current knowledge of water fluxes across agricultural landscapes in the United States is largely incomplete. For areas the size of a field, studies in agroecosystems focus on individual components of the water budget, often overland or subsurface runoff, or evapotranspiration (e.g., Bosch et al., 2012; Buckley et al., 2010). For large watersheds, water budget estimates are often based on models, which are calibrated with streamflow data measured at the outlet of the watershed (Afinowicz et al., 2005; Green et al., 2006; Schilling et al., 2008), or not calibrated if the modeling objective is to understand the primary hydrologic processes (Abatzoglou and Ficklin, 2017; Gobin et al., 2017). Regional research networks provide an opportunity to benefit from long-term ecological and hydrologic process site studies across a gradient of climatic conditions, land use, and land management. For example, data from the U.S. Long-Term Ecological Research network as well as other North American networks have helped identify forest-type susceptibility to climate warming (Creed et al., 2014).

The Long-Term Agroecosystem Research (LTAR) network is a partnership of 18 long-term research sites maintained by the U.S. Department of Agriculture (USDA) Agricultural Research Service (ARS) and academic institutions (Spiegal et al., 2018; Walbridge and Shafer, 2011). The LTAR network was established in 2014 to provide information in support of research for improved sustainability and intensification of U.S. agriculture over the next 20 to 50 years (Kleinman et al., 2018). The LTAR network includes 18 experimental watersheds (11 USDA-ARS) and ranges where precipitation and other hydro-meteorological variables have been systematically measured and archived for decades.

The LTAR network offers an opportunity to estimate and compare water budget components across a gradient of agroecosystems and climatic conditions as a baseline from which to evaluate the impacts and sensitivity of management in a changing climate. These water budgets provide a mechanism to identify deficiencies in monitoring instrumentation, the availability of data for additional comparative studies, and the identification of aspirational goals for regional watershed management. These data also provide an opportunity to evaluate the uncertainty of water budget components for accurate cross-site and regional analysis.

The objectives of this study were to: 1) characterize the hydrologic variability across the LTAR network; 2) identify data gaps in the water budgets across the LTAR network; and 3) identify opportunities to leverage the LTAR network to improve understanding of water budgets across agricultural landscapes. Analyses were conducted for 13 small catchments (< 50 ha) and 13 large catchments (> 400 ha) distributed among the 18 LTAR site locations.

2. Methods

2.1. Study sites

A water budget assessment was conducted at 26 study areas across 18 LTAR sites (Fig. 1). Each LTAR site was responsible for selecting one or more representative study areas, determining a period for which data were available, and calculating the mean and standard deviation of annual values for each water budget component. The assessments cover a range of soil, land use (Supplemental Table S1), and climatological conditions (Supplemental Fig. S1). The 26 locations were divided based on the size of the drainage area and uniformity of land use: 13 small catchments were smaller than 50 ha and had uniform land use; 13 large catchments were greater than 400 ha and could include multiple land uses. Even though some of the study areas were large plots (190 m^2) that did not meet the hydrologic definition of a natural catchment, artificial boundaries at these sites prevented the inflow of surface and subsurface water. As a result, they did behave as a catchment and were included in the analysis.

2.2. Water budget equation

We used the following general equation for the annual water budget:

$$P + I + Q_{in} = ET + Q_{out} + \Delta S \quad (1)$$

where

P is annual precipitation
I is annual irrigation
Q_{in} is annual water flow into the catchment
ET is annual evapotranspiration
Q_{out} is annual water flow out of the catchment
ΔS is the annual change in water storage.

For small catchments, the water budgets were derived for the soil profile system, down to the maximum of the rooting depth or 150 cm; therefore, water storage was limited to soil water storage, and water flow out of the system included surface flow, subsurface lateral flow, and downward percolation beyond the monitored soil profile/rooting zone (Fig. 2). For large catchments, the water budgets were also determined for the soil profile system, but for these catchments the maximum depth extended down to and including the aquifer that provides base flow. Water storage included soil storage, ponds and reservoirs, and the aquifer. Water flow out of the system included streamflow measured at the outlet of the catchment and deeper percolation, which was considered to replenish deeper regional aquifers that did not contribute to the water storage or flow within the catchment. Thus, system water storage and percolation did not have the same meaning for small and large catchments.

2.3. Water budget component estimation and uncertainty

Each site used their own datasets and methods to develop the water budgets (Supplemental section S3). Supplemental Tables S4 through S15 provide metadata about estimation methods and estimate uncertainty for each water budget component specific to each site. Sources of uncertainty may include measurement errors, random or systematic errors in the estimation of derived variables (extrapolated/interpolated data, scaled data), temporal and spatial variability, and data quality control and management issues (Harmel et al., 2006, 2009; McMillan et al., 2012; Montgomery and Sanders, 1986). Below, we provide a summary of the methods used to estimate each component of the water budget and determine its uncertainty. All uncertainties are assumed to be bi-directional.

2.3.1. Precipitation

Precipitation data ranged from 3 to 50 years (Supplemental Tables S4 and S5). For all the sites but the R.J. Cook Agronomy Farm (CAF), the gauge(s) were very near or within the catchment. At two sites, Lower Chesapeake Bay (LCB) and CAF, precipitation gauges were the responsibility of a different organization and metadata were not available. At most sites, precipitation was measured with tipping bucket or 20-cm diameter Belfort weighing rain gauges, using calibration and

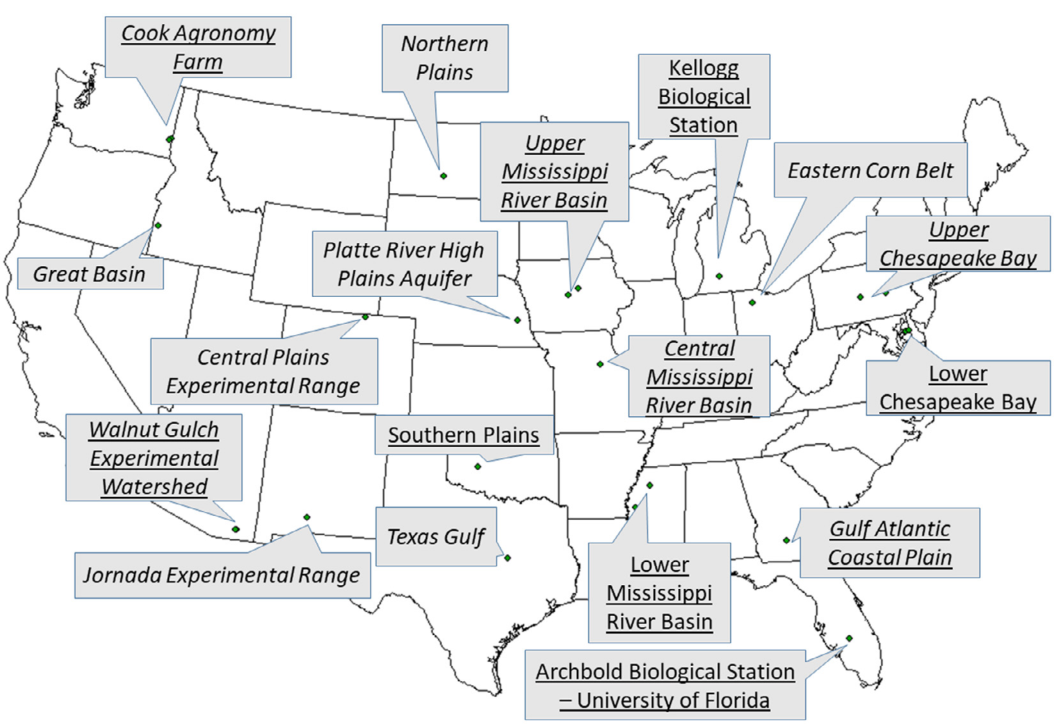

Fig. 1. Location of the Long-Term Agroecosystem Research sites. Italicized sites have a small catchment, underlined sites have a large catchment, italicized and underlined sites have both.

