Global Analysis of the Role of Terrestrial Water Storage in the Evapotranspiration Estimated from the Budyko Framework at Annual to Monthly Time Scales^①

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ABSTRACT

Recent studies have extended the applicability of the Budyko framework from the long-term mean to annual or shorter time scales. However, the effects of water storage change ΔS on the overall water balance estimated from the Budyko models (BM) at annual-to-monthly time scales were less investigated, particularly at the continental or global scales, due to the lack of large-scale ΔS data. Here, based on a 25-yr (1984–2008) global gridded terrestrial water budget dataset and by using an analytical error-decomposition framework, we analyzed the effects of ΔS in evapotranspiration (ET) predicted from BM at both grid and basin scales under diverse climates for the annual, wet-seasonal, dry-seasonal, and monthly time scales. Results indicated that the BM underperforms in the short dry (wet) seasons of predominantly humid (dry) basins, with lower accuracy under more humid climates (at annual, dry-seasonal, and monthly scales) and under more arid climates (at wet-seasonal scale). When the effects of ΔS are incorporated into BM, improvements can be found mostly at annual and dry-seasonal scales, but not notable at wet-seasonal and monthly scales. The magnitudes of ΔS are positively correlated with the errors in BM-predicted ET for most global regions at annual and monthly scales, especially under arid climates. Under arid climates, the variability of ET prediction errors is controlled mainly by the ΔS variability at annual and monthly time scales. In contrast, under humid climates the effect of ΔS on ET prediction errors is generally limited, particularly at the wet-seasonal scale due to the more dominant influences of other climatic factors (precipitation and potential ET) and catchment responses (runoff).

1. Introduction

The partitioning of precipitation (P) into evapotranspiration (ET), runoff (R), and changes in terrestrial water storage (ΔS) is controlled by climate conditions and catchment characteristics such as soil, topography and vegetation (Zhang et al. 2008). Budyko (1958) postulated that the first-order control on the partition of

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P is the balance between the available water (represented by P) and energy [represented by potential evapotranspiration (PET)]. The proposed empirical relationship, widely known as the Budyko's curve, has shown remarkable agreement with the long-term water balance data in many watersheds globally (Budyko 1974). Based on the Budyko hypothesis, various functional forms associated with the relations between the evaporation ratio (ET/ P) and climate aridity index (PET/ P) have been developed for quantifying the long-term water balances (Pike 1964; Fu 1981; Choudhury 1999; Zhang et al. 2001, 2004; Porporato et al. 2004; Yang et al. 2008; Gerrits et al. 2009). The Budyko model (BM) has long been considered as a useful tool to investigate the catchment-scale interactions between hydroclimatic variables and catchment characteristics under the long-term steady state (e.g., Donohue et al. 2007, 2010, 2011; Yang et al. 2009; Roderick and Farquhar 2011; Wang and Hejazi 2011; Xiong and Guo 2012; Yang and Yang 2011; Li et al. 2013; van der Velde et al. 2014; Zhang et al. 2016; Liu et al. 2017; Wu et al. 2017, 2018a,b).

However, the dynamics of catchment water balance at annual and monthly time scales are generally not at the steady state, and controlled not only by the difference in water supply (P) and energy supply (PET) but also by other factors related to catchment properties such as topography and vegetation (Carmona et al. 2014; Zeng and Cai 2015, 2016). Numerous efforts were directed to extend the applicability of BM from the originally designed long-term mean-annual perspective to the shorter temporal scales such as annual (Koster and Suarez 1999; Sankarasubramanian and Vogel 2002; Zhang et al. 2008; Yang et al. 2007, 2009; Potter and Zhang 2009; Cheng et al. 2011; Tekleab et al. 2011; Carmona et al. 2014; Yu et al. 2013; Wang et al. 2018), seasonal (Chen et al. 2013), and monthly time scales (Zhang et al. 2008; Tekleab et al. 2011; Du et al. 2016). Koster and Suarez (1999) were the first to propose the analytical framework to quantify the interannual variability of Budyko-based ET estimates and compared the theoretical framework with the global climate model simulations. Zhang et al. (2008) extended BM to predict water balance at the long-term mean annual, annual, monthly, and daily scales in Australia, and concluded that it performs well in most catchments at the long-term mean-annual and annual scales, while the more complicated models are required at the shorter time scales primarily due to the effects of water storage change ΔS . Additionally, Yang et al. (2009) incorporated the impacts of vegetation coverage into BM to improve parameter estimation in the coupled water–energy balance equation. Donohue et al. (2010) evaluated the effects of the

incorporating remotely sensed vegetation information on the accuracy of BM. Chen et al. (2013) extended BM to the seasonal time scale and developed a model for incorporating the interannual variability of ET and ΔS .

The ΔS is a significant contributor to water balance variability at the annual or shorter time scales in many regions of the world (Eltahir and Yeh 1999; Yeh and Famiglietti 2008; Yokoo et al. 2008; Istanbuluoglu et al. 2012; Wang and Alimohammadi 2012; Wang 2012; Chen et al. 2013). The effects of ΔS in modulating climatic fluctuations are generally larger at the shorter scales, and it even dominates the temporal variability of water balances over certain extremely arid regions (Wu et al. 2017). Therefore, BM should be extended to incorporate ΔS effects for the applications at the shorter annual-to-monthly time scales (Zhang et al. 2008; Zeng and Cai 2015; Wang et al. 2018). The common approach of accounting for ΔS effects under the nonsteady state condition is to replace P in BM by the effective precipitation (i.e., P minus ΔS) (Wang 2012). For example, Wang and Alimohammadi (2012) introduced the effective precipitation in BM to analyze the influences of ΔS in ET and found that the ET variability can be overestimated if assuming negligible ΔS in annual water balance, in particular under the water-limited conditions. Xing et al. (2018) extended the BM into monthly time scale with the consideration of ΔS , and found that ΔS plays a significant role in the monthly water balance under various climatic conditions across China. It is reasonably anticipated that the ΔS controls on BM performance are different under diverse climate conditions since the hydrologic response to the temporal variability of climatic forcing involves various region-specific processes such as snow thawing–melting and vegetation growth (Zeng and Cai 2016). Although advances have been made to quantify the ΔS effects on the water balances estimation within the Budyko framework, our knowledge on the roles of ΔS in water balance partition and its influences on BM performance at the shorter time scales is still limited given the large spatiotemporal variability in most water budget variables and the associated hydrologic processes.

Wu et al. (2018b) developed an analytical error-decomposition framework and incorporated ΔS effects to evaluate the accuracy of BM-predicted ET and the associated climatic and hydrologic controlling factors at annual and monthly scales. This new analytical framework, which will also be used in this study, provides a sound theoretical tool for systematically analyzing the ΔS effects on BM-predicted ET under different climatic conditions. Different from Wu et al. (2018b), which focused on the entire China regions,

the present study focuses on the global scale for examining the roles of ΔS in BM-predicted ET at the annual-to-monthly time scales. Here, based on a 25-yr (1984–2008) global monthly gridded terrestrial water budget dataset recently developed by Zhang et al. (2018) from multiple sources, this study aims to 1) evaluate the performance of the original BM and the extended BM (which incorporates ΔS effect) in ET prediction under globally diverse climates and across a wide spectrum of time scales (i.e., annual, wet seasonal, dry seasonal, and monthly) as the ΔS effects become increasingly important, and 2) investigate and quantify the influences of ΔS and the errors in ET predicted from BM under diverse climatic conditions globally from the annual to monthly time scales. This paper is organized as follows: section 2 introduces the methods, study domains, and the global water budget datasets used in this study. The results and discussion are presented in sections 3 and 4, respectively, and the main findings and conclusions are summarized in section 5.

