The role of soil moisture accounting in estimation of soil evaporation and transpiration

Sadegh Ghazanfari, Saket Pande, M. J. M. Cheema, Amin Alizadeh and Alireza Farid

ABSTRACT

In this study, we explore how the differences in soil moisture accounting affect the estimation of actual soil evaporation (*E*) and transpiration (*T*). The main objective is, therefore, a comparative assessment of a vapor flux estimation method which has explicit soil moisture accounting, against a vapor flux estimation method that uses satellite observed soil moisture data. Three methods with different representations of water supply dynamics are compared: (1) ETLook, wherein *E* and *T* are estimated using Advanced Microwave Scanning Radiometer – Earth Observing System (AMSR-E) derived soil moisture data; (2) a simple evaporation transpiration scheme (SETS) that has a similar vaporization representation as ETLook but with soil moisture accounting based on the MOSAIC Land Surface Model; and (3) SETS-AMS which is similar to SETS except that the AMSR-E derived soil moisture controls the top layer mass balance. The schemes are compared on the Indus River Basin for the year 2007 at 1 km spatial resolution. The results suggest that downward soil water flux influences the estimation of *E* and *T*. This effect is especially dominant in areas with high soil moisture content. The comparative assessment reveals how lack of explicit soil moisture accounting may lead to an overestimation of *E* and underestimation of *T*, especially in irrigated areas.

Key words | ETLook, Indus Basin, land surface scheme, soil evaporation, subsurface hydrology, transpiration

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INTRODUCTION

Evaporation from interception, soil and water bodies, and transpiration from canopy are two distinct sources of atmospheric moisture in the hydrological cycle (Brubaker & Entekhabi 1995, 1996; Brolsma & Bierkens 2007; Baudena *et al.* 2008; van der Ent *et al.* 2010). These fluxes affect human livelihoods through crop production (Pande *et al.* 2011a, 2011b) and by affecting livestock production (Sonneveld *et al.* 2009). Syed *et al.* (2004) showed that potential evaporation is the second most dominant process controlling the spatial variability of the hydrologic cycle (after precipitation) over the continental United States. Since transpiration is part of the biophysical process of biomass production, it is useful to consider transpiration as distinct from other evaporation processes (Savenije 2004).

Deep layer soil moisture is strongly related with drought, which indicates the importance of soil moisture as an indicator of weather extremes (Lakshmi *et al.* 2004). Soil evaporation (*E*) and transpiration (*T*) influence the soil water content and the water table fluctuations by affecting the downward flux to the deep water table and the capillary rise to the root zone during shallow water table conditions (Fan *et al.* 2007). Since *E*, *T* and the water movement to deep soil layers depend on the top layer soil moisture, a simultaneous estimation of all components in a mass balance equation is important (Khepar *et al.* 2000). The absence of one may cause overestimation or underestimation of the other two fluxes (Christiansen & Awadzi 2000).

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Data-driven techniques such as evolutionary polynomial regression, genetic programming, artificial neural networks and mixture models have been extensively employed to estimate soil moisture and other hydrological variables (Lakshmi & Susskind 2000; Cheng *et al.* 2005; Muttil & Chau 2006; Wu *et al.* 2008; Elshorbagy & El-Baroudy 2009; Coleman & Niemann 2013; Taormina & Chau 2015). Lakshmi *et al.* (2004) investigated the utility of satellite remote sensing data in hydrological models, especially in the prediction of ungauged basins. Baymani-Nezhad & Han (2013) modeled effective rainfall conditioned by temperature or observed total evaporation data. Sánchez *et al.* (2010) instead used a hydrological model called HIDROMORE and Food and Agriculture Organization (FAO) methodology to assimilate remotely sensed land cover data and produce soil moisture fields that were consistent with observed data. Lu *et al.* (2012) assimilated microwave remote sensing data and general circulation model outputs with land surface models (LSMs) and found superior performance with other soil moisture products, such as National Centers for Environmental Prediction and Systems Integration Branch outputs. Fang & Lakshmi (2014) used a thermal inertial relationship between soil moisture and daily temperature change modulated by vegetation to downscale soil moisture fields. Crow *et al.* (2008) compared the soil moisture estimation by water energy balance-based soil–vegetation–atmosphere transfer (SVAT) model with a version of SVAT that assimilated remotely sensed surface temperature. The latter appeared to improve soil moisture estimation. Neale *et al.* (2013) used a satellite-based two source energy balance model assimilated into water balance of the root zone to estimate root zone soil moisture. The authors reported an improvement in root zone soil moisture over that of when total evaporation estimated by the energy balance model is not assimilated into the soil water balance calculations.

On the other hand, E and T have been extensively estimated as a function of soil moisture and land cover (Running & Coughlan 1988; Nemani & Running 1989; Dolman *et al.* 1991; Maurer *et al.* 2001; Mu *et al.* 2007; Pelgrum *et al.* 2010; Brolsma *et al.* 2010). Many such studies have used satellite observation-based soil moisture data sets to estimate E and T (e.g., Choi & Jacobs 2008; Mu *et al.* 2009; Mireles *et al.* 2011; Bastiaanssen *et al.* 2012). The Penman–Monteith (Penman 1948) or Priestly–Taylor (Priestley & Taylor 1972) methods along with the Jarvis scheme for estimating canopy resistance (Jarvis & McNaughton 1986) are commonly used to estimate these fluxes as a function of land cover, atmospheric forcing, and soil moisture content. El-Baroudy *et al.* (2010) used data-driven techniques, such as polynomial regression, genetic programming, and artificial neural networks, to estimate total evaporation as a function of lagged meteorological forcing. Shivakoti *et al.* (2011) used remote sensing to estimate transpiration coefficient and estimated total evaporation in a bucket hydrological model. Vinukollu *et al.* (2011) compared three energy-based methods that included Penman–Monteith and Priestly–Taylor to estimate total evaporation at global scale and found good agreement with climatologically estimated total evaporation for 26 global river basins. Su *et al.* (2003) verified a relationship between relative evaporation and relative soil moisture to estimate drought severity index based on satellite derived relative evaporation based on land surface energy balance. Camporese *et al.* (2014) used a switching boundary condition parameter on soil water balance to successfully distinguish between energy limited from water limited evaporation condition.

Several other methods explicitly conceptualized the downward movement of water (Xue *et al.* 1991; Robock *et al.* 1995; Maurer *et al.* 2001, 2002; Brolsma *et al.* 2010; Rihani *et al.* 2010) in the estimation of total evaporation. Chen *et al.* (2005) integrated a LSM with remotely sensed vegetation type and leaf area index (LAI) and improved the vegetation-related component of the water balance, such as transpiration and interception. The authors highlighted the importance of modeling hydrological processes in mapping total evaporation. Bittelli *et al.* (2010) instead coupled a detailed hydrological model with a surface energy-based model with the capacity to better simulate plant growth.

