Maped Hydroclimatology of Evapotranspiration and Drainage Runoff Using SMAP Brightness Temperature Observations and Precipitation Information

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Abstract The partitioning of incident precipitation into evapotranspiration, runoff, drainage and storage change, and hydrologic fluxes depends on the soil moisture state. With the availability of global remotely sensed soil moisture fields, the functional dependence of each flux on soil moisture may be identifiable. In this study we develop an observation-driven approach to map key hydroclimatology fields using remotely sensed soil moisture and gauge-based precipitation data only. National Aeronautics and Space Administration’s Soil Moisture Active Passive (SMAP) low-frequency microwave brightness temperature observations and precipitation fields, from the National Centers for Environmental Prediction, are the sole inputs into an adjoint-state variational estimation framework. Furthermore, the proposed methodology does not rely on micrometeorological information, or land surface models. The approach is flexible by design so that almost any partitioning pattern can result from estimation and corresponding evapotranspiration and drainage fields can be quantified. Three-year averaged summer season evapotranspiration estimates are compared with available vapor flux at in situ AmeriFlux eddy-covariance sites. Basin-averaged drainage over major U.S. hydrologic units is also compared with U.S. Geological Survey streamgages measurements. The remote sensing-based estimated hydroclimate fields explain about 70% of the variance in the in situ measurements. This exploratory study adds to the body of evidence emerging in literature that a significant amount of hydrologic information is encoded in the dynamic fields of remotely sensed soil moisture. Observation-driven hydroclimate data fields that are independent of land surface models can provide valuable insights into the state of the water cycle and guide future development of land surface models.

1. Introduction

The partitioning of surface precipitation into evapotranspiration (ET), runoff, and storage changes influences landscape hydrology. Furthermore, this partitioning also affects the surface energy balance and biogeochemical cycles, most notably the carbon cycle. Determination of this partitioning requires information on ET and drainage (D) rates and surface precipitation-runoff transformation. Direct (in situ) measurements of these quantities are available, but they are not pervasive enough to allow regional or global mapping. Furthermore, they are also often not coincident such that they can be used to close the water budget without aggregating closure errors into one or more of the unobserved fluxes.

ET flux is measured using eddy covariance or energy balance Bowen-ratio suite of instruments. Networks of such instruments are in operation and provide valuable direct measurements of ET (Chu et al., 2017). They are, however, sparse in their spatial coverage and do not allow comprehensive mapping. In order to achieve a more complete data set with spatial and temporal coverage, ET models or land surface hydrology are typically used in conjunction with their required inputs. ET is thus estimated as the output of a constrained model integration. These approaches are viable, but they bear a heavy signature of the model used in the process (Jiménez et al., 2011; McCabe et al., 2016; Wang & Dickinson, 2012; Zhang et al., 2016). There are a wide variety of other model-based approaches such as Penman-Monteith (Mu et al., 2011), Priestley-Taylor (Fisher et al., 2008; Martens et al., 2017; Miralles et al., 2011; Purdy et al., 2018), water balance residual (Wan et al., 2015), eddy covariance tower upscaling methods (Jung et al., 2009), and boundary layer constraints (Rigden & Salvucci, 2015). ET estimates from these models are, in general,
reasonable across different climates. However, due to model differences (Mueller et al., 2013; Zeng & Cai, 2018) and different spatial resolutions of hydrometeorological inputs (Wang & Dickinson, 2012), inconsistencies may arise. Discrepancies in ET estimates among models may further increase when neglecting to account for variations in terrestrial water storage (Han et al., 2015).

Stream flow losses from the landscape are directly measured using streamgage and current velocity sensors. These measurements have an altogether different support area (the draining watershed) and are heavily influenced by diversions, storage reservoirs, and flow across the surface and subsurface. Estimation of global runoff fields using precipitation as the principal input, and hydrologic models as the mean for estimating the fraction that is runoff, is also heavily affected by the choice of model and model construct (Beck et al., 2017). Observation-derived global mapped fields of precipitation partitioning into ET, runoff, and storage change cannot be assembled using such examples of direct measurements.

In recent years a new data set relevant to global hydrology has become available that may allow an alternate approach to this problem. We now have access to global and dynamic fields of surface soil moisture through satellite missions such as the C-band Advanced Scatterometer (Figa-Saldaña et al., 2002), the Advanced Microwave Scanning Radiometer, and its follow-up Advanced Microwave Scanning Radiometer 2 (Kawanishi et al., 2003) as well as the L-band European Space Agency’s Soil Moisture and Ocean Salinity (SMOS) that was launched in 2009 (Kerr et al., 2010) and the National Aeronautics and Space Administration’s Soil Moisture Active Passive (SMAP) that was launched in 2015 (Entekhabi et al., 2010). These satellite missions provide frequent (about three times weekly each) and global surface water content estimates at about 40-km spatial resolution. Furthermore, SMAP and SMOS both use low-frequency (1.4 GHz) microwave emission measurements to sense the soil water content in the top few centimeters (typically 5 cm) of the soil. Dynamics of subsurface soil moisture are linked to surface soil moisture. Therefore, the observed surface soil moisture dynamics are typically indicative of more than the 5-cm sensing depth in the context of a water balance model (Akbar et al., 2018b).

Soil moisture is the state variable of the surface hydrologic system and hence a determinant of the partitioning of precipitation into ET, runoff, and storage change. The availability of remotely sensed soil moisture—from SMAP and SMOS, for example—and precipitation information raises the question whether it is possible to improve the estimation of this partitioning globally. Land data assimilation and state-estimation systems achieve this goal by using such measurements to constrain hydrologic models (see, e.g., Rasmussen et al., 2015). However, data assimilation outputs typically bear signatures of the hydrologic forecast model, either as the background field or statistical prior.

This study examines the possibility of using global and dynamic fields of sensed surface soil moisture and precipitation to make quantitative maps of surface ET and runoff fields without invoking an already-parameterized hydrologic or land surface model (LSM). The challenge is to use only these two data streams, without heavy reliance on land use classification, soil hydraulic parameters, radiative fluxes, winds, and other surface micrometeorology data sets. The key enabling factor, however, is the availability of information on the dynamics of the hydrologic state variable—especially soil moisture.

Recently, basin-scale water balance and closure studies have assessed the suitability of SMAP and other remotely sensed soil moisture estimates to track terrestrial water storage dynamics (Crow, Chen, et al., 2017; Crow, Han, et al., 2017), estimating precipitation (Brocca et al., 2013; Koster et al., 2016), enhancing remote sensing-based rainfall products (W. Crow et al., 2011; Pellarin et al., 2008), and improve streamflow forecasting via direct usage of SMAP soil moisture or as inputs into land data assimilation models (Crow, Chen, et al., 2017; Crow, Han, et al., 2017). Furthermore, a number of studies have made estimates of the total hydrologic loss function (sum of ET and runoff) using precipitation and SMAP information on surface soil moisture dynamics (Akbar et al., 2018b; Jalilvand et al., 2018; Koster et al., 2018, 2017). A key challenge is to partition this total loss function among its constituent ET and D losses components.

In this study we propose an observation-driven estimation technique to decode and maximally extract available, yet hidden, information within SMAP data fields. Specifically, we will investigate whether local surface water vertical fluxes such as ET and D can be quantified using SMAP observations and precipitation. The focus is only over the Continental United States since we can use the relatively dense part of the FLUXNET (AmeriFlux) eddy-covariance and the U.S. Geological Survey (USGS) streamgage networks to evaluate the results using strictly independent in situ measurements.
Our approach is minimalistic and is implemented without the need for an already parameterized hydrologic model, for example, a LSM. Instead, in this study the soil water loss function components (ET and D) follow functions whose shapes are based on known physical considerations. The parameters that shift and scale the ET and D functions are allowed to vary freely within the proposed method. As a consequence, almost any flux partitioning may result when using SMAP brightness temperature (TB) and precipitation data within a variational estimation framework to estimate the ET and D function parameters. Overall, the proposed variational approach is distinct from unconstraint parameter estimation or brute force search techniques in that mass balance is enforced using an adjoint state model via Lagrange multiplier variables.