2. Methods and data

a. Dry and wet seasons

For a given catchment, the 12 months from January to December are classified into either dry or wet based on the following long-term mean aridity index calculated for each month (Chen et al. 2013):

$$A_m = \frac{\overline{\text{PET}}_m}{\overline{P}_m - \frac{d\overline{S}_m}{dt_m}}, \quad (1)$$

where $\overline{\text{PET}}_m$, $\overline{P}_m$, and $d\overline{S}_m/dt_m$ are the long-term mean monthly (climatology) PET, P , and ΔS , respectively. The classification is based upon the simple criterion of $A_m \geq 1$ for the dry month and $A_m < 1$ for the wet month. Accordingly, the dry-seasonal and wet-seasonal accumulated P , PET, and ΔS can be calculated by summing up the quantities in all identified dry and wet months. The dry and wet months identified over the 32 selected global river basins are summarized in Table S1 in the online supplemental material, which shows that not all basins have both wet and dry seasons. Furthermore, the variations of water budget variables (including PET, P , ET, R , and ΔS) in dry (wet) season tend to increase (decrease) from the humid to arid basins (Table S2).

b. The Budyko model

The following relationships developed by Fu (1981) is one of the most commonly used BM for estimating the long-term mean-annual ET (Zhang et al. 2004):

$$\frac{\text{ET}_i}{P_i} = F(\phi_i) = 1 + \phi_i - [1 + (\phi_i)^\omega]^{1/\omega}, \quad (2)$$

where $\phi_i = \text{PET}_i/P_i$ is the aridity index at the i th time interval and ω is a free parameter representing the effects of unaccounted land surface characteristics and climate seasonality on the water balance partitioning (Li et al. 2013; Wu et al. 2017). Similar to Budyko (1958), the Fu's equation assumes that the equilibrium water balance is controlled by water availability and atmospheric demand and it is considered more applicable for estimating the long-term mean-annual ET than other available empirical equations of BM (Zhang et al. 2004).

As the time scale becomes shorter, the fluctuations of ΔS are generally increased and become more significant in terms of water budgets closure, since ΔS buffers water supply and demand with the potential delayed effect on the dependent water fluxes (Chen et al. 2013). Wang (2012) incorporated the effects of ΔS into BM by replacing P with the effective precipitation $P_{e,i}$ ($P_{e,i} = P_i - \Delta S_i$), thus Eq. (2) becomes

$$\frac{\text{ET}_i}{P_{e,i}} = F(\phi'_i) = 1 + \phi'_i - [1 + (\phi'_i)^\omega]^{1/\omega}, \quad (3)$$

where $\phi'_i = \text{PET}_i/P_{e,i}$.

In this study, the original BM [Eq. (2)] and the extended BM [Eq. (3)] are applied to the following four time scales: annual, dry-seasonal, wet-seasonal, and monthly scales. The parameter ω is estimated at both basin and global grid scales by using the least squares method based on the global water budget data. The model performance is evaluated by using the Nash–Sutcliffe coefficient of efficiency (CE; Nash and Sutcliffe 1970) and the mean relative error (MRE), which are expressed as follows:

$$\text{CE} = 1 - \frac{\sum_{i=1}^N (\text{ET}_{a,i} - \text{ET}_{p,i})^2}{\sum_{i=1}^N (\text{ET}_{a,i} - \overline{\text{ET}}_{a,i})^2}, \quad (4a)$$

$$\text{MRE} = \frac{\overline{\text{ET}}_{p,i} - \overline{\text{ET}}_{a,i}}{\overline{\text{ET}}_{a,i}} \times 100\%, \quad (4b)$$

where $\text{ET}_{a,i}$ and $\text{ET}_{p,i}$ are the actual and predicted ET at the i th time step, respectively. Parameters $\overline{\text{ET}}_{a,i}$ and $\overline{\text{ET}}_{p,i}$ represent the mean actual and predicted ET over the N time steps. CE ranges from $-\infty$ to 1, and a CE closer to 1 indicates more efficient model performance.

In addition, the absolute value of errors in the extended BM-predicted ET (i.e., the extended BM-predicted ET minus the actual ET) minus that of errors in the original BM-predicted ET (the original BM-predicted ET minus

the actual ET), denoted as IM_{ET} , is used to quantify the improvement of the extended BM over the original BM in ET prediction. A negative (positive) IM_{ET} indicates a better (worse) performance of the extended BM than the original BM.

c. Variance decomposition of error variance in the predicted ET

The error-decomposition framework developed previously (Wu et al. 2018b) for analyzing the accuracy of

BM-predicted ET expresses the time series of errors in predicted ET (i.e., BM-predicted ET minus the actual ET) as a function of 1) the hydroclimatic anomalies (i.e., the deviations from the corresponding long-term mean) of P , PET, R , and ΔS , 2) the long-term mean ΔS , and 3) the mean difference between predicted and actual ET. The mean error variance of the predicted ET is decomposed into the following variance and covariance terms of P , PET, R , and ΔS (Wu et al. 2018b):

$$\sigma_{Er}^2 = W_P^2 \sigma_P^2 + W_{PET}^2 \sigma_{PET}^2 + \sigma_R^2 + \sigma_{\Delta S}^2 + 2W_P W_{PET} \text{cov}(P, PET) + 2W_P \text{cov}(P, R) + 2W_P \text{cov}(P, \Delta S) + 2W_{PET} \text{cov}(PET, R) + 2W_{PET} \text{cov}(PET, \Delta S) + 2\text{cov}(R, \Delta S), \quad (5)$$

where σ^2 and cov denote the variance and covariance term, respectively, and W represents the weighting factors which quantify the contribution from P and PET variance/covariance sources to error variance and can be analytically calculated from the long-term mean aridity index ($\bar{\phi} = \overline{PET/P}$):

$$W_P = F(\bar{\phi}) - \bar{\phi} F'(\bar{\phi}) - 1, \quad (6a)$$

$$W_{PET} = F'(\bar{\phi}), \quad (6b)$$

where $F(\bar{\phi})$ and $F'(\bar{\phi})$ denote Fu's equation and its first-order derivative, respectively. The value of W_P (W_{PET}) ranges between -1 and 0 (0 and 1) as identified and reported in Wu et al. (2018b).