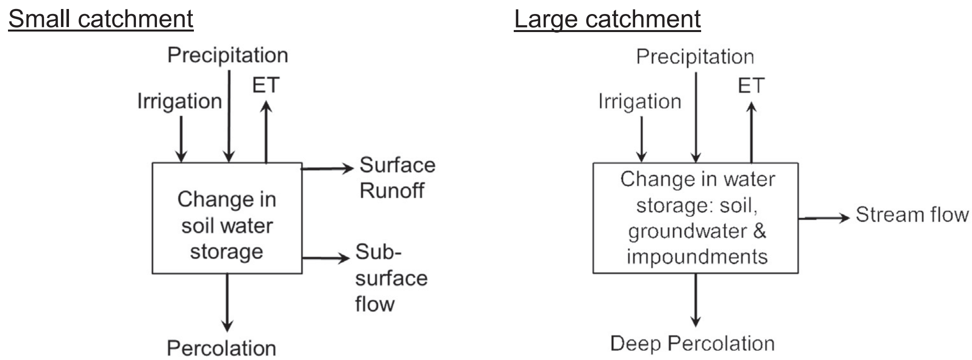

Fig. 2. Schematic for the water budget for a small and large catchment.

maintenance procedures recommended by Brakensiek et al. (1979). The Belfort gauge diameter varied, larger or smaller, for a few sites. Several sites used load cells to detect and quantify precipitation at a pre-defined frequency. The CAF site used a non-recording rain gauge and measurements were manual. The greatest uncertainty in precipitation measurement was the undercatch, which we estimated as a function of winter precipitation and whether a wind shield was present. Details for the estimation of precipitation uncertainty are provided in Supplemental section S4.

2.3.2. Irrigation

In the small catchments, crops were irrigated at only two sites: Platte River and High Plains Aquifer (PR-HPA) in Nebraska and Gulf Atlantic Coastal Plains (GACP) in Georgia (Supplemental Table S6). Among the large catchments, irrigation was a component of the water budget at the Southern Plains (SP), Beasley Lake watershed in the Lower Mississippi River Basin (LMRB), and Archbold Biological Station-University of Florida (ABS–UF) sites (Supplemental Table S7). Irrigation was quantified using farmer reports (ABS–UF and LMRB) or model estimates (SP). Irrigation was present but was either judged to be insignificant at the Upper Mississippi River Basin (UMRB), Central Mississippi River Basin (CMRB), and Kellogg Biological Station (KBS) sites because the irrigated area was small relative to non-irrigated cropland or it was unknown (GACP).

Irrigation in the small catchments was under the control of the scientists. Therefore, a 5% uncertainty was assigned to account for application uncertainty, unless a different value was provided. In the large catchments, irrigation amounts estimated from farmer reports were assigned a 10% uncertainty to account for reporting errors. A 25% uncertainty was assigned when estimates were based on model-simulated water stress.

2.3.3. Evapotranspiration

Infrastructure measuring ET was only recently established at most LTAR sites. Four sites had ET data from eddy covariance (EC) flux towers (CAF, Great Basin (GB), Walnut Gulch Experimental Watershed (WGEW), and Northern Plains (NP, Supplemental Tables S8 and S9). In addition, the KBS site was able to use eddy covariance data to validate the ET estimates obtained by residual of the water balance equation. The Texas Gulf (TG) site measured pan evaporation. Seven sites used modeling to estimate ET. These models combine potential ET [e.g., based on the meteorological parameter-based FAO-56 Penman-Monteith model (Allen et al., 1998)] with a crop growth model and available soil moisture to calculate crop water uptake. At ABS-UF, vegetation coefficients were calibrated using lysimeters in lieu of a crop growth model. The FAO-56 method combined with vegetation coefficients yields accurate estimates of potential ET for monocrop agriculture under well-watered conditions, i.e., where water availability does not limit transpiration (Anderson et al., 2017; McMahon et al., 2013; Pereira et al., 2015). All other sites assumed closed systems and estimated ET by subtraction from the water balance equation assuming small, unquantified components of the system were negligible. Uncertainty of ET varies with the method used to estimate its value. Supplemental section S5 provides details about ET measurement uncertainty estimation.

The uncertainty of ET estimates based on the water budget residual was a function of the uncertainties of the quantified components. Where percolation and changes in water storage were not quantified, the uncertainty of these components was also unknown. We assumed that average annual change in water storage and its uncertainty were both equal to 0. We further set the absolute uncertainty of percolation to be 16% of average annual precipitation, based on the average ratio of percolation uncertainty to average precipitation among the sites where percolation was quantified.

Modeled ET estimates also had uncertainties. Except for ABS-UF, the uncertainty associated with modeled ET estimates was not quantified. As for other water budget components, a 25% modeling uncertainty was assigned. The models used for estimating ET included the Soil and Water Assessment Tool (Arnold et al., 2012), the Agricultural Policy Environmental Extender (Wang et al., 2012), and the Annualized Agricultural Non-Point Source pollution model (Bingner and Theurer, 2001). In these, ET is calculated as a function of potential ET and crop growth, which is constrained by available nutrients and soil water. These models had been calibrated for crop or biomass yields, surface outflows, and sometimes for drainage or subsurface flow, but not for ET or percolation. Modeling errors on crop yields are typically 20% (Wang et al., 2012); and models are often considered acceptable if errors are within 25% of measured values (Moriasi et al., 2015). Thus, a 25% modeling uncertainty was assigned. However, we wanted to avoid the possibility that the uncertainty of ET would be greater when modeled with a calibrated model than when estimated as the residual of the water budget. When all other components were quantified, modeled ET uncertainty was assigned the lowest of the uncertainty of the water budget residual calculated by uncertainty propagation or 25%, as explained later. When some components were not quantified, the modeled ET uncertainty was set at 25%.

2.3.4. Surface and subsurface outflows

Discharge (surface or subsurface) was measured at all but three small catchments (Supplemental Table S10). Surface runoff was assumed to be negligible at the Jornada Experimental Range (JER, Gutschick and Snyder, 2006), the NP Area IV Farm, and the Central Plains Experimental Range (CPER, Dodd and Lauenroth, 1997). Surface runoff was assumed to be a fraction of precipitation at the PR-HPA site (Szilagyi et al., 2005). Most other sites used pre-calibrated flumes or weirs to quantify discharge from stage data and were rarely overtopped. Exceptions included the Upper Chesapeake Bay (UCB) Kepler farm where water volumes flowing through a structure were measured directly with tipping buckets. At UMRB Kelley farm, surface flow was considered negligible. In some small catchment studies (CAF, UMRB, UCB, Eastern Corn Belt (ECB), and GACP), investigators also measured subsurface flow using a subsurface drain. At UMRB, subsurface drainage was measured with in-line flow meters.

Discharge (streamflow) was directly measured at all the large catchment outlets (Supplemental Table S11), which makes it the second most frequently measured component. For all the large catchments except the Beasley Lake watershed (LMRB), discharge measurement consisted of continuous stage (water depth) measurement with a pressure transducer, float, or sonic sensor. The stage data were then converted to discharge rates using an established stage-discharge relationship derived from flow measurements or a pre-calibrated weir or flume. The stage-discharge relationship of the control structure was complemented by streamflow measurements for high flows that overtopped the control structure. For the Beasley Lake watershed, streamflow was estimated with a calibrated model (Yasarer et al., 2020). In the present study, the uncertainty in streamflow, surface runoff and subsurface flow was estimated with the procedure of Harmel et al. (2006) and is described in Supplemental section S6.

2.3.5. Percolation

For practical reasons, only two small catchments estimated percolation of water beyond the monitored root zone using independent measurements: TG measured percolation by measuring groundwater levels in wells placed throughout the catchment and WGEW estimated no percolation based on measured chloride concentrations as a function of soil depth (Supplemental Tables S12 and S13). For the large catchments, only the WGEW site had independent estimates of deep percolation, which occurs primarily in depressions and ephemeral channels and was estimated using multiple methods (Goodrich et al., 2004). At other sites, percolation was estimated as the residual of the water balance. Alternatively, some sites used a literature value (e.g., GACP, 1% of precipitation, Rawls and Asmussen, 1973), or modeling (e.g., CMRB).