Section 2 briefly discusses the data sources. In section 3 the variational estimation method is outlined. This section also introduces the water balance equation, the soil water loss function, and its components. Section 4 examines, in detail, derived fields and parameters. This section also contains results comparing the climatology of ET and D fluxes against independent and direct in situ measurement. Potential shortcomings, inherent caveats, and other discussions are also included in section 5.

2. Data Sources

The presented methodology is minimalistic in that it uses two data sources: remotely sensed information on surface soil moisture and gauge-based precipitation. The study duration spans warm-season (May–September [MJJAS]) for 2015 to 2017 and covers the conterminous United States.

TB observations from the National Aeronautics and Space Administration SMAP Mission are the first primary data source (O’Neill et al., 2014, 2016). In this study we use the 36-km gridded data, which has a resolution of about 30 to 40 km, depending on position within the swath. The unit area of study is therefore large (about 1,200+[km²]) but with complete geographical coverage that allows mapping. SMAP TB data files also contain the necessary electromagnetic emission model parameters—such as physical soil temperature, soil texture, vegetation water content, and vegetation specific electromagnetic parameters. These latter parameters are required to link the observed microwave emission to the geophysical soil moisture variable and are optimized for use in SMAP soil moisture estimation algorithms. We extract these parameters from the same SMAP TB data files. In this, and similar studies, regardless of whether SMAP soil moisture products are used, or SMAP TB, these emission model petameters are required. Hence, we denote both the SMAP soil moisture product and the TB coupled with an emission model as soil moisture information without distinction. Furthermore, note that the baseline SMAP soil moisture product uses only vertically polarized TB. Here, instead, we opt to use both V- and H-polarized TB since both polarizations contain valuable soil moisture information. Inversion in the presence of noisy measurements is better posed when both channels are utilized.

The estimation framework of this study always has a prior soil moisture estimate available, which lends itself to direct radiance assimilation. The use of TBs rather than soil moisture products also allows future extension of the approach to estimate canopy water content, which reduces emission inversion uncertainty and opens the path to studies of water relations in the soil-plant continuum. Estimation and optimization of TB specific parameters are currently beyond the scope of this manuscript; however, they are suitable for SMAP soil moisture estimation. This parameter set is independent from the ET and D “hydrological” parameter set, which will be estimated in this work.

The second primary data source is precipitation. Consistent with a series of prior analysis over the United States (Akbar et al., 2018a, 2018b; Koster et al., 2017), high-quality gauge-based daily precipitation data from the National Centers for Environmental Prediction’s Climate Prediction Center (CPC; NCAR, 2017) are used. CPC precipitation is resampled to 6-hourly time steps and then reprocessed to the same SMAP 36-km TB grid. Thus, for each pixel, time series of both TB and precipitation are available. Temporal resampling to 6-hourly time steps is performed by simply diving each day’s precipitation into four equal 6-hr intervals.

To evaluate the consistency of estimated ET and D fluxes, in situ measurements are required. Monthly streamflow data for all major hydrologic unit basins (HU-2; Seaber et al., 1987) are from the USGS streamgage measurements located at basin outlets (USGS, 2012). The USGS runoff map is estimated using streamflow from about 6,000 USGS streamgagees divided by their respective D basin boundaries (https://water.usgs.
Runoff from areas of geographical intersection is weighted by their relative coverage to form a single weighted-average runoff value for each of the about 2100 USGS hydrologic cataloging units (HUC8s). In this study HUC8 watershed boundary data are extracted from the National Hydrography Dataset at USGS and used to compare the spatial patterns of year-by-year streamflow and their deviation from 3-year averages. The USGS data cover the period of SMAP data used in this study.

Multiyear-averaged ET estimates from the proposed estimation method are also compared with climatology of evaporation from latent heat flux eddy covariance measurements over the United States. The climatology is calculated by averaging all available measurements from the AmeriFlux Network (http://ameriflux.lbl.gov/) across all available times and all sites. AmeriFlux sites do not update often. Only a few sites include data coincident with the record period of SMAP data used in this study. Therefore, the summer season climatology at each site is formed from all available data in the AmeriFlux record and compared with climatology of SMAP-derived ET for the 3 years used in the study. We therefore expect some errors if the 3 years are consistently anomalous with respect to the longer-term climatology. See Table 1 for a list of sites.

SMAP pixels and flux sites that contain significant waterbodies (water fraction >1%), large vegetation water content (>7 kg/m²), or negligible mean precipitation (< ¼ mm/day) are excluded. Surface Water fraction and Vegetation Water Content (VWC) information are readily available from SMAP (O’Neill et al., 2016). The spatial resolutions of the final results, based on SMAP data, are all provided at the 36-km resolution. The proposed method can also be applied to finer resolution 9-km SMAP observations as well.

3. Methodology

The adjoint-state variational approach is an efficient way of solving parameter estimation problems with constraints (Evensen et al., 1998). The cost function to be minimized is the sum of the squared differences between TB observations and predictions. The water mass balance in (1) is the dynamic constraint and is included within the cost function through a Lagrange variable. The solution to the variational problem is a set of estimated parameters and state variables that satisfy the dynamical constraint model and also minimize the misfit between observed and predicted TB (in the least squares sense).

The technique merges the state and parameter estimation problems with the underlying hypothesis that both observations and physical constraints convey useful information regarding the state variable and should be used concurrently (more in section 3.2). Prior application examples of variational estimation of ET include estimation of various land-atmospheric states and fluxes using remotely sensed land surface temperature or TB (Bateni et al., 2013; Reichle et al., 2001), estimating land surface energy balance components (Caparrini et al., 2004), and ET partitioning into soil-evaporation and canopy transpiration (Xu et al., 2016) over an irrigated crop site.

The following section begins with a water balance formulation and introduces a parametric soil water loss function (section 3.1). Then, the overall objective function and optimization approaches are discussed in section 3.2.

3.1. Water Balance and Loss Function

The temporal dynamics and evolution of soil moisture within a simple hydrologically active control volume, with depth \(\Delta z\) [L], can be described by the water balance formulation:

\[
\Delta z \frac{d\theta}{dt} = P(t) - L(\theta),
\]