Note that under the extremely arid climates, the weighting functions associated with W_P and W_{PET} are close to zero (see Fig. 2 in Wu et al. 2018b), meaning that the contributions of P and PET fluctuations to the error variance of predicted ET are negligible. Parameter R can also be negligible since nearly all P is consumed by ET or ΔS , suggesting that ΔS is the sole dominant factor in determining the errors of BM-predicted ET under the extremely arid climates. Thus, Eq. (5) can be further simplified to

$$\sigma_{Er}^2 = \sigma_{\Delta S}^2. \quad (7)$$

d. Data

A long-term (1984–2010) global monthly water budget dataset (including P , ET, R , and ΔS) with the $0.5^\circ \times 0.5^\circ$ grid resolution was recently developed by Zhang et al. (2018) by using the constrained Kalman filter data assimilation technique (available at http://stream.princeton.edu:8080/opensap/MEaSURES/WC_MULTISOURCES_WB_050/). This dataset is based on multiple sources, including in situ observations, remote sensing retrievals, land

surface model simulations, and global reanalysis data. These multiple data sources can effectively bridge the gaps between the sparsely gauged or ungauged regions and the regions with abundant ground observations in developing the global-scale datasets for numerous hydrologic applications. Here we used the 25-yr (1984–2008) monthly P , ET, R , and ΔS time series from this dataset in this study. In addition, the corresponding 1984–2008 global monthly PET data with the $1^\circ \times 1^\circ$ grid resolution were obtained from the Terrestrial Hydrology Research Group of Princeton University (<http://hydrology.princeton.edu/data.pdsi.php>). The PET was computed from the physically based Penman equation (Penman 1948; Shuttleworth 1993) using the updated meteorological dataset from Sheffield et al. (2006) with an empirical estimate of net radiation (Sheffield et al. 2012). All the hydrologic data (P , ET, R , and ΔS) used in this study were disaggregated into the same $1^\circ \times 1^\circ$ grids globally based on the linear interpolation.

In this study, the BM was first tested at four different time scales, that is, annual, dry-seasonal, wet-seasonal, and monthly scales. The P , ET, and PET data are used to fit the Fu's equation (i.e., the ΔS effects is not incorporated). For the extended BM, P is replaced by effective P calculated as $P - \Delta S$ to fit Fu's equation at the annual and other finer time scales. In the following, the ET of the terrestrial water budget dataset of Zhang et al. (2018) will be termed as the “actual ET,” while the ET predicted by BM in both Eqs. (2) and (3) will be termed as the “predicted ET.”

A total of 32 global large river basins (Fig. 1) under the widely diverse climates with areas ranging from 200 000 to 5 900 000 km² are chosen for analyses in this study. Table 1 summarizes their basin characteristics and the corresponding long-term (1984–2008) mean water balances. According to McVicar et al. (2012), these 32 river basins can be broadly classified into the following three

FIG. 1. Global map showing the locations of the following selected 32 global large river basins: 1) Mississippi, 2) Yukon, 3) Mackenzie, 4) Columbia, 5) Amazon, 6) Parana, 7) Senegal, 8) Niger, 9) Nile, 10) Congo, 11) Limpopo, 12) Danube, 13) Dnieper, 14) Don, 15) Volga, 16) Northern Dvina, 17) Ob, 18) Indus, 19) Yenisei, 20) Lena, 21) Indigirka, 22) Kolyma, 23) Amur, 24) Yellow, 25) Yangtze, 26) Pearl, 27) Mekong, 28) Darling, 29) Ural, 30) Southeast, 31) Huaihe, and 32) Haihe.

groups based on the mean annual aridity index ($\bar{\phi}$): 1) 3 energy-limited basins with $\bar{\phi} < 0.76$ (Southeast, Amazon and Pearl), 2) 14 intermediate basins with $\bar{\phi}$ ranging from 0.76 to 1.35 (Northern Dvina, Yangtze, Mekong, Danube, Yenisei, Congo, Volga, Dnieper, Mackenzie, Huaihe, Parana, Mississippi, Lena basins, and Ob), and 3) the remaining 15 water-limited basins with $\bar{\phi} > 1.35$ (Table 1).

Table 2 summarizes the standard deviation, as the quantification of temporal variability, of the 25-yr (1984–2008) monthly ΔS ($\sigma_{\Delta S}$) and the ratio of the standard deviation of monthly ΔS over that of monthly actual ET ($\sigma_{\Delta S}/\sigma_{ET}$) for the 32 river basins at annual, wet-seasonal, dry-seasonal, and monthly time scales. As seen, the temporal variability of ΔS is generally larger at annual than monthly scale. The $\sigma_{\Delta S}/\sigma_{ET}$ ratio is generally larger at annual than monthly scale, suggesting the larger ΔS effects on annual ET than monthly ET. For most basins, the temporal variability of ΔS is generally larger than that of ET at the annual, dry-seasonal, and wet-seasonal scales, but at the monthly scale this is valid mainly in more humid basins (e.g., Southeast, Amazon, Pearl, Mekong) or in some intermediate (e.g., Congo and Parana) and arid basins (e.g., Nile, Niger, Darling, and Senegal). Figure 2 presents the scatterplots between $\sigma_{\Delta S}$ and the mean annual aridity index $\bar{\phi}$ at the four time scales for all the global grids. As seen, $\sigma_{\Delta S}$ is generally decreased with increased $\bar{\phi}$ at annual and dry-seasonal time scales, and its magnitude tends to be negligible in the extremely dry grids due to the highly limited water supply. At the wet-seasonal scale, the temporal variability of ΔS is general higher for the intermediate range of $\bar{\phi}$ (~ 0.25 – 1.0) and tends to

be limited for both extremely dry and humid climates. However, at the monthly scale, the temporal variability of ΔS can still be significant in the extremely dry grids, consistent with the finding mentioned above at the basin scale.

3. Results

a. Evaluation of model performance at various time scales

The statistics (i.e., CE and MRE) of the predicted ET from the original BM and from the extended BM for each of the 32 basins are compared in Table 3 at the annual, dry-seasonal, wet-seasonal, and monthly time scales. Although the MRE of the original BM is relatively low ($<1\%$) for most basins at annual and dry-seasonal time scales, the CE at these time scales is generally negative for most basins. This is particularly significant for humid basins (e.g., Mekong and Pearl) at the dry-seasonal time scale, suggesting that BM tends to underperform in the short dry seasons of predominantly humid basins. In contrast, although the CE of the original BM at the monthly scale is positive for most basins, the MRE is relatively large (negative value) for most basins. At the wet-seasonal scale, the validation of BM-predicted ET against the actual ET in all the 21 basins with the identified wet-seasonal months indicates the inadequacy of the original BM in predicting ET accurately, particularly in the arid basins with a large MRE and a negative CE.

As shown in Table 3, the improvement in ET prediction by the extended BM [Eq. (3)] over the original

TABLE 1. Basin characteristics and the long-term (1984–2008) mean water balances in the selected 32 global large river basins; P : precipitation, PET: potential evapotranspiration, R : runoff, ET: evapotranspiration, ΔS : water storage change, PET/ P : mean annual aridity index $\bar{\phi}$. The data of P , ET, R , and ΔS were obtained from the global monthly water budget dataset developed by [Zhang et al. \(2018\)](#). The PET data were obtained from the Terrestrial Hydrology Research Group of Princeton University.

