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Review paper

An overview of uncertainties in evapotranspiration estimation techniques

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ABSTRACT

Accurate estimation of evapotranspiration (ET) is essential both at the regional and local scales for many management tasks. Numerous methods for estimating ET with various complexities and combinations exist which may be broadly classified as direct and indirect methods. Information on ET estimation uncertainties cannot be overemphasized and ignoring them can misguide decision-making in management of water resources. This study reviews the uncertainties in ET estimations and suggests ways to reduce them. Identified in this study are uncertainties associated with ET methods and input data, uncertainties due to spatial and temporal scales, and uncertainties based on region. Many studies have the ET method related uncertainties. The ground-based techniques generally used as a standard for comparing other methods have considerable uncertainty (10–30%) associated with the input components. The errors from the input reflect in the estimated ET output irrespective of the model used. Datasets from satellite products are based on in-situ network forcing as well as on model's estimation and remote sensing (RS), and they are prone to errors as a result of differences in in-situ measurements, scale, sensor calibration and basics of model theory and parametrization. Generally, uncertainties associated with ET were found to vary temporally. Also, homogeneity and stability of potential evapotranspiration (PET) were worse in space than in time, indicating that the temporal distribution of PET was more uniform and stable compared to spatial distribution. Some ET RS products showed less uncertainty in coarse resolution and comparatively high uncertainty in fine resolution. This study identified five ways to minimize uncertainties in ET estimations. Minimizing uncertainty in ET estimation will definitely improve planning, management and use of water resources especially where accurate estimations are required.

Keywords: evapotranspiration methods; evapotranspiration uncertainty; reducing uncertainty; potential evapotranspiration; actual evapotranspiration

Evapotranspiration (ET) represents the combination of water loss through evaporation from the bare soil and surfaces of open water bodies as well as transpiration from plants (Allen *et al*., 1998; Obalum *et al*., 2011a; Vinukollu *et al*., 2011; Guillevic *et al*., 2019). In the environmental system, ET is a key part of the water balance representing the dominant mechanism driving the hydrological cycle (Byun *et al*., 2014; Badgley *et al*., 2015; Baik and Choi, 2015; Tadesse *et al*., 2015). It is also an essential land surface mechanism in climatology, terrestrial energy and carbon cycles (Du and Sun, 2012; Yuan *et al*., 2012; Zhu *et al*., 2013). Beven (2001) noted that, in many environments, ET is a greater proportion of the catchment water balance than stream discharge, though this is largely influenced by the vegetation. The ET could influence groundwater recharge especially because its variation with vegetation is not just about the density of the vegetation and associated degree of shielding the soil from evaporative losses, but also about vegetation interception of rainwater (Ouyang *et al*., 2019). Total loss by ET may account for about three quarters of all precipitation in a year, even in humid regions (Knapp, 2002), and sometimes may be more than the annual precipitation particularly in semi-arid or arid regions.

At the global scale, ET is the most outgoing water flux in the

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hydrologic cycle and together with precipitation determines water availability (Long *et al*., 2014; Rajib *et al*., 2018). Generally, ET may be categorized into actual evapotranspiration (AET) and potential evapotranspiration (PET) which reflect crop water demand and meteorological water demand, respectively, the latter of which reflects the upper limit of crop water demand. The AET is the actual water loss from natural environment (Allen *et al*., 1998; Buttafuoco *et al*., 2010; Verstraeten *et al*., 2008; Baik and Choi, 2015; Wang *et al*., 2015; Liaqat and Choi, 2017; Khan *et al*., 2018; Yang *et al*., 2019). The PET represents the utmost capacity of evaporation across the terrestrial surface when water is not limiting. In croplands of monoculture where there are reliable data for the other components of soil water balance such as runoff and drainage, it is possible to measure AET (Obalum *et al*., 2011b, c).

When the emphasis is on crop production, PET is called reference ET (ETo), commonly defined as the ET from well-watered hypothetical 8-15 cm tall green grass of uniform height, actively growing and shading the ground (Allen *et. al.*, 1998; Obalum and Azuka, 2021). The concept of ETo examines the evaporative power of the atmosphere at a specific location regardless of crop type, developmental stages of the crop, soil factors and management practices (Buttafuoco *et al*., 2010). Climatic attributes are mostly the factors affecting ETo and therefore it can be calculated using weather data. The PET determines the upper limit of AET (Wang *et al*., 2017a). On the other hand, AET links the energy and water balances by designating energy in hydrosphere, geosphere and biosphere to reflect the synergy among land surface systems and climate change (Chen, 2017). According to Yang *et al*. (2019), AET is the most important parameter for describing hydrological cycle.

