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Estimating basin scale evapotranspiration (ET) by water balance and remote sensing methods†

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Abstract:

Evapotranspiration (ET) is an important hydrological process that can be studied and estimated at multiple spatial scales ranging from a leaf to a river basin. We present a review of methods in estimating basin scale ET and its applications in understanding basin water balance dynamics. The review focuses on two aspects of ET: (i) how the basin scale water balance approach is used to estimate ET; and (ii) how 'direct' measurement and modelling approaches are used to estimate basin scale ET. Obviously, the basin water balance-based ET requires the availability of good precipitation and discharge data to calculate ET as a residual on longer time scales (annual) where net storage changes are assumed to be negligible. ET estimated from such a basin water balance principle is generally used for validating the performance of ET models. On the other hand, many of the direct estimation methods involve the use of remotely sensed data to estimate spatially explicit ET and use basin-wide averaging to estimate basin scale ET. The direct methods can be grouped into soil moisture balance modelling, satellite-based vegetation index methods, and methods based on satellite land surface temperature measurements that convert potential ET into actual ET using a proportionality relationship. The review also includes the use of complementary ET estimation principles for large area applications. The review identifies the need to compare and evaluate the different ET approaches using standard data sets in basins covering different hydro-climatic regions of the world. Copyright © 2011 John Wiley & Sons, Ltd.

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INTRODUCTION

Evapotranspiration (ET) is an important process in completing the hydrological cycle through the exchange of mass and energy between the soil–water–vegetation system and the atmosphere. ET comprises two sub-processes: evaporation and transpiration. Evaporation occurs on the surfaces of open water bodies, vegetation, and bare ground. Transpiration involves the withdrawal and transport of water from the soil/aquifer system through plant roots and stem and eventually from the plant leaves into the atmosphere. Knowledge of the rate and amount of ET for a given location is an essential component in the design, development, and monitoring of hydrological, agricultural, and environmental systems. For example, ET is a key variable in irrigation scheduling, water allocation, crop modelling, understanding water dynamics in wetlands, and quantifying energy–moisture exchange between the land surface and the atmosphere.

Evapotranspiration can be studied and estimated at multiple spatial scales ranging from a leaf to a forest stand to a river basin. The focus of this paper is on basin ET, which is the magnitude of ET representing a watershed scale of any size. We present a review of methods in estimating basin scale ET and its applications in understanding basin water balance dynamics. In addition, an application of a basin scale water balance approach and a 'direct' estimation of ET using a diagnostic modelling approach will be presented. The review of basin scale ET focuses on two aspects of ET: (i) how the basin scale water balance approach is used to estimate ET; and (ii) how direct measurement and modelling approaches are used to estimate basin scale ET.

BASIN WATER BALANCE APPROACH

Deriving a basin water balance is the process whereby water fluxes (actual ET, precipitation, groundwater recharge, surface and subsurface runoff) and storage changes (soil–water storage changes, snow and ice changes, groundwater changes, and reservoir storage changes) are balanced in a given hydrological basin (watershed). The procedure is also known as the inflow–outflow or mass balance approach; it can be applied over large integrated areas that consist of water and different land cover types (Allen *et al.*, 2011).

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The calculation can be done at any temporal scale (hours to years) and any spatial scale (plots to large watersheds) at which the fluxes and storage changes are known. Basin water balances can be lumped by considering the whole basin as a unit or distributed by calculating the water balance at the level of sub-units of the basin. The water balance equation for basins under natural conditions (i.e. with no significant trans-basin water transfers) is solved for actual evapotranspiration *ET* from the following water balance equation:

$$P - ET - Q - \Delta\theta = \mu \tag{1}$$

where P is rainfall, ET is actual ET, Q is runoff (basin discharge), $\Delta\theta$ is change in water storage from the different reservoirs, and μ is the discrepancy of the water balance. This discrepancy should be 0.0 when all components are measured accurately.

The change in water storage can be written in the form of Equation 2.

$$\Delta\theta = \Delta W + \Delta G + \Delta S + \Delta R \tag{2}$$

whereΔW = changes in soil moisture;ΔG=changes in groundwater storage;ΔS=changes in snow cover and ice; andΔR=changes in lakes, reservoirs, and rivers.

The $\Delta\theta$ terms comprises the changes of water storage in the soils, groundwater, lakes, rivers, reservoirs, and snow and ice systems during a given period ($\Delta\theta = \theta_t - \theta_{t-1}$), where θ_t is the sum of the water stored in the different storage systems (soil, lakes, etc) at the end of the period denoted by t, and P and Q are the precipitation and streamflow fluxes, respectively, during the same period. The overall error term (μ) is the divergence from 0.0 and represents the net cumulative error in measurement of all water balance components, given that some errors may be compensating (Dooge, 1975).

When the calculation of the water balance is carried out for annual values and for multiple years, the $\Delta\theta$ term can be considered small enough to be ignored. The basin water balance approach for ET estimation (difference between precipitation and discharge) is more appropriate at a yearly time scale because the assumption of no net storage may not be valid at seasonal or shorter time scales. However, water balance calculations in shorter periods, such as seasonal and monthly, can be used to compare the characteristics of different basins (Chang, 2003).

Large variations of basin scale ET are generally observed because of differences in climate, land use/land cover, and hydrology. For example, the relative ET ratio (annual ET to annual precipitation) on forested watersheds can vary from a low of 15% to about 90% in different parts of the world (Zhang *et al*., 2008).

In an annual water balance calculation, determining the hydrological calendar is important. The determination of the initial month of the hydrological year entails establishing the period for the specific hydro-climatic region when the least change is observed in the cycle of moisture accumulation and discharge (Zhuravin, 2004). This will help minimize the effects of interannual basin-wide moisture storage changes. The choice of the water year varies depending on the hydro-climate of the basin. For example, 1 October to 30 September is the water year in the USA, but Zhuravin (2004) established December to November to be the appropriate water year for the Nizhnedevitsk watershed in Russia.

Furthermore, Louie *et al*. (2002), using the Mackenzie Basin, Canada, reported the presence of a substantial lagged relationship between ($P - E$) and Q in large basins. They determined the correlation between ($P - E$) and Q is highest at a 3-month lag. This suggests that the discharge water year of October to September corresponds best with a ($P - E$) year defined to be July to June, or with a 3-month lag to the hydrological water year.