Remote sensing-based algorithms implicitly account for subsurface soil moisture by using variables such as LAI and normalized difference vegetation index (NDVI), which are available from various sources. Therefore, remote sensing algorithms are easy to employ. In this study, we investigate how well such implicit accounting of soil moisture compares with an explicit accounting scheme in the estimation of E and T. The objective of this paper is to quantify the effect that explicit soil moisture accounting has on the estimation of vapor fluxes in a virtual experimental set-up. A method that explicitly incorporates soil moisture accounting is compared, stepwise, to a method that instead uses satellite observation-based soil moisture to control the estimation of the fluxes. This study is therefore a comparative assessment of a vapor flux estimation method having explicit soil moisture accounting against a vapor flux estimation method that uses satellite observed soil moisture data.

The overall effect of not explicitly accounting for soil moisture accounting but instead using satellite-based soil moisture data on the estimation of total evaporation is decomposed into two constitutive effects. The constitutive effects are the individual effects of bias in satellite-based soil moisture data and the absence of explicit soil moisture accounting. This controlled decomposition of the effect separates the effect of explicit soil moisture accounting on the estimation of vapor fluxes from the bias introduced by any error in satellite derived soil moisture data (Hurvich & Tsai 1990).

The framework for the decomposition of effects is similar to a stepwise regression (Efroymson 1960; Hocking 1976; Hurvich & Tsai 1990) but extended to hydrological modeling. It resembles a bidirectional elimination approach that first adds a soil moisture accounting scheme to a method that estimates soil *E* and *T* based on satellite observed soil moisture data. ETLook (Bastiaanssen *et al.* 2012) is the method that uses satellite-based soil moisture observations to estimate *E* and *T* fluxes. The framework then removes the dependence of the method on satellite observed soil moisture data. Accordingly, we develop a simple evaporation transpiration method based on MOSAIC-LSM (Koster & Suarez 1996) that explicitly accounts for soil moisture. The vaporization scheme of our MOSAIC-LSM inspired method is first independently validated on a field-scale total evaporation data set before the comparative assessment. We call our MOSAIC inspired evaporation transpiration scheme simple evaporation transpiration scheme (SETS). A variant of SETS, called SETS-AMS, is also developed as an intermediary between SETS and ETLook for robust comparative assessment. The novelty of this study is in using SETS-AMS that uses a satellite-based soil moisture data while explicitly accounting for soil moisture. A stepwise comparison of results of the three model set-ups clarifies the role of subsurface moisture accounting in estimating *E* and *T*.

MATERIALS AND METHODS

The three methods used to estimate *E* and *T* in this paper differ in the manner in which soil moisture available for *E* and *T* is modeled. These three methods are called ETLook, SETS, and SET-AMS, and are described below.

ETLook (Bastiaanssen *et al.* 2012; Samain *et al.* 2012) is a method that estimates E and T separately using a two-layer Penman–Monteith equation. E is estimated as a function of surface soil moisture that is obtained from the Advanced Microwave Scanning Radiometer – Earth Observing System (AMSR-E) data set (Njoku *et al.* 2003). It estimates *T* based on land use information and root zone moisture. The root zone soil moisture is estimated from LAI and AMSR-E derived top layer soil moisture. The LAI was computed from NDVI values from the Land Processes Distributed Active Archive Center, using standard asymptotic relationships between LAI and VC (for additional details see Bastiaanssen *et al.* 2012).

SETS, is a MOSAIC-LSM (Koster & Suarez 1996) inspired method that has the *E* and *T* formulations of ETLook. It, however, explicitly accounts for soil moisture using three layer mass balance equations of MOSAIC LSM.

SETS-AMS (simple evaporation transpiration scheme – AMSR-E) is a variant of SETS that has similar *E* and *T* schematization as ETLook and uses AMSR-E derived soil moisture to control the top layer soil moisture. It incorporates the partitioning of soil moisture differences at each time step (8 days) into vapor flux and downward water flux to the next soil layer using the mass balance equations of MOSAIC-LSM. Since SETS-AMS and ETLook models have similar equations for *E* and *T* and the same soil moisture condition at the top layer, the only difference is the explicit representation of water mass balance and water movement. SETS-AMS explicitly represents the vertical movement of water and the mass balance of water. Therefore, the estimation of *E* by SETS-AMS can be used to assess the limiting effect of percolation and top layer soil moisture accounting on evaporation by comparing it with the estimation of ETLook.

A summary of the three methods is provided in Table 1. Further details of the methods are provided in the following sections.

We do not explicitly calculate interception by canopies in any of the three methods even though it is an important process in the hydrological cycle (Savenije 2004). We consider interception partly (a part of interception from top saturated soil layer) by estimating the evaporation from the top soil layer.

ETLook model description

The ETLook algorithm (Bastiaanssen *et al.* 2012) estimates E and T fluxes using surface soil moisture, spectral vegetation index, surface albedo, solar radiation, land use/land cover (LULC), soil physical properties, and weather data such as temperature, relative humidity, and wind speed.

ETLook calculates E for bare soil and T for canopy separately based on the Penman–Monteith equation (Penman 1948). E is estimated as a function of surface soil moisture using AMSR-E soil moisture data. T is a function of lower layer soil saturation, which ETLook estimates as a function of top soil moisture (AMSR-E) and LAI at each time step (Bastiaanssen *et al.* 2012). Readers are referred to Bastiaanssen *et al.* (2012) for additional details.

SETS model description

SETS has two layers of upper soil (a thin top layer that is 5 cm thick and a root zone) similar to the MOSAIC-LSM (Koster & Suarez 1996) and an unsaturated layer of deep soil above the water table (Daly *et al.* 2004). The difference between the SETS and MOSAIC-LSM scheme is in the mass balance of the top soil layer. In MOSAIC-LSM, transpiration is extracted from the top layer. SETS, however, estimates transpiration from the second layer (the root zone) soil moisture and evaporation (E) from the top layer soil moisture. Therefore E and T appear, separately, in the mass balance equations of the top and second soil layers, respectively. The mass balance equations for top soil layer (Equation (1)), the root zone (Equation (2)), and the third soil layer (Equation (3)) are defined below:

$$z_1 \frac{d\theta_1}{dt} = q_1(t) + I(t) - E(t) \tag{1}$$

$$z_2 \frac{d\theta_2}{dt} = q_2(t) - q_1(t) - T(t) \tag{2}$$

$$z_3 \frac{d\theta_3}{dt} = q_3(t) - q_2(t) \tag{3}$$

where $\theta_1(t)$, $\theta_2(t)$ and $\theta_3(t)$ are soil moisture content in the first, second, and third soil layer (m^3/m^3), respectively, $E(t)$ and $T(t)$ are evaporation and transpiration at each time step (m/day). The fluxes $q_1(t)$, $q_2(t)$ and $q_3(t)$ are vertical water fluxes (m/day) at time t (day) and z_1, z_2, z_3 are thicknesses of the first, second, and third layers, respectively (m). $I(t)$ is infiltration (m/day) into the first layer. It is defined as the minimum of the precipitation rate, $P(t)$, and the saturated hydraulic conductivity of the first layer, K_{s1}. If the saturated hydraulic conductivity is less than the precipitation rate, the difference between the precipitation