No.	Basin ($\bar{\phi}$)	Basin area (10^6 km^2)	P (mm yr^{-1})	PET (mm yr^{-1})	ET (mm yr^{-1})	ΔS (mm yr^{-1})	R (mm yr^{-1})	ET/ P	ET/PET	R/P
1	Southeast (0.5)	0.2	1739.5	865.8	770.7	−1.0	969.9	0.44	0.89	0.56
2	Amazon (0.65)	5.9	2177.6	1420.3	1151.2	0.4	1026.0	0.53	0.81	0.47
3	Pearl (0.65)	0.4	1488.9	972.4	746.7	0.7	741.3	0.50	0.77	0.50
4	Northern Dvina (0.8)	0.4	623.3	501.0	328.1	−0.8	299.5	0.53	0.65	0.48
5	Yangtze (0.82)	1.8	1093.9	900.8	562.3	−0.6	532.5	0.51	0.62	0.49
6	Mekong (0.83)	0.8	1529.7	1276.0	894.7	0.7	634.5	0.58	0.70	0.41
7	Danube (0.96)	0.8	776.4	745.5	497.4	−2.3	282.7	0.64	0.67	0.36
8	Yenisei (1.03)	2.6	479.3	495.1	264.2	1.9	218.7	0.55	0.53	0.46
9	Congo (1.06)	3.7	1452.9	1537.0	1049.3	−1.0	404.5	0.72	0.68	0.28
10	Volga (1.09)	1.4	588.5	643.5	385.3	−1.4	206.9	0.65	0.60	0.35
11	Dnieper (1.18)	0.5	571.0	671.5	462.8	−4.0	113.6	0.81	0.69	0.20
12	Mackenzie (1.2)	1.7	430.1	515.3	248.4	1.3	186.0	0.58	0.48	0.43
13	Huaihe (1.22)	0.3	873.8	1065.7	567.2	−1.1	307.9	0.65	0.53	0.35
14	Parana (1.23)	2.7	1168.6	1434.8	893.6	−0.7	275.5	0.76	0.62	0.24
15	Mississippi (1.31)	3.2	797.1	1042.5	576.5	−0.9	222.6	0.72	0.55	0.28
16	Lena (1.31)	2.4	373.4	490.2	245.0	0.2	132.5	0.66	0.50	0.35
17	Ob (1.34)	2.6	452.3	608.3	311.2	0.0	144.4	0.69	0.51	0.32
18	Amur (1.37)	1.9	513.8	702.7	348.0	−0.4	167.1	0.68	0.50	0.33
19	Yukon (1.4)	0.9	318.4	446.2	179.3	1.4	142.3	0.56	0.40	0.45
20	Kolyma (1.43)	0.7	276.3	394.7	166.1	−0.7	113.4	0.60	0.42	0.41
21	Indigirka (1.49)	0.3	256.8	382.6	137.5	−0.6	123.2	0.54	0.36	0.48
22	Columbia (1.56)	0.7	613.6	959.1	330.2	−2.7	289.6	0.54	0.34	0.47
23	Don (1.66)	0.4	494.3	821.6	404.9	−3.5	93.7	0.82	0.49	0.19
24	Haihe (2.28)	0.3	515.6	1173.3	428.0	−2.1	90.0	0.83	0.36	0.17
25	Yellow (2.59)	0.9	435.6	1127.6	335.8	−1.0	101.4	0.77	0.30	0.23
26	Ural (2.59)	0.2	340.8	884.1	279.8	−0.7	64.1	0.82	0.32	0.19
27	Limpopo (2.86)	0.4	538.5	1542.2	498.5	0.0	40.2	0.93	0.32	0.07
28	Indus (3.01)	1.1	443.8	1337.4	268.9	−0.3	176.7	0.61	0.20	0.40
29	Nile (3.05)	3.8	624.6	1902.7	507.0	−0.1	117.7	0.81	0.27	0.19
30	Niger (3.37)	2.2	636.8	2149.0	428.2	0.1	207.9	0.67	0.20	0.33
31	Darling (3.7)	1.1	427.1	1580.2	391.9	−2.4	37.1	0.92	0.25	0.09
32	Senegal (4.4)	0.8	473.6	2085.5	357.6	−1.1	117.0	0.76	0.17	0.25

BM [Eq. (2)] can be found in most basins at both annual and dry-seasonal scales, in particular over the arid basins with larger CE, smaller MRE, and negative IM_{ET} (e.g., Yellow, Ural, Limpopo, Indus, and Darling), suggesting that the extended BM can better predict ET at annual and dry-seasonal scales. However, no substantial improvement can be found at the wet-seasonal scale, particularly in the arid basins (e.g., Ob, Amur, Yukon, Kolyma, and Indigirka) of which CE and MRE are even worse than that of the original BM prediction. Similarly, the extended BM is unable to provide any substantial improvement over the original BM at the monthly scale, and still considerably underestimates monthly ET for most basins. Despite the MRE of the extended BM is larger than that of the original BM in 16 out of the total 32 basins, significant improvement of the extended BM can only be found in several basins such as Amazon, Mekong, Congo, Nile, Niger, and Darling.

Figure 3 compares the temporal variability (standard deviation) of the actual ET and that of predicted ET from both the original and the extended BM for all global grids at all four time scales. The r between the actual and predicted ET for all grids at four time scales ranges from 0.635 to 0.856 in the original BM. The original BM tends to overestimate ET variability at annual, dry-seasonal, and monthly scales (particularly at the dry-seasonal scale). For the extended BM, the r between the actual and predicted ET ranges from 0.828 (annual) to 0.922 (dry seasonal), larger than that of the original BM. Generally, the overestimated ET variability (particularly at the dry-seasonal scale) can be corrected by the extended BM (Figs. 3b,d). However, compared to the original BM, the improvement of the extended BM at the wet-seasonal scale (Fig. 3f) is generally limited for most grids globally (Fig. 3e), suggesting the necessity of using more sophisticated

TABLE 2. Standard deviation of ΔS and the ratio of the standard deviation of ΔS over that of ET in the selected 32 global river basins. The numbers inside the parentheses after the basin names are the long-term (1984–2008) annual mean aridity index values. The symbol “—” indicates no dry-seasonal or wet-seasonal months being identified.