One of the prominent uses of a water balance approach for ET estimation is its application for calibration or validation of hydrological models or remote sensing-based models (Allen *et al*., 2011). For example, Immerzeel *et al*. (2008) calibrated the Soil and Water Assessment Tool (SWAT, Arnold *et al*., 1998) hydrological model by minimizing the difference between basin-wide model-simulated ET and remote sensing-based ET from the Surface Energy Balance Algorithm for Land (SEBAL) algorithm (Bastiaanssen *et al*., 1998).

Because of the lumping effect of basin scale ET, estimates do not differentiate the contributions from different cover types and do not account for short-time variability. However, at coarse spatial and temporal scales, good agreement has been reported between basin scale ET and measured ET using eddy flux data (Wilson *et al*., 2002; Scott, 2010).

The challenges of a basin scale ET are obtaining good quality precipitation and discharge data over the basin and accounting for changes in the various storages within the basin. Zhuravin (2004) discovered that for a forest-steppe watershed in Russia, a major source of the water balance error comes from an incomplete accounting of the moisture stored in a transition layer between the root zone and lower part of the water bearing groundwater zone where moisture is stored for 4 to 6 years, that is, the annual water balance is affected when water bearing soil horizons are not draining completely within the annual cycle.

Evapotranspiration occurs at the land surface and in the shallow unsaturated soil zone as well as from the water table. ET from the water table occurs from uptake by plants that use groundwater (phreatophytes) and through direct evaporation of groundwater through shallow soils. ET from the subsurface is referred to as 'groundwater ET'. The importance of land-surface ET *versus* groundwater ET depends on the part of the hydrological system under consideration. Those studying the fate of precipitation and applied irrigation water must consider ET at the land surface and in the shallow soil as an important component in their water budgets. On the other hand, those studying various aspects of aquifer systems must quantify groundwater ET, where it occurs. Being a subcomponent of the general basin water balance, water budgets for aquifer systems are of the general form:

$$Inflows - Ouflows = \Delta G \tag{3}$$

where inflows and outflows are components of water entering and leaving the aquifer, respectively, and ΔG is change in storage within the aquifer.

Components of inflow, outflow, and change in storage are expressed as a volume per unit time. Inflow components commonly include subsurface flow from adjacent aquifers, infiltration of precipitation that reaches the water table, infiltration from human sources that reaches the water table, and direct movement of water from surface-water features to the aquifer. Outflow components commonly include subsurface flow to adjacent aquifers, groundwater ET, direct removal of water through wells and drains, and discharge of groundwater springs and surface-water features.

An important characteristic of groundwater budgets is that not all components are well known from available information. A common practice is to estimate one unknown component as a residual in the water budget, assuming that all other components can be adequately estimated. However, if two or more major components are unknown, an individual component cannot be computed as a water budget residual. It is therefore important to independently estimate as many components as possible, including groundwater ET, to develop a complete understanding of an aquifer system.

The importance of groundwater ET in aquifer system water budgets is widely variable. For groundwater ET to be a factor, an aquifer must have areas where the water table is within about 10 m below land surface. For hydrogeological areas in the Basin and Range Physiographic Province of the southwestern USA, Anning and Konieczki (2005) developed a 'groundwater/surface-water interactions index' that included the presence of shallow water tables. Using their classification (Figure 1), 'directly connected' and 'indirectly and intermittently connected' areas are most likely to have groundwater ET as a major water-budget component. In some areas of this region with internal groundwater drainage, nearly all the natural aquifer outflow is through groundwater ET.

Hydrologists develop groundwater models so that resource managers can better understand effects of development of groundwater resources and climate variations on available water supplies. Groundwater models require knowledge of spatial and temporal distributions of the water budget components mentioned previously, as well as knowledge of spatial distributions of aquifer properties such as hydraulic conductivity and storage coefficient. However, aquifer properties are poorly known and are commonly estimated through inverse modelling. The most commonly available observations for use in inverse modelling are measured groundwater levels (head) measured in wells. However, flow components also are needed to constrain the solution (Hill and Tiedeman, 2007). For models of groundwater systems in which groundwater ET is a major component of the water budget, prior estimation of groundwater ET could be critical in successful model calibration.

Groundwater models such as modular finite difference flow (MODFLOW) (Harbaugh, 2005) have traditionally used a simple piece-wise linear function to quantify the groundwater ET flux (Figure. 2A), which is a flow per unit area. On the basis of the model-calculated position of the water table, the ET flux is multiplied by the area of the model cell to get a volumetric rate of groundwater ET for a given time step. The function includes an extinction level (or depth below land surface) below which ET ceases and another level at which ET flux reaches a maximum. ET flux varies linearly as a function of position of the water table between these two levels. Baird and Maddock (2005) developed a more sophisticated approach that allows for reductions in groundwater ET as the water table rises into the root zone (Figure 2B). Their approach, called the 'Riparian ET Package' for MODFLOW, also allows definition of different ET curves for different plant functional groups that may exist in different areas or within the same area. Use of the Riparian ET Package may be of advantage if the focus of the groundwater study is on the groundwater-dependent riparian areas.

Uncertainty in basin scale ET

The estimation of ET from the basin water balance approach requires accurate measurement of the important fluxes such as precipitation, runoff, and in shorter time scales, storage changes. Thus, the uncertainty associated with ET is a result of a combination of uncertainties from the estimation of precipitation, discharge, and storage changes.

Assuming that the measurement errors of each term in Equation 1 are independent and random, and given that each term has an uncertainty σ^2, then the standard deviation associated with estimating actual evapotranspiration ET by the water balance may be estimated as follows (Lesack, 1993):

$$\sigma_{ET} = \left(\sigma^2_{\Delta\theta} + \sigma^2_P + \sigma^2_Q\right)^{1/2} \tag{4}$$

Traditionally, stream discharge Q is measured with rating curves based on flow stage at gages. Sauer and Meyer (1992) found that the errors for individual discharge measurements by stage gages range from as low as 2% to as high as 20% of estimated discharge, with most errors between 3% and 6%. Precipitation P is most often measured from tipping-bucket rain gages and/or Doppler radar. The uncertainty of measured P is generally negatively correlated with the observation time scale and the density of the network. Habib *et al.* (2001) and Ciach (2003) reported rainfall estimated with a rain gage network had standard errors of 6.4% and 4.9% for a 5-min duration rainfall, and 2.3% and 2.9% for a 15-min averaged rainfall. The error caused by the density of observing rain gages is small if the density of the gages exceeds one rain gage per 15 km (Seed and Austin, 1990). These instrumental and network measurement uncertainty errors can be translated