Table 1 | Summary of the three methods and their components

Method	*E* and *T* equations	Top layer moisture	Root zone moisture	Precipitation	Irrigation
ETLook	Penman–Monteith	AMSR-E	Derived from AMSR-E and LAI	Absent	Absent
SETS-AMS	Penman–Monteith	AMSR-E control on mass balance, van Genutchen–Mualem parameterization	Mass balance control, van Genutchen–Mualem parameterization	TRMM (calibrated with observations)	PARC (1982)
SETS	Penman–Monteith	Mass balance control van Genutchen–Mualem parameterization	Same as SETS-AMS	Same as SETS-AMS	Same as SETS-AMS

rate and infiltration contributes to direct runoff. $I(t)$ is defined as:

$$I(t) = \begin{cases} P(t) & \text{if } K_{s_1} \geq P(t) \\ K_{s_1} & \text{if } K_{s_1} < P(t) \end{cases} \quad (4)$$

Figure 1 illustrates the three unsaturated soil layers and related variables.

The runoff from each pixel supplements the precipitation rate of a lower elevation pixel in the direction of steepest descent with travel time based on Manning's equation (Gauckler 1867; Molnar & Julien 2000; Bjerklie *et al.* 2005).

The vertical water flux q_i in each unsaturated layer, i.e., for $i = 1$ (top layer) or 2 (second layer), is estimated by Darcy's law (Freeze & Back 1983). Since the soil layers are in series, harmonic mean is used for hydraulic conductivity (Dykaar & Kitanidis 1992).

Several methods are available to estimate unsaturated hydraulic conductivity. Three commonly used models are: the Brook–Corey's model, Mualem–van Genuchten model and experimental models (Nesseri & Daneshbod 2008). The hydraulic properties are often described using the pore size distribution model of Mualem in combination

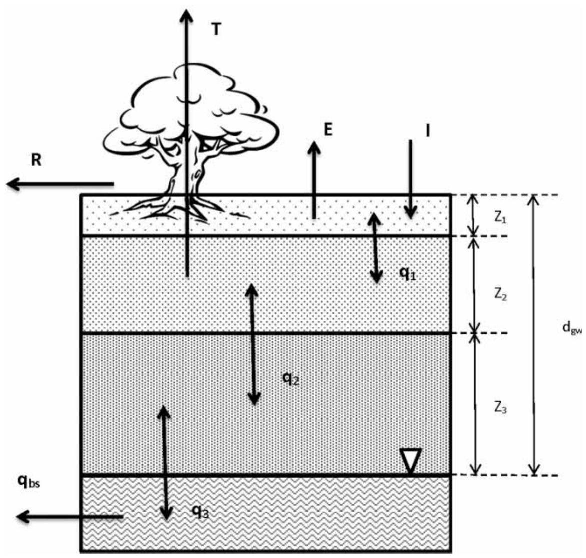

Figure 1 | Three unsaturated soil layers and corresponding water fluxes in SETS. Symbols are: E, evaporation; T, transpiration; I, infiltration; q_1, vertical water flux between the top soil layer and the root zone; q_2, vertical water flux between the root zone and the deep unsaturated layer; q_3, vertical water flux between the deep unsaturated layer and the saturated zone; z_1, top soil depth; z_2, root zone depth; z_3, deep unsaturated layer depth; d_{gw}, water table depth.

with a water retention function introduced by van Genuchten (1980) (Schaap & van Genuchten 2006). The Mualem–van Genuchten model matches experimental data more satisfactorily than the other two (Nesseri & Daneshbod 2008). The Mualem–van Genuchten relationship is employed to calculate the unsaturated hydraulic conductivity (van Genuchten 1980).

SETS-AMS model description

The mass balance equations of SET-AMS are slightly different from those of SETS. Similar to SETS, it has three unsaturated soil layers above the water table. However, the top soil layer in SETS-AMS is controlled by AMSER-E soil moisture time series. Thus the top soil layer moisture in SETS-AMS is always the same as in ETLook. Consequently, the estimation of E by SETS-AMS based on calibrated AMSR-E data set (Cheema *et al.* 2011) is comparable to ETLook estimation of E. On the other hand, it explicitly represents water mass balance and water movement in all the three layers. This makes its estimation of E and T comparable to SETS estimation of E and T as well.

SETS-AMS is a hybrid method that has distinguishing features of both SETS and ETLook. At each time step, the change in top soil moisture is equated to the corresponding change in AMSR-E soil moisture. By mass balance, this change is equal to the sum of E, q_1 and I. The Calibrated Tropical Rainfall Measuring Mission (TRMM) is used to estimate infiltration at each time step (see Equation (4)).

The first assumption by SETS-AMS which was discussed above, is that $d\theta_1/dt$ (rate of soil moisture change) in the top layer is equal to the difference in AMSR-E soil moisture observations at time t (W_t) and $t+1$ (W_{t+1}) (m^3/m^3).

$$\frac{d\theta_1}{dt} \approx W_{t+1} - W_t \quad (5)$$

The top layer mass balance equation for SETS-AMS then is:

$$(W_{t+1} - W_t)z_1 = q_1 - E + I \quad (6)$$

The second assumption is invoked when the sum of evaporation demand (E_d) (m/day) and potential vertical soil moisture flux (q_p) (m/day) (or total demand, $D_f = E_d + q_p$) (m/day) in the top soil layer is greater than the available supply of moisture (the sum of soil moisture difference and infiltration, S_a).

Here, by evaporation demand we mean the evaporation rate based on atmospheric demand and the soil moisture content in the top layer at time t which is equal to AMSR-E soil moisture at that time. The P-M equation for E is used to estimate evaporation demand with bare soil resistance r_{bs} at top soil moisture content, $\theta_1(t)$ at time t. By potential soil moisture flux (q_p) we mean the rate of moisture flux based on soil moistures in the first and second layers at time t. Potential moisture flux for the top soil layer is estimated using the same equations as SETS.

