



19

20 Jianyu Liu¹, Qiang Zhang^{2,3*}, Vijay P. Singh⁴, Changqing Song^{2,3}, Yongqiang Zhang⁵, Peng

21 Sun⁶

22

23 ¹Laboratory of Critical Zone Evolution, School of Earth Sciences, China University of
24 Geosciences, Wuhan 430074, China

25 ²Key Laboratory of Environmental Change and Natural Disaster, Ministry of Education, Beijing
26 Normal University, Beijing 100875, China

27 ³Faculty of Geographical Science, Academy of Disaster Reduction and Emergency
28 Management, Beijing Normal University, Beijing 100875, China

29 ⁴Department of Biological and Agricultural Engineering and Zachry Department of Civil
30 Engineering, Texas A&M University, College Station, Texas, USA

31 ⁵CSIRO Land and Water, GPO Box 1700, Canberra ACT 2601, Australia

32 ⁶College of Geography and Tourism, Anhui Normal University, Anhui 241000, China

33



34 **Abstract:** The partitioning of water and energy, governed by the controlling parameter in the
35 Budyko framework (i.e., n parameter in the Choudhury and Yang equation), is critical to assess
36 the water balance at global scale. It is widely acknowledged that the spatial variation of this
37 controlling parameter is affected by landscape characteristics, but characterizing its temporal
38 variation remains yet to be done. Considering effective precipitation (P_e), the Budyko
39 framework was extended to the annual water balance analysis. To reflect the mismatch between
40 water supply (precipitation, P) and energy (potential evapotranspiration, E_0), a climate
41 seasonality and asynchrony index (SAI) were proposed in terms of both phase and amplitude
42 mismatch between P and E_0 . Considering streamflow changes in 26 large river basins as a case
43 study, SAI was found to be the key factor explaining 46% of the annual variance of parameter n .
44 Furthermore, the vegetation dynamics (M) remarkably impacted the temporal variation of n ,
45 explaining 67% of the variance. With SAI and M , a semi-empirical formula for parameter n
46 was developed at the annual scale to describe annual runoff (R) and evapotranspiration (E). The
47 impacts of climate variability (P_e , E_0 and SAI) and M on R and E changes were then quantified.
48 Results showed that R and E changes were controlled mainly by the P_e variations in most river
49 basins over the globe, while SAI acted as the controlling factor modifying R and E changes in
50 the East Asian subtropical monsoon zone, E_0 in the temperate maritime climate of Europe, and
51 M in the temperate grassland zone of South America.

52

53 **1. Introduction**

54 Climate variability, vegetation dynamics and water balance are interactive, and this interaction
55 is critical in the evaluation of the impact of climate change and vegetation dynamics on water



56 balance at the basin scale and for the management of water resources (Milly, 1994; Yang et al.,
57 2009; Weiss et al., 2014; Zhang et al., 2016c). The models that can quantify the climate-
58 vegetation-hydrology interactions without calibration using observed evapotranspiration/runoff
59 are particularly needed for hydrological prediction in ungauged basins (Potter et al., 2005).
60 Furthermore, quantifying the influence of climate variability and vegetation dynamics on
61 hydrological variability is critical in differentiating the factors that drive the hydrological cycle
62 in both space and time (Yan et al., 2014; Dagon and Schrag, 2016; Zhang et al., 2016a).

63 The Budyko framework was developed to quantify the partitioning of precipitation into
64 runoff and evapotranspiration (Koster and Suarez, 1999; Xu et al., 2013), and was widely used
65 to evaluate interactions amongst climate, catchment characteristics, and hydrological cycle
66 (Yang et al., 2009; Cai et al., 2014; Liu et al., 2017b; Ning et al., 2017). However, the controlling
67 parameter of the Budyko framework usually needs to be calibrated, based on observed data. If
68 the controlling parameter can be determined using the available data, then the Budyko
69 framework can be employed in modelling the hydrological cycle in ungauged basins (Li et al.,
70 2013). That is why considerable attention has been devoted to quantifying the relationship
71 between the controlling parameter and explanatory variables (e.g. Yang et al., 2009; Abatzoglou
72 and Ficklin, 2017). Most of the relationships were evaluated at a long-term scale (Abatzoglou
73 and Ficklin, 2017; Gentine et al., 2012; Li et al., 2013; Xu et al., 2013; Yang et al., 2009; Yang
74 et al., 2007; Zhang et al., 2016c) due to the steady-state assumption of the Budyko model.
75 However, hydrological processes, such as water storage, are usually nonstationary due to
76 climate change and human activities (Greve et al., 2015; Ye et al., 2015). It should be noted
77 here that the variability of controlling parameters from year to year may be considerably large



78 in a specific river basin, which can be significantly affected by variations in vegetation cover
79 and climate conditions. Hence, it is necessary to develop a model to estimate annual variations
80 of controlling parameters. In a recent study, Ning et al. (2017) established an empirical
81 relationship of the controlling parameter at the annual scale in the Loess Plateau of China.
82 However, the annual values of the optimized controlling parameter in their study were
83 calibrated with the Fu equation without consideration of the annual water storage changes (ΔS).
84 But ΔS was identified as a key factor causing annual variations of water balance in most river
85 basins, particularly in river basins of arid regions (e.g. Chen et al., 2013). Therefore, considering
86 water storage changes, the effective precipitation (P_e), which is the difference between
87 precipitation and water storage change (Chen et al., 2013), was used to extend the Budyko
88 framework to annual-scale water balance analysis and was used to calibrate n .