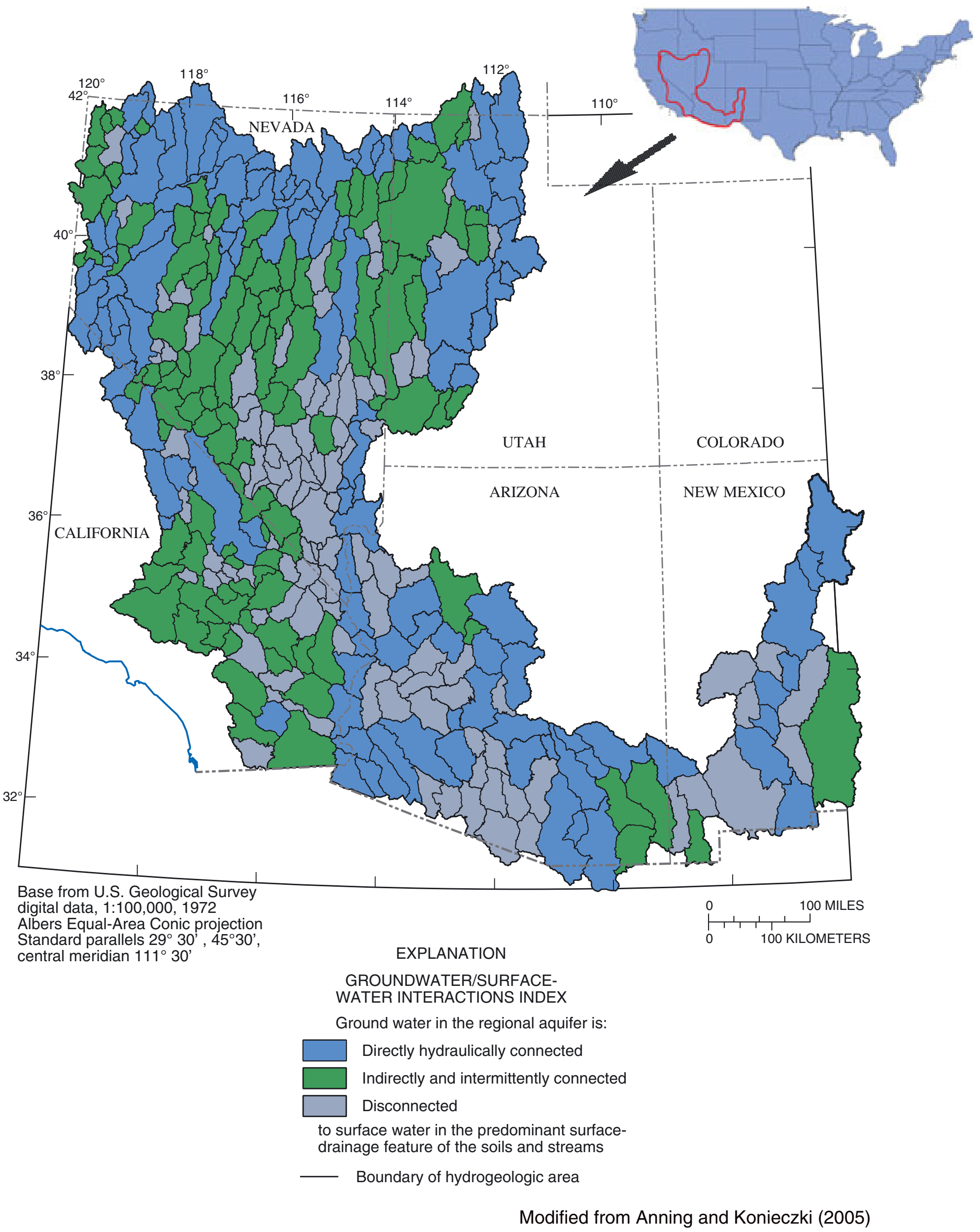

Figure 1. Distribution of the groundwater/surface-water interaction index for hydrogeologic areas of the Basin and Range physiographic province in the Southwestern USA. Groundwater evapotranspiration (ET) is most likely to be a significant component of groundwater budgets in areas shaded blue or green

to uncertainties in water balance components. For a confidence level of 95%, the standard error of the estimated flux will be as follows:

$$S = \frac{\sigma * \bar{X}}{1.96} \tag{5}$$

where σ and $\bar{X}$ are the standard deviation and mean value of the flux, respectively.

For example, the annual P and Q of an arbitrary basin in the southeastern USA are 1270 and 441 mm/year, respectively. The uncertainties of measured P and Q were reported to be 8 and 5%, respectively. Thus, the water balance-estimated annual ET is $1270 - 441 = 829$ mm/year, with an uncertainty σ_{ET} of $[(102)^2 + (22)^2]^{1/2} = 104$ mm/year.

When data are not available to conduct a water balance (e.g. mainly rainfall and discharge) or when shorter time interval ET is desired for a basin, a direct estimation of ET is conducted using a combination and integration of hydrological modelling and meteorological, flux tower, and remotely sensed data.

DIRECT ESTIMATION OF BASIN SCALE ET

A direct estimation of ET for a basin can be achieved using an integration of methods and data sources. Depending on availability of data and the purpose of ET estimation, different methods can be used. The methods can be grouped into three broad classes: (i) point measurements and some form of regionalization; (ii) areal estimates based on weather data and hydrological modelling; and (iii) spatially explicit estimates based on remotely sensed data and modelling.