Then, actual evaporation E (m/day) and actual vertical flux q_1 (m/day) are given by Equations (7) and (8). These equations ensure that the ratio of existing fluxes is equal to the ratio of corresponding flux demands. These flux equations are equivalent to first order approximations of corresponding flux equations of a complex rainfall–runoff model.

$$E = [(W_{t+1} - W_t)z_1 - I]\big(E_d/(E_d + q_p)\big) \quad (7)$$

$$q_1 = [(W_{t+1} - W_t)z_1 - I]\big(q_d/(E_d + q_p)\big) \quad (8)$$

The above flux Equations (7) and (8) ‘assimilate’ the AMSR-E soil moisture observations into the mass balance equations of SETS. Hence, the SETS model with these assimilation steps is called SETS-AMS. The above construct of SETS-AMS allows one to assess the effect of the absence of explicit subsurface vertical water flux on the estimation of vapor fluxes (comparison between ETLook and SETS-AMS).

SETS-AMS estimates transpiration (T) using Penman–Monteith equation and extracts it from the second layer. The other two layers in SETS-AMS (root zone and the third unsaturated soil layer) have the same equations as SETS.

On the design of comparative assessment

The three methods have been deliberately chosen to learn about the role of explicit soil moisture accounting in the estimation of evaporative fluxes in a stepwise manner. The design of the comparative assessment is akin to stepwise regression. Stepwise regression is an approach wherein predictors of a regression are either added to or removed from a regression problem in a stepwise manner (Hurvich & Tsai 1990). This allows a modeler to assess the relevance or irrelevance of a predictor on the effect of another predictor on model outcomes. Consider a linear regression problem of predicting y as a function of $x1$ and $x2$. A stepwise estimation of effects (of having $x1$ or $x2$ on y) is needed to estimate additional (marginal) utility of one predictor over the other when $x1$ and $x2$ are correlated or have overlapping information. We are thus interested in understanding the effect of $x1$ on y in the presence of another predictor $x2$. Generally we would start with a null hypothesis that $x1$ has no effect on y. We begin with a model of y and $x2$ and model y as a function of $x2$. We then add $x1$ to the model and estimate y as a function of $x1$ and $x2$. We study the difference, say A, between modeling y as a function of $x1$ and $x2$ and modeling y as a function of $x2$ only. The comparison A informs us about the relevance of $x1$, conditioned on $x2$, in modeling y. We then remove $x2$ and estimate y as a function solely of $x1$. We then study the difference, say B, between modeling y as a function of $x1$ and modeling y as a function of both $x1$ and $x2$. The comparison B informs us on the relevance of $x2$, conditioned on $x1$, in modeling y. The transition from A to B is the transition from a model that solely has $x1$ to a model that solely has $x2$, which enables us to study the marginal relevance of predictors in a stepwise manner.

The null hypothesis is that soil moisture accounting does not affect the estimation of evaporative fluxes. The benchmark model is ETLook (Bastiaanssen *et al.* 2012). The roles of predictors are played out by the use of AMSRE soil moisture data and explicit soil moisture accounting scheme. The motivation behind the comparative assessment is to study the marginal relevance of explicit soil moisture accounting scheme on modeling evaporation fluxes. ETLook uses AMSRE soil moisture data to control for the top and second soil layer soil moisture and does not have an explicit moisture accounting scheme for these two layers. The other two models, SETS-AMS and SETS, are built such that they retain the same E and T estimation schemes but gradually build up the explicit soil moisture accounting scheme in the estimation of E and T. The explicit moisture accounting scheme that is incorporated closely follows that of the MOSAIC LSM. The first of these two models, SETS-AMS, acts an intermediate modeling step between ETLook and SETS. It retains the AMSRE control over the top layer soil moisture yet it allows for soil moisture accounting in the two layers. This is achieved by assimilating AMSRE soil moisture in the top layer soil moisture mass balance. SETS departs from SETS-AMS by not assimilating the AMSRE soil moisture. Thus, through the three models, we have AMSRE controlled E and T estimation at one end (ETLook) and at the other end we have E and T estimation solely based on soil moisture accounting (SETS).

The design of the models is robust and allows a sound comparative assessment that elucidates the effect of explicit soil moisture accounting on E and T estimation. This is so in spite of dry bias in AMSRE. Only two models (ETLook and SETS) would have been needed if there was no bias in AMSRE, since then there would have been no need to control for the effect of AMSRE bias in the estimation of E and T. A comparison between ETLook and SETS-AMS controls for the bias in AMSRE (through the assimilation step in the latter) while investigating the effect of explicit soil moisture accounting on E and T estimation. Meanwhile, a comparison between SETS-AMS and SETS controls for the explicit soil moisture accounting scheme to bring out the sole effect of AMSRE bias in the estimation of E and T. Thus the design of the models ensures that we control for the bias in AMSRE when investigating the effect of explicit soil moisture accounting on the estimation of E and T.

Data set and the study area

ETLook, SETS, and SETS-AMS methods are used to estimate vapor fluxes in the Indus River Basin which encompasses parts of Pakistan, India, China, and Afghanistan. This basin has a total area of 116.2 Mha and lies between latitude 24°38′ to 37°03′ N and longitude 66°18′ to 82°28′ E. The basin has heterogeneous topography, rainfall, and land use. Its elevation ranges from 0–8,000 m above mean sea level. The mean annual rainfall is approximately 200 to 1,500 mm/yr. During 2007, the average rainfall was 383 mm/yr (Cheema & Bastiaanssen 2012). The basin has two distinct agricultural seasons: the wet monsoon season (May to October) and the dry season (November to April). Wheat is a major dry season crop while rice and cotton are major wet season crops. The irrigated area covers about 23% of the basin and surface irrigation is the major irrigation system (Bastiaanssen *et al.* 2012).

A LULC map for the year 2007 prepared by Cheema & Bastiaanssen (2010) using SPOT-Vegetation NDVI time series, is used in this study. Figure 2 illustrates the land use map of the study area (Cheema & Bastiaanssen 2010). A TRMM rainfall data set at 25 km spatial resolution is used (Huffman 2006) that has been calibrated and validated by Cheema & Bastiaanssen (2012). An FAO soil map is used to obtain the Mualem–van Genuchten parameters such as n, residual (θ_r) and saturated (θ_s) soil moisture content, and saturated hydraulic conductivity K_s. Other atmospheric data (including wind speed, radiation, temperature, and relative humidity) have been obtained from the Pakistan Meteorological Department and the World Meteorological Organization (Bastiaanssen *et al.* 2012). All data sets have been applied at a 1 km spatial resolution. The coarser resolution TRMM data set is downscaled based on the effective saturation methodology adopted by Bastiaanssen *et al.* (2012). AMSR-E data set is downscaled to 1 km using a bilinear re-sampling technique. Both the downscaled data sets have been validated for the study area (Cheema *et al.* 2011; Cheema & Bastiaanssen 2012). The irrigation scheme applied for irrigated land uses was based on the recommendations provided by the Pakistan Agricultural Research Council, PARC (1982) and Ahmad (2009). The actual dates vary spatially and temporally. For example, wheat crop is sown between 1 and 30 November and irrigation depths may vary from 45 to 105 mm, while the number of irrigations may vary from 3 to 5. The growing seasons rabi and kharif represent winter and summer seasons.