2.3.6. Soil water storage

Soil water content was measured in seven small catchments (Supplemental Table S14) and one large catchment (SP, Supplemental Table S15). In all of these, soil moisture sensors were installed in multiple locations and at multiple depths. For SP, Starks et al. (2014) describe in detail the network of 15 soil moisture sites in the Fort Cobb watershed and the processing of the data to obtain water storage across the full catchment. Soil water measurements exist in the GACP large catchment but were not used for this analysis. Measurement methods included gravimetric measurements, neutron probes, time domain reflectometry, and other soil moisture sensors. Uncertainty associated with these measurements ranged from 2.5 to 5.5%. For the other sites, change in soil water storage was either not quantified, or was estimated via modeling or by applying the water balance equation. As for other modeled water budget components, a 25% uncertainty was assigned to change in soil water storage estimated by modeling. If the water balance equation was used, the uncertainty was dependent on the uncertainty of the other water budget components. When several water budget terms were unavailable, e.g., percolation and change in soil water content, the difference in known sources and sinks of water was attributed to percolation and changes in soil water content were assumed to be negligible. Changes in soil water storage were estimated with the water balance equation only when all the other terms were estimated by other means.

2.4. Effect of missing data

Missing data introduce a bias by underestimating the annual value of the measured component. However, filling missing data, often performed by regression with relevant time series, results in reduced spatial and temporal variability of the data. Guzman et al. (2014) demonstrated this effect across dozens of precipitation time series (5-min time step) in the Little Washita and Fort Cobb Experimental Watersheds. For sites with less than 10% missing precipitation data, the reduction of the coefficient of variation caused by infilling missing data was less than 2% and considered acceptable. Imputing data gaps was considered preferable to the use of incomplete datasets for analysis of spatial and temporal trends. In this study, uncertainties in the average annual value for datasets with missing data were derived from the Guzman et al. (2014) study of precipitation data. If missing data consisted of no more than 1% of the dataset, no additional uncertainty was applied to the average annual value. If the amount of missing data was greater than 1%, the uncertainty of the average annual value was increased by the greater of 2% or the percentage of missing data, unless the missing data were imputed. In that case, the uncertainty was increased by 2%.

Occasionally there was no information about missing precipitation and discharge data. In those cases, we used the upper bound of missing data percentages among the sites that provided this information: 14% for precipitation, and 11% for discharge. An uncertainty value of 40% was assigned to component values estimated from the literature.

2.5. Combination and propagation of uncertainties

The square root of the sum of squares equation was used to estimate uncertainty resulting from several steps or factors (e.g., discharge uncertainty, Supplemental section S6) and to estimate the uncertainty of data resulting from addition or subtraction. For example, when a component (e.g., *ET*) was estimated from precipitation and outflow (Eq. (2)), then the uncertainty of that component was derived from those of the other components, as in Eq. (3).

$$ET = P - Q \tag{2}$$

$$U_{ET} = \sqrt{U_P^2 + U_Q^2} \tag{3}$$

To estimate the uncertainty of data resulting from multiplication or division, the uncertainties were expressed in percentages (relative errors) before applying the quadrature formula. For example, the runoff coefficient, Q_{coeff}, was calculated from Eq. (4), and its uncertainty was estimated by Eq. (5):

$$Q_{coeff} = Q/P \tag{4}$$

$$\frac{U_{Qcoeff}}{Qcoeff} = \sqrt{\left(\frac{U_Q}{Q}\right)^2 + \left(\frac{U_P}{P}\right)^2} \tag{5}$$

2.6. Determination of inter-annual variability

Our analysis was based on average annual values. Availability of measured or simulated data across the network was highly variable, ranging from ≤ 3 years for some components of the budget for some study areas, to 30–50 years for all components at others. In order to use estimates based on different lengths of datasets, measures of uncertainty of the means caused by interannual variability were calculated. We used the standard error of the mean to quantify the range of possible values of the true mean given the sample size and its standard deviation.

2.7. Hydrologic characterization of each site

For each small and large catchment, hydrologic characterization was based on the runoff and ET coefficients (runoff and ET as a fraction of precipitation and irrigation) and on the closure of the water balance equation. The closure indicates the extent to which the water budget was balanced when taking into account the uncertainties of each component. Measured components as well as those estimated via modeling, expert knowledge, or literature values were included with the corresponding uncertainties.

All inputs to the system (i.e., precipitation and irrigation) were summed and the total input uncertainty calculated by combining uncertainties of individual components. The same was done for all the outputs from the system (i.e., surface runoff, subsurface discharge, artificial drainage if any, evapotranspiration, percolation to groundwater, and changes in soil water storage). While not an output of the system per se, changes in soil water storage are one possible use of the water inputs. A loss in soil water storage was represented with a negative value. The water budget uncertainty Δ*water* (Eq. (6)) quantifies the closure of the average annual water budget.

$$\Delta water = \sum inputs - \sum outputs + \sqrt{inputuncertainty^2 + outputuncertainty^2} \quad (6)$$

The relative water budget uncertainty (Eq. (7)) expresses the water budget uncertainty as a function of the inputs.

$$Relative\Delta water = \Delta water / \sum inputs \quad (7)$$

Additionally, the smallest possible water budget uncertainty for each catchment was estimated based on the hypothesis that best measurement practices would be used everywhere over a 30-year period so that both the measurement error and the interannual variability would be minimized. We also assumed that there were no missing data or that data gaps had been filled.

2.7.1. Use of the Budyko framework

The wide range of precipitation and solar insolation across North America leads to large differences in evapotranspiration, which in turn strongly affect water availability for agriculture and downstream ecosystems. LTAR sites lie along gradients of water availability, and solar insolation or energy limitation. A graphical way to distinguish between water limited and energy limited sites is the Budyko framework (Budyko, 1974). This framework describes the partitioning of catchment precipitation into evapotranspiration and discharge in terms of water and energy availability (Arora, 2002; Gunkel and Lange, 2017; Sposito, 2017). Budyko's assumption was that evapotranspiration is limited by water in semi-arid regions and by energy in wet regions (Zhang et al., 2001).

The Budyko curve is the theoretical relationship between the aridity index (Potential ET/Precipitation) and the evaporative fraction (Actual ET/Precipitation, Westhoff et al., 2016). Potential ET is primarily a function of solar radiation and is equivalent to the actual ET under conditions of no water limitation. Actual ET is limited by available water and/or energy available for the evaporation of water. Reported average annual actual ET and precipitation, and average annual potential ET derived from MODIS16 (Mu et al., 2007, 2011) were used to compare the relative energy and water limitations across all small and large catchments at the LTAR sites. An aridity index and evaporative fraction characterized each site. If a site had multiple catchments, average values of actual ET, precipitation and potential ET were used so that each LTAR site was represented by a single point. The Budyko curve was developed based on the relationship modified by Zhang et al. (2001) to include vegetation type effects on ET and is expressed as (Eq. (8)):