Since water loss through ET is enormous, accurate estimation of it is essential for many tasks, e.g., proper management, planning and adequate use of water resources, drought predictions, irrigation scheduling, weather forecasting and crop yield estimation, etc. both at the regional and local scales (Khan *et al*., 2018; Sorensson and Ruscica, 2018). However, the ET quantification is usually influenced by many hydro-meteorological factors and heterogeneous land surface characteristics over space and time (Chen *et al*., 2018). The complicated ecosystem as well as the large variety of physical processes and their interactions makes it challenging to accurately quantify ET. Numerous methods exist for estimation of ET with various degrees of complexities and combinations. However, the complicity of climate change, varied environmental conditions, land surfaces, and their temporal and spatial variability usually lead to qualitative and quantitative uncertainties in the ET estimations (Khan *et al*., 2018). Yu *et al*. (2016) noted that the main driver of water budget variability in hydrologic simulation is ET uncertainty. Improved knowledge on quantification of ET would definitely help in reducing these uncertainties especially in future climate projections. Therefore, this study reviews the uncertainties in ET estimations and predictions and suggests ways to minimize the uncertainties.

EVAPOTRANSPIRATION ESTIMATION TECHNIQUES

Various methods for estimating ET exist ranging from point scale observations or ground based techniques with fine temporal resolution to satellite remote sensing (RS) products and process modelling with coarse spatial and temporal resolution (Sorensson and Ruscica, 2018). The ET techniques can be broadly grouped into two namely direct and indirect methods.

Direct method

The ET can be directly measured using lysimeters, scintillometers, energy balance by eddy covariance towers or Bowen ratio systems, etc. (Hupet *et al*., 2004; Courault *et al*., 2005; Gowda *et al*., 2007; Yuan *et al*., 2010; Morton *et al*., 2013; Zhu *et al*., 2013; Gu *et al*., 2018). Previously, ET estimations to support agriculture were done using only pan evaporation method and weighing lysimeters, though these methods are still widely used. According to Vinukollu *et al*. (2011), eddy covariance system for measuring water and other fluxes was developed in the 1970s. Now there are many eddy covariance flux towers globally for measurements of water flux, carbon dioxide and energy between the atmosphere and terrestrial surface. For wider coverage of this system, there are flux networks (under global program called FLUXNET) in different regions such as AsiaFlux, OzFlux, AmeriFlux, EuroFlux, etc. (Vinukollu *et al*., 2011). Eddy covariance systems measure fluxes on the order of few hundred meters of upwind distance (Lee *et al*., 2015; Valayamkunnath *et al*., 2018). Non-closure of the energy budget on the order of 20 to 30% is a limitation associated with the eddy covariance tower (Vinukollu *et al*., 2011); thus, they are frequently forced to achieve the closure (Jung *et al*., 2010; Wohlfahrt *et al*., 2009). Also, the footprint of eddy covariance systems changes with meteorological conditions especially in a heterogeneous land surface (Yee *et al*., 2015). Scintillometer is another method for measuring ET; it can measure path integrated fluxes up to 10 km and meteorological conditions have small impact on its footprint (Yee *et al*., 2015; Liu *et al*., 2011). According to Valayamkunnath *et al*. (2018), scintillometers are most suitable for the accurate error estimation of satellite RS, for both measured and simulated sensible heat fluxes due to its path lengths that are larger compared to footprints of EC systems. These ground-based techniques generate AET datasets at local fields and are usually considered to have high accuracy over homogeneous areas; however, there are measurement errors and scaling issues associated with these methods (Khan *et al*., 2018; Byun *et al*., 2014). They cannot acquire regional or global ET because the measurement is on point-scale usually over a homogenous land surface (Valayamkunnath *et al*., 2018). According to Valayamkunnath *et al*. (2018), large-aperture scintillometer, however, has potential for measuring area-averaged fluxes from heterogeneous land surfaces. This information is yet to be widely validated.