SETS and SETS-AMS are forced by daily precipitation from TRMM data set at 25 km spatial resolution is used (Huffman 2006) that has been calibrated and validated by Cheema & Bastiaanssen (2012). The data set used for SETS is at a spatial resolution of 1 km and produces output at a daily resolution. However, the temporal resolution of ETLook and SETS-AMS is at 8 days due to the

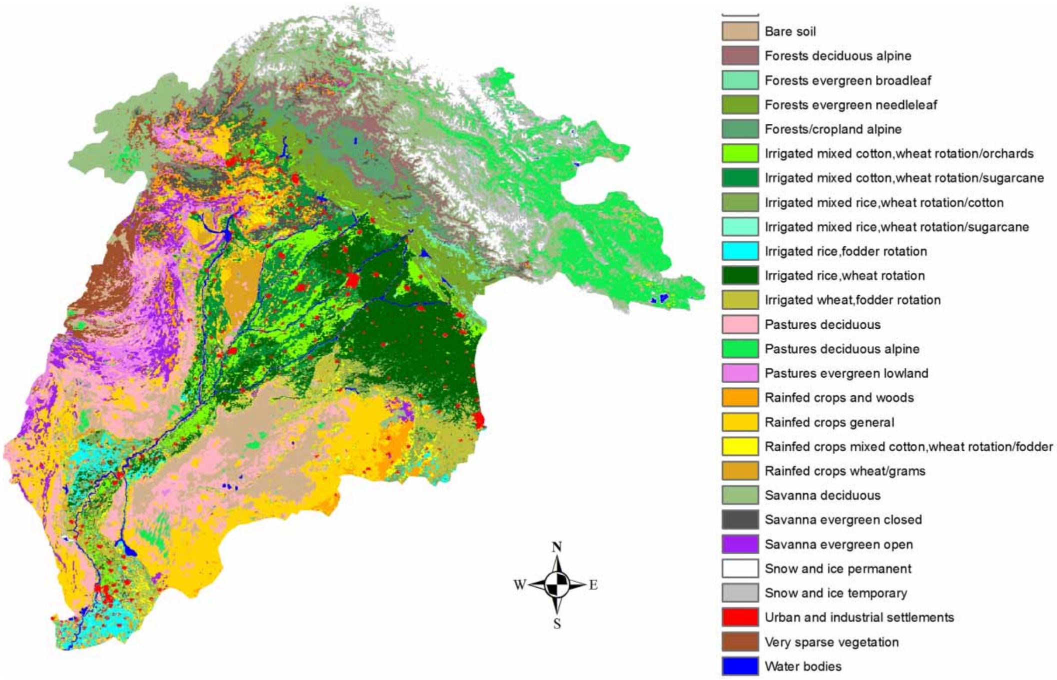

Figure 2 | The land use map of the Indus River Basin (Cheema & Bastiaanssen 2010).

temporal resolution of AMSR-E. Eight-day averages of SETS daily outputs are then used to compare it with the other two models.

The Manning's roughness coefficient, which is used for runoff calculations, is derived from a LULC map based on the National Land Cover Dataset (Usery *et al.* 2004). Slopes for each pixel are derived from a digital elevation model at 1 km resolution (Bastiaanssen *et al.* 2012).

RESULTS AND DISCUSSION

Comparative assessment of ETLook and SETS-AMS

Figure 3 shows the difference between annual mean E for ETLook and SETS-AMS, for each pixel in the year 2007. The 0-value pixels have no significant difference in annual mean E estimates of ETLook and SETS-AMS based on

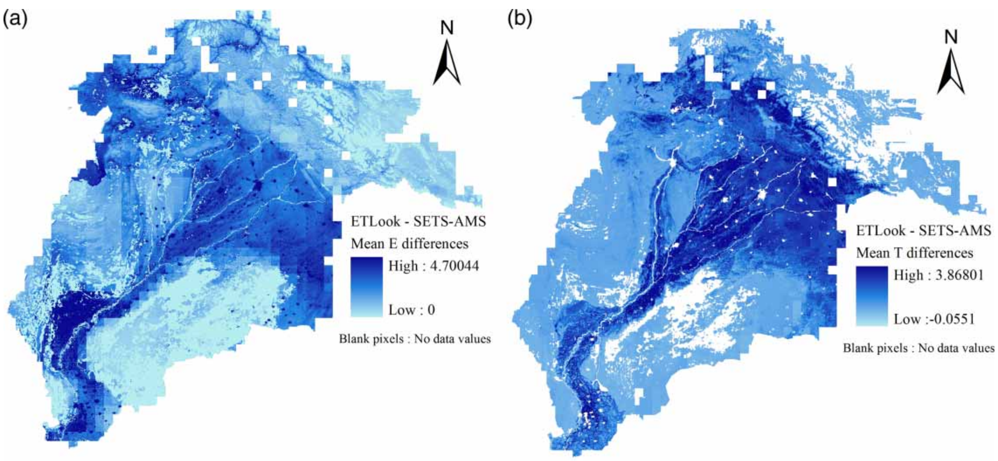

Figure 3 | (a) Annual mean E and (b) T (mm/day) differences between ETLook and SETS-AMS. Positive values show lower estimation by SETS-AMS; blank pixels are no data values.

least significant difference (Gomez & Gomez 1984). The ETLook E flux estimation is relatively higher than the SETS-AMS estimation (Figure 3(a)), with the difference higher in irrigated areas where sufficient water is available for E (see for example, irrigated areas in Figure 2).

ETLook estimates E using the Penman–Monteith equation. It also uses a power function of top layer soil moisture to estimate soil resistance which is needed for the estimation of E. Therefore, the estimation of E is driven by atmospheric forcing and the top layer AMSR-E based soil moisture content. We distinguish the E estimate of ETLook from mass balance controlled estimation of E flux due to the reasons provided below.