where \(\theta\) [-] is volumetric soil moisture and \(P(t)\) is measured precipitation [LT\(^{-1}\)]. \(L(\theta)\) is the soil water loss function [LT\(^{-1}\)] that captures moisture divergence from the control volume in the form of ET and D. \(\Delta z\) [L] is the unknown depth, or characteristic length scale, of the control volume that is required to ensure water balance closure (Akbar et al., 2018a). The L-band sensing depth is limited to about 50 mm although it varies depending on the soil moisture and temperature profiles. More moist soils have shallower emission depths than drier soils. The hydrologic length scale \(\Delta z\) (to be estimated) uses the sensing-depth soil moisture dynamics as an indicator of the soil moisture profile. It includes the actual sensing depth and is also tied to the dynamics of soil moisture below the sensing depth (Akbar et al., 2018b).
| Site name | Lat  | Long   | Start | End  | Citation               |
|----------|------|--------|-------|------|------------------------|
| A32      | 36.8193 | −97.8198 | 2015 | 2018 | (Kueppers et al., 2018a) |
| A74      | 36.8085 | −97.5489 | 2015 | 2018 | (Kueppers et al., 2018b) |
| AR1      | 36.4267 | −99.42  | 2009 | 2013 | (Billesbach & Bradford, 2016a) |
| AR2      | 36.6358 | −99.5975 | 2009 | 2013 | (Billesbach & Bradford, 2016b) |
| ARM      | 36.6058 | −97.4888 | 2002 | 2014 | (Torn, 2016c) |
| ARb      | 35.5497 | −98.0402 | 2005 | 2007 | (Torn, 2016a) |
| ARc      | 35.5465 | −98.04  | 2005 | 2007 | (Torn, 2016b) |
| Aud      | 31.5907 | −110.5104 | 2002 | 2012 | (Meyers, 2016a) |
| Bo1      | 40.0062 | −88.2904 | 1996 | 2009 | (Meyers, 2016b) |
| Bo2      | 40.009  | −88.29  | 2004 | 2009 | (Bernacchi, 2016) |
| Br1      | 41.9749 | −93.6906 | 2005 | 2012 | (Parkin & Frueger, 2016a) |
| Br3      | 41.9747 | −93.6936 | 2005 | 2012 | (Parkin & Frueger, 2016b) |
| CZ4      | 37.0675 | −118.9867 | 2009 | 2016 | (Goulden, 2018a, 2018b) |
| Cop      | 38.09  | −109.39 | 2001 | 2008 | (Bowling, 2016) |
| Ctn      | 43.95  | −101.8466 | 2006 | 2010 | (Meyers, 2016c) |
| Elm      | 25.5519 | −80.7826 | 2008 | 2015 | (Oberbauer & Starr, 2016) |
| FFe      | 48.3077 | −105.1019 | 2000 | 2009 | (Meyers, 2016d) |
| FR2      | 29.9495 | −97.9962 | 2005 | 2009 | (Litvak, 2016a) |
| FR3      | 29.94  | −97.99  | 2004 | 2013 | (Heilman, 2016) |
| Fmf      | 35.1426 | −111.7273 | 2005 | 2011 | (Dor & Kolb, 2016a) |
| Fuf      | 35.089  | −111.762 | 2005 | 2011 | (Dor & Kolb, 2016b) |
| FwF      | 35.4454 | −111.7718 | 2005 | 2011 | (Dor & Kolb, 2016c) |
| GBT      | 41.3658 | −106.2397 | 1999 | 2007 | (Massman, 2017) |
| GLE      | 41.3665 | −106.2399 | 2004 | 2017 | (Massman, 2016) |
| IB1      | 41.8593 | −88.2227 | 2005 | 2018 | (Matamala, 2016a) |
| IB2      | 41.8406 | −88.241  | 2004 | 2018 | (Matamala, 2016b) |
| KFS      | 39.0561 | −95.1907 | 2007 | 2013 | (Brunsell, 2016) |
| LWW      | 34.9604 | −97.9789 | 1997 | 1999 | (Meyers, 2016e) |
| MOz      | 38.7441 | −92.2   | 2004 | 2016 | (Gu, 2016) |
| Mpj      | 34.4384 | −106.2377 | 2008 | 2018 | (Litvak, 2016b) |
| Ne1      | 41.1651 | −96.4766 | 2001 | 2014 | (Suyker, 2016a) |
| Ne2      | 41.1649 | −96.4701 | 2001 | 2014 | (Suyker, 2016b) |
| Ne3      | 41.1797 | −96.4397 | 2001 | 2014 | (Suyker, 2016c) |
| ORv      | 40.0201 | −83.0183 | 2011 | 2012 | (Bohrer, 2016) |
| Ohno     | 41.5545 | −83.8438 | 2004 | 2014 | (Chen, 2016) |
| Pon      | 36.7667 | −97.1333 | 1997 | 2001 | (Verma, 2016a) |
| Rls      | 43.1439 | −116.7356 | 2014 | 2017 | (Flerchinger, 2018) |
| Rms      | 43.0645 | −116.7486 | 2014 | 2017 | (Flerchinger, 2017a) |
| Ro4      | 44.6781 | −93.0723 | 2014 | 2018 | (Baker & Griffis, 2018a) |
| Ro5      | 44.691  | −93.0576 | 2017 | 2018 | (Baker & Griffis, 2018b) |
| Ro6      | 44.6946 | −93.0578 | 2017 | 2018 | (Baker & Griffis, 2018c) |
| Rws      | 43.1675 | −116.7132 | 2014 | 2017 | (Flerchinger, 2017b) |
| SCh      | 33.8079 | −116.7717 | 2006 | 2015 | (Goulden, 2018a, 2018b) |
| SFP      | 43.2408 | −96.902  | 2007 | 2010 | (Meyers, 2016f) |
| SO2      | 33.3738 | −116.6228 | 1997 | 2007 | (Oechel, 2016a) |
| SO3      | 33.3771 | −116.6226 | 1997 | 2007 | (Oechel, 2016b) |
| SO4      | 33.3845 | −116.6406 | 2004 | 2007 | (Oechel, 2016b) |
| SRC      | 31.9083 | −110.8395 | 2008 | 2015 | (Kurc, 2016) |
| SRG      | 31.7894 | −110.8277 | 2008 | 2017 | (Russell Scott, 2016a) |
| SRM      | 31.8214 | −110.8661 | 2003 | 2017 | (Russell Scott, 2016b) |
| Seg      | 34.3623 | −106.7019 | 2007 | 2018 | (Litvak, 2016c) |
| Sex      | 34.3349 | −106.7442 | 2007 | 2018 | (Litvak, 2016d) |
| Shd      | 36.9333 | −96.6833 | 1997 | 2001 | (Verma, 2016b) |
| Sta      | 41.3966 | −106.8024 | 2005 | 2010 | (Ewers & Pendall, 2016a) |
| Wdm      | 40.7838 | −106.2618 | 2006 | 2009 | (Ewers & Pendall, 2016b) |
| Whs      | 31.7438 | −110.0522 | 2007 | 2017 | (Russell Scott, 2016) |
| Wjs      | 34.4255 | −105.8615 | 2007 | 2018 | (Litvak, 2016c) |
| Wkg      | 31.7365 | −109.9419 | 2004 | 2016 | (Russell Scott, 2016c) |
| Wlr      | 37.5208 | −96.855  | 2001 | 2004 | (Cook & Coulter, 2016) |
Soil water losses from this hydrologic volume—with length \(\Delta z\)—are partitioned into soil moisture (\(\theta\)) dependent ET and D functions as

\[
L(\theta) = ET(\theta; a, b) + D(\theta; c, d).
\]

(2)

At this stage parameterized models for ET and D would be necessary in order to integrate the water balance model in (1). Here, instead, only the shapes of these functions are considered. We require that the two fluxes obey some functional form (shape), which is guided by the physics of evaporation and D. The unknown parameters \(a, b, c,\) and \(d\) are free and will be determined using variational estimation (see paragraphs below).

The ET function’s dependence on soil moisture is taken to be a flexible hyperbolic tangent function that begins at zero when soil moisture is dry and gradually increases to an asymptote when the soil is moist. The parameters \(a\) and \(b\) determine where, on the soil moisture scale, the function makes the transition from zero (suppression of ET by low soil moisture) to its asymptote—where ET from the moist soil is limited by available energy (potential evaporation). The transition from water-limited to energy-limited evaporation regimes is controlled by the \(b\) parameter. \(a\) is the level of the asymptote and is constant over time for the warm-season estimation period in this study (MJIAS). Both parameters are allowed to obtain any value and can form ET functions essentially spanning all possible transitional and potential evaporation regimes (see the supporting information for examples). A candidate function that can achieve this level of flexibility with only two parameters is

\[
ET(\theta; a, b) = \frac{a}{2} \left[ 1 + \tanh \left( b \cdot \left( \frac{\theta}{\theta_b} - \sigma(b) + 0.25 \right) \right) \right] \text{[LT}^{-1}] ,
\]

(3)

where the \(b\) parameter is wrapped within a sigmoid function, that is, \(\sigma(b) = \frac{1}{1 + e^{-b}}\), so it is unbounded within the optimization process (section 3.2), yet \(\sigma(b) \in [0, 1]\).

The parameter \(\phi\) in (3)—and later used in (4)—is the soil porosity. Its use is optional, and its specification could easily be circumvented. It is included here for implementation and results-interpretation purposes only. The parameter \(\phi\) can be incorporated into the definition of \(b\) in (3)—and \(c\) in (4)—since they are free to vary in the estimation. Global harmonized data sets on soil texture at 1- to 36-km resolutions are available from SMAP (Das, 2013), which over the United States primarily uses the State Soil Geographic Dataset (Soil Survey Staff, 2010). For each pixel, we use the corresponding sand and clay fractions to calculate and approximate soil porosity \(\phi = (\text{sand} \times 0.395) + (\text{clay} \times 0.482) + (1 - \text{sand} - \text{clay}) \times 0.451\).