Indirect method

Direct measurement of ET is difficult and time consuming. Use of recent advanced equipment is very expensive. Alternatively, mathematical models based on meteorological data are usually employed to estimate ET (Yang *et al*., 2019). The indirect methods calculate ET using various existing models with meteorological data from weather sensors or the satellite RS method (Chen *et al*., 2018). Numerous models for estimating PET range from single weather variables (e.g., air temperature, radiation or relative humidity) to equations that combine two or more variables. Typical examples of such models include (Thompson, 1999; Wang *et al*., 2017a; Phad *et* *al*., 2019; Sarma and Bharadwaj, 2020; Bakr *et al*., 2021):

i. temperature-based models (e.g., Blaney-Criddle, Hamon, Hargreaves, Ivanov, Khrrufa, Thornthwaite, etc.);

ii. radiation-based models (e.g., Christiansen, Doorenbos-Pruitt, Jensen-Haise, Priestley-Taylor, Turc, etc.); and

iii. combination methods (e.g., FAO-56 Penman-Monteith, Hargreaves-Samani, Penman, Ritchie's, Schendel, Makkink, Jensen-Haise, Tabari, etc.).

Among these examples of the categories of ET models, the FAO-56 Penman-Monteith equation (equation 1) which is classified as a radiation and aerodynamic combination-based (energy-balanced) method has been widely tested and assumed to be the most suitable for various climatic conditions because of its physically-based characteristic (Xu *et al*., 2006; Wang *et al*., 2017a; Sarma and Bharadwaj, 2020). In a study comparing different methods of ET estimation somewhere in India, Makkink's model was found to give values closest to those obtained by FAO-56 Penman-Monteith model (Bhat *et al*., 2017), suggesting that the combination methods involving both temperature and radiation appear to give more reliable estimates of ET than those than involve either. The FAO-56 Penman-Monteith model often regarded as the standard method of ET estimation is (Wang *et al*., 2017a):

$$\lambda E = \frac{\Delta_e H + \rho_a C_p \left(e_s\left(T_a\right) - e_z\right)/r_a}{\Delta_e + \gamma\left(1 + r_c / r_a\right)} \quad ; \qquad (1)$$

where H is the total energy available for ET ($H \approx R_n$) (Beven, 2001); R_n is net radiation, ρ_a is the density of the air (kg m^{-3}), $\lambda = 2.47 \times 10^6$ J kg^{-1}, C_p is the specific heat capacity of the air (MJ kg^{-1} °C^{-1}), E is the ET rate (mm s^{-1}), e_z is the vapour pressure (kPa), and γ is the psychrometric constant (kPa °C^{-1}) (FAO 56 document), Δ_e is the slope of the saturation vapour pressure versus temperature curve, e_s(T) is the saturated vapour pressure (kPa), r_a, is the aerodynamic resistance (sm^{-1}) and r_c canopy resistance (sm^{-1}).

However, the FAO-56 Penman-Monteith method requires proper measurements of multiple meteorological variables, including net radiation and soil heat flux that are rarely measured in common agronomy-oriented meteorological installations and this prevents its use in data-sparse areas. These limitations have made popular the use of either radiation- or temperature-based methods that require less climatic data than the Penman-Monteith equation. With respect to reference evapotranspiration (ETo), it has been demonstrated that radiation-based models could be developed with just solar radiation and air temperature data in sub-humid climatic conditions of developing countries where availability and reliability of weather data remains a problem, and that such local models could be give more reliable estimates under these conditions than other more popular radiation-based models (Tomar, 2016).