$$AET/P = (1 + w(PET/P))/(1 + w(PET/P) + (P/PET)) \quad (8)$$

where AET is actual ET; P is precipitation; w is the plant-available water

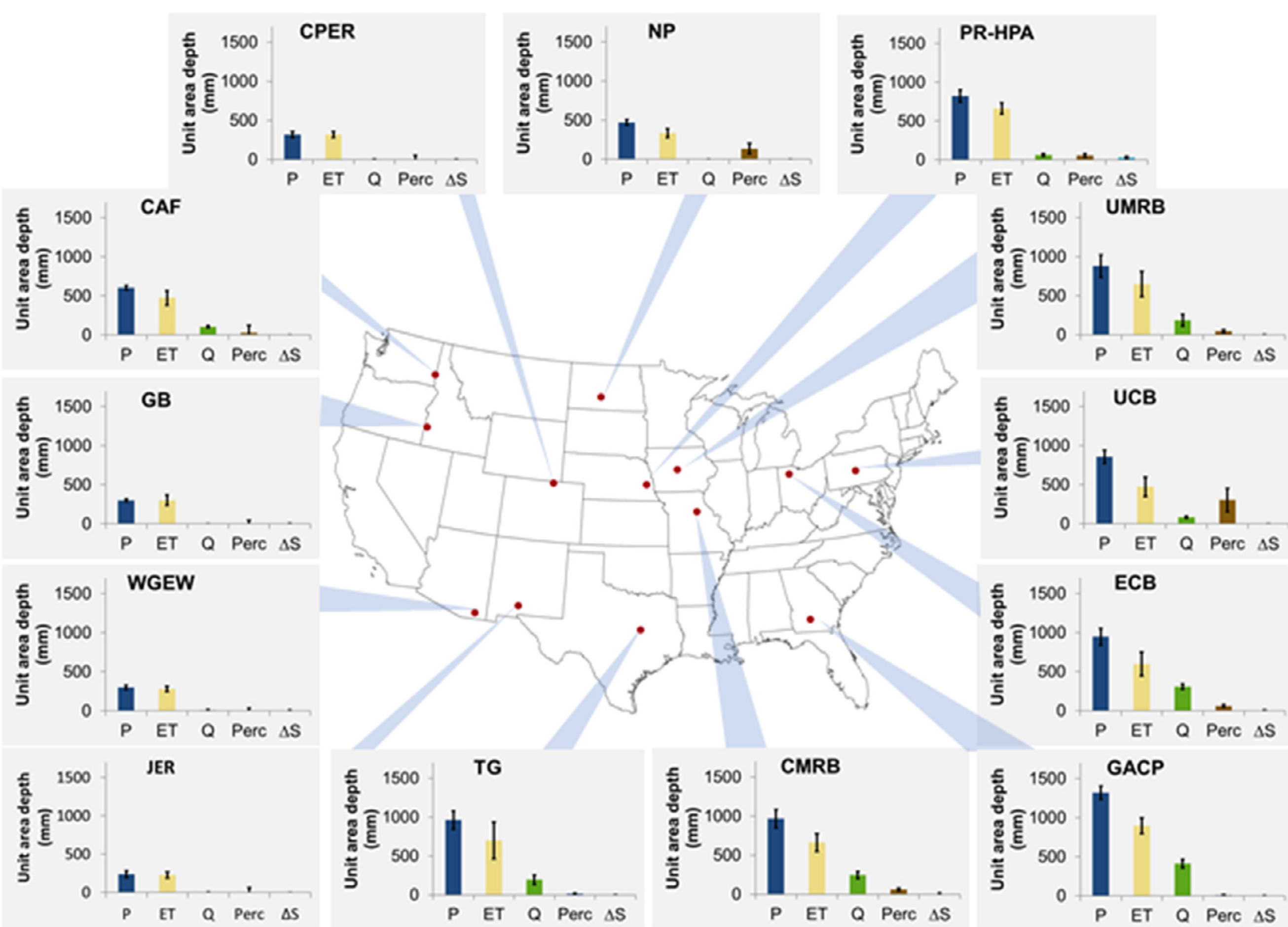

Fig. 3. Water budgets at each of the 13 Long-Term Agroecosystem Research network small catchment sites.

coefficient, with a value of 0.5 for cropland, 1 for grassland and 2 for forest, based on a study of over 300 catchments worldwide (Zhang et al., 2001); and PET is potential ET.

3. Results

3.1. Water budgets across the LTAR network

The magnitudes and uncertainty of each water budget component are described for each catchment in Supplemental Tables S16 and S17 and are summarized in Figs. 3 and 4 and Tables 1 and 2. The LTAR network covers a gradient of precipitation from 240 mm yr^{-1} at JER to 1400 mm yr^{-1} at LMRB. Precipitation was the component measured with the smallest relative uncertainty (5%-17%, Tables 1 and 2). However, it was also the largest component and the absolute uncertainties related to precipitation were the second largest among all water budget components (19 to 237 mm). The smallest uncertainties (< 10%) were obtained with shielded rain gauges, generally installed at the northern sites where snow conditions dominate for more than half of the year (NP, GB, CAF, and KBS), or with unshielded gauges at the southern sites where snow conditions are very rare (ABS-UF, GACP, and WGEW). At the remaining sites, winter precipitation was significant, but not compensated for by gauge shielding. Consequently, precipitation uncertainties were greater than 10%.

ET values ranged from 228 mm yr^{-1} at JER to 1080 mm yr^{-1} at ABS-UF. The variety of methods used to estimate ET across LTAR sites (Supplemental Tables S8 and S9) is reflective of the spectrum of independent approaches used worldwide, each with its own sources of uncertainty (Allen et al., 2011). When ET was obtained as the water budget residual, the uncertainties of each of the components contributed to the uncertainty associated with the ET estimate, as did the terms that were omitted from the budget. Modelled results had a different set of uncertainties associated with model assumptions and parameter measurements, as well as the inability in some cases to obtain site-specific calibration or customization of the models. Relative uncertainties in ET ranging from 8% to 38% resulted in absolute uncertainties ranging from 32 to 325 mm.

Surface and subsurface flows at the small catchments, and streamflow at the large ones were also affected by the gradient of precipitation and ET, ranging from none or negligible amounts (< 10 mm yr^{-1}) at the driest sites (GB, WGEW, JER, and Central Plains Experimental Range (CPER)) to more than 550 mm yr^{-1} at LMRB. However, differences between soils had a strong influence. Runoff at the NP site was negligible because permeable soils (hydrologic soil group B) favored percolation (> 100 mm yr^{-1}). At UCB, surface runoff was low at the small catchment site (Kepler farm) in comparison to that measured at the WE-38 watershed because of the presence of karst features at Kepler farm, which promote downward movement of water.

Percolation was measured only at TG and WGEW. At the small catchments where percolation was quantified, percolation below the monitored root zone ranged from 0 mm at WGEW to 136 mm yr^{-1} at NP. For the large catchments, percolation to the deep aquifer ranged from 5 mm yr^{-1} at CMRB to 460 mm yr^{-1} at ABS-UF. Because most sites estimated that component, uncertainties were large, sometimes larger than the mean value (e.g., 374% at CAF small catchment; or 76% at ABS-UF) and led to considerable uncertainty about water movement. At the CAF small catchment, runoff and subsurface runoff were quantified at 105 ± 13 mm, while ET was 474 ± 92 mm, which led to