No.	Basin ($\bar{\phi}$)	$\sigma_{\Delta S}$ (mm)				$\sigma_{\Delta S}/\sigma_{ET}$			
		Annual	Dry seasonal	Wet seasonal	Monthly	Annual	Dry seasonal	Wet seasonal	Monthly
1	Southeast (0.5)	60.18	—	60.10	37.59	2.37	—	2.37	1.27
2	Amazon (0.65)	33.00	—	33.00	49.62	1.27	—	1.27	6.45
3	Pearl (0.65)	53.00	39.61	57.47	37.57	1.79	3.48	2.18	1.61
4	Northern Dvina (0.8)	29.90	—	29.89	31.89	1.46	—	1.46	1.04
5	Yangtze (0.82)	33.14	23.87	31.44	20.04	2.11	3.47	2.27	0.76
6	Mekong (0.83)	32.45	19.24	33.99	53.36	1.73	1.83	2.13	3.58
7	Danube (0.96)	45.86	24.26	45.74	30.35	2.42	2.74	2.89	0.91
8	Yenisei (1.03)	23.09	26.98	26.99	27.74	2.68	3.88	6.37	1.07
9	Congo (1.06)	44.03	18.41	38.84	23.17	2.07	1.73	2.90	2.10
10	Volga (1.09)	40.69	44.08	38.33	31.93	2.73	3.09	14.77	0.96
11	Dnieper (1.18)	46.76	46.89	—	32.34	2.33	2.34	—	0.91
12	Mackenzie (1.2)	18.57	17.72	17.66	16.82	1.49	1.41	8.62	0.76
13	Huaihe (1.22)	75.06	59.93	49.27	26.87	3.42	5.01	3.58	0.87
14	Parana (1.23)	70.49	55.96	46.38	29.90	2.93	2.89	4.51	1.14
15	Mississippi (1.31)	35.02	39.14	17.85	22.21	2.18	2.59	5.77	0.68
16	Lena (1.31)	21.12	17.98	8.55	16.31	2.27	2.12	4.70	0.64
17	Ob (1.34)	27.05	25.28	11.82	22.96	2.16	2.04	11.81	0.82
18	Amur (1.37)	26.01	25.11	4.76	11.17	1.58	1.52	4.03	0.39
19	Yukon (1.4)	12.84	10.78	12.40	12.62	1.51	1.26	7.22	0.76
20	Kolyma (1.43)	23.74	21.86	10.45	18.18	2.87	2.67	6.42	0.96
21	Indigirka (1.49)	21.49	20.50	8.11	12.44	2.30	2.15	4.81	0.79
22	Columbia (1.56)	50.04	32.47	44.01	37.16	2.37	1.55	11.69	1.76
23	Don (1.66)	41.63	41.65	—	29.02	2.28	2.28	—	0.95
24	Haihe (2.28)	52.25	52.19	—	21.27	2.33	2.33	—	0.74
25	Yellow (2.59)	32.49	32.37	—	11.63	2.84	2.83	—	0.53
26	Ural (2.59)	31.90	31.72	—	22.95	1.50	1.49	—	1.00
27	Limpopo (2.86)	64.81	64.80	—	24.59	1.27	1.27	—	0.98
28	Indus (3.01)	24.81	24.72	—	15.31	1.07	1.07	—	1.10
29	Nile (3.05)	30.03	30.08	—	19.02	2.00	2.00	—	1.34
30	Niger (3.37)	26.89	26.83	—	30.70	3.14	3.13	—	1.69
31	Darling (3.7)	26.35	26.17	—	17.25	0.53	0.52	—	1.41
32	Senegal (4.4)	34.83	34.80	—	26.53	2.24	2.24	—	1.11

water balance models for the prediction of ET in the wet season.

As mentioned above in [section 2d](#), the entire global grids can be classified into the following three categories according to the long-term (1984–2008) annual mean aridity index: 1) energy-limited (humid) regions with $\bar{\phi} < 0.76$, 2) water-limited (dry) regions with $\bar{\phi} > 1.35$, and 3) intermediate regions ($0.76 < \bar{\phi} < 1.35$). [Figure 4](#) compares the cumulative distribution functions (CDFs) of the CE statistics of ET predicted from the original and the extended BM over all global humid and dry grids (regions), from which large differences in CE can be seen between the humid and dry regions. Given a fixed CE ranging from 0 to 1, the CDF of the humid regions is significantly larger than that of the dry regions for the original BM at the annual, dry-seasonal, and monthly scales ([Figs. 4a,c,g](#)), and for the extended BM at all four time scales ([Figs. 4b,d,f,h](#)), indicating that both

the original and extended BM perform better over arid regions than humid regions at all these time scales. However, the CDF is larger in dry regions than humid regions for the original BM at the wet-seasonal scale ([Fig. 4e](#)), suggesting that the original BM underperforms in the short wet seasons of predominantly dry regions.

b. Relationships between ΔS and errors in BM-predicted ET

[Figure 5](#) plots the global distribution of the correlation coefficients (r) between ΔS and the errors in predicted ET (i.e., predicted ET minus actual ET) at four time scales. As seen, the errors in predicted ET show positive correlations with ΔS for most global regions at the annual, dry seasonal and monthly scales ([Figs. 5a,b,d](#)), implying that the larger ΔS is mostly associated with the overpredicted ET at these three time scales. Specifically, a larger positive correlation

FIG. 2. Scatterplots between the standard deviation of ΔS (mm) and the mean aridity index $\bar{\phi}$ for all 1° grid points globally at the (a) annual, (b) dry-seasonal, (c) wet-seasonal, and (d) monthly time scales. In this figure, the ΔS data and the long-term P data used to calculate $\bar{\phi}$ are from the global water budget dataset developed by Zhang et al. (2018). The PET data are from the Terrestrial Hydrology Research Group of Princeton University.

($r > 0.67$) is found mainly in Africa, South America, southern North America, Australia, and Southwest Asia. In contrast, a negative correlation is mainly found over northeast North America, northern South America, and southern Asia at the annual scale, and over the northern North America and Asia at the monthly scale. At the wet-seasonal scale, there are relatively weak (either positive or negative) correlations between the errors in predicted ET and ΔS , with the negative correlations scattering in northern South America, northern North America, and northern Asia (Fig. 5c). At the basin scale as shown in Table 4, ΔS and the errors in predicted ET are positively correlated in nearly all basins (except for the Southeast basin in China) at annual, dry-seasonal, and monthly scales, and the correlations tend to be larger over the drier basins at annual and monthly scales, suggesting that the temporal variability of ΔS can be the main factor contributing to the variability of ET prediction errors under arid climates. For the 21 basins with the wet seasons identified, the correlations are generally small or even negative at the wet-seasonal scale,

suggesting more complicated effects of ΔS on ET prediction errors at the wet-seasonal scale than at other time scales.

c. Roles of ΔS in the error variance of BM-predicted ET

The (1984–2008) error variance of the BM-predicted ET as derived in Eq. (5), is compared with the error variance calculated based on the actual errors in the BM-predicted ET (i.e., predicted ET minus actual ET) in Fig. 6 for all 1° grids globally at all the four time scales. As seen, Eq. (5) performs well at the annual, dry-seasonal and wet-seasonal scales with $r \sim 0.99$ at all three time scales. However, the error variance derived in Eq. (5) is generally overestimated at the monthly scale, suggesting other important controlling factors in determining the error variance of BM-predicted ET in addition to those recognized hydrometeorological factors included in the difference terms in Eq. (5).

Figure 7 plots the relative percentage contributions of the ΔS variance term ($\sigma_{\Delta S}^2$) and the three ΔS -associated

TABLE 3. The performance statistics of the original BM (O-BM) and the extended BM (E-BM) in the selected 32 global river basins at the annual, dry-seasonal, wet-seasonal, and monthly time scales. The numbers inside the parentheses after the basin names are the long-term (1984–2008) mean annual aridity index values. Diff: the E-BM-predicted ET minus the O-BM-predicted ET; IM_{ET}: the absolute value of errors in the E-BM-predicted ET (i.e., the E-BM-predicted ET minus the actual ET) minus that of errors in the O-BM-predicted ET (the O-BM-predicted ET minus the actual ET); CE: the Nash-Sutcliffe Coefficient of Efficiency; MRE: Mean Relative Error. The symbol “—” indicates no dry-seasonal or wet-seasonal months being identified.