For given AMSR-E-based top layer soil moisture, a gradient exists for moisture flux from the top layer to the second layer. This is due to a difference in the soil moisture contents of the two layers. Since actual evaporation flux and actual soil moisture flux from the top to the second layer must be equal to the sum of a given soil moisture change (given by the AMSR-E soil moisture data set) and the precipitation input, the actual E flux is not always equal to the E flux based solely on AMSR-E top layer soil moisture. This especially holds when the sum of E estimation based on top layer soil moisture (in ETLook it is based on AMSRE soil moisture data) and the potential soil moisture flux (q_p in Equations (7) and (8)) is larger than the sum of a change in soil moisture and precipitation over a time step. Hence we call ETLook estimate of E as soil evaporative demand (E_d in Equations (7) and (8)).

SETS-AMS estimates E that obeys the conservation of mass in the top layer and assimilates ASMR-E top layer soil moisture (Equation (7)). The E flux estimated by SETS-AMs is then less than or equal to the E flux estimated by ETLook (as a function of atmospheric forcing and soil moisture content).

Downward soil moisture flux, or percolation, from the first layer to the root zone (q_1) is an important term in the mass balance. It reduces water available for E in the first layer, resulting in E that is different from the potential rate. This effect however is nonlinear in the top layer soil moisture content. This is evident from Equation (7) which states that E is proportional to $1/(1+q_p/E_d)$. Since q_p is a higher order function of relative soil moisture content (S_e) than E_d, the ratio $q_p/E_d \to 0$ for small values of $S_e < 1$ (see Equations (5) and (7)), so the effect of downward flux on estimation of E is negligible in drier areas while E deviates the most from the potential rate in areas where S_e is high, such as in irrigated areas.

Figure 4 shows scatterplots of E estimated by ETLook and SETS-AMS for (30% of the total) randomly picked pixels in four land cover types (bare soils, irrigated croplands, rainfed croplands, and forests). ETLook and SETS-AMS estimates were more correlated in dry areas than irrigated areas. For bare soils, rainfed crops and forest land cover types, R^2 values are 0.93, 0.92, and 0.87, respectively. The R^2 statistic for irrigated areas is 0.19. This demonstrates that the control of percolation on E is dominant in irrigated areas (or areas with high soil moisture content). Thus, an estimation of E that is solely based on top layer soil moisture observations is positively biased in irrigated areas.

Figure 5(a) demonstrates that while E is a cubic function of relative soil moisture (based on bare soil resistance), the vertical water flux between the first and the second layer is an even higher order nonlinear function of relative soil moisture (that depends on soil specific van Genuchten parameter 'n'; see Equation (5)). The curve q_1/E (the ratio of vertical soil water flux to E flux) against Se is made by altering relative soil moistures (Se) from 0 to 1. All other parameters in the Penman–Monteith equation that is used to calculate E and van Genuchten equation that is used to calculate q_1 are assumed constant. Here, q_1 is calculated using only Equation (5) and assuming free drainage at the bottom of the layer. The ratio of vertical soil water flux to E flux (q_1/E) appears to be an exponential function of relative soil moisture (Se) (see Figure 5(a) where $n = 1.1$ is assumed, the most frequent value in the basin). The downward vertical flux (q_1) transports a larger fraction of available soil moisture at higher S_e than at lower values of S_e. Thus, for irrigated areas where S_e is high, deep percolation limits E. We observe this in Figures 3(a) and 4, where R^2 between the two estimations is lowest for irrigated areas when compared to other land cover types (bare soil, rainfed crop, and forest).

Annual mean T difference between ETLook and SETS-AMS for the basin is illustrated in Figure 3(b). The results for annual mean difference show insignificant difference for all land cover types except for irrigated areas (Figure 3(b)),

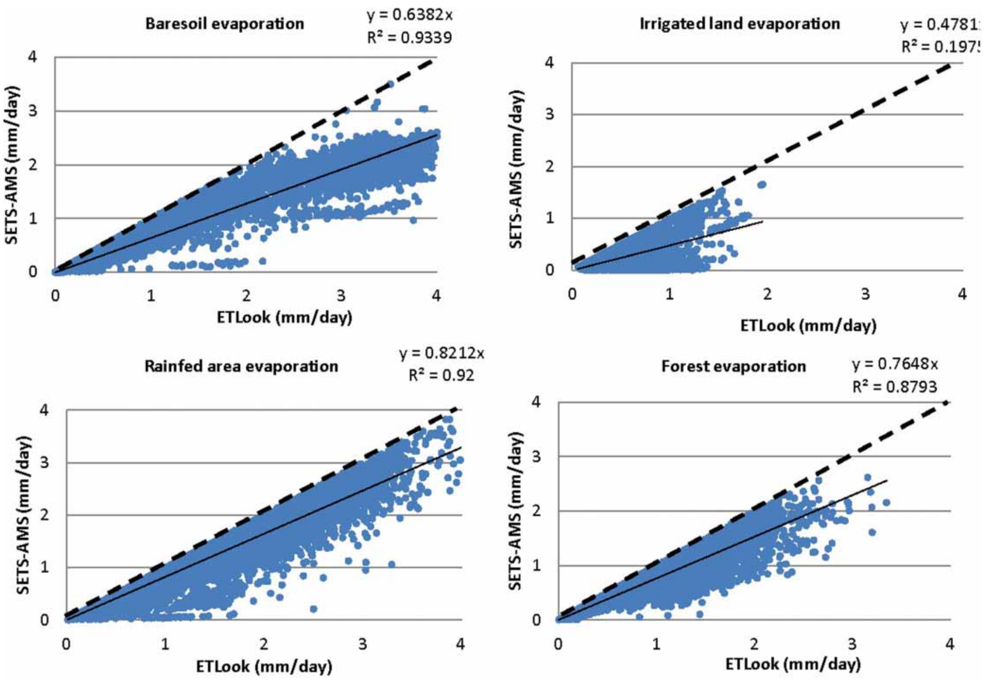

Figure 4 | Comparison between E (mm/day) estimates of SETS-AMS and ETLook for different land cover types.

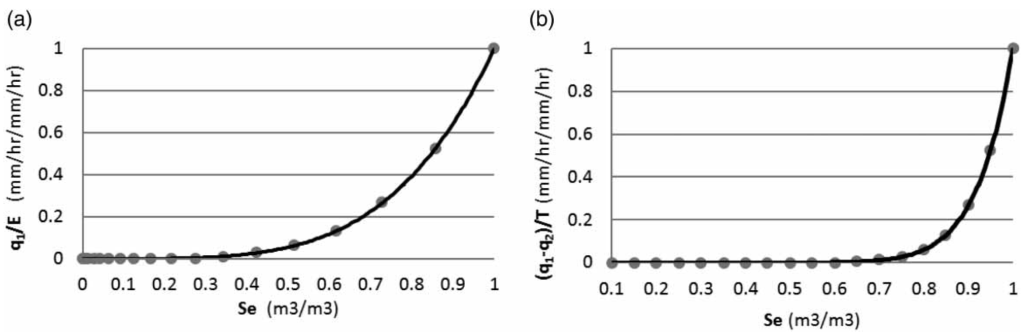

Figure 5 | The relation between relative soil moisture (S_e) (dimensionless) and the ratio of: (a) downward soil moisture flux q_1 to soil evaporation (E), (b) net downward moisture flux ($q_2 - q_1$) to transpiration (T). These are derived using equations for soil resistance, canopy resistance, and vertical flux within soil layers (Equation (5)), as a function of relative soil moisture (Se) (all other parameters are assumed constant).