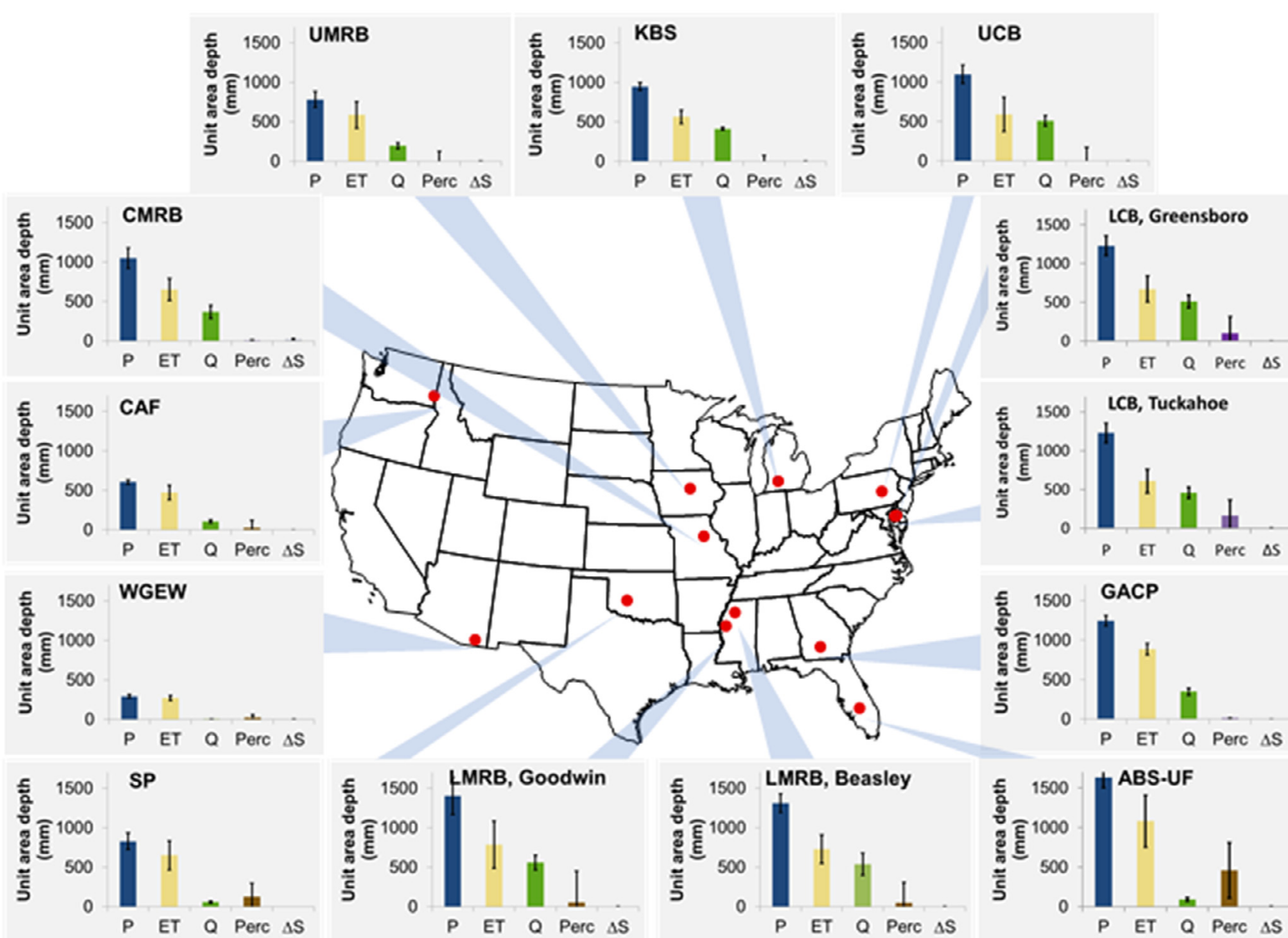

Fig. 4. Water budgets at each of the 13 Long-Term Agroecosystem Research network large catchment sites.

Table 1
Distribution of water budget component magnitude and uncertainties at the small (< 50 ha) catchments of the Long-Term Agroecosystem Research (LTAR) Network.

	Precipitation	Irrigation	ET*	Surface and subsurface runoff	Percolation	ΔS**
Magnitude (mm)						
Average value	661	31	506	147	65	2
Minimum value	240	0	228	0	0	–22
Maximum value	1172	250	895	413	303	31
Relative uncertainty (%)						
Average value	11%	8%	19%	28%	122%	194%
Minimum value	5%	5%	9%	8%	0%	6%
Maximum value	18%	10%	34%	52%	666%	487%
Absolute uncertainty (mm)						
Average value	71	16	99	29	43	13
Minimum value	19	7	33	0	0	0
Maximum value	144	25	235	75	150	28

* ET: Evapotranspiration.
** ΔS: Change in soil water storage.

Table 2
Distribution of water budget component magnitude and uncertainties at the large (> 400 ha) catchments of the Long-Term Agroecosystem Research (LTAR) Network.

	Precipitation	Irrigation	ET*	Streamflow	Deep percolation	ΔS**
Magnitude (mm)						
Average value	1005	148	657	319	90	3
Minimum value	293	0	270	2	5	−16
Maximum value	1402	414	1080	558	460	21
Relative uncertainty (%)						
Average value	10%	12%	24%	18%	161%	37%
Minimum value	5%	0%	8%	5%	25%	25%
Maximum value	17%	25%	38%	26%	702%	50%
Absolute uncertainty (mm)						
Average value	102	21	163	54	169	7
Minimum value	24	0	32	0	3	5
Maximum value	237	46	325	141	393	8

Note that results at small and large catchments cannot be compared because only five sites had both large and small catchments.
* ET: Evapotranspiration.
** ΔS: Change in catchment water storage.

percolation being 26 ± 98 mm. While runoff and subsurface runoff were measured with good accuracy, the uncertainties on ET and percolation make it difficult to state whether percolation was a significant output at most sites. For example, at the ABS-UF site, runoff through the ditch-canal network was quantified at 92 ± 24 mm, while ET was 1080 ± 325 mm, which resulted in percolation being 460 ± 349 mm. This could indicate percolation or seepage was a significant loss of water from the catchment, similar to or even larger than surface runoff, a distinct possibility given high hydraulic conductivity of sandy soils at ABS-UF. At these sites and others, more precise and accurate quantification of ET and runoff will lead to improved quantification of percolation and an improved understanding of water movement.

In this study, the net change in water storage (soil water for small catchments, and soil, shallow aquifer, and impoundments for large catchments) over the data analysis period (3–35 years) was always close to zero. Annual changes could be either positive or negative for years that were abnormally dry or wet but leveled out as weather patterns returned to normal. However, changes in system water storage may be more significant and meaningful when investigating water movement over periods ranging from a few months to a single year.

3.2. Irrigated sites

Irrigation was used in only three of the large catchments (Fort Cobb at the Southern Plains (SP) site, Beasley Lake at the LMRB site, and the BIR35 catchment at the ABS-UF site) and two of the small catchments (Site 1 at the PR-HPA site and Gibbs Farm at the GACP site). It was used in the two large LCB catchments but not quantified. Among these five irrigated LTAR sites, the ABS-UF site is rangeland, while the other four sites are predominantly cropland. The growing season starts from April to June and ends in October at the cropland sites (Table 3). Applied water ranged from 121 mm yr^{-1} in the Fort Cobb watershed (SP) to 238 mm yr^{-1} at Site 1 (PR-HPA). Those amounts represent 17% to 35% of the total growing season water inputs. ABS-UF is a subtropical humid rangeland site with the peak growing season coinciding with the rainy season from April to October. Hence, irrigation occurs primarily during the dry season to maintain pastures from January to April, contributing up to 53% of the monthly water inputs to the system on average during these months. The source of irrigation water was always outside of the system considered: ponds outside the fields considered (GACP), canal water for ABS, or groundwater (LMRB, PR-HPA, and SP, see Supplemental information).

Irrigation application values and percentages should not be compared from site to site as each location has a different approach for estimating the irrigation applied. For the small catchments, the values shown in Table 3 are only from irrigated plots. Small catchment irrigation was controlled by researchers and has low uncertainty. For the larger catchments, irrigation values were determined using the total catchment size (Fort Cobb and ABS-UF) or the area of total cropland (Beasley Lake). Irrigation application rates for these sites were estimated based on modeled values for Fort Cobb, farmer-reported values for Beasley Lake, and measured input values from canals at ABS-UF. The number of years of data availability differed at each site. The irrigation method also influenced irrigation application estimates. For example, at Beasley Lake, both center pivot and furrow irrigation are common, but furrow irrigation has application rates two to three times

Table 3
Average growing season precipitation, irrigation applied, and irrigation as a percent of total water inputs (irrigation and precipitation) during the growing season for five irrigated LTAR sites.

Site (LTAR name)	Growing Season	Number of years	Period	Average Growing Season Precipitation (mm)	Average Irrigation Applied (mm)	Irrigation as percent of water inputs during growing season
Small catchments						
Site 1 (PR-HPA)	April – October	10	2002 – 2012	446 (± 111)	238 (± 73)	35% (± 11%)
Gibbs Farm (GACP)	May – October	10	2000 – 2009	618 (± 89)	130 (± 68)	17% (± 9%)
Large catchments						
Fort Cobb (SP)	June – October	15	2000 – 2014	525 (± 162)	121 (± 74)	19% (± 11%)
Beasley Lake (LMRB)	May – October	5	1998 – 2002	597 (± 171)	152 (± 28)	22% (± 8%)
BIR35 (ABS-UF)	April - October	10	2008 – 2017	983 (± 190)	189 (± 110)	18% (± 10%)

that of center pivot systems. Therefore, the efficiency of the application method is an important characteristic to consider when evaluating the irrigation component in the water budgets.

3.3. Water budget uncertainty

Relative water budget uncertainty ranged from 11% to 47% of inputs for the small catchments, and 9% to 40% for the large catchments. The average relative uncertainty was not affected by scale and was within 25% for both small and large catchments. Median values were 23% and 28% for small and large catchments, respectively.

For small catchments, the largest sources of uncertainty came from evapotranspiration with an average uncertainty contribution of 99 mm, followed by uncertainties in precipitation, percolation, surface and subsurface flows, irrigation, and change in soil water (Table 1). For large catchments, the greatest contributors to the uncertainty of the water budget were deep percolation and evapotranspiration, followed by precipitation, stream discharge, irrigation, and change in water storage (Table 2). The difference in the contribution of percolation from the small vs. large catchments to the overall water budget uncertainty was largely attributed to the small and large catchments being located at different LTAR sites. Only six sites had both large and small catchments, four of which had estimated percolation: WGEW, CAF, CMRB, and GACP. For two sites, the contribution of percolation uncertainty to the overall water budget uncertainty was very similar for the small and large catchments: close to 100 mm at CAF for ~25 mm of percolation, and 3 mm at GACP for 12 mm of percolation. At CMRB, the percolation contribution to the water budget uncertainty was 18 mm for the small catchment and 5 mm for the large one while at WGEW, it was 0 mm for the small catchment and 40 mm for the large one.