Satellite-based ET estimation

Sparse ET monitoring networks globally restrict quantification of ET over larger areas. Satellite RS method is one of the indirect methods for estimating ET spatially from point to large landscape (Byun *et al*., 2014; Wang *et al*., 2016; Wang *et al*., 2007). Recently, hydrological variables are monitored spatially using multi-temporal and multi-spatial sensors. Obviously, spatial resolution is gaining more ground at the expense of lower temporal coverage (Mccabe and Wood, 2006). In the last few decades, efforts have been made to combine ground-based methods with advancements in satellite RS technique to produce global AET datasets. Satellite RS technology has some advantages; it ignores other complex hydrological variables while estimating ET but instead derives residual energy balance directly from pixel up to regional scale (Liaqat and Choi, 2017). The RS generally increases the user's capacity to estimate ET spatially and at different scales (Glenn *et al*., 2007). Its algorithms are based on (i) simple atmosphere-land exchange models together with RS data and (ii) statistical and empirical methods on RS vegetation index and surface temperature methods (Glenn *et al*., 2007; Sorensson and Ruscica, 2018). The RS approaches for estimating AET are based on (a) residual method of surface energy balance and (b) ground-based methods combined with RS data, e.g., the physically-based Penman-Monteith method with MODerate resolution Imaging Spectroradiometer (MODIS, e.g., MOD16) imagery and the Priestly-Taylor equation with Advanced Very High Resolution Spectroradiometer (AVHRR), Breathing Earth System Simulator (BESS) model (Liaqat and Choi, 2017; Chang *et al*., 2018; Du and Sun, 2012; Mu *et al*., 2011; Jiang and Ryu, 2016), and Global Land Evaporation and Amsterdam Model (GLEAM) (Khan *et al*., 2018; Martens *et al*., 2016; Paca *et al*., 2019). Measurements from stations are scaled to large landscape units using RS vegetation indices (VIs). These indices such as normalized difference vegetation index (NDVI)) or leaf area index together with surface meteorological data are used with surface resistance in the Penman-Monteith equation to estimate ET globally.

Other residual energy balance algorithms that are equally used include SEBS (surface energy balance system), SEBAL (surface energy balance algorithm for land) and METRIC (mapping evapotranspiration at high resolution with internalized calibration) (Liaqat and Choi, 2017; Long *et al*., 2014; Jin *et al*., 2011; Byun *et al*., 2014; Morton *et al*., 2013). These algorithms are used to determine AET spatially and temporally but they differ from one another because of their complex formulations and structural design. The SEBAL and METRIC are image-processing algorithms, but their major disadvantage is inability to optimize extreme hydrological events (dry and/or wet scaling) which often leads to errors in the final outputs at large scale (Liaqat and Choi, 2017). Morton *et al*. (2013) assessed METRIC uncertainty due to calibration and its automation for computing ET over agricultural areas and found that uncertainty was low for fields with high ET and high for fields with low ET. It was also noted that automated methods can produce first-order ET results that are close to the one estimated by manual methods. On the other hand, SEBS does not demand pre-defined dry and/or wet scaling but it requires huge amounts of vegetation attributes from satellite imagery and meteorological inputs for its implantation and estimation of aerodynamic resistance. Results obtained by Byun *et al*. (2014) support the application of RS-based ET models across heterogeneous as well as homogeneous regions; however, these authors noted that more studies are needed to accurately parameterize roughness height across areas of heterogeneous and tall vegetation to enhance SEBS's performance. Also, ET is estimated as a residual in the water budget equation using gravity recovery and climate experiment (GRACE) (Long *et al*., 2014). The GRACE gives information on differences in gravity field that are controlled particularly by water distribution differences. It is used to calculate spatial change in total water storage (such as groundwater storage, surface water and soil moisture) for better understanding of water budget (Long *et al*., 2014).

Land surface models

Land surface models (LSMs) are part of global climate models (GCMs) that simulate land surface processes using provided meteorological conditions as inputs and produce outputs such as latent heat flux, sensible heat flux, etc. (Abramowitz *et al*., 2008). The LSMs are based on principles of biophysical and biogeochemical processes. With climate models or observed atmospheric data, LSMs can estimate ET of previous and current climate. The ET at scales such as grid to global scales can be obtained using LSMs which include mosaic, noah, variable infiltration capacity (VIC), community land model (CLM), sacramento soil moisture accounting (SAC), etc. (Rodell *et al*., 2004; Chen, 2017; Zhang *et al*., 2017; Khan *et al*., 2018). In addition, global land data assimilation system (GLDAS) employs advanced and sophisticated LSMs and data assimilation technique to generate land surface fluxes. The GLDAS runs multiple LSMs and provide continuous datasets of AET globally (Khan *et al*., 2018). It uses new ground and space-based observation systems, and applies constraints in two ways: (i) forcing the LSMs with observation meteorological fields hence avoiding atmospheric model biases; and (ii) using data assimilation approaches thereby restricting unrealistic model states that use observations of land surface states (Rodell *et al*., 2004).