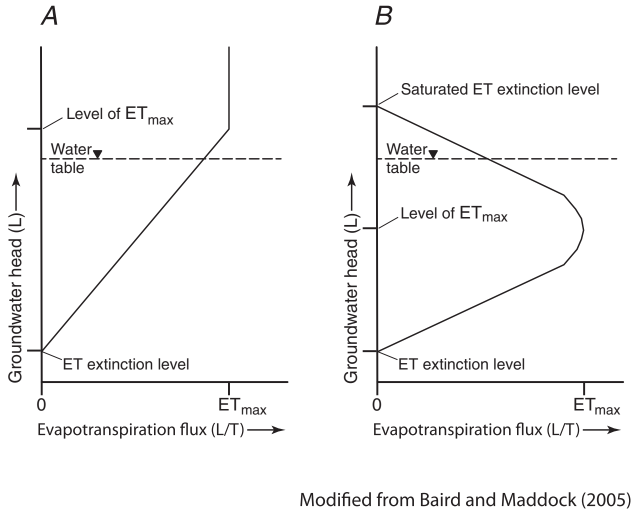

Figure 2. Functions used to calculate groundwater ET flux from water-table position in groundwater models using modular finite difference flow. A, The traditional approach used in the Evapotranspiration Package. B, The more sophisticated approach used in the Riparian-ET Package

Regionalizing point ET measurements

Scaling up from point measurements of spatially variable, complex processes to meso-scale and macro-scale models often involves relating such measurements to landscape features that can be lumped spatially and treated as homogeneous units (Metcalfe and Buttle, 1999). The most commonly used point estimates of ET for regionalization are the Bowen ratio–energy balance (BREB, Bowen, 1926) and the eddy covariance (EC, Wilson *et al*., 2002) approaches. Nagler *et al*. (2005a, 2005b) have demonstrated a successful application of using remotely sensed vegetation indices (VIs) to scale up point ET measurements/estimates for riparian corridors over large stretches of the western USA with a potential error of up to 25%. They established regression equations between point ET estimates (dependent) from EC and BREB instrumentations and VIs from remotely sensed imagery along with air temperature measurements as independent variables. Scott *et al*. (2008) applied a similar regression approach where measured ET was regionalized using a VI and land surface temperature instead of air temperature for estimating a riparian ET in a groundwater-dominated system.

One of the important considerations in extrapolating flux tower ET is in the handling of the energy balance closure issue. Wilson *et al*. (2002) pointed out that studies that use EC measurements apply the standard energy balance closure ratio (ratio of the sum of latent heat and sensible heat energy to the difference between net radiation and ground heat flux) to evaluate the accuracy and efficacy of their results. A common practice is to conduct a forced closure of the energy balance using the Bowen ratio method when the available energy (net radiation) is known and the errors in the measurement are modest (Twine *et al*., 2000). Both Nagler *et al*. (2005b) and Scott *et al*. (2008) applied the Bowen ratio closure method in which both latent heat and sensible heat energy were adjusted equally based on the closure ratio before applying them in their regression equations.

In addition to understanding energy balance closure issues, the representativeness of point measurements with respect to the land cover and hydro-climatic conditions of the basin is important. Metcalfe and Buttle (1999) pointed out the presence of a potential error in extrapolating ET from flux tower sites to a basin if water table levels in the respective landscape units are significantly different from those at the towers, noting that evaporation decreases noticeably as the water table level drops below ground surface (Dooge, 1975).

Meteorological data and hydrological models

Basin scale ET has been estimated by various researchers from meteorological data. This approach can be broadly grouped into those that are based on a complementary relationship and those that are based on a proportional relationship between actual ET and potential ET (ET_p).

Hobbins *et al*. (2001) explained the complementary theory of Bouchet (1963) by arguing that at regional scales, actual ET and potential ET (ET_p) are not independent of each other. Because of a complex feedback mechanism at the land-atmosphere interface in relation to whether the soil can meet the atmospheric demand and the resultant effect on surface energy distribution, Bouchet (1963) hypothesized that 'when, under conditions of constant energy input to a given land surface–atmosphere system, water availability becomes limited, ET falls below its potential, and a certain amount of energy that would otherwise evaporate water instead is converted to sensible heat and/or long wave back radiation, that increase the temperature and reduces the humidity gradient of the overpassing air and lead to an increase in ET_p equal in magnitude to the decrease in ET' (Hobbins *et al*., 2001).

Hobbins *et al*. (2001) presented the complementary relationship using Equation 6.

$$ET + ETp = 2ETw \tag{6}$$

where ET_w is the wet environment condition when ET and ET_p are equal. ET_p is defined as the ET that would take place from a moist surface under the prevailing atmospheric conditions, limited only by the amount of available energy.

Hobbins evaluated the complementary relationship hypothesis for regional annual ET using a water balance of 120 natural basins over 26 years (1962–1988) in the USA and found the accuracy (difference between estimated ET by the complementary equation and the water balance ET) to be within 11% of precipitation.

In a proportional relationship, an increase or decrease in ET_p will result in a similar directional increase or decrease in ET. Peterson *et al*. (1995) showed that a decrease in pan evaporation data in the USA and Russia resulted in a decrease in actual ET and an increase in runoff. Cong *et al*. (2008) reported the presence of the evaporation paradox in the Yellow River basin, China, in which evaporation data showed an unexpected decline with increasing air temperature in the basin. However, they also reported that ET_p and ET exhibited a complementary relationship in space (both observed as a function of precipitation), but a temporal analysis of the data showed a proportional relationship where both declined in the period between 1950 and 2000.

Commonly used water balance models apply the proportional relationship to estimate actual ET from potential ET. The basic principle is based on the fact that a correction coefficient will be applied to adjust the potential ET (unlimited water supply to an ideal reference crop) for soil moisture supply and vegetation condition (type and stage). Allen *et al.* (1998) have documented the application of this principle for crop water use estimation. For example, Equation 7 can be used to estimate ET based on a simple soil water balance model.

$$ET = Ks * Kc * ETo \tag{7}$$

where ET_o is a special case of potential ET for a standardized reference grass crop, K_c is the crop coefficient (0.2–1.2) (Allen *et al.*, 1998), and K_s is a soil stress coefficient (0–1) derived from a soil water balance model (e.g. Allen *et al.*, 1998; Senay and Verdin, 2003; Senay, 2008). A linear function can be used to vary *K*s values from 0.0 at wilting point to 1.0 at 50% of the water holding capacity (WHC) of the soil (difference between field capacity and wilting point). The *K*s factor remains 1.0 once the soil moisture is above 50% of the WHC.

K_c values that use remotely sensed data such as NDVI can be estimated from land surface phenology (Senay, 2008; Allen *et al.*, 2011). Other researchers, such as Groeneveld *et al.* (2007) and Nagler *et al.* (2005a, 2005b, 2009), applied an NDVI-based coefficient (similar to K_c) to estimate ET. ET can be estimated for each land cover type in the basin, and an area-weighted average can be used to represent the basin ET. Similar soil stress correction factors also have been applied by McCabe and Wolock (1999) in combination with the Hamon (Hamon, 1961) equation, a variant of the Thornthwaite (1948) potential ET for estimating ET in a monthly time step.