When dominant soils, elevation, climate, and land use and management in the large catchment match those in the small catchment, percolation for small catchments should be greater than for large catchments. That is because percolation from small catchments replenishes the aquifer that provides base flow. This was the case at CMRB. Yet when biophysical characteristics are different (soils, climate, karst features), percolation from one scale cannot inform percolation at the other scale. Differences between the hydrologic soil group of the small catchment soils and dominant large catchment soils existed at CAF, WGEW, UMRB, and UCB.

3.4. Hydrologic characterization of the LTAR network

Relationships between precipitation and ET, and precipitation and surface runoff + artificial drainage for small catchments, or streamflow for large catchments (Fig. 5) were all significant and generally stronger at the small catchment scale. The relationships illustrated in Fig. 5 allowed the identification of groups of sites and anomalies. The four driest sites (i.e., GB, JER, WGEW, and CPER) anchored those plots: ET and P were less than 400 mm and close to each other, and surface flow was very small. The coefficients of determination obtained without values from these driest sites were smaller and the relationship between precipitation and ET was not significant. On the other end of the precipitation spectrum, maximum small catchment ET and precipitation were at the GACP site. Maximum large catchment ET was at ABS-UF because of 400 mm of irrigation, while maximum precipitation was at LMRB.

Anomalies in these graphs include the irrigated sites and those where percolation is important relative to runoff. For example, the ABS-UF site sits clearly above the regression line in the ET graph of Fig. 5b and below it in the streamflow graph. As discussed previously, ABS-UF receives on average 400 mm irrigation during the low rainfall season; and there are strong interactions between surface water and groundwater, with percolation being similar or greater than runoff. The coefficients of determination for the ET graphs increase to 0.93 for small catchments and 0.80 for large ones when plotted against

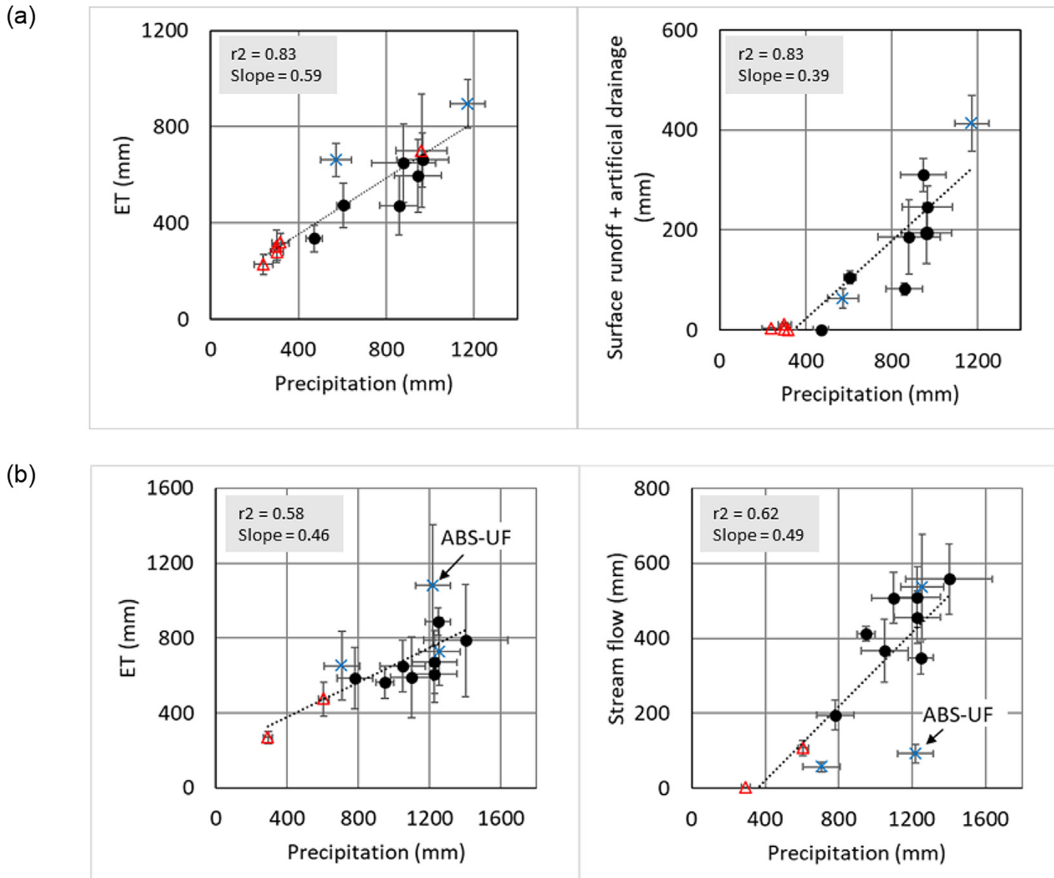

Fig. 5. Water budget components and characteristics as a function of precipitation for a) small and b) large catchments. Open triangle markers indicate rangeland sites; full circles correspond to cropland sites; and crosses are irrigated sites.

precipitation + irrigation. Irrigation typically occurs during the growing season, when plants quickly use it and there are few opportunities for runoff or percolation. Similarly, including percolation increases the strength of the relationship (to $r^2 > 0.87$) between precipitation and water outflow (runoff, drainage, and percolation), as the proportion of runoff to percolation is sensitive to the effects of crops, tillage, and soil type on surface runoff. In contrast, adding irrigation to precipitation when relating it to runoff or runoff + percolation decreases the strength of the relationship, indicating that, in these watersheds, most irrigators apply water at a low enough rate to limit surface runoff and percolation. Consequently, the proportion of runoff and percolation during irrigation is minimal and is not reflective of the hydrologic processes occurring during natural rainfall.

3.4.1. Budyko plot

The Budyko plot (Fig. 6) spatially divides the LTAR sites into three

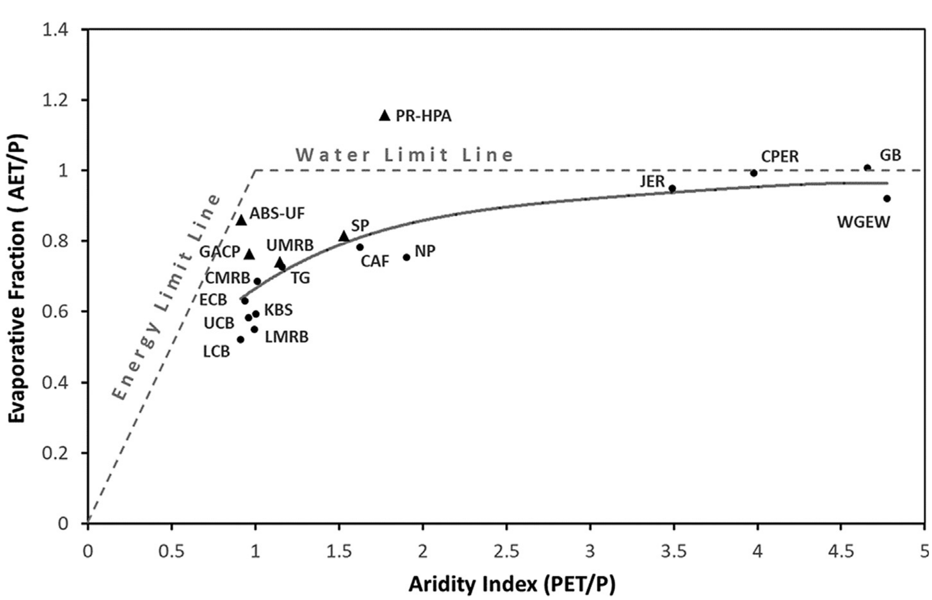

Fig. 6. Budyko plot displaying LTAR sites along gradients of increasing water limitation (increasing aridity index) and decreasing energy limitation (increasing evaporative fraction). Circles represent sites with no irrigation, triangles represent irrigated sites, and the black curve is the theoretical Budyko curve. If a site had multiple catchments, average values of actual ET, precipitation and potential ET were used so that each LTAR site was represented by a single point.