where ETLook estimation of T is larger than SETS-AMS. Figure 5(b) shows the variation of the ratio of net vertical flux (q_2–q_1) and T and S_e. The fluxes for the second layer are calculated in the same manner as for the first layer. Equation (5) is used to estimate q_1 and q_2 for the two layers under the assumption that relative soil moisture content is the same in both the layers, i.e., $S_{e_1} = S_{e_2}$. The ratio $(q_2–q_1)/T$ (vertical soil water flux to transpiration) is not as sensitive to the variation in S_e as q_1/E (Figure 3(a)). Thus, deep percolation q_1 does not significantly affect lower layers' soil moisture. Unlike SETS-AMS, ETLook estimates T as a function of second layer soil moisture that is determined from top soil effective saturation and LAI. In irrigated areas, the top layer soil moisture and LAI are always high. This leads to higher values of the second layer soil moisture estimates by ETLook than those by SETS-AMS.

The reason behind higher estimation of T by ETLook in irrigated areas is similar to the reason behind its higher estimation of E. The net downward flux q_2-q_1 reduces the amount of moisture available for T in the second layer, especially at high S_e values of the second layer. However, the critical value of S_e where downward flux begins to control the vapor flux is higher for the second layer than for the top layer. Hence, the area over which ETLook predicts E higher than SETS-AMS is larger than the area over which it predicts higher values of T (Figure 3(a) and 3(b)).

The comparative assessment of ETLook with SETS-AMS reveals that percolation controls E and T fluxes under high soil moisture condition. Therefore, E and T fluxes may be overestimated in irrigated areas if percolation is not explicitly accounted for.

Comparative assessment of SETS-AMS and SETS

The difference between SETS-AMS and SETS is in the variation of top layer soil moisture. In the case of SETS-AMS, it is controlled by AMSR-E. Figure 6(a) shows the annual mean E difference between SETS-AMS and SETS. It shows that SETS almost always estimates higher E flux than SETS-AMS.

Higher estimation of E by SETS compared to SETS-AMS can only be explained by higher top layer soil moisture in the case of the former, since the remaining schematization is the same in the two methods. ASMRE soil moisture data controls the top layer soil moisture of SETS-AMS. Higher top layer soil moisture estimated by SETS causes bare soil resistance to be lower and, consequently, higher estimation of E.

Many studies have shown that AMSR-E data underestimates soil moisture (e.g., Zhan et al. 2004; Sahoo et al. 2006, 2008; Choi & Jacobs 2008; Rüdiger et al. 2009; Blankenship et al. 2010). Blankenship et al. (2010) observed dry bias and small dynamic range for AMSR-E soil moisture estimation. Choi & Jacobs (2008) found extremely low temporal variability for AMSR-E data sets in the Little River region (Georgia, USA). Rüdiger et al. (2009) reported that AMSR-E underestimates soil moisture and lacks soil moisture dynamics when compared with observed data and calibrated version of AMSR-E (Cheema et al. 2011).

The SETS algorithm uses calibrated TRMM data set for precipitation (Cheema & Bastiaanssen 2012). Thus, higher estimation of top layer soil moisture by SETS than AMSR-E may be due to the dry bias and small dynamic range in AMSR-E. The resampling of AMSR-E data from 25 to 1 km may also have led to lower estimation of E by SETS-AMS.

While E is extremely sensitive to soil moisture variation (bare soil resistance is a nonlinear function of relative soil moisture), the canopy resistance (and hence T) that is a function of four variables (soil moisture, radiation, humidity, and air temperature) is not as sensitive. Consequently, the difference in annual mean T between SETS-AMS and SETS is not significant except in irrigated areas along the river where SETS estimates higher T (Figure 6(b)). The darker pixels in Figure 6(b) are irrigated areas, which

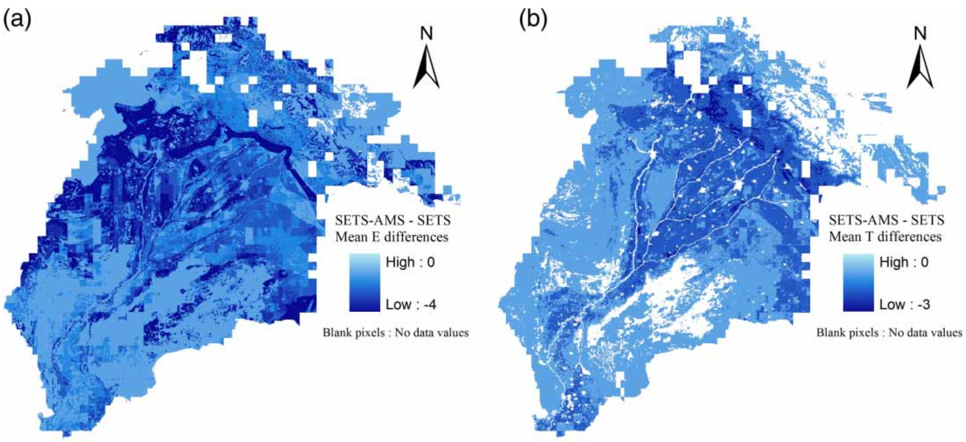

Figure 6 | (a) Annual mean E and (b) T difference between SETS-AMS and SETS (mm/day). Negative values show higher estimation by SETS; blank pixels are no data values.

always have high top layer soil moisture with enough water available for *E* and deep percolation.

Comparison of SETS with other evapotranspiration data sets

The results from SETS and ETLook are now compared with two other standard products. The first one is the MODerate Resolution Imaging Spectroradiometer (MODIS) algorithm product (Mu *et al.* 2007, 2011). MODIS derived evapotranspiration (ET) (sum of evaporation and transpiration) has a spatial resolution of 1 km and a 8-day temporal resolution. The second is the ET product from MOSAIC LSM (Koster & Suarez 1996). MOSAIC LSM provides total ET, which is the summation of direct evaporation from bare soil, canopy water evaporation, evaporation from snow, and transpiration. The ET data set from MOSAIC LSM has a spatial resolution of 0.125 degree and hourly temporal resolution (Ghazanfari *et al.* 2013). Figure 7 shows the timeseries for the year 2007 averaged over the Indus Basin for all four data sets. ET in all the cases is the sum of evaporation and transpiration.