The D loss function in (2)—at the SMAP scale of about 36 km by 36 km pixels—represents the divergence of soil water within the control volume that is due to subsurface lateral and vertical soil water flow. At these large spatial scales (1,200 + km²) we assume that infiltration-excess (runoff) is mostly reinfiltrated across the landscape and streamflow is ultimately fed water from within the hillslope soils. This drained water from the hillslope soils is accumulated across the landscape and contributes to stream discharge. The vertical D or soil water flux from each pixel unit is limited by the capacity of the deeper subsurface soil column to absorb water. The rate of D can be high and approaching the soil hydraulic conductivity for well-drained soils (generally exceeding the ET rate that is less than a few millimeters per day). It can be reduced for poorly drained soil columns or soil columns with high clay fraction. The D rate is also regulated by the soil volumetric moisture content. In the limit of gravity D, the flow rate approaches the unsaturated hydraulic conductivity, which is a scaled power law in soil volumetric moisture content (e.g., Clapp & Hornberger, 1978). Following Koster et al. (2018) and Jalilvand et al. (2018), we also invoke a D function that is inspired by this physical consideration but has parameters that are estimated using the soil moisture and precipitation data input streams and (1):

\[
D(\theta; c, d) = c \left( \frac{\theta}{\theta_b} \right)^d \text{[LT}^{-1}] .
\]

(4)

The \(c\) parameter controls the maximum rate of loss, and the \(d\) parameter controls the reduction of this loss by the level of soil moisture saturation. With flexible \(c\) and \(d\) parameters, the D function can...
assume a variety of forms, allowing for a wide range of water balance partitioning spanning from D dominated to ET dominated. The dependence on the soil moisture level is captured by $d$ (to be estimated) in (4), which controls at what soil moisture level D loss dominates over ET and how this loss rate varies with soil moisture content.

We note that the estimated parameters $c$ and $d$ are not necessarily the effective unsaturated soil hydraulic parameters (equal to gravity D). Instead, they are landscape D parameters that may include an element of gravity-driven flow but also reflect other factors such as poor landscape D due to topography and lithological characteristics.

The value of precipitation as an input is primarily to scale these functions by influencing parameters that also have physical units ($a$ and $c$ in millimeters per day and $\Delta z$ in millimeter). Precipitation rate lends its length unit to shaping mass balance in equation (1). The key development consideration, therefore, is that the D parameter with a scale ($c$ in $[LT^{-1}]$) also complements the scaled ET parameter ($a$ in $[LT^{-1}]$), but its magnitude can be similar or far different. Additionally, the loss function and its components are non-linear functions of soil moisture. Hence, observed soil moisture changes between overpasses paired with the starting value at the beginning of this change, that is, the local slope or rate of soil moisture dynamics and its dependence on soil moisture contribute to the estimation of the dimensionless shape parameters $b$ and $d$. The estimation framework will use the implicit information on the rate of soil moisture reduction during dry downs to partition total soil moisture loss between ET and D.

The functional form of $L$ in (2)—as the sum total of the ET and D functions—typically yields the familiar three-stage soil water loss function (Rodriguez-Iturbe & Porporato, 2007; Salvucci, 2001). Hence, it is applicable to the body of literature analyzing soil moisture dynamics using stochastic rainfall and analytical loss functions. Overall, however, the shape of $L$, and the resulting soil moisture, is determined by the unknown parameter vector $X = [a [LT^{-1}], b [-], c [LT^{-1}], d [-], \Delta z [L]]$ and no further constraints are placed on its shape. Figure S1 shows how changes in each parameter affect the shape of the ET and D functions, and Figure 1c is an example estimated $L(\theta)$.

Alternatively, and in the recent applications with SMAP data, the loss function can be reconstructed by calibrating a piecewise linear function to SMAP soil moisture (Koster et al., 2017) or by analyzing the rates of SMAP soil moisture dry down and their temporal increments (Akbar et al., 2018a). Such observation-driven loss functions are notably model free but cannot distinctively partition the total loss into ET and runoff D components.
3.2. Objective Function and Parameter Estimation

The cost function \( J \) to be minimized consists of a TB-only objective function, \( J_{TB} \), which is constrained—or adjoined—with mass balance in (1):

\[
J = J_{TB} + J_0
\]  

or

\[
J = \frac{1}{N} \sum_{t=1}^{N} \left( \frac{TB_p(t) - TB_p(\emptyset(t)))^2}{NE\Delta T} \right) + \sum_{i=1}^{N} \lambda(t) \left[ \frac{\partial}{\partial t} \left( \frac{P(t)-L(\emptyset, X)}{\Delta T} \right) \right] dt. \tag{6}
\]

\( J_0 \) is known as the adjoint term with the Lagrange multiplier \( \lambda(t) \) and through variational analysis becomes zero. This term ensures state estimates of soil moisture are physically consistent with respect to precipitation and the loss function in (2). \( X \) is the vector of all unknown model parameters. The first term in (6) estimates \( X \)—and as result soil moisture—by minimizing the mismatch between SMAP observed \( TB_p(t) \) and modeled \( TB_p(\emptyset(t)) \) TBs for both H- and V-polarizations over the period of record \( (N = 153 \text{ days}) \). This mismatch is normalized by the expected SMAP TB error standard deviation, \( NE\Delta T = 1.5 \text{ K} \), and does not change the location of the minima. \( TB_p(\emptyset) \) is the well-known zeroth-order solution to the radiative transfer equation, that is, \( \tau = \omega \) model. The near-linear relationship between soil moisture and TB is well understood (Ulaby & Long, 2014) and not discussed in this study. The necessary input parameters to \( TB_p(\emptyset) \)—including physical temperature, vegetation water content and opacity, single scattering albedo, and surface roughness parameter—are available from SMAP (O’Neill et al., 2016).

After interchanging \( \lambda(t) \) using integration by parts, the first variation of the objective function, \( \delta J = \delta J b \delta a \), with respect to each parameter is calculated to arrive at analytical forms to the objective function’s gradients:

\[
\frac{\delta J}{\delta a} = \sum_{t=1}^{N} \left( \frac{\lambda(t)}{\Delta T} \right) \left[ \left( 1 + \tanh \left( 8 \frac{\emptyset(b) - \sig(b) + 0.25}{\phi} \right) \right) \right] dt, \tag{7a}
\]

\[
\frac{\delta J}{\delta b} = \sum_{t=1}^{N} \left( \frac{\lambda(t)}{\Delta T} \right) \left[ -4a \cdot e^b \cdot \sech \left( \frac{\emptyset(b) - \sig(b) + 0.25}{(e^b + 1)^2} \right) \right] dt, \tag{7b}
\]

\[
\frac{\delta J}{\delta c} = \int_{t=1}^{N} \frac{\lambda(t)}{\Delta T} \left( \frac{\emptyset}{\phi} \right)^d dt, \tag{7c}
\]

\[
\frac{\delta J}{\delta d} = \int_{t=1}^{N} \frac{\lambda(t)}{\Delta T} \left[ c \left( \frac{\emptyset}{\phi} \right)^d \cdot \log \left( \frac{\emptyset}{\phi} \right) \right] dt, \tag{7d}
\]

\[
\frac{\delta J}{\delta \Delta T} = \int_{t=1}^{N} \frac{\lambda(t)}{\Delta T^2} \left[ P(t) - L(\emptyset) \right] dt. \tag{7e}
\]

All these of parameters, \([a,b,c,d,\Delta T] \), start from an initial guess and are iteratively updated using the gradients in (7). Equations (7a)–(7e) show the distinction between unconstrained parameter optimization (e.g., gradient descent, Newton and quasi-Newton, and heuristic) approaches and the adjoint-state variational approach. The gradients in (7a)–(7e) are integrals over the estimation period and include a time-variable response to observations provided by \( \lambda(t) \) inside the integral. The variable \( \lambda(t) \) incorporates the influence of all measurements within the estimation window and scales their contributions to the estimate of the gradient distributed over time. The Lagrange multiplier is itself forced by measurement misfits, and the sensitivity to observations between observation times evolves according to the characteristics of the constraining dynamical system. Furthermore, \( \lambda(t) \) is governed by a dynamical system with terminal conditions.
The first variation of $J$ with respect to soil moisture takes a different form than the gradients in (7).