UNCERTAINTIES IN ET ESTIMATIONS

ET estimation methods and input data uncertainty

ET estimation methods described above and their respective input data present some level of uncertainties when modelling PET or AET. Some studies have demonstrated varying levels of uncertainties among ET models when simulating ET (Chen *et al*., 2014; Thompson *et al*., 2014; Xu *et al*., 2018). Chen *et al*. (2014) compared eight ET models (three process-based models and five empirical models) with the purpose of giving guidance on choosing and improving ET methods. They found that the ET simulated using the eight models varied between 61 and 80% when compared with 23 eddy covariance towers in and around the study region. Xu *et al*. (2018) assessed the relative uncertainty of upscaled regional ET from five machine learning methods (artificial neural network, random forest, deep belief network, Cubist and support vector machine) and noted that random forest algorithm had lowest relative uncertainty compared to other methods. Similarly, Thompson *et al*. (2014) assessed the PET-related uncertainty in climate change impacts on river flow using six PET alternative methods in MIKE SHE models namely Priestley–Taylor, Linacre, Blaney–Criddle, Hargreaves–Samani, and Penman and Hamon. Uncertainty associated with PET method was confirmed in the low and high flows direction. They further noted that PET method-related uncertainty under climate variability is considerably less compared to global climate models (GCMs) uncertainty. Wang *et al*. (2015) also obtained similar results after using different ET formulations and different input data to determine if there was potential uncertainty in projection of future ET change. Their findings show that there is still uncertainty, the approximate performance adopted in simulating general trends notwithstanding.

The ground-based techniques considered to have high accuracy and which are usually used as a standard for comparing other methods have considerable level of uncertainty (Westerhoff, 2015). According to Glenn *et al*. (2007), moisture flux towers and micrometeorological stations which are ground-based techniques that provide continuous measurements of AET or PET have uncertainty of 10–30%. When data from these ground-based techniques are used, the errors in the input usually propagate towards the output of the calculated ET irrespective of the model used (Buttafuoco *et al*., 2010). Buttafuoco *et al*. (2010) noted that the ET prediction quality depends on the uncertainties of the data used in the analysis. Sometimes uncertainty associated with the input data could be contributed by faulty measurement equipment or sensors. Chen *et al*. (2018) assessed the performance of solar radiation and leaf-area-index sensors on ET model uncertainty for indoor cultivation and found that sensors were main cause of uncertainty. They further noted that there is need to improve environmental variables measurement to enhance predictive capacity of ET models for greenhouse environmental control and irrigation management.

Satellite products utilize ET ground-based estimates. Datasets from satellite products are based on in-situ network forcing as well as model's estimation and RS. These are subject to errors associated with scale and underlying model assumptions and parametrization, in-situ measurements itself and sensor calibration (Khan *et al*., 2018). This is in spite of the fact that global satellite products contain more noise compared to ground-based estimates (Westerhoff, 2015). Khan *et al*. (2018) evaluated uncertainty characterization of AET satellite dataset (GLEAM, GLDAS and MOD16) with eddy-covariance flux data over nine Asia Flux sites using an extended triple collocation method. Their results showed that random error on an average of 1.5–5.5 mm/8 day came from in-situ AET and this reduced the accuracy of other related datasets. Of the three satellite datasets (GLEAM, GLDAS and MOD16), GLEAM performed better consistently with least relative and absolute uncertainties across forest surfaces compared to grassland surfaces and rice paddy. The GLDAS had similar errors like GLEAM across grassland surfaces and rice paddy whereas MOD16 had relatively high uncertainties across all vegetation types. Furthermore, based on height of vegetation, all datasets had large uncertainties (> 25%) for low vegetation than the tall canopies (Khan *et al*., 2018). Long *et al*. (2014) also assessed uncertainty in ET output from two RS-based products (AVHRR and MODIS), four LSMs (Mosaic, Noah, VIC, and SAC in NLDAS-2) and GRACE satellites using three cornered hat method. Uncertainties in ET are low in LSM ET, moderate in AVHRR or MODIS and high in GRACE. Even the improved MODIS *Et al*gorithm by Mu *et al*. (2011) still needs more improvement, though accuracy was enhanced with uncertainty within the 10–30% of reported uncertainties in ET measurements.