Better correlation is found between MOSAIC LSM and SETS ($R^2 = 0.97$, RMSE = 0.38 mm/day) than between MOSAIC LSM and ETLook ($R^2 = 0.95$, RMSE = 0.67 mm/day) due to the same soil moisture accounting schemes in SETS and MOSAIC LSM. However, results show better agreement between MODIS and ETLook ($R^2 = 0.75$, RMSE = 0.79) than between MODIS and SETS ($R^2 = 0.74$, RMSE = 0.96). MODIS derived data set underestimates ET during spring (Figure 7). Ramoelo *et al.* (2014), who validated MODIS derived ET with tower data flux in South Africa, found similar results. The authors showed underestimation of ET by MODIS data set for the year 2007 and suggested local calibration of the P-M equation that is used by the MODIS algorithm to calculate

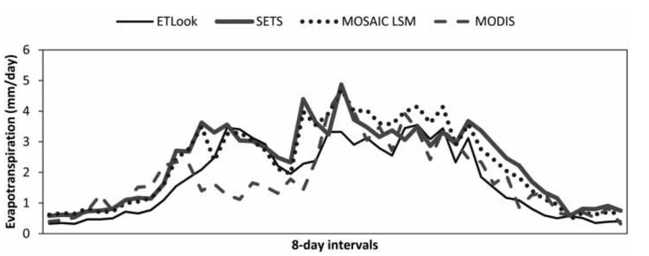

Figure 7 | Comparative assessment of ET results from SETS, ETLook, MODIS, and MOSAIC LSM.

ET. MOSAIC LSM, ETLook, and SETS thus appear to perform more similarly than the MODIS product in ET estimates. Finally, among the first three, SETS appears to be more flexible in its estimation of ET. It is most closely aligned with MOSCAIC LSM during the spring season while in other time periods it is aligned with ETLook and MODIS.

SUMMARY AND CONCLUSIONS

Three methods for estimating were compared. SETS was developed based on *E* and *T* conceptualization of ETLook with an explicit representation for soil water balance. SETS was validated with measured data from three micro-lysimeters as well. SETS-AMS was developed as an intermediary between SETS and ETLook with the same subsurface representation as SETS and with the same top layer soil moisture (AMSR-E at each time step) as ETLook. SETS-AMS provided E estimates comparable with ETLook and *T* estimations comparable with SETS.

ETLook estimated higher *E* fluxes than SETS-AMS for nearly all time steps and land cover types, especially in irrigated areas. Higher *E* flux estimation by ETLook was due to the absence of soil water accounting. The only flux variable that removed water from the top layer in ETLook is evaporation. However, the evaporation flux in SETS-AMS is controlled by the mass balance equation. Percolation flux competes with evaporation flux for water in the SETS-AMS method. It therefore also removes water from the first layer to the next. Consequently, there were always fewer water supplies for evaporation in SETS-AMS than ETLook. This demonstrated the dominant role of percolation from the top layer at higher relative soil moisture level. Thus, the correlation between E estimates of ETLook and SETS-AMS was lower in irrigated areas (where relative soil moisture is always high). Mean annual *T* differences were not always significant, but ETLook estimated slightly higher *T* in irrigated areas due to high soil moisture and LAI (which functionally determined the second layer moisture in ETLook). Furthermore, mass balance controlled *T* from the second layer, as was seen in SET-AMS, was always equal or lower than available water, unlike ETLook.

Table 2 summarizes the pairwise comparison of *E* and *T* fluxes between the three methods. The upper diagonal

Table 2 | The summary of the pairwise comparison of *E* and *T* fluxes between the three methods

Models' outputs		*E* SETS	SETS-AMS	ETLook
SETS	T	–	SETS > SETS-AMS	
SETS-AMS		SETS-AMS < SETS	–	SETS-AMS < ETLook
ETLook			ETLook > SETS-AMS	–

entries order the methods (in a pairwise manner) in terms of the estimation of *E* while the lower diagonal entries order the methods in terms of the estimation of *T*. As we can note from Table 2, the dry bias in AMSRE (comparison between SETS and SETS-AMS) led to an underestimation of both *E* and *T* fluxes. Meanwhile, the lack of explicit soil moisture accounting but with control on AMSRE bias (comparison between ETLook and SETS-AMS) led to an overestimation of *E* and *T* fluxes. What is interesting here is that the lower estimation effect of AMSRE bias dominated the overestimating effect of lack of soil moisture accounting in the case of *E* flux while the opposite happened in the case of *T* flux. Hence we found SETS estimation of *E* flux was larger than that of ETLook while the reverse held for the estimation of *T* flux.

Based on the pairwise comparative assessment of three methods, we found that the absence of mass balance constraints can lead to higher estimation of *E* and *T*. Vertical water flux from the first soil layer to the root zone played an important role in the mass balance equation of the top layer, especially in irrigated areas. It decreased the availability of water for *E* in the top layer and therefore controlled the estimation of *E*. The downward soil water flux played a more critical role in the top layer than in the root zone. We found that the estimation of *T* in irrigated areas was higher when root zone moisture was estimated as a function of LAI and surface soil moisture than when it was a result of coupled soil moisture accounting in different soil layers. Low soil moisture variability in the top layer also led to lower estimation of root zone soil moisture and, consequently, lower estimation of *T*. We showed that dry bias and low dynamic variation of AMSR-E soil moisture which has been reported in many studies (e.g., Zhan *et al.* 2004; Sahoo *et al.* 2006, 2008; Choi & Jacobs 2008; Rüdiger *et al.* 2009; Blankenship *et al.* 2010) led to lower estimation of *E* when it was assimilated in the mass balance equation of top soil layer.

Finally, we compared the estimation of evaporation flux by SETS and ETLook with MOSAIC LSM and MODIS and found SETS estimation to be most flexible in aligning with estimations by other products in different parts of the year. This may be due to the control of soil moisture accounting on the estimation of *E* and *T*, which may vary in different parts of the year.

The presented study can be improved in various aspects. The sensitivity of the model set-ups to its parameters can provide further insights into the significance of the role of soil moisture accounting. Such a sensitivity analysis may even be extended to assessing the sensitivity of model performance to model concepts, such as which formulation is used to estimate unsaturated hydraulic conductivity. The comparative assessment and the conclusions drawn would be further strengthened if it is performed on more data sets. Empirical evidence for the assumptions would further strengthen the results. We envisage improvements in these directions in future studies.

Model parameterization and using the best relations and values are important in hydrological modeling. Although SETS and SETS-AMS models are built in a way to be comparative with the ETLook approach, better model development could be achieved by implementation of a prototype knowledge-based system (Chen & Chau 2006).

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