$$
\frac{\delta J}{\delta \theta} = \sum_{i=1}^{t-N} \frac{\partial \mathcal{L}(\theta)}{\partial \theta} \Delta t + \frac{1}{\lambda} \mathcal{L}(\theta) \frac{\partial \mathcal{L}(\theta)}{\partial \theta} \frac{2}{N} \sum_{p=h,y}^{N} \sum_{i=1}^{\lambda} \left( \frac{\partial \mathcal{L}(\theta)}{\partial \theta} \right) \left( \frac{1}{\Delta t \theta_{TB_p - TB_p(\theta)}} \right),
$$

whereby setting this term equal to zero we obtain the Euler-Lagrange equation as

$$(8)$$

$$(8)$$

with the terminal condition $\lambda(N) = 0$. Equation (8) is in fact a first-order linear ordinary differential equation with time-variable coefficients: $\lambda(t) = \lambda(t) \cdot h(t) - tb(t)$; the symbol indicates time derivative. The first two terms in (8) define the homogenous part of the ordinary differential equation and depend only of the first derivative of (1) with respect to soil moisture $l(t) = \frac{1}{\lambda} \frac{\delta l(\theta)}{\delta \theta}$. The last term in (8) is known as the adjoint model forcing term $tb(t) = \sum_{p=h,y}^{N} \left( \frac{\partial \mathcal{L}(\theta)}{\partial \theta} \right) \left( \frac{1}{\Delta t \theta_{TB_p - TB_p(\theta)}} \right)$ evaluated only at TB observation times ($\Delta \theta$ is the Kronecker delta function)—in the case of SMAP this will be every 1–3 days where observations are actually ingested, or assimilated, in to the optimization. The Euler-Lagrange equation is solved using an implicit backward Euler approach, that is, backward in time, and can be numerically discretized as $\lambda_{t+1} = \lambda - h_{t+1} \Delta t \theta_{TB_p - TB_p(\theta)}$.

Having obtained the Euler-Lagrange equation and the object function’s gradients, for each pixel, the optimization and estimation steps are as follows:

1. Start with an initial guess of each parameter $\tilde{X}_0 = [a_0, b_0, c_0, d_0, \Delta z_0]$.
2. Forward simulate (1) to obtain an initial soil moisture time series. Precipitation is known here.
3. Integrate (8) backward in time to determine $\lambda(t)$.
4. Calculate the objective function gradients in (7).
5. Apply a gradient decent-like update term to $\tilde{X}_0$ and evaluate (6), for example, for iteration $i$: $x_{i+1} = x_i - \alpha \frac{\delta J}{\delta \theta}$. 
6. Repeat steps 2–5 till the objective function is minimized or other termination criterion are satisfied.
7. Report the optimum, or estimated, parameter vector $\tilde{X}$ (estimate variables are indicated with $\tilde{\cdot}$).

In this manner, the variational framework essentially becomes a parameter estimation tool, guided by the underlying physics of emission and water balance. The steps above are applied to warm-season (MJJAS) SMAP TB observations over the United States for 2015, 2016, and 2017. For each pixel, the optimization is performed for 10 different initial guesses of $\tilde{X}_0$, and the final $\tilde{X}$ with the smallest objective function value among all initial sets is selected, $J_{\text{opt}}$. Then, $\tilde{X}$ is used to generate a time series of soil moisture via the two loss function components $\tilde{E}T = ET(\tilde{\theta} ; \tilde{\alpha}, \tilde{\beta})$ and $\tilde{D} = D(\tilde{\theta} ; \tilde{\gamma}, \tilde{\delta})$, that is, time series of evaporation and Ds losses. The partitioning of mean $\tilde{E}T$ and $\tilde{D}$ with respect to CPC precipitation is examined and later compared to in situ observations.

4. Results

4.1. Pixel Level Example

Adjoint-state variational estimation for an example single pixel located in Western United States is shown in Figure 1. The pixel’s corresponding SMAP TB observations (not shown) and colocated precipitation measurements are inputs in to the optimization as outlined in section 3. This process then outputs estimates for each parameter $\tilde{X} = [\tilde{a}, \tilde{b}, \tilde{c}, \tilde{d}, \Delta \tilde{z}]$. $\tilde{X}$ defines the shape of the $ET$ and $D$ and functions, Figure 1c, which are then used to forward generate a time series of estimated soil moisture $\tilde{\theta}$, Figure 1a (black line). For comparison, the figure also shows the time series of SMAP soil moisture $\theta_{\text{SMAP}}$. The latter is independently retrieved from SMAP baseline algorithms (O’Neill et al., 2014). Furthermore, note that $\theta_{\text{SMAP}}$ is only available at discrete observation times, while $\tilde{\theta}$ is generated with a 6-hourly time step. As expected, both time series respond appropriately with respect to precipitation (black bars). In-between precipitation events the soil water loss function in Figure 1c (black line) determines the rate and amount of water loss for $\tilde{\theta}$.
By explicitly evaluating the \( \text{ET} \) and \( D \) functions, time series estimates of evaporative loss, D loss, and their sum total can be quantified, Figure 1b. These time series provide an insight into soil water fluxes and dynamics. D is predominantly zero, or near zero, except when \( \hat{\theta} \) becomes large due to precipitation. \( \text{ET} \), by nature of (1)–(2), closely tracks soil moisture and increases with increasing precipitation or soil wetness.

In this example, the D function begins to dominate the total loss function when \( \hat{\theta} > 0.285 \), for example, around July 2015 \( L(\theta) \approx D(\theta) \). Below this level, soil water losses are guided entirely by \( \text{ET} \), that is, \( L(\theta) \approx \text{ET}(\theta) \). On average, this pixel is moderately wet; thus, \( \text{ET} \) is small for \( \hat{\theta} < 0.1 \) since the function is shifted to the right via the \( b \) parameter.

\( \text{ET} \) reaches its max at \( b = 6 \text{ mm/day} \) when \( \hat{\theta} > 0.4 \), that is, energy limited domain.

From May to September 2015 the time-averaged fluxes are \( E[\text{ET}] = 2.54 \text{ mm/day} \) and \( E[D] = 0.22 \text{ mm/day} \), with a mean precipitation \( E[P] = 2.85 \text{ mm/day} \). Thus, the ratio of time-averaged \( E[\text{ET}] \) to \( E[P] \) is \( \sim 89\% \), while \( E[D] / E[P] \) is \( \sim 7.7\% \), and the residual difference is attributed to a small change in storage—wetter at the end of the time series by 0.03 m³/m³. In other words, precipitation is predominantly partitioned into evaporative losses. In later sections \( E[\text{ET}] \) and \( E[D] \) will be examined in more detail. Note that by enforcing water mass balance in (6), neither \( E[\text{ET}] \) nor \( E[D] \) can exceed \( E[P] \).

The evolution of the Lagrange multiplier \( \lambda(t) \) over the optimization course is given in Figure 1e, starting from the initial guess (red line) to the optimum point (black line). Due to the adjoint forcing term in (8) TB-observations induce jumps in \( \lambda(t) \)—analogous to giving more or less weight to observations. In-between observations \( \lambda(t) \) decays to zero at rate determined by \( \frac{\partial H}{\partial \theta} \) and \( \Delta \theta \). Overall, as \( J \) converges to zero, with less than 20 forward model integrations, Figure 1d, \( \lambda(t) \) also tends to zero (transition from the red line for \( J \sim 10^3 \) to the black line for \( J = 4.08 \)). The Lagrange multiplier \( \lambda(t) \) at early times shows distinct seasonality and hence influences the search for the optimal parameters by transferring the sensitivity for parameter estimation across seasons. The patterns in the Lagrange multiplier \( \lambda(t) \) time series reflect the mismatch between observations and simulated measurements given the parameters.

Figure 1 is showing the estimation process for one SMAP pixel location. The SMAP TB fields and precipitation data are however available over all land surfaces. Therefore, the methodology can be applied to create dynamic fields of estimated parameters and, through (3) and (4), maps of ET and D fluxes.