The responses of ET to climate change are different among climate models because of different parameterizations which connect surface radiation and soil moisture to ET (Sorensson and Ruscica, 2018). Current climate models do not have the capacity to estimate PET directly (Wang *et al*., 2017a); however, the data can be incorporated with some indirect ET estimation methods. Consequently, PET is exposed to uncertainty because of lots of existing formulae and different input data reliabilities when modelling hydrological response in relation to future climate change. Wang *et al*. (2017a) evaluated the differences in runoff projection by four different PET estimation approaches namely radiation-based empirical Priestley-Taylor equation along with good reliable downscaled data, physically based Penman-Monteith model with less dependable input variables, and simple Hamon equation (temperature-based) with the most dependable downscaled variable. The magnitudes of PET over the period 2021–2050 were slightly different for summer and spring seasons. The discrepancy in response to future runoff as well as diverse change for summer and spring months showed there was PET uncertainty especially in some basins. Also, uncertainties in numerical weather prediction reanalysis data limit the capacity to accurately simulate the terrestrial water system (Rawlins *et al*., 2006). Rawlins *et al*. (2006) estimated PET using a hydrological model forced with three climate datasets to understand the impact of uncertainties in numerical weather prediction reanalysis data on simulated water fluxes. They found a high degree of uncertainty in climate data as well as the water fluxes obtained from model drivers. Thus, there is need for proper examination of model requirements as well as the biases in forcing data because the uncertainties in the input data would definitely propagate to the model output translating into a huge problem at the long run.

Spatial and temporal uncertainty

Quantifying the spatial and temporal patterns of ET is important for understanding the local, regional and global hydrological cycle but this remains considerably uncertain (Pan *et al*., 2014; Wagle *et al*., 2016). According to Badgley *et al*. (2015), ET trend at watershed and regional scales have little agreement. Limited long-term hydrological datasets have made it difficult to fill this knowledge gap. Uncertainty associated with this ET trend at both scales is contributed to by the diverse models and limited inputs data used in estimating ET. In some situations, inadequacy of data necessitates the utilization of simple ET methods that require few meteorological inputs data which invariably adds uncertainty to estimated ET (Hosseinzadehtalaei *et al*., 2016). Hosseinzadehtalaei *et al*. (2016) assessed uncertainty in ET projections for future runoff and water availability using seven simple radiation and temperature-based methods (Jensen-Haise, Blaney-Criddle, Makkink, Schendel, Turc, Hargreaves-Samani, and Tabari) against standard Penman-Monteith FAO 56 method on the basis of 12 general circulation model outputs from the coupled model inter-comparison project phase 5 for four future greenhouse gas scenarios (RCP2.6, RCFP4.5, RCP6.0 and RCP8.5). Their findings showed a lack of agreement on the amount of ET obtained from the seven ET methods and that uncertainty associated with ET methods is more for daily than monthly ET estimates. Similarly, Badgley *et al*. (2015) assessed the uncertainty in global ET estimates attributable to each class of input forcing datasets using one of Priestly–Taylor JPL models together with 19 different combinations of forcing data which included three meteorological datasets, three net radiation products and three vegetation index products. They found that uncertainty is more for monthly average terrestrial ET compared to the annual estimates, while also noting greatest discrepancy between input forcing arises from choice of net radiation dataset. In their evaluation of differences in runoff projection by four PET methods, Wang *et al*. (2017a) obtained similar monthly patterns of results among the four methods. On annual time scale, Liu *et al*. (2016) presented a worldwide assessment of nine ET products: 3 LSM simulations, 3 reanalysis-based and 3 diagnostic products against ETo estimated using the water balance method over 23 years across 35 global river basins and found no significant intra-category discrepancy in the estimated annual ET. Almost all products relatively estimated the ET annual means but systematically underestimated the inter-annual variability and could not estimate ETo trend adequately. The uncertainties recorded in the nine ET products may be attributed to the discrepancies in the forcing datasets and model structural limitations (Liu *et al*., 2016). Generally, uncertainty associated with ET varies temporally. On the same time scale, however (e.g., monthly), the pattern for some ET methods might be similar but differ in magnitude.