Although any of the above proportional approaches can provide a reliable estimate of ET when soil moisture accounting is conducted properly, a major drawback of the method is the requirement to estimate rainfall accurately for soil moisture estimation (K_s factor) and the inability to account for the contribution of irrigation, groundwater, and capillary rise to the total ET.

The shortcoming of a water balance approach, particularly the requirement for rainfall, can be resolved using remotely sensed data. There are two important approaches in estimating ET using remotely sensed data using the proportional ET principle: (i) the use of optical channel-based VIs with a potential ET without taking into account soil moisture; and (ii) the use of thermal data sets in an energy balance approach.

Remote-sensing-based approach for basin scale ET

Unlike soil water balance principles, these remote sensing-based methods summarized below do not require information on rainfall or soils. A brief review of these methods is presented using application examples for water balance studies.

Models based on VI. Vegetation index models are useful for calculating ET from phreatophyte communities in arid and semiarid regions because ET is dominated by Transpiration (T) (Scott *et al.*, 2008). VI models for estimating ET are based on the observation that foliage density on the ground, as measured by satellite VIs, often is strongly correlated with ET (Glenn *et al.*, 2010). VI methods must be combined with meteorological data to calculate atmospheric water demand and the energy available to evaporate water. Furthermore, the algorithms used to calculate ET in VI models need to be regressed against ground measurements of ET in the biome of interest to develop empirical relationships between ET, meteorological data, and VIs (Glenn *et al.*, 2010). Thus, the accuracy of the VI model for ET is constrained by the accuracy of the ground measurements of ET by which they are calibrated and by the degree of correlation between foliage density and ET.

Several VI methods for estimating ET have been developed for phreatophyte communities. Groeneveld *et al.* (2007) used the NDVI approach with summer Landsat images to estimate ET of a wide variety of phreatophyte communities in the western USA. NDVI is based on the ratio reflectance in the red and near infrared (NIR) bands; vegetation strongly absorbs red light and reflects NIR, providing a quantitative measure of green plant cover over a landscape. They converted raw NDVI data into scaled values ($NDVI^*$) by setting bare soil values at 0 and values for dense agricultural fields representing fully transpiring crops at 1.0. This step normalizes NDVI values between bare soil ($NDVI^* = 0$, $ET = 0$) and full vegetation cover ($NDVI^* = 1.0$, ET = maximum). Then, they estimated ET using Equation 8:

$$ET = ET_r{}^* NDVI^* \tag{8}$$

where ET_r is the alfalfa reference ET (ET_r is about 20% more than ET_o) determined by ground meteorological data using the Penman Monteith (PM) equation (Brouwer and Heibloem, 1986) and $NDVI^*$ is NDVI scales between bare soil (set at 0) and a fully transpiring agricultural field assumed to be the maximum rate (set at 1.0). ET_r represents the maximum possible ET of a hypothetical, freely transpiring reference alfalfa crop under a given set of meteorological conditions. Groeneveld *et al.* (2007) found that annual phreatophyte ET calculated using Equation 8 predicted the actual ET rate measured at moisture flux tower sites with a coefficient of determination (r^2) of 0.95.

The VI approach developed by Groeneveld *et al.* (2007) was modified by Nagler *et al.* (2009) for agricultural and riparian plants on the lower Colorado

River by using the enhanced vegetative index (EVI) products (Huete *et al.*, 2002) from the Moderate Resolution Imaging Spectroradiometer (MODIS) sensor on the Terra satellite (obtained from http://daac.ornl.gov/MODIS/modis.shtml) instead of the NDVI products from the Landsat images. MODIS provides near real-time imagery of most of the earth at daily intervals. Images with 250 × 250-m pixel resolution in the red and NIR bands and 500 m in the blue band are georectified and radiometrically and atmospherically corrected. MODIS products are commonly used in phenological and change-detection studies, which require stable VI values over time (Glenn *et al.*, 2010). EVI is closely related to NDVI but includes a soil correction factor by including the blue band. MODIS EVI products give consistently better predictions of ET than MODIS NDVI products (Glenn *et al.*, 2010), which is why they were used in that study.

Similar to the approach of Groeneveld *et al.* (2007), EVI* was scaled from EVI between bare soil and maximum vegetation using values for EVI_{min} and EVI_{max} from Nagler *et al.* (2005a):

$$EVI^* = 1 - \left(\frac{0.542 - EVI}{0.542 - 0.091}\right) \tag{9}$$

The ET model using EVI* developed for crops and riparian vegetation on the Lower Colorado River (Nagler *et al.*, 2009) took the following form:

$$ET = 1.22EVI^* * ET_{BC} \tag{10}$$

Equation 10 differs from Equation 8 in two ways. First, the factor 1.22 was included based on the linear regression equation of best fit between measured ground ET and EVI^* x ET_{BC}. Second, the potential ET was calculated using the Blaney–Criddle (BC) method rather than the PM method. The BC method requires only mean daily air temperature, which is available from numerous cooperative reporting stations in the USA, and latitude to determine hours of daylight, whereas the PM method requires temperature, humidity, radiation, and wind speed measurements, which are not available for the watershed. Furthermore, the least squares fit of the residuals of the fit between ET_{BC} and ground data was lower than the residuals obtained from ET_r for ET calculations along the Lower Colorado River. Equation 10 predicted measured ET of alfalfa, cottonwood, tamarisk, and arrowweed ET with a standard error of 20% compared with ground measurements, which is within the range of error inherent in the sap flow and flux tower methods used on the ground.

Energy balance (thermal band) estimates of ET

Generally, energy balance models for ET estimation are driven by the land surface temperature. The spatial or temporal variation in land surface temperature provides critical information on the partitioning of the net radiation among latent heat (ET), sensible and ground heat flux (Equation 11).

The surface energy balance equation is generally expressed in the following form:

$$LE = Rn - G - H \tag{11}$$

where LE = latent heat flux (energy consumed by ET) (W/m^2), Rn = net radiation at the surface (W/m^2), G = ground heat flux (W/m^2), and H = sensible heat flux (W/m^2).

Surface energy balance methods have been used by several researchers (Jackson *et al.*, 1981; Moran *et al.*, 1996; Bastiaanssen *et al.*, 1998, 2005; Kustas and Norman, 2000; Roerink *et al.*, 2000; Su, 2002; Allen *et al.*, 2005, 2007a, 2007b; Su *et al.*, 2005; Anderson *et al.*, 2007) to estimate agricultural crop water use and terrestrial ET. A comprehensive summary of the various surface energy balance models is presented by Gowda *et al.* (2008) and Kalma *et al.* (2008). Applications of the energy balance ET for ecohydrological studies have been demonstrated by several researchers (e.g. Oberg and Melesse, 2006; Melesse *et al.*, 2008).The approach of most energy balance models requires solving the energy balance (Equation 11) at the land surface, where the latent heat flux – energy used to evaporate water – is calculated as the residual of the net radiation, sensible heat flux (energy used to heat the air), and ground heat flux (energy stored in the soil and canopy).