### 4.2. Estimated Model Parameters Over the United States

Five parameters are estimated over the entire United States, at the 36-km spatial resolution, and examined more closely in this section. The evaporation-only parameters are shown in Figure 2. Section 3.1 defined the
The evaporative-loss parameter $\tilde{a}$, shown in Figure 2a, is equivalent to potential evaporation. This is typically defined as the maximum evaporation level assuming unlimited moisture supply, that is, energy-limited evaporation. In Figure 2a $\tilde{a}$ is largest in Southwest United States (ranging from 10 to 12 mm/day) and gradually decreases to 4–6 mm/day in the Midwest and Upper Great Plains. Along the U.S. west coast, $\tilde{a}$ is unusually low. This regional feature is possibly affected by a mix of errors. The region has almost no summer precipitation, which limits the application of (1). Its eastern edge has high vegetation water content in the Sierras, which affects SMAP TB measurements. Similarly, parts of the Michigan Upper Peninsula and Northeast United States also show low $\tilde{a}$ values, which is due to increased number of waterbodies within SMAP pixels—these regions are excluded in further analysis. Nonetheless, the spatial pattern and distribution of 3-year averaged $\tilde{a}$ from high in the southwest to lower in the Midwest as well as its dynamics range (~3–12 mm/day) is consistent with recent multidecade warm-season Penman, Priestley-Taylor, and pan-evaporation analysis by (Hember et al., 2017). Other regional patterns for $\tilde{a}$ are also observed, such as lower values near the Mississippi embayment (<3 mm/day) as well as larger values (>10 mm/day) in the southeast. It should also be noted that in (3), the $a$ parameter is considered constant over the warm-season period of study. This implementation may not be suitable for longer time series, for example, including winter and fall, and an additional time- and season-dependent function should be included in (3).

When the soil moisture in (1) exceeds the transition point, gradually separating the water- and energy-limited evaporation regimes, further evaporative moisture losses are independent of soil moisture, that is, energy-limited evaporation regime. However, the soil moisture time series itself can transition from one evaporation regime to another. Each location will have a transition soil moisture level that depends on its climate, soil texture, and vegetation. We estimate this transition point through the flexible $\tilde{b}$ parameter. Instead of mapping $\tilde{b}$, we map the mean estimated $ET/\tilde{ET}$ divided by its potential value $\tilde{a}$. This approach isolates $b$ in (3) while presenting a meaningful physical quantity: What is the average seasonal soil moisture control on evaporative loss? This is the ratio of seasonal actual evaporation to potential evaporation. Figure 2b shows a strong longitudinal gradient in this quantity with low values in the western arid and semiarid regions and larger values and closer to the unity limit in the east. The field in Figure 2b also indicates that ET is principally energy-limited in the Florida peninsula and along the Mississippi River where water is plentiful and available for evaporation. Other regions that are also dominated by energy-limited evaporation and have $\tilde{b}$ approaching unity are northern New England and the Minnesota and Wisconsin environs where the summer season is short (relative to remainder of the country) and radiation limits available energy. The diagnostics in Figure 2b are indicative of the $b$ parameter and show how strongly and how often soil moisture is a limiting factor in evaporative losses.

Multiyear averaged estimated D parameters, $\tilde{c}$ (millimeters per day) and $\tilde{d}$ (−), at the 36-km spatial resolution, are shown in Figures 3a and 3b, respectively. While soil-specific soil hydraulic parameters are typically constant, the estimation implementation of the D process allows each of the parameter $c$ and $d$ to vary year by year. D is affected by conditions such as cumulative subsurface moisture storage, which would vary from year to year. Multiyear averaged $\tilde{c}$ and $\tilde{d}$ estimates show regional and spatially coherent dependencies,
indicating physiographical controls on these fluxes and parameters. There are coherent regions apparent with relatively low D capacity. Figure 3a shows that the loess region of the Mississippi valley as a coherent region of poor D. Also, the wetland soils of the prairie region in the upper Midwest as well as the Florida peninsula are coherent regions of low D capacity. The same is evident for the northern New England pine wetland soils. The low D capacity region along the Pacific Northwest coast is more difficult to interpret because this region has both volcanic soils and soils with high clay content. The results over Southern California should be interpreted with caution. Summers in this region have few precipitation events, and hence, the estimation based on soil moisture response to intermittent precipitation is challenged and highly suspected. The estimated $\hat{d}$ parameter also reflects the $\hat{c}$ fields with the addition of desert soils in the southwest as having D only at high soil water levels.

Equation (1) represents mass balance within a hydrologically active control volume with a depth $\Delta z$ such that input precipitation is balanced with outgoing fluxes. Akbar et al. (2018b) expanded this concept and quantified $\Delta z$, (hereafter $\Delta z_{2018b}$) over the United States using CPC precipitation and an observation-based technique to reconstruct $L(\hat{d})$ via analysis of SMAP soil moisture dry downs. The spatial variability in $\Delta z_{2018b}$ was predominantly explained by mean precipitation, such that larger $\Delta z_{2018b}$ was observed in wetter regions. The estimated length-scale map of this study ($\Delta z$) is shown in Figure 4 and are compared to $\Delta z_{2018b}$ estimates from (Akbar et al., 2018b). Some differences are expected due to the underlying estimation approaches. Both methods use the same CPC precipitation measurements; however, $\Delta z_{2018b}$ is based on a dry-down derived loss function, while here the loss function is given in (2)-(4). Furthermore, a different $\Delta z$ is retrieved for each year—Figure 4 shows the 3-year averaged—while $\Delta z_{2018b}$ is constant for MJJAS 2015–2016. Nevertheless, we observe remarkably similar spatial patterns across the United States and a similar probability distribution. The median $\Delta z$ is slightly larger compared to $\Delta z_{2018b}$, 150 and 120 mm, respectively.

A growing number of studies have established the need for a hydrologic length-scale distinct from the sensing depth scale when analyzing different water balance components such as basin-scale closure (Crow, Chen, et al., 2017; Crow, Han, et al., 2017); precipitation (or streamflow) estimation using soil moisture, for example, SM2RAIN algorithm and its variants (Brocca et al., 2014, 2013; Crow et al., 2009; Koster et al., 2016); or D estimation from soil moisture dry downs (Jalilvand et al., 2018). $\Delta z$ is an estimate of such a length scale due to the inclusion of water balance constraint as an adjoint to the estimation process.

### 4.3. ET and D Fields

Figure 5 shows the seasonal averaged 36-km ET ($E[\hat{E}T]$) and D ($E[\hat{D}]$) fields in millimeters per day. Both fields are generated via a parameter estimation framework using principally SMAP TB and National Centers for Environmental Prediction CPC precipitation inputs. What allows flux partitioning into realistic proportions is the rate of soil moisture decline and its dependence on soil moisture, which drives the parameters estimation.

**Figure 4.** (a) Map of 3-year averaged hydrologic length-scale $\Delta z$ (millimeter). (b and c) Planes compare $\Delta z$ with similar estimates from Akbar et al. (2018b), that is, $\Delta z_{2018b}$. The later has a slightly lower median value of 120 mm compared to 150 mm for $\Delta z$. 

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The hydroclimatology of summer season mean ET transitions from lower values in the west (<1 mm/day) to larger values in the east and south east (>4 mm/day), Figure 5a. This spatial pattern is expected and consistent with other observation based ET estimates such as (Wan et al., 2015; Zhang et al., 2016). The observed hydroclimatology in Figure 5a raises a key question: Is the magnitude of $E_{\text{hi}}$ also consistent with independent and direct measurements in terms of bias and proportionality? There is a wide range of bias among available ET products, and the consistency question is addressed in the next section.

The seasonal D, Figure 5b, is generally five times smaller than ET. Highest D values are seen east of the Mississippi, with notable local variations in the Florida peninsula, coastal Texas, upper Midwest prairies, and New England. In the southwest where mean precipitation is low in this season (approximately <1.5 mm/day), $E_{\text{hi}}$ and $E_{\text{hi}}$ are also low. However, as expected, due to high atmospheric demand in these regions, precipitation is mostly partitioned into evaporative losses (>85%).

Figure 5 shows a path forward to map seasonal hydroclimatology of ET, D, and landscape storage change across the globe using two currently available remotely sensed data streams: SMAP TB and precipitation information. The imposed constraints are that (1) ET can transition from water-limited to energy-limited evaporation depending on soil moisture, (2) D losses leading to streamflow are related to soil moisture with strong increase for more moist soils, (3) ensure mass balance among the various fluxes, and (4) impose minimal constraints or preparameterized hydrologic model. In the implementation, the parameters could converge to estimates that make all hydrologic losses D, all water-limited evaporation or all energy-limited evaporation, and every other possibility in between.