No.	Basin ($\bar{\phi}$)	Annual				Dry seasonal				Wet seasonal				Monthly			
		CE		MRE (%)		CE		MRE (%)		CE		MRE (%)		CE		MRE (%)	
		O-BM	E-BM	O-BM	E-BM	Diff (mm)	IM _{ET} (mm)	O-BM	E-BM	O-BM	E-BM	O-BM	E-BM	O-BM	E-BM	O-BM	E-BM
1	Southeast (0.5)	-0.26	-0.62	-0.59	-0.55	0.34	-0.34	—	—	-0.26	-0.62	-0.59	-0.55	0.34	-0.34	0.84	0.82
2	Amazon (0.65)	-0.57	-0.51	0.18	0.16	-0.20	-0.20	—	—	-0.57	-0.51	0.18	0.16	-0.20	-0.20	0.31	0.44
3	Pearl (0.65)	-1.02	-0.74	0.60	0.32	-2.08	-2.08	-4.78	0.72	-0.90	-0.73	0.65	0.33	-1.94	-1.94	3.74	3.74
4	Northern Dvina (0.8)	0.05	0.21	0.26	0.12	-0.46	-0.46	—	—	0.05	0.21	0.27	0.13	-0.46	-0.46	0.77	0.82
5	Yangtze (0.82)	-1.14	-0.67	0.26	0.13	-0.70	-0.70	-1.21	0.10	-0.51	-0.32	0.24	0.10	-0.61	-0.61	0.86	0.83
6	Mekong (0.83)	-2.20	-1.48	0.24	0.13	-1.03	-1.03	-1.69	0.54	-0.99	-1.06	0.32	0.32	0.00	0.00	-2.65	0.74
7	Danube (0.96)	-0.25	0.32	0.32	-0.07	-1.91	-1.25	-0.99	0.57	-0.77	0.38	0.54	-0.11	-2.45	-1.64	0.77	0.82
8	Yenisei (1.03)	-0.83	-0.11	0.35	0.11	-0.62	-0.62	-4.92	-1.13	-1.12	0.27	0.19	0.84	0.26	0.26	0.79	0.82
9	Congo (1.06)	-0.73	0.05	0.08	0.00	-0.80	-0.80	-1.23	0.18	-0.44	-0.86	-0.04	0.17	0.00	-0.95	-0.09	0.77
10	Volga (1.09)	-0.99	0.01	0.49	0.11	-1.45	-1.45	-7.00	0.19	-1.17	-0.81	-1.13	-0.65	0.10	-0.10	0.77	0.84
11	Dnieper (1.18)	-0.09	0.51	0.22	0.07	-0.71	-0.71	-0.09	0.51	-0.71	—	—	—	—	—	0.64	0.82
12	Mackenzie (1.2)	0.09	0.47	0.23	0.02	-0.51	-0.51	-0.65	0.45	-0.97	-2.56	-2.54	-4.65	-0.53	-0.53	0.89	0.91
13	Huaihe (1.22)	-4.81	-0.76	1.66	0.39	-7.21	-7.21	-10.46	-0.59	-2.19	-0.08	0.73	-0.46	-2.97	-0.67	0.72	0.79
14	Parana (1.23)	-0.98	0.52	0.23	0.00	-2.04	-2.03	-2.51	0.70	-0.40	0.00	0.00	-0.10	-1.83	-1.20	0.66	0.91
15	Mississippi (1.31)	-1.64	0.11	0.36	0.11	-1.43	-1.43	-3.83	0.28	-1.42	0.29	0.06	0.78	0.32	0.32	0.77	0.91
16	Lena (1.31)	-0.92	0.43	0.55	0.20	-0.87	-0.87	-2.33	0.32	-0.84	-12.06	-47.93	-47.93	0.00	0.00	0.81	0.90
17	Ob (1.34)	-1.06	0.20	0.42	0.09	-1.02	-1.02	-2.60	0.14	-0.48	-26.39	-57.97	-57.97	0.00	0.00	0.81	0.90
18	Amur (1.37)	0.01	0.52	0.20	-0.07	-0.95	-0.43	-0.03	0.55	-0.49	-9.56	-39.29	-39.82	-0.04	0.04	0.93	0.93
19	Yukon (1.4)	-0.11	0.33	0.24	0.02	-0.40	-0.40	-0.30	0.35	-0.41	-17.85	-53.93	-54.03	-0.01	0.01	0.91	0.92
20	Kolyma (1.43)	-1.15	0.47	0.94	0.15	-1.32	-1.32	-3.40	0.46	-1.56	-11.70	-75.34	-75.57	-0.02	0.02	0.81	0.83
21	Indragkha (1.49)	-0.69	0.40	1.09	0.26	-1.14	-1.14	-1.13	0.38	-1.40	-12.00	-76.52	-76.52	0.00	0.00	0.80	0.72
22	Columbia (1.56)	-0.01	0.40	0.47	0.15	-1.05	-1.05	-0.27	0.54	-0.88	0.59	0.63	1.08	0.05	0.05	0.31	0.90
23	Don (1.66)	-0.92	0.62	0.40	0.00	-1.63	-1.59	-0.92	0.62	-0.40	0.00	0.00	—	—	—	0.59	0.86
24	Hahe (2.28)	-2.89	0.61	0.81	0.09	-3.08	-3.08	-2.89	0.61	-3.08	—	—	—	—	—	0.83	0.92
25	Yellow (2.59)	-3.57	0.51	0.62	0.04	-1.95	-1.95	-3.57	0.51	-1.95	—	—	—	—	—	0.88	0.87
26	Ural (2.59)	-0.19	0.88	0.72	-0.02	-2.06	-1.97	-0.19	0.88	-0.72	-0.02	-2.06	-1.97	—	—	0.58	0.91
27	Limpopo (2.86)	-0.13	0.98	0.20	0.03	-0.86	-0.86	-0.13	0.98	-0.86	—	—	—	—	—	0.59	0.99
28	Indus (3.01)	0.51	0.61	0.51	0.12	-1.07	-1.07	0.51	0.61	-1.07	—	—	—	—	—	0.46	0.87
29	Nile (3.05)	-2.60	0.01	0.31	0.07	-1.21	-1.21	-2.60	0.01	-1.21	—	—	—	—	—	-0.02	0.96
30	Niger (3.37)	-6.33	-2.57	0.42	0.19	-0.99	-0.99	-6.33	-2.57	-0.99	—	—	—	—	—	-0.40	0.89
31	Darling (3.7)	0.82	0.99	0.12	-0.02	-0.54	-0.41	0.82	0.99	-0.41	—	—	—	—	—	-0.15	0.99
32	Senegal (4.4)	-2.12	0.33	0.76	0.20	-2.00	-2.00	-2.12	0.33	-2.00	—	—	—	—	—	0.66	0.72
	Average	-1.15	0.09	0.43	0.08	-1.34	-1.32	-8.08	0.28	-6.14	-4.50	-16.76	-16.73	-0.47	-0.38	0.39	0.85

FIG. 3. Comparisons of the temporal variability (i.e., standard deviation) of the actual ET and the ET predicted from the original BM [Eq. (2)] for all 1° grid points globally at the (a) annual, (c) dry-seasonal, (e) wet-seasonal, and (g) monthly time scales, and that predicted from the extended BM [Eq. (3)] at the (b) annual, (d) dry-seasonal, (f) wet-seasonal, and (h) monthly time scales.