A basin scale estimate of ET is achieved by simple basin averaging of the individual pixel values at any temporal scale. The energy balance approach has some advantages over the water balance approach: cover types do not need to be classified, sources of water (irrigation, rainfall, groundwater, etc) do not need to be estimated, and there are no assumptions on vegetation phenology in terms of water use patterns or on agronomic conditions (soil types, salinity, etc) and disease and pest conditions.

Although energy balance is a powerful tool to estimate ET in well-defined irrigation basins, for continental application, the method is sensitive to changes in environmental conditions other than soil moisture variability, such as cloud cover, elevation, and latitudinal differences. Different methods handle these issues differently. One approach is presented in the next section that demonstrates the application of a simplified surface energy balance approach in estimating pixel-based and basin scale ET and its performance against a water balance approach in the conterminous USA (CONUS).

Example of simplified surface energy balance modelling approach to ET

The simplified surface energy balance (SSEB) modelling approach (Senay *et al.*, 2007, 2011) works similar to the more complex surface energy balance models in the sense that LST (or simply T_s) is used as a primary scalar. However, whereas in the complex models, the temperature scalar is applied in an aerodynamic estimation of sensible heat flux (H) that is in turn subtracted from estimates of net radiation and soil heat flux to determine ET, the SSEB temperature scalar is multiplied directly by the estimate of maximum ET. The SSEB approach estimates ET using the relative ET fractions scaled from thermal imagery in combination with a spatially explicit maximum reference ET.

We used the 8-day average Terra MODIS LST (MOD11A2, LP DAAC, 2010) to calculate ET fractions (Equation 12). Corresponding period MODIS NDVI were used to select the hot (bare areas with NDVI < 0.2) and cold (NDVI > 0.7) reference pixels. Gridded grass reference ET (ET_o), calculated at the USGS EROS Center from six-hourly weather datasets obtained from the Global Data Assimilation System (GDAS) was used (Senay *et al.*, 2008). In addition, high-resolution (4 km) monthly air temperature (resampled to 8-day) from PRISM was used with the LST to calculate ET fractions according to Equation 11. (http://www.prism.oregonstate.edu/).

For the water balance calculation, annual (October to September) precipitation was created from monthly PRISM data sets. Similarly, annual runoff (October to September) data were acquired from the USGS at the eight-digit hydrologic unit code (HUC). (http://waterwatch.usgs.gov/). The median annual difference between precipitation and runoff for the period between 2000 and 2009 was used in this study to compare with modelled median ET (2000–2009) at a watershed scale.

The main modelling principle of the SSEB approach in Senay *et al.* (2007, 2011) is the combined use of ET_o and land surface temperature data for actual ET estimation. The surface energy balance is first solved for a reference crop condition (assuming full vegetation cover and unlimited water supply) using the standardized PM equation (Allen *et al.*, 1998). A global operational application of the PM equation for daily ET_o is demonstrated using GDAS (Kanamitsu, 1989) data sets in Senay *et al.* (2008). The ET fractions (ET_f) account for differences in water availability and vegetation condition in the landscape and are used to adjust the reference ET based on the land surface and air temperatures of the pixel (Equation 12). In essence, ETf is the equivalent of the product of Kc and Ks (Kc*Ks) in the water balance formulation in Equation 7.

In the revised SSEB model formulation, ET_f is calculated from the LST and air temperature data sets based on the assumptions that a *hot* pixel experiences little or no ET (Bastiaanssen *et al.*, 1998; Allen *et al.*, 2005) and a *cold* pixel represents 'maximum' ET. With the simplified assumption, ET can be scaled between these two values in proportion to LST and air temperature difference. The linearity assumption also was applied by Jackson *et al.* (1981), Menenti and Choudhury (1993), and Moran *et al.* (1996) but not in combination with the hot and cold pixel approaches of SEBAL or METRIC.

The main driver for the ET fraction is the difference between LST and air temperature in relation to the same difference with the reference locations (hot and cold). For a given location, when the difference between T_s and T_a is small, we expect high ET (i.e. less sensible heat); on the other hand, when the difference is high, we expect low ET (i.e, high sensible heat).

The *hot* pixels were selected using an NDVI image as a guide to identify the locations of dry and non-vegetated (or sparsely vegetated) areas that exhibit very low NDVI values (< 0.2). Similarly, the *cold* pixels were selected from well-watered, healthy, and fully vegetated areas that have very high NDVI values (> 0.7).

A temporally dynamic set of hot and cold pixels selected from representative locations [cold generally from the southeast USA (wetter area) and hot pixels (dry areas) in the western high plains of the USA] have been used for the entire CONUS data set. It should be noted that, although the hot and cold pixels remain in the same region, the LST values generally vary from season to season, so we prepared a unique set of hot and cold pixels for each period from the same region that met the requirements. What is unique in this revised SSEB approach is the use of a single set of hot and cold pixels to scale across the CONUS for each 8-day period. In addition, both the hot and cold reference values were temporally smoothed using a three 8-day period moving average. The average hot and cold land surface temperature values were differenced with their respective air temperature values as follows for ET_f calculation.

ET_f is calculated for each pixel 'x' by applying Equation 12 to each of the 8-day LST grids.

$$ETf = \frac{dT_h - dT_x}{dT_h - dT_c} \tag{12}$$

where dT_h = the difference between surface temperature (Ts) and air temperature (Ta) at the hot reference; dT_c = the difference between Ts and Ta at the cold reference; and dT_x = the difference between Ts and Ta at a given pixel 'x'.

The basic principle that relates instantaneous satellite measurements to daily and weekly ET estimation is the fact that the ET fractions are stable throughout the day (Allen *et al.*, 2005, 2007a). By extension, 8-day ET fractions generated from the available 8-day MODIS thermal datasets represent the average ET fractions for the period. Because the ET fractions are average representations of the period, the day-to-day variability of ET is captured by the magnitude of daily total ET_o, which is largely driven by the net radiation and aerodynamic forces experienced by the modelling unit (pixel).