4.4. Evaluation of Seasonal Estimated Fluxes Using Independent Direct In Situ Measurements

Season-averaged ET estimates are compared with eddy-covariance measurements of vapor flux (millimeters per day) from the AmeriFlux Network. Figure 6 shows the AmeriFlux MJJAS seasonal ET climatology plotted against the closest $E_{\text{hi}}$ pixel. Ground-truth climatology is determined by calculating the time average in situ flux measurements over all available sites and over all available times—excluding those near large water bodies (water fraction >1%) or irrigated sites. $E_{\text{hi}}$, on the other hand, is estimated based only on SMAP TB and CPC precipitation. On-average and across all available sites, both evaporation fields correspond well with about 71% explained variance ($R^2$) and low bias (approximately) 0.34 mm/day. The line in Figure 7 is the line with slope equal to unity. The estimated seasonal ET is generally unbiased and scales proportionally with in situ ground truth across the range of climates over the United States.
The overall objective of this work is to examine, and estimate, the hydroclimatology of ET, that is, season long averages. However, some insight can be gained by also examining time series of ET with respect to AmeriFlux sites. Figure 7 shows four example ET times series for MJJAS 2016. Sites are selected after filtering for high vegetation, water fraction, and ensuring at least 5 months of data is available for each of the 2015, 2016, and 2017 years. Both ET quantities are within the same range and exhibit dynamic behavior in response to precipitation. Similar to Figure 1, the ET time series (blue lines) generally increase during and after precipitation. Some discrepancies and difference are naturally expected. First the spatial resolution of ET is 36 km, while the corresponding AmeriFlux site is a point, or field-scale, measurement. Higher dynamics at the field scale (e.g., larger standard deviation) are expected. Furthermore, the estimated ET and D parameters consider all available precipitation and SMAP data and are effectively season-long parameters. To improve daily, or weekly, temporal ET comparisons, the estimate window should be shortened according. Overall across all suitable AmeriFlux sites, and for all three seasons combined (MJJAS 2015–2017), the mean bias between daily ET and field data is ~1 mm/day, with an error standard deviation of 1.61 mm/day. The correlation coefficient, $R^2$, is variable and ranges from 0.05 to 0.6. Additional figures and tabulated statistics are given in the supporting information (Figures S4a–4l; Table S1).

Similar to the analysis in Figure 6, we compare D estimates to in situ data sets by quantifying the total amount of water lost due to percolation and D within the soil. Since evaporative and D losses are separately defined in (2), explicit calculation of soil water losses, which are attributed to D and percolation, is possible. In section 3.1 the process of surface runoff and subsurface soil water flux-divergence were tied to streamflow when considered over large areas. In our case, the unit area of application is a square with about 36 km edge covering over 1,200 km². Infiltration excess is considered to be reinfiltinated over such scales, and the hill-slope subsurface soil D is ultimately the source of streamflow water.

For each 36-km pixel, we evaluate the time-average estimated $\overline{D}$ (millimeters per day) aggregated over the watershed of ground-based streamgages. The 3-year mean rate (MJJAS 2015–2017) is spatially averaged over major Hydrologic Unit basins (HU-2; Seaber et al., 1987) and compared to USGS streamflow measurements per unit contributing to the same basins (Figure 8) for the same time period (MJJAS 2015–2017).
latter USGS streamflow quantities are area-weighted direct steamgage measurements, and without any ancillary data or modeling. Basin-averaged $E[D]$ — shown as the blue markers in Figure 8 — is well correlated with HU-2 streamflow ($R^2 = 0.69$) and of similar magnitude. The figure also shows the slope of best fitting linear line ($y = \beta \cdot x$, without intercept) as 1.14.

$E[D]$ is a snapshot of hydrologic events when they occur whereas the USGS streamflow represents the accumulation of the contributing $D$ that reaches the basin outlet and at the streamgage. There is a time lag due to transmission of soil water through the hillslopes. Furthermore, the streamflow from the river network has a routing time lag. The total time lag is dependent on the scales of hillslope and extent of the river network. As a test we also compare basin-average estimated $D$ with 1-month lagged USGS streamflow measurements, that is, only lag streamflow to JJASO, rather than MJJAS. $E[D]$ does not change. The 1-month time-lagged streamflow averages are shown as the red colored markers in Figure 8. Overall, the correlation improves—from 0.69 to 0.74—and the linear slope changes from 1.14 to 0.99. The optimal time lag for different basins may be different and a worthy subject for in-depth analysis.

Runoff rate maps based on steamgage information are subject to errors due to constructed storage (dams and reservoirs) as well as water abstractions and return flows (irrigation, municipal and industrial water supply, thermal power plants, etc.). Restriction of streamgage data to those gages that are relatively free of diversions (if that can even be known with certainty) biases the set to small and upland watersheds away from centers of human activity. We opt to use instead the larger set of all USGS steamgages. The USGS runoff map uses around 6,000 steamgages across the domain and estimates the runoff. Northeast United States and the Florida Peninsula to Eastern Texas show similar values in the estimated D map, actual D within the Mississippi River floodplain and environs is low, but upland areas along the Appalachia contribute to runoff. Northeast United States and the Florida Peninsula to Eastern Texas show similar values in Figures 9a and 9b. The USGS map shows anomalies in the northeast along the Canada international border. This may be due to rivers and contributing areas straddling the border and improperly accounted for in estimating runoff per unit area.
Figure 9. Top row: (a) map of 3-year averaged $E[D]$ for May–September (b) U.S. Geological Survey (USGS) HU-8 total May–September streamflow per contributing basin area averaged over all 3 years. Row 2: 2015 differences with respect to 3-year averages (c) $E[D]$ and (d) USGS. Row 3: 2016 differences with respect to 3-year averages (e) $E[D]$ and (f) USGS. Row 4: 2017 differences with respect to 3-year averages (g) $E[D]$ and (h) USGS. All units are in millimeters per day.
hi and HU-8 USGS runoff maps may also be analyzed for year-by-year deviations from the 3-year mean (Figures 9c–9h). Hydrologic drought is defined as persistent deficit in streamflow. These maps show that both the estimated D fields $E[D]$, and HU-8 USGS runoff maps capture some of the main hydrologic droughts in the 2015–2017 time frame. The Texas drought of summer 2015 is evident in both fields. Also evident is the New England drought of summer 2016. The above-average conditions returned to Texas (and parts of the southern states) in summer 2017, and both the estimated and independent direct in situ measurements maps show consistent positive anomalies across the region.

5. Discussion

The approach proposed in this study is aimed at providing observation-driven information on key hydroclimate fields that have global coverage and are, as much as possible, free of preparameterized models, that is, LSMs. The variational method estimates parameters of soil moisture-dependent loss functions, which conform to known physical functional forms, that is, ET and D function shapes. For both functions, the unknown scaling and shifting parameters are estimated by minimizing the mismatch between observed and predicted TB, while constrained—or adjoined—with a dynamical soil water balance model.

This approach yields dynamic fields of soil moisture, ET, and D that are all part of a closed water budget but were estimated only with precipitation and soil moisture information. In this respect, the hydroclimatological fields are considered to be principally observation-driven and relatively independent of parameterizations and LSM ancillary data.

This independence has value since the acquired partitioning of precipitation into hydrologic flux components may now be used to guide LSM model development. Today’s LSMs have often evolved by adopting components over time (such as new bare soil evaporation, new infiltration capacity, new percolation, and groundwater) without wholistic perspective on their main function, which is partitioning the precipitation from the atmospheric component into hydrologic outfluxes (ET and runoff divergence). LSMs can be driven toward more realistic performances by utilizing observation-driven global hydroclimatology maps of hydrologic partitioning of precipitation into ET and D components.

Even with the limited study region and season reported in this exploratory investigation, we can map the hydrologic partitioning across continental scales. We start with the major hydrologic units—across all major HU-2 basins. The hydrologic partitioning of mean precipitation between ET and D runoff is given in Figure 10. The figure is sorted with respect to increasing mean seasonal precipitation with dry basins on the left and wetter regions on the right. Water balance closure and partitioning is exact when, in addition to evaporation and D fluxes, the estimate change in storage, $\Delta S$, is included:

$$E[P] - \Delta S = E[ET] + E[D],$$

in blue, $E[ET]$ in red, and $E[D]$ is in green. In all cases $E[P] = E[ET] + E[D]$, maintaining water mass balance. The inset plot shows the boundary of major HU-2 basins.