FIG. 4. The CDFs of Nash–Sutcliffe CE for the original BM-predicted ET in all humid grids ($\bar{\phi} < 0.76$) and dry grids ($\bar{\phi} > 1.35$) globally at the (a) annual, (c) dry-seasonal, (e) wet-seasonal, and (g) monthly time scales. The CDF of CE for the extended BM-predicted ET in all humid grids ($\bar{\phi} < 0.76$) and dry grids ($\bar{\phi} > 1.35$) globally at the (b) annual, (d) dry-seasonal, (f) wet-seasonal, and (h) monthly time scales. The mean annual aridity index $\bar{\phi}$ at each grid was computed based on the long-term (1984–2008) annual P and PET data from Zhang et al. (2018).

covariance terms [i.e., $2W_p \text{cov}(P, \Delta S)$, $2W_{\text{PET}} \text{cov}(\text{PET}, \Delta S)$, and $2\text{cov}(R, \Delta S)$] in Eq. (5) to the error variance of BM-predicted ET at all four time scales over 32 river basins. Similar analyses but for the global (grid) scale are plotted in Fig. 8 for the annual scale and Fig. 9 for the

monthly scale. The order of basins in Fig. 7 is arranged from the left to right according to the increasing long-term (1984–2008) mean aridity index. Also notice that the numbers of basins identified with the dry-seasonal and wet-seasonal months are 29 and 21, respectively.

FIG. 5. Global maps of the correlation coefficients between ΔS and the error in the BM-predicted ET (i.e., BM-predicted ET minus actual ET) at the (a) annual, (b) dry-seasonal, (c) wet-seasonal, and (d) monthly time scales.

As shown, the relative contribution of the ΔS variance term tends to increase from humid to arid basins at the annual, wet-seasonal, and monthly scales, but this tendency is not evident at the dry-seasonal scale. The temporal variability (variance) of ΔS can enhance the error variance of predicted ET at all four time scales in both humid and arid basins, consistent with the positive correlations found between ΔS and the errors in BM-predicted ET identified over the most parts of the world at the annual and monthly scales (Fig. 5). In contrast, the ΔS -associated covariance terms in Eq. (5) tend to decrease the error variance of predicted ET in both humid and arid basins at all four time scales. This effect is particularly significant in arid basins at the wet-seasonal scale (up to 50% of contribution), a consistent finding with the weak correlation between ΔS and the errors in BM-predicted ET at the wet-seasonal scale (Table 4).

At the global (grid) scale, the temporal variability of ΔS dominates the error variance of BM-predicted ET mostly in arid regions, such as the southern and northeastern North America, southern South America, northern and southern Africa, southwestern Asia, and southern Australia, with the percentage contribution close to 100% (Figs. 8a and 9a). For the three covariance terms associated with ΔS in Eq. (5), the negative

contribution to the error variance is located in most regions of the world, especially for high latitudes such as northern North America and northern Asia, while the positive contribution to the error variance is found to scatter in the dry and hot climate zones, such as Africa, the southwestern parts of Asia, and Australia (Figs. 8b and 9b). Furthermore, it is noted that the contributions from ΔS and its associated terms are more significant at the monthly than the annual scale, suggesting that the effect of ΔS on the errors in BM-predicted ET is more significant at the shorter time scales.

4. Discussion

This study highlights the important role of ΔS in ET prediction within the Budyko framework at the annual and shorter time scales via the error variance decomposition method, which is well supported by the findings from previous studies of the Budyko framework (Zhang et al. 2008; Donohue et al. 2010; Chen et al. 2013; Wu et al. 2017). Due to the effects of ΔS , the original BM fails to capture the variability of ET in most basins with the large errors at annual or finer temporal scales (Table 3). The predicted ET from the original BM tends to be more accurate under arid climates than humid

TABLE 4. Correlation coefficients ($p < 0.01$) between ΔS and the error in the original BM-predicted ET (i.e., the original BM-predicted ET minus the actual ET) in the selected 32 global river basins at the annual, dry-seasonal, wet-seasonal, and monthly time scales. The numbers inside the parentheses after the basin names are the long-term (1984–2008) mean annual aridity index values. The symbol “—” indicates no dry-seasonal or wet-seasonal months being identified.

No.	Basin ($\bar{\phi}$)	Annual	Dry seasonal	Wet seasonal	Monthly
1	Southeast (0.5)	−0.41	—	−0.41	0.32
2	Amazon (0.65)	0.23	—	0.23	0.80
3	Pearl (0.65)	0.40	0.94	0.29	0.66
4	Northern Dvina (0.8)	0.40	—	0.41	0.39
5	Yangtze (0.82)	0.51	0.79	0.36	0.67
6	Mekong (0.83)	0.56	0.86	0.34	0.86
7	Danube (0.96)	0.67	0.86	0.81	0.82
8	Yenisei (1.03)	0.62	0.64	0.32	0.30
9	Congo (1.06)	0.68	0.82	0.66	0.86
10	Volga (1.09)	0.67	0.90	0.04	0.69
11	Dnieper (1.18)	0.79	0.79	—	0.87
12	Mackenzie (1.2)	0.71	0.74	−0.32	0.30
13	Huaihe (1.22)	0.85	0.91	0.24	0.67
14	Parana (1.23)	0.88	0.95	0.79	0.88
15	Mississippi (1.31)	0.85	0.92	0.53	0.88
16	Lena (1.31)	0.86	0.75	−0.03	0.58
17	Ob (1.34)	0.80	0.78	−0.40	0.60
18	Amur (1.37)	0.73	0.77	0.25	0.56
19	Yukon (1.4)	0.69	0.61	−0.67	0.38
20	Kolyma (1.43)	0.85	0.83	0.14	0.42
21	Indigirka (1.49)	0.85	0.79	0.10	0.27
22	Columbia (1.56)	0.64	0.29	0.34	0.76
23	Don (1.66)	0.89	0.89	—	0.88
24	Haihe (2.28)	0.96	0.96	—	0.85
25	Yellow (2.59)	0.95	0.95	—	0.84
26	Ural (2.59)	0.94	0.94	—	0.83
27	Limpopo (2.86)	1.00	1.00	—	0.89
28	Indus (3.01)	0.49	0.46	—	0.88
29	Nile (3.05)	0.86	0.86	—	0.98
30	Niger (3.37)	0.73	0.72	—	0.94
31	Darling (3.7)	0.98	0.98	—	0.96
32	Senegal (4.4)	0.89	0.89	—	0.88

climates at the annual, dry-seasonal, and monthly time scales, while at the wet-seasonal time scale the original BM tends to perform better under humid climates than arid climates (Fig. 4). When incorporating the effect of ΔS into BM, significant improvements can be found for most basins (particularly for the arid basins) at the annual and dry-seasonal scales with the negative IM_{ET} (Table 3). The overestimated variability of BM-predicted ET (particularly at the dry-seasonal scale) is largely improved by the extended BM (Fig. 3). However, no substantial improvement can be identified at the wet-seasonal and monthly time scales (particularly at the wet-seasonal time scale) for most of the identified basins (as shown in Table 3) due to the significant effect of ΔS on BM-predicted ET. This suggests the necessity of more sophisticated water balance models for simulating more detailed important physical processes at these time scales. The results further indicate that ΔS is strongly correlated

($r > 0.7$) with the errors in BM-predicted ET over most parts of the world at the annual and monthly scales, and the correlation is larger under more arid climates (Fig. 5). However, the correlation between ΔS and prediction errors at the wet-seasonal scale is generally smaller than that at other time scales, implying only little impacts of ΔS on ET prediction errors at the wet-seasonal scale.