The basic approach of calculating ET involves two steps (Equations 12 and 13). ET is simply a product of the ET_f and ET_o (Equations 12 and 13).

$$ET = ET_f{}^{*} \alpha ET_o \tag{13}$$

where ET_o is the grass reference *ET* for the location; α is a coefficient that scales up grass reference *ET* into the level of a maximum *ET* experienced by an aerodynamically rougher crop.

There is a constant relationship between clipped grass reference ET and other cover types. For example, (Allen RG, personal communication) suggests using ($\alpha = 1.2$) factor to estimate the maximum ET for crops such as alfalfa, corn, and wheat, which are aerodynamically rougher than the clipped grass reference and have greater leaf area and thus greater canopy conductance (Allen *et al.*, 1998).

For basin scale studies using coarse satellite data sets such as MODIS (1 km), we recommend a calibration and validation process to determine this coefficient. In this study, α was set to 1.0 after initial evaluation of the results in comparison with the HUC8 water balance values.

Validation using a water balance approach

Although the Landsat-based SSEB ET model was validated successfully by Gowda *et al*. (2009) using lysimeter data, MODIS-based ET is more difficult to validate using lysimeter data because of its coarse spatial resolution at 1 km. In this study, we used a water balance approach to evaluate how the SSEB ET compares with the annual difference between precipitation and runoff at the HUC-8 level in the CONUS. The major assumption was that net-storage changes are negligible at an annual time scale at the watershed level. Thus, this comparison does not take into account inter-basin transfers for irrigation. To account for this, sub-basins that had a runoff coefficient (precipitation to runoff) of > 0.5 were excluded from the analysis to reduce the inclusion of sub-basins with large regional flows, that is, subsurface runoff joining from other sub-basins. Furthermore, basins with a high ET to precipitation ratio (ratio > 0.8) were also removed to exclude irrigated basins where the source of ET is probably groundwater or diversion from other basins. The median of 10 years of precipitation, runoff, and ET were used for this exercise. A scatterplot of annual SSEB ET plotted against the difference between precipitation and runoff was created using 1399 HUC8 watersheds in the CONUS. The coefficient of determination (R^2) and slope of linear regression was calculated by treating ET as the dependent variable and the difference between precipitation and runoff as the independent variable.

The SSEB model has been implemented in different parts of the world for water budget analysis and drought monitoring. Figure 3 shows sample model outputs showing annual total (median of 2000–2009) ET distribution in the USA. The SSEB model has been validated using four lysimeter data in the Texas High Plains with an $r^2 = 0.84$ for daily total comparisons (Gowda *et al*., 2009) and was compared with other well-established ET models such as METRIC (Allen *et al*., 2005) and provides comparable performance (Senay *et al*., 2011) in irrigated basins.

According to Figure 3, the SSEB ET captures well the spatial distribution of continental scale ET, with higher ET being mapped in high rainfall and irrigated regions, whereas low ET dominates the arid and semiarid regions. Furthermore, wetland areas and tree covered regions with access to groundwater show as high ET regions. Furthermore, preliminary results from recent validation work with a water balance approach are shown in Figures 4 a–c. The annual differences between precipitation (P) and runoff (Q) at 1399 HUC-8 level watersheds were compared with annual SSEB ET estimates with an r^2 of 0.90 and a mean bias of -67 mm or -11% of the difference between observed P and Q. The high r^2 (0.90) demonstrates the precision and reliability of the approach in diverse ecosystems.

The SSEB ET shows a general underestimation especially in the lower ET region (ET < 600 mm) compared with higher ET zones. This could be explained by the fact that coarse scale MODIS is averaging over larger areas that do not contribute to ET in arid and semiarid regions. The use of grass reference ET without adjustment also may contribute to the general underestimation, but the effect seems to be limited in higher ET regions. This is probably because of other compensation effects in the modelling assumptions. Some of the scatter in Figure 4c can be caused by the assumption that regional flow and net storage changes are negligible. The uncertainty level in these assumptions needs to be checked especially in small watersheds.

CONCLUSION

This review shows that several modelling approaches have been developed to estimate landscape and basin-wide ET. Although we did not find literature that presents an inter-comparison of the different modelling approaches

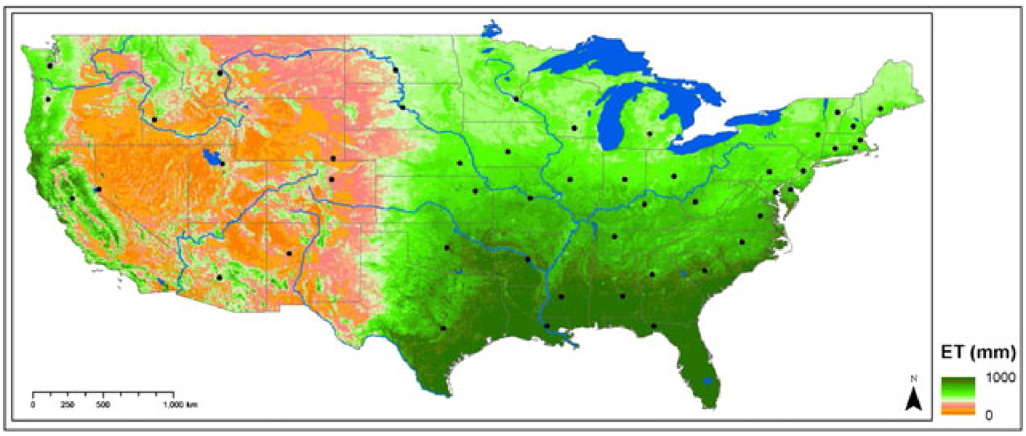

Figure 3. Annual simplified surface energy balance (SSEB) ET (median of 2000–2009) showing the general spatial pattern in the conterminous USA. Green indicates high water use in high-rainfall and irrigated/wetland regions. Brown indicates low water use in arid regions