Change in storage, $\Delta S$, is calculated as $\frac{\Delta S}{\Delta t}$, where $\Delta \vartheta$ is the difference between the last and first soil moisture value, $\Delta \vartheta = \bar{\vartheta}_N - \bar{\vartheta}_1$. $\Delta \bar{z}$ is the corresponding depth estimate for each pixel, Figure 4. Furthermore, as in...
the case of Figure 5a, partitioning to ET is larger than partitioning to D runoff, that is, \( \frac{E_{ET}}{E[P]} > \frac{E_D}{E[P]} \) for all major basins. Quantitatively, this partitioning is three to five times larger in favor of ET.

For all pixels over the United States we calculate the 3-year time-averaged \( \bar{ET} \) and \( \bar{D} \) and determine their ratios with respect to mean precipitation, \( \frac{E_{ET}}{E[P]} \) and \( \frac{E_D}{E[P]} \). Across the United States, precipitation is predominantly partitioned in to ET as shown in Figure 11a, with a median \( \frac{E_{ET}}{E[P]} \approx 83\% \), while D constitutes a smaller fraction, median \( \frac{E_D}{E[P]} \approx 17\% \) as shown in Figures 1a and 1b. In both figures, regions with very low precipitation (< ¼ mm/day) are excluded to avoid extremely large ratios—these regions are mostly concentrated in Southern California. In parts of the Midwest and Great Plains, \( \frac{E_{ET}}{E[P]} \) is visibly, albeit slightly, smaller—consequently \( \frac{E_D}{E[P]} \) is slightly larger (approximately 0.4 vs 0.6). The spatial extent and boundary of this regional feature is indeed consistent with hydro-regime classification in Akbar et al. (2018a) where a larger percentage of SMAP soil moisture estimates was classified to be in stage I (energy-limited) evaporation regime or D dominated.

The results of this study further reinforce the fact that significant amounts of information on hydrologic fluxes and the partitioning of precipitation into various hydrologic outfluxes are encoded in the dynamics of soil moisture. Similar basin-focused analyses also echo this point. For example, Crow, Chen, et al. (2017) and Crow, Han, et al. (2017) examined the application and utility of remotely sensed soil moisture to annual water storage and closure in medium-scale basins. While such estimates reflect surface-only soil moisture conditions, they found that remotely sensed soil moisture does indeed convey and retain statistically significant amount of information regarding total storage dynamics. Additionally, Koster et al. (2018) demonstrated that SMAP soil moisture estimates can be used, to a reasonable degree, to estimate medium-size basin precipitation and streamflow quantities and quantify large-scale water budgets.

In this study in order to maintain parsimony, a number of assumptions had to be made, which merit revisit and further investigations. In (3), the ET function’s \( a \) parameter, equivalent to potential ET, is constant over time for the warm-season (MJJAS) period of study. This assumption, in general, is not suitable when considering longer time ranges with seasonal effect. The ET function in (3) can be modified to include a time-dependent can be modified includes a time-dependent seasonal basis function, \( f(t) \), to address this issue, that is, \( a \rightarrow a \cdot f(t) \). For example, \( f(t) \) can be a function of net solar radiation or top-of-atmosphere solar angle. This new implantation will be considered in future studies.

Figure 11. Three-year time-averaged maps of (a) \( \frac{E_{ET}}{E[P]} \) and (b) \( \frac{E_D}{E[P]} \). The median value of \( \frac{E_{ET}}{E[P]} \approx 83\% \), while \( \frac{E_D}{E[P]} \approx 17\% \). Regions with less than ¼ mm/day precipitation—mostly concentrated in Southern California (summer season)—are excluded.
In (2), lateral movement of soil water in the subsurface and infiltration-excess runoff is assumed to be negligible at large spatial scales. It is assumed that they are small compared to vertical moisture fluxes due to precipitation, evaporation, and D. However, we do acknowledge that subpixel and presaturation runoff may occur, especially in humid and wet regions where the soils maybe locally saturated. Therefore, this may result in over, or under estimation of hydrologic properties, for example, larger Δz in Mississippi region in Figure 4, where incident precipitation does not fully contribute to storage and loss changes.

Furthermore, finer subpixel processes and heterogeneity may also exist and be present. This study focuses on whether or not there is adequate information in the surface soil moisture and precipitation fields in order to identify the partitioning of precipitation into hydrologic outflux components. More complicated physical representations that capture other hydrologic processes can be explored in follow-on studies beyond this exploratory investigation.

Within the variational estimation approach, the ET and D functions are flexible, and by construct is unconstrained. Their final shape, and associated parameters, is primarily dictated by precipitation patterns, dynamics of TB (i.e., soil moisture), and the optimization process adjoined with the water mass balance equation in (1). The overall optimization process is implemented with at least 10 different initial starting points and sufficient number of iterations. This standard approach enables the process to select and report the globally optimum parameter set \([a, b, c, d, \Delta z]\). For a limited number of pixels, however, the final ET and D portioning based on \([\hat{a}, \hat{b}, \hat{c}, \hat{d}, \Delta \hat{z}]\) may be affected by lack of observed temporal dynamics in TB (soil moisture). The result is that evaporative and D processes cannot be completely distinguished. Therefore, one of the loss function components (ET or D) may dominate the entire variational estimation process yet at the same time yield a globally minimum objective function. This effect can be seen in the few speckled pixels in Figure 11b, where \(E[D]/E[P] \) is almost 1.

### 6. Conclusions

The goal of this study is to address the question: Is it possible to use global and dynamic fields of remotely sensed surface soil moisture information and precipitation to make quantitative maps of surface ET and runoff fields without invoking an already-parameterized hydrologic model? The challenge is to use only these two remote sensing data streams for two reasons: (1) open the path toward global mapping of key hydrologic fluxes using satellite information only and (2) avoid heavy reliance on parameterized LSMs and their corresponding input ancillary data sets. The objective is to produce seasonal maps of surface precipitation-partitioning into hydrologic outflux components. The use case for these partitioning maps is to guide the development of LSMs, since the latter—regardless of construction—should accurately characterize the partitioning of precipitation among hydrologic fluxes at the land surface. This study demonstrates that global observation-driven partitioning of precipitation, with minimally parameterized models, is reasonably possible.

SMAP low-frequency microwave TB and CPC precipitation fields are inputs into a variational estimation framework with an adjoint state model that imposes water mass balance. The parameters to be estimated scale and shift flexible functions that relate to the principal outfluxes—ET and D. The functions and parameters are flexible enough to allow a wide range of responses with either flux dominating the other at almost any soil moisture level. The estimated fields of ET and D share the spatial scales of the input SMAP and precipitation fields (about the 40-km scale at best).

Over the United States, the estimated summer season ET and D fields are consistent with available in situ measurements. Three-year-averaged estimated ET are compared with available vapor flux at in situ AmeriFlux eddy-covariance sites. At these locations, the estimated ET has an explained-variance \(R^2 = 0.71\) with respect to long-term seasonal climatology of available in situ eddy covariance flux measurements. The bias is low (0.4 mm/day underestimation) and the slope across the dynamic range of climates across the United States is nearly unity. Similarly, basin-averaged total D, over the 3-year warm season duration, correlates well with USGS streamflow totals with \(R^2 = 0.69\); the correlation slightly improved (0.74) when 1-month lag is applied to streamflow data. The estimated D's year-to-year deviations from the
3-year average broadly track similar streamflow dynamics. Major known deficits in streamflow (definition of hydrologic droughts) are also reflected in the estimated D fields.

Overall, over the 3-year record, we find that precipitation is primarily partitioned in to ET and D with an almost 5:1 ratio, \( \frac{E}{ET} \approx 83\% \), with a larger fraction observed in the western half of the U.S. Percolation, and D losses constitute less than 20% of precipitation, \( \frac{E}{P} \approx 17\% \).

This exploratory study adds to the body of evidence emerging in the literature that a significant amount of hydrologic information is encoded in the dynamic fields of surface soil moisture and SMAP and SMOS remote-sensing fields. Observation-driven estimation techniques can be employed to gain insights into the state of the water cycle and guide future LSM development activities.

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