The RS from satellites seems to be the only possible way for estimating the ET spatial distribution across larger landscape units. However, this RS still has some issues that are yet to be resolved like spatial scale mismatch among coarser meteorological forcing and fine vegetation data as well as cloud-free images, therefore resulting in large uncertainties in ET estimations (Long *et al*., 2014). In the quest to reduce uncertainty due to scale, Wang *et al*. (2016) evaluated a new technique called multi-scale thermal infrared RS in combination with three-temperature model, but not without uncertainty. Wang *et al*. (2017b) carried out uncertainty analysis of PET and its influencing factors in Heihe River and found that homogeneity and stability of PET were worse in space than in time, indicating that temporal distribution of PET was more uniform and stable compared to spatial distribution. They noted that, similar to mean temperature, wind speed and sunshine hours, PET increased spatially from the south of Heihe River to the north, and was opposite to relative humidity. Similarly, spatial regression analyses of seasonal satellite-derived ET by Tadesse *et al*. (2015) indicate comparatively poor yearly spatial relation for all the crop growing zones of their study.

The LSMs is another satellite-based ET estimation method that can forecast ET continuously both spatially and temporally; however, it goes with greater uncertainties compared with in situ observations or RS retrievals (Chen, 2017). These uncertainties could be as a result of errors in the large-scale meteorological data sets used to force LSMs, shortcomings in the model structure, errors due to unrepresentative model parameters, incomplete model parameterization, etc. (Garrigues *et al*., 2015; Chen, 2017). According to Garrigues *et al*. (2015), although LSMs were originally developed to work together with hydrological or atmospheric models across large landscape, their spatial integration is based on coarse-resolution of ca. 1–10 km maps of parsimonious parametrization. Surface parameters drive a large part of LSM uncertainties and explain most discrepancies between models (Garrigues *et al*., 2015). From the ET uncertainty analysis done by Long *et al*. (2014) using four LSMs (two RS based products and

GRACE satellites), there is a balance between uncertainty and spatial resolution with high uncertainty in the fine-resolution of ca. 1–8 km and low uncertainty in the coarse-resolution LSM ET of approximately 14 km and relative.

According to Dong and Dai (2017), studies conducted between 1982 and 2010 have reported considerable changes in terrestrial ET and the causes of these changes remain unclear. Because of that, relative contributions of internal and external climate variability to recent ET changes were examined using three global terrestrial ET datasets and multi-model ensembles mean ET. Dong and Dai (2017) found that there are large discrepancies of the ET estimates, in terms of their trend and variability among the three datasets. This shows large uncertainties in the estimated recent decades of global terrestrial ET.

ET uncertainty based on region

Not much has been done on quantifying ET uncertainty based on region. Since factors affecting ET vary among different regions, it is worthwhile knowing how ET uncertainty varies among these regions. Sorensson and Ruscica (2018) examined the uncertainties of a set of ET products (RS, land surface models and reanalysis) across climatologically distinct zones of South America. The results showed that the metrics exhibited different spatial patterns of uncertainty with maximum relative uncertainties of mean annual ET occurring in dry region. Also, Soria (2013) assessed the relevance of the predictive uncertainty in PET calculations using Monte Carlo approach in order to improve surface water balance calculations in remote high-elevation catchments. They found that the variations in the PET affected the water balance in Andean mountainous systems under arid conditions more than their humid counterparts. The uncertainty could have been propagated by the imperfect PET measuring network. Thus, it is important to characterize the uncertainty analysis of these error sources in order to use ET datasets with greater confidence in water resources and hydro-meteorological applications (Khan *et al*., 2018).

QUANTIFICATION OF ET UNCERTAINTY

Quantification of ET uncertainty, also known as uncertainty analysis (Chen *et al*., 2018), is done in different ways but it can be broadly grouped into two; quantification through the statistical analysis of observations, and quantification through other information about the ET measurement. The statistical analysis used ranges from simple observations such as means and standard deviations to complex approaches. Apart from these statistical methods, other approaches include three-cornered hat method (Long *et al*., 2014; Xu *et al*., 2018), extended triple collocation (Khan *et al*., 2018), and Monte Carlo analysis (Buttafuoco *et al*., 2010; Soria, 2013). The three-cornered hat method (also known as Grubb's estimator) is based on theory that observational errors are normally distributed. Its advantage is that no prior knowledge on ET value is needed. Extended triple collocation employs a statistical technique with temporally collocated and spatially coincident datasets to derive random error (Khan *et al*., 2018). Monte Carlo analysis samples factors from their distribution and with assumption that the factors are independent (Saltelli *et al*., 2008). In addition to the above methods, Chen *et al*. (2018) adopted the ISO GUM (International Organization for Standardization, Guides to the expression of Uncertainty in Measurement) concept in studying the effect of sensors on the uncertainty of the two ET models. The ISO GUM method evaluates the uncertainty using statistical analysis of observations and other information about the measurement.