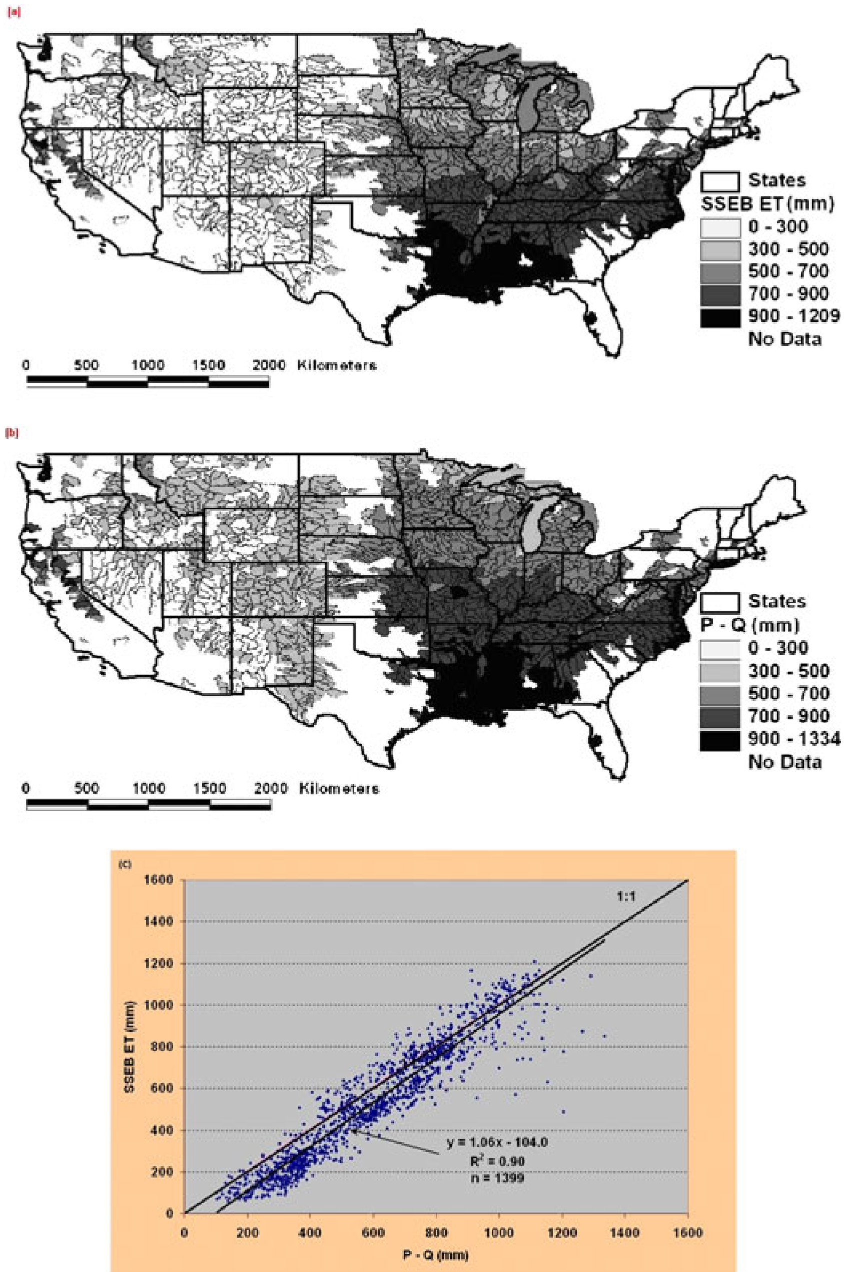

Figure 4. Validation of SSEB annual ET against watershed water balance (precipitation minus discharge, Q) using 1399 HUC8 watersheds in the conterminous USA: (a) HUC8 spatially averaged annual SSEB ET for the median year of (2000–2009); (b) HUC8 spatially averaged annual water balance ET (P – Q). Blank areas are those that were excluded from analysis because of irrigation or suspected regional flows outside the HUC8 boundary. (c) Scatterplot between remote sensing ET and water balance ET

using standardized data, we present a summary of the characteristics of the different approaches (Table I). Table I simply compares and contrasts the data input types and obvious advantages and limitations of the different methods.

We grouped basin scale ET into a 'traditional water balance' and a 'direct' approach. The traditional water balance approach is ideal to estimate ET on well-gauged basins at annual time scales, which can be used to validate the other direct ET methods. We have grouped direct ET methods further as 'complementary' *versus* 'proportional' principles in relation to the potential ET. Under the proportional ET principle, there are three major independent ET techniques: (i) based on soil moisture accounting; (ii) based on a relationship between NDVI and flux tower data; and (ii) using the land surface temperature data in an energy balance modelling approach. Because most of the methods use remotely sensed data in some form and do ET calculations in a grid cell, spatial averaging is the most commonly used method to obtain the basin-wide ET. The study also showed how basin scale ET can be used to estimate groundwater ET when combined with precipitation information. This study points to the need to evaluate the different modelling techniques under different hydro-climatic regions using standardized datasets.

Table I. Summary characteristics of the different evapotranspiration estimation approaches

Element	Basin balance	Soil moisture	NDVI-based	LST-based
Key inputs	P and Q	P, PET, water use phenology, water balance model	NDVI, flux tower data, regression model	LST, PET, Ta and energy balance model
Basin Estimate	Average difference of Q and P	Basin average ET	Basin average ET	Basin average ET
Scale: temporal	Seasonal/annual	Daily	Daily	Daily
Scale: spatial	Basin scale	Pixel	Pixel	Pixel
Advantage	Does not depend on model formulation reliable for model validation at longer time steps	useful for agro-hydrological monitoring with information on soil moisture and runoff daily simulation possible usually models ET that is based on rainfall	does not depend on rainfall or hydrologic models ET estimate comprises various sources (rainfall, irrigation, or groundwater)	does not depend on rainfall or hydrological models Estimate total ET (rainfall, irrigation, groundwater) with better handling of stressed vegetation and ET from bare areas
Limitations	Requires measurements of P and Q does not resolve shorter than seasonal or annual time scales assumptions of zero net storage change may not be valid in some basins	requires rainfall and information on soils accuracy also depends on model inputs and formulation does not estimate ET from irrigation or groundwater sources	may underestimate ET from stressed vegetation and may underestimate ET from bare areas. representativeness of flux-tower ET to the basin-wide condition may not be appropriate	solving the energy balance involves more assumptions and parameterization. LST is affected by other factors such as elevation and latitudinal differences thus tends to produce some spurious results
Major Applications	ET model validation at a basin scale	Rainfed crop monitoring runoff estimation	crop, drought, and carbon monitoring	crop, drought, and carbon monitoring

LST: land surface temperature.
P: precipitation.
PET: potential ET.
Ta: air temperature.
Q: stream discharge.

DISCLAIMER: Any use of trade, firm, or product names is for descriptive purposes only and does not imply endorsement by the U.S. Government.

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