Under arid climates, the partitioning of P into ET and R is mainly controlled by P (Zhang et al. 2004, 2008; Yang et al. 2009), and ΔS can have a significant or even predominant impacts on ET variability (Wu et al. 2017). Wang et al. (2018) pointed out that the dominant control of P on ET makes the ET prediction within the Budyko framework more accurate in nonhumid regions. However, our study indicated that the performance of BM-predicted ET is dominated by the variability of ΔS under arid climates [Eq. (7)], particularly at the monthly scale (Figs. 7d and 9). Since the partitioning of

FIG. 6. Comparisons of the long-term (1984–2008) mean actual error variance and that predicted by Eq. (5) over all global 1° grids points at the (a) annual, (b) dry-seasonal, (c) wet-seasonal, and (d) monthly time scales.

P into ET and R under humid climates is largely controlled by PET (Zhang et al. 2004, 2008; Yang et al. 2009; Zeng and Cai 2015), the temporal variability of ET is dominated by that of PET (Wu et al. 2017). It is likely that the relatively poor performance of the original BM under humid climates is associated with other important hydrometeorological factors or catchment characteristics with greater impacts on BM-predicted ET than ΔS , which is well supported by Eq. (5) stating that the variance and covariance terms of P , PET, R , and ΔS are comparably important in controlling the error variance of BM-predicted ET under humid climates (Wu et al. 2018b). In addition, at the wet-seasonal scale the impacts of ΔS temporal variability on the error variance of predicted ET tend to be less than that of the covariances between ΔS and hydrometeorological factors (Fig. 7c). Therefore, the effects of other important controlling factors (such as the interactions between hydrometeorological factors and catchment characteristics) on the performance of BM need to be explored in order to identify more sophisticated models to better represent controlling physical

processes under humid climates and/or at the wet-seasonal time scale.

Note that although the error-decomposition method generally works well for most cases analyzed in this study, there are still relatively large residual errors found in certain grids particularly at the monthly scale (Fig. 6d). The residual errors can be partially attributed to the uncertainty in the gridded water budget variables, especially for ET merged from multiple data sources such as satellite remote sensing, land surface model, and reanalysis (Zhang et al. 2018). On the other hand, the linear approximation of the Budyko hypothesis in the derivation of the error decomposition framework [Eq. (5)] neglecting the effects of higher-order terms also contributes to the uncertainty in the predicted error variance of ET, particularly for the significantly nonlinear Budyko curves at the finer temporal scales (Wu et al. 2018b). Additionally, more complicated interactions between catchment characteristics, climate, terrestrial storage, and human activity at the shorter time scales could also lead to more difficulties in predicting ET error variance at the intra-annual (seasonal) scale than

FIG. 7. The percentage contribution of the ΔS term ($\sigma_{\Delta S}^2$) and the terms associated with ΔS [i.e., $2W_{P\text{cov}}(P, \Delta S)$, $2W_{\text{PETcov}}(\text{PET}, \Delta S)$, and $2\text{cov}(R, \Delta S)$] in Eq. (5) to the error variance of BM-predicted ET in the selected 32 global basins at (a) annual, (b) dry-seasonal, (c) wet-seasonal, and (d) monthly time scales. The order of basins is arranged from left to right with the increasing long-term (1984–2008) mean aridity index.

that in the interannual scale. The analysis framework of the error variance of BM-predicted ET used in this study partially accounts for the effects of catchment characteristics via the parameterization of the BM. As pointed from Wu et al. (2018b), the parameter estimation of the BM shows different impacts on the

weighting functions of P and PET under different climatic conditions [Eq. (6)], and hence resulting in different contributions from P and PET to the error variance of predicted ET. However, a clear understanding of the interactions between catchment characteristics, climate, terrestrial storage, and human activity over the

FIG. 8. The contribution of (a) ΔS term ($\sigma_{\Delta S}^2$) and (b) the terms associated with ΔS [i.e., $2W_p \text{cov}(P, \Delta S)$, $2W_{\text{PET}} \text{cov}(\text{PET}, \Delta S)$, and $2\text{cov}(R, \Delta S)$] to the error variance of BM-predicted ET over the world at the annual scale.

finer time scales is still a grand challenge, which need to be systematically explored in the future.

5. Conclusions

On the basis of a unique multiple-source, global gridded long-term (1984–2008) monthly terrestrial water budget dataset recently developed by Zhang et al. (2018), this study presents a global analysis of the role of ΔS in the Budyko Model (BM) predicted ET variability and errors at the annual, wet-seasonal, dry-seasonal, and monthly time scales under a wide variety of climatic conditions. The performances of the original and the extended BM (incorporating the effect of ΔS) are compared at these four time scales over the globally selected 32 large river basins as well as the global grids. The effects of ΔS on the error variance of the BM-predicted ET are quantified under various climate conditions using an analytical framework of error decomposition.

The predictions of the original BM are more accurate under arid climates than humid climates at the annual,

dry-seasonal, and monthly time scales, while at the wet-seasonal time scale the original BM performs better under the humid than arid climates. Overall, the original BM underperforms in the short dry seasons of predominantly humid basins and the short wet seasons of predominantly dry basins. The extended BM incorporating the effect of ΔS mostly improve ET prediction particularly under arid climates and at the annual and dry-seasonal time scales (with the negative IM_{ET} in Table 3). The overestimated ET variability predicted by the original BM, particularly at the dry-seasonal scale, is found to be largely corrected by the extended BM, but no substantial improvement can be identified at the wet-seasonal and monthly scales (Fig. 3). The magnitudes of ΔS show positively correlations ($r > 0.7$) with the errors in BM-predicted ET over most global regions (with larger correlations found under more arid climates) at annual and monthly scales, while no significant correlations can be found at the wet-seasonal scale.

The contribution of the temporal variability of ΔS to the error variance of BM-predicted ET tends to be

FIG. 9. As in Fig. 8, but for the monthly scale.

larger moving from humid to arid climates at the annual, wet-seasonal, and monthly time scales. Under arid climates, the error variance of BM-predicted ET is dominated solely by the variability of ΔS , particularly at the monthly scale. In contrast, the effect of ΔS on the error variance of predicted ET under humid climates is generally limited particularly at the wet-seasonal scale due to the effects of other important hydroclimatic factors (P and PET) and catchment responses (R). This study highlights the important roles of ΔS in predicting ET within the Budyko framework under arid climates and at the annual or shorter time scales, and we conclude that more sophisticated water balance models incorporating more physical processes than BM are required particularly under humid climates and at the wet-seasonal time scale.

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