WAY FORWARD

Minimizing uncertainty in ET estimation will definitely improve planning, management and use of water resources. This study suggests five ways to minimize uncertainty in ET estimation: 1) increasing ground-based measurement stations; 2) minimizing measurement errors; 3) sensitivity assessment of ET dataset; 4) enhancements of model physics and global forcing data; and 5) hybrid approach with RS products with lower uncertainty in order to constrain the uncertainty.

Increasing ground-based measurement stations should not be done at the expense of accuracy. For eddy covariance observations, for instance, instrumentation at all sites across the eddy covariance network should be standardised and all variables must be acquired and measured using standardised procedure (Rebmann *et al*., 2018). Extension of eddy covariance network should focus not only on new ecosystems but also on spatial replications of measurements. Large-scale ET is usually estimated from observed measurements which are still problematic because of sparse network of observed stations and the high spatial heterogeneity and temporal variability of ET. Recent research has tried to address the problem associated with observed measurements by coming up with global ET products which include RS-based products, reanalysis outputs, LSM simulations, and the estimates based on empirical upscaling of in situ observations (Liu *et al*., 2016). However, global and regional applications of these ET products have been constrained due to the lack of reference observations (Liu *et al*., 2016). Increasing ground-based measurement stations would definitely make more ET data available especially in data sparse regions. Also, some ET models including physically based models use RS data to determine ET. According to Glenn *et al*. (2007), errors in predicting ET by both empirical and micrometeorological data methods need to be reduced to at least 10% or less especially for highly sensitive applications that require accurate wide-area ET estimates.

Therefore, improving ground methods for measuring ET and minimizing measurement errors will help in accurate quantification of ET which can also be scaled up to larger landscapes. However, recent advances in global network, FLUXNET, have tried to improve ground measurement which enables researchers to evaluate terrestrial ET at different time scales across many areas of multiple vegetation types. According to Liu *et al*. (2016), when evaluating ET at regional scales, eddy-covariance measurements must be treated with caution because of their sparse spatial coverage, relatively short period and lack of energy balance closure. Alternatively, ET products can also be compared with the ET obtained from the terrestrial water budget for closed basins (Liu *et al*., 2016). Depending on region and nature of study to be conducted, characteristics of individual data sets are also important, suggesting that sensitivity assessment of ET dataset would help in minimizing uncertainty in ET estimation (Sorensson and Ruscica, 2018).

Some studies have revealed large uncertainties associated with current ET models, pointing to the need for further validation and improvements in ET models which can be achieved by reviewing various ET model structures, critical model parameters as well as associated component estimates (Chen *et al*., 2014). According to Liu *et al*. (2016), enhancements of model physics and global forcing data will definitely improve the calculation and predictions of global ET thereby reducing uncertainty. Long *et al*. (2014) also recommended hybrid approach that combines the strengths of satellite-based and LSMs products in order to reduce ET uncertainties.

CONCLUSION

There is need to enhance estimates of ET for improved practical applications and to better understand the water budget and its relation with climate change both on spatial and temporal scales. Accurate quantification of ET is difficult but improvement can be made on the existing methods despite the heterogeneity of the land surface and some factors such as climate, soil properties, plant biophysics and topography influencing such estimations. The two broadly classified methods could be improved on or slightly modified in order to reduce uncertainties in ET estimations. The ones identified in this study are uncertainties due to ET methods and input data, uncertainty associated with spatial and temporal scale and uncertainty based on region. Studies reviewed confirm that there are PET method-related uncertainties and that errors in the input data contribute to these uncertainties. Despite effort towards approximating the performance of the ET methods in simulating general trends in some studies, there is still PET method related uncertainty. The recent need to monitor hydrological variables from space should also consider the uncertainties associated with scale. Notably, uncertainty associated with ET varies temporally just as homogeneity and stability are worse in space than in time. Some ET RS products show low uncertainty in the coarse-resolution and relative to high uncertainty in the fine-resolution. More efforts should be geared towards reducing ET uncertainty further especially in this era of increased spatial resolution for proper planning, management and efficient use of water resources. The above suggested ways would further reduce the uncertainties associated with ET estimation methods and scale for better management of water resources and other associated applications.

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