groups, based on their water and energy availability: semi-arid sites (aridity index greater than 3: JER, CPER, GB, and WGEW), intermediate sites (aridity index between 1.5 and 2: CAF, SP, NP, and PR-HPA), and mesic sites (aridity index less than 1.3: ABS-UF, UMRB, TG, GACP, CMRB, UCB, LCB, ECB, KBS, and LMRB). This last group represents the optimal conditions for agriculture, where the aridity index is around 1. The sites with the smallest values of this ratio correspond to energy-limited northeast conditions (UCB, LCB, and ECB), where cloudiness decreases available solar energy (Arora, 2002). Many sites have similar PET/P but vary in AET/P, from 0.4 for ECB to 0.8 for GACP and 0.9 for ABS-UF, indicating that as a site gets warmer (higher solar insolation), the fraction of precipitation lost as evapotranspiration increases. The lowest value of the aridity index among these agricultural sites was 0.8. An aridity index less than 0.8 would indicate a strongly energy limited system, which would severely limit agricultural productivity. In contrast, Jones et al. (2012) and Vadeboncoeur et al. (2018) have estimated lower aridity indices for unmanaged forested small watersheds. Unmanaged grassland and desert sites had aridity indices in the same range as this set of agricultural sites (Jones et al., 2012).

On the right-hand side of Fig. 6, AET/P approaches 1 while the aridity index is greater than 3. The high energy availability and low water availability drive these high values of the aridity index.

The majority of the LTAR sites lie under the water limit line where AET/P = 1, which is consistent with the observation that direct precipitation is the main water source for these sites. Low and medium aridity points above the Budyko curve at GACP, UMRB, ABS-UF, SP, and PR-HPA may be caused by uncertainty in the component estimates or suggest that irrigation may be contributing to AET. At PR-HPA, irrigation was on average 250 mm per year (30% of all inputs) and AET/P was greater than one. Irrigation was also applied at GACP and ABS-UF. In contrast at UMRB, there is no irrigation and the position of the corresponding point above the theoretical Budyko curve may be caused by uncertainties.

4. Discussion

4.1. Opportunities for reducing uncertainties

These results highlight opportunities to reduce measurement uncertainties and to improve closure of the water budgets. Longer datasets and concurrent measurements for all the components, which is one objective of the LTAR network, will produce more accurate annual mean values. However, greater measurement accuracy is achievable as well. We discuss here opportunities for reducing errors and setting achievable goals.

Given that precipitation is the largest component of the water budget, improving its measurement accuracy would improve smaller water budget uncertainties, as well as modelling of the processes that control water movement across agricultural landscapes. While this was the most accurately measured component (Supplemental Tables S4-S5), previous research indicates that errors ≤ 4% are attainable with careful monitoring, calibration, and data quality control (Groisman and Legates, 1994; Shedekar et al., 2016). Comparative experiments to measure undercatch with specific gauges are underway at several sites, including WGEW, CMRB, and ECB. Use of wind speed data may help determine the undercatch more accurately. However for larger basins, spatial variability across the basin may be a larger source of uncertainty than actual measurement errors.

Among the ET estimation methods, model simulation led to the greatest uncertainties (25% on average). Uncertainty averaged 19% when ET was based on the water budget residual and 17% when based on EC measurements. These results highlight the current difficulty estimating ET via direct measurement. The complexity of the land surface affecting turbulence, atmospheric stability, and the existence of multiple land use types in proximity to the EC tower footprint influence measurement accuracy. The lack of energy balance closure associated with eddy flux measurements is yet another source of uncertainty and is currently an active area of research (Foken, 2008; Leuning et al., 2012). The energy balance problem creates uncertainty in the ET estimate as some proportion of the residual energy from the lack of closure is missing from the latent heat flux, causing an underestimation of total ET. How best to redistribute the missing energy is not well understood for EC measurements, however methods do exist for measurements made with the Bowen ratio method (e.g., Twine et al., 2000). All sites that reported ET based on EC data underestimated the total amount of ET by some unknown amount due to this lack of closure. In spite of these limitations, all sites have installed EC towers, sometimes on land with contrasted management, thus providing improved estimates of the largest water budget component, reducing overall uncertainties of the water budget, and answering the question whether agricultural management can alter ET. Comparing ET estimates by using different methods can increase their reliability and overall errors as low as 10% may be achievable (Allen et al., 2011; Hamilton et al., 2018).

While water limitations affect ET, the Penman-Monteith estimate is considered to be the upper bound of ET estimates obtained through other methods (Allen et al., 2011). Another source of uncertainty in ET arises from species-level transpiration differences within mixed plant communities, such as in multi-crop agriculture or in rangelands containing wetlands and woodlands (Douglass, 1965). Further research is needed to reduce uncertainty under these conditions.

The amount of percolation varies with climate. In semiarid regions, there is substantial evidence that deep percolation or recharge to the groundwater occurs only in small portions of the basin where runoff is concentrated, such as depressions and ephemeral stream channels (Goodrich et al., 2004), or where redistribution and drifting of snow causes concentrated input to the soil (Chauvin et al., 2011). There is little to no deep percolation in small upland or inter-channel watersheds due to: 1) plant adaptation to extract vadose zone moisture under large negative pressure; 2) thick vadose zones; and 3) upward temperature gradients (Coes and Pool, 2005; Goodrich et al., 2004; Heilweil and Solomon, 2004; Plummer et al., 2004; Scanlon et al., 1997, 2003; Scott et al., 2000; Walvoord et al., 2002). In more humid regions, percolation and groundwater recharge occur throughout the upland catchment area.

In this study, percolation was the component with the greatest uncertainty. Yet, this variable is essential to our understanding of the sustainability of agriculture and regional water resources. To ensure maximum crop growth, precipitation needs to infiltrate into the soil where plants can utilize it. Water not used by vegetation nor evaporated can percolate and contribute to aquifer recharge and stream base flow. Greater and slower percolation through the soil reduces the magnitude of floods and droughts, respectively. As such, it is essential that percolation be adequately quantified. Since percolation is difficult to measure directly, it is frequently derived by subtraction as the water budget residual. Accuracy of the water balance method to estimate percolation will improve as other components are measured with greater certainty. In addition, some of the techniques discussed in the percolation section (2.3.5) could possibly be extended from semi-arid watersheds to other LTAR watershed sites. As for ET, the concurrent use of multiple methods to measure percolation may increase the reliability of percolation estimates.

Soil water content drives plant growth and production in agroecosystems, yet it is often poorly measured and carries a high degree of uncertainty across the LTAR network. Fortunately, there are many methods available for measuring soil water content (Vereecken et al., 2008; 2014), which can increase our understanding of water dynamics at various spatial and temporal scales. Point-based measurements with electromagnetic sensors (e.g., capacitance probes, time-domain reflectometry) can monitor temporal variability in soil water content at a single location, or can be linked through wireless sensor networks to increase spatial coverage (Vereecken et al., 2014). Air- and space-borne sensors can map near-surface soil water content at larger spatial scales where point-based measurements are not feasible (Mohanty et al., 2017; Vereecken et al., 2014). By increasing our understanding of soil water dynamics in agroecosystems, we will improve our water budget estimates, and provide valuable information for agricultural production and water management.

4.2. The role and detection of climate-induced changes

With LTAR sites spanning the United States, potential changes in temperature and precipitation at each site will vary by region (Romero-Lankao et al., 2014). While these potential differences in climate trajectory are not explored here, changes in mean, high and/or low extremes in temperature (Garbrecht et al., 2014b), and precipitation (Feng et al., 2016) have been directly observed at some long-term site locations and are likely to be occurring at others (Garbrecht et al., 2014a; Lu et al., 2015; Nayak et al., 2010). Knowledge of the effects of these changes on the water budgets components for agricultural land will inform the management of water resources in agricultural watersheds under future climate. Currently, the effects are simulated based on climate and hydrologic models. LTAR sites have explored climate change impacts through modeling at various scales and U.S. locations: impacts on winter wheat production and erosion in the Southern Plains (Garbrecht and Zhang, 2015; Garbrecht et al., 2015, 2016; Zhang, 2012); hydrologic impacts in the Goodwater Creek Experimental Watershed in the Central Mississippi River Basin (Gautam et al., 2018; Phung et al., 2019); impacts on evapotranspiration, water stress, and productivity in sagebrush ecosystems (Flerchinger et al., 2019); and impacts on runoff, sediment, and nutrient loads in Beasley Lake watershed (Yasarer et al., 2017). Monitoring of the different water budget components is necessary to provide evidence-based demonstration of these effects, verify model results, and encourage adoption of management practices that mitigate the effects of future climate.

Yet, at these LTAR sites, the expected changes in discharge and ET caused by an increase in temperature or precipitation are expected to remain small ($<$ 10%) and smaller than the current measurement uncertainties for these components. Thus, direct observation of these trends will require improved measurement techniques and uncertainty quantification, as well as a reduction of these uncertainties at or below the magnitude of the expected changes. In addition, potential divergence of conclusions based on model results and monitoring data should enable the improvement of these models. Ultimately, modeling uncertainties cannot be smaller than the uncertainties of the data used to develop and calibrate the models. Thus, the use of models to inform adaptation to climate change requires high quality data to develop and calibrate these models. The LTAR network is addressing these monitoring challenges. With respect to evapotranspiration, the EC towers installed at most LTAR sites will allow for long-term measurements of ET over a wide range of conditions and may be useful for detecting trends related to climate change. These towers will add to the growing body of data broadly collected through networks such as Ameriflux and ensure that a variety of agricultural systems are represented in these long-term databases (Thompson et al., 2011).

Extremes in the current climate regime are also a challenge to quantify accurately and present an opportunity for the LTAR network to contribute new methods. Tipping bucket rain gauges typically underestimate precipitation volumes during high rainfall events (Michaelides et al., 2009). Expected increases in precipitation intensity may result in more events that exceed the capacity of current measuring systems to accurately measure precipitation volume and rates (Kunkel et al., 2013; Shedekar et al., 2016). With LTAR sites developing field-based infrastructure to measure climatic variables in agroecosystems across climatic regions, there is potential to test and implement new technologies for direct measurement of precipitation and to provide comparisons for remotely sensed radar and satellite methods.

An increase in extreme precipitation events may also cause flooding and bankfull flow conditions that exceed the current range of observed flows or the feasibility of a measurement. Such extreme conditions increase the uncertainty in quantification of flows (Baffaut et al., 2014; Hamilton and Moore, 2012; Harman et al., 2008). When on-the-ground data collection is not safe or feasible, use of aerial imagery, Light Detection and Ranging (LiDAR) data, or satellite measurements may fill in some gaps (Bjerklie, 2007; Mount et al., 2003; Schumann et al., 2011). The diverse expertise within the LTAR network in the fields of remote sensing, field hydrology, and hydrologic modeling provides strong potential for collaborations across these methodologies for improved quantification and understanding of the impacts of extreme events on agroecosystems.

4.3. The impact of sustainable management

Spiegal et al. (2018) identified the dominant sustainability goals of agricultural intensification across the LTAR network, including the protection and improvement of regional water quality (sought in 16 of 18 sites) and water supply (sought in 8 of 18 sites). The three most frequently cited water-related goals at these sites include: reducing runoff, increasing infiltration or percolation, and increasing soil water content or water holding capacity by amounts ranging from 10% to 20%. These goals collectively support the general objectives of increasing water use efficiency for plant growth. Such aspirational outcomes can be achieved by techniques adapted to the specific conditions at each site.

Sites having excessive runoff or percolation have the opportunity to explore alternative cropping systems or rotations that increase crop production and therefore ET and reduce water losses. In some locations, like the CAF site, this may mean a transition to more fall seeded crops to take advantage of winter and early spring soil moisture. In other locations, this may mean exploring cover cropping or intercropping. However, this analysis has shown that the uncertainty of the components was greater than the expected impact these practices may have on water budget components, i.e., 10%-20%. Therefore, improved measurement of the water budget components is necessary to evaluate the suitability of these practices and the quantification of water resources in agricultural watersheds if these practices are widely adopted. Conversely, there are few opportunities to intensify cropping systems in regions with very low percolation and runoff. Crop production and agroecosystem sustainability will be highly vulnerable to future shifts in the climate and irrigation may have an important role in these regions.

The relative lack of irrigation use among the LTAR sites reflects the rationale for the historical establishment of these research sites: long-term water quality problems, which are often associated with runoff and/or drainage, or rangeland sites in semi-arid climatic regions, which are typically not irrigated. Nevertheless, the role of irrigation in major U.S. regions such as the Central and Southern Plains, the Lower Mississippi River Basin, the Southeast, and the California central valley will likely continue to grow as climate becomes less predictable (Döll, 2002). Furthermore, any water limited (i.e., semi-arid) region could benefit from irrigation. However, reliance on irrigation modifies the magnitude of some of the water budget components at field and watershed scale. In addition, it increases vulnerability to future reductions in water availability. Accurate determination of water budgets under irrigation management is therefore critical. Water supply limitations in many of these regions have resulted in initiation of new research on irrigation efficiency and the development of water saving approaches (Bryant et al., 2017; Kebede et al., 2014; Payero et al., 2009). As the LTAR network continues to evaluate long-term water budgets across the United States, it will be important to consider the changing role of irrigation use and efficiency on growing season water inputs. As irrigation becomes a more significant requirement in the future, the LTAR network will need to address it as a component of aspirational management scenarios.

An ongoing challenge to LTAR network research is that percolation and soil water content are poorly quantified. Demonstrating the benefits of these aspirational goals will require additional investment in the development and utilization of monitoring equipment to improve estimates of percolation and soil water content and to further reduce uncertainty in estimation of these water budget components.

5. Conclusions

Water budgets were developed using multi-annual data from small and large catchments at the 18 LTAR sites in the United States by estimating precipitation, evapotranspiration, surface outflows (surface and subsurface flow), percolation, and change in water storage. Hydrologic characterization of each catchment was performed using indicators such as evapotranspiration and surface outflow. A Budyko plot of all the sites illustrates the spectrum of network sites across gradients of water and energy limitation as viewed through this framework.

CRediT authorship contribution statement

Claire Baffaut: Conceptualization, Methodology, Formal analysis, Writing - original draft, Writing - review & editing. **John M. Baker:** Writing - original draft, Writing - review & editing. **Joel A. Biederman:** Writing - review & editing. **David D. Bosch:** Investigation, Data curation, Writing - review & editing. **Erin S. Brooks:** Writing - original draft, Writing - review & editing. **Anthony R. Buda:** Investigation, Data curation. **Eleonora M. Demaria:** Visualization, Data curation, Writing - review & editing. **Emile H. Elias:** Visualization, Data curation, Writing - review & editing. **Gerald N. Flerchinger:** Data curation, Writing - review & editing. **David C. Goodrich:** Conceptualization, Data curation, Writing - review & editing. **Stephen K. Hamilton:** Investigation, Data curation, Writing - review & editing. **Suart P. Hardegree:** Data curation, Writing - review & editing. **R.Daren Harmel:** Investigation, Methodology, Writing - original draft, Writing - review & editing. **David L. Hoover:** Investigation, Data curation, Writing - original draft, Writing - review & editing. **Kevin W. King:** Investigation, Writing - review & editing. **Peter J. Kleinman:** Data curation, Writing - review & editing. **Mark A. Liebig:** Investigation, Data curation, Writing - review & editing. **Gregory W. McCarty:** Data curation, Writing - review & editing. **Glenn E. Moglen:** Writing - review & editing. **Thomas G. Moorman:** Investigation, Data curation, Writing - review & editing. **Daniel N. Moriasi:** Data curation, Writing - review & editing. **Jane Okalebo:** Data curation, Writing - original draft. **Fred B. Pierson:** Data curation. **Eric S. Russell:** Writing - original draft, Writing - review & editing. **Nicanor Z. Saliendra:** Data curation, Writing - original draft, Writing - review & editing. **Amartya K. Saha:** Investigation, Writing - original draft, Writing - review & editing. **Douglas R. Smith:** Writing - review & editing. **Lindsey M.W. Yasarer:** Data curation, Writing - original draft, Writing - review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jhydrol.2020.125021.

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