89 Climate seasonality (SI) was identified to reflect the non-uniformity in the intra-annual
90 distribution of water and energy, which plays a role in the variation of controlling parameter in
91 the Budyko model (Woods, 2003; Ning et al., 2017; Yang et al., 2012). It is noted that
92 distributions of water and energy were reflected not only by differences of seasonal amplitudes
93 of P and E_0 but also by the phase mismatch between P and E_0 . In this case, we proposed a
94 climate seasonality and asynchrony index (SAI) to reflect the seasonality and asynchrony of
95 water and energy distribution. Vegetation coverage has also been found to be closely related to
96 the spatial variation of the controlling parameter (Yang et al., 2009). Li et al. (2013) and Xu et
97 al. (2013) used vegetation coverage to model the spatial variation of the controlling parameter
98 in 26 river basins over the globe at a long-term scale. However, the effect of climate variability
99 was not considered, and the impact of vegetation dynamics on the temporal variation of the



100 controlling parameter was not fully investigated. Zhang et al. (2016c) established the
101 relationship of parameter n with vegetation changes over northern China and suggested that the
102 relationship needed to be further assessed in other river basins across the globe. Also, they
103 confirmed the impact of climate seasonality on parameter n , and suggested future studies on its
104 impacts on n . Therefore, this study developed a semi-empirical formula for parameter n with
105 SAI and M as predictor variables at the annual scale, using meteorological and hydrological
106 data from 26 large river basins from around the globe with a broad range of climate conditions.

107 Much work has been done, addressing water balance variations (e.g., Liu et al., 2017a; Zeng
108 and Cai, 2016; Zhang et al., 2016a; Zhang et al., 2016b). For instance, Zeng and Cai (2016)
109 evaluated the impacts of P , E_0 and ΔS on the temporal variation of evapotranspiration for large
110 river basins. However, little is known about the influence of M and SAI on the hydrological
111 cycle, particularly on their contributions to variations of runoff and evapotranspiration. The
112 impact of M and SAI on the water balance is critical for water balance modelling. Therefore,
113 based on the developed semi-empirical formula, this study further assessed the causes of
114 variation of R and E . Therefore, the objectives of this study were: (1) to propose a climate
115 seasonality and asynchrony index, SAI, to reflect the mismatch of water and energy; (2) to
116 develop an empirical model for the controlling parameter n at the annual scale using data from
117 26 large river basins from around the globe; and (3) to investigate the impact of SAI and other
118 factors on the R and E variations.

119

120 **2. Data**

121 Monthly terrestrial water budget data covering a period of 1984-2006 was collected from 32



122 large river basins from around the globe (Pan et al., 2012). The data set, including P , E , R and
123 ΔS , combined data from multiple sources, such as in situ observations, remote sensing retrievals,
124 model simulations, and global reanalysis products, which was obtained using assimilation
125 weighted with the estimated error. For more details on this dataset, reference can be made to
126 Pan et al. (2012). This dataset, which was deemed to one of the best water budget estimates,
127 has already been applied to assess the impact of vegetation, topography, latitude, and terrestrial
128 storage on the spatial variability of the controlling parameter in the Budyko framework and the
129 evapotranspiration variability over the past several years (Arnell and Gosling, 2013; Li et al.,
130 2013; Xu et al., 2013; Zeng and Cai, 2016). The dataset has been designed to explicitly close
131 the water budget. And that the use of data assimilation might lead to unphysical variability. As
132 a result, Li et al. (2013) found that more than 20% of data in six basins among the 32 global
133 basins were beyond the energy and water limits, and suggested analysis on water-energy
134 balance using the remaining 26 basins. Following Li et al. (2013), we evaluated the impact of
135 climate variability and vegetation dynamics on the spatiotemporal variation of the controlling
136 parameter and the water balance of the 26 river basins. Detailed information about the
137 characteristics of the 26 basins is given in Table 1. Monthly potential evapotranspiration (E_0)
138 data from 1901 to 2015 at a spatial resolution of 0.5° was obtained from Climatic Research Unit
139 of University of East Anglia ([https://crudata.uea.ac.uk/cru/data/hrg/cru_ts_3.24.01/
140 cruts.1701201703.v3.24.01/pet/](https://crudata.uea.ac.uk/cru/data/hrg/cru_ts_3.24.01/cruts.1701201703.v3.24.01/pet/)). Monthly normalized difference vegetation index (NDVI)
141 covering a period of 1981-2006 was obtained from Global Inventory Modeling and Mapping
142 Studies (GIMMS) (Buermann, 2002; Li et al., 2013).

143 **3. Methods**144 **3.1 The Budyko framework at annual scale**

145 Based on the Budyko framework, Choudhury (1999) and Yang et al. (2008) deduced a water-
146 energy formula as:

$$147 \quad E = \frac{PE_0}{(P^n + E_0^n)^{1/n}} \quad (1)$$

148 where n is the controlling parameter of the Choudhury-Yang equation which is one of the
149 formulations of the Budyko framework.

150 The basin stores precipitation first and then releases it as runoff and evapotranspiration
151 (Biswal, 2016). Affected by water storage changes, E is always not equal to the difference
152 between P and R for a short time interval. Previous studies have found that storage changes
153 have impacts on water balance at the annual scale (Donohue et al., 2012). To consider the
154 influence of variation of water storage, Wang (2012) suggested to use effective precipitation
155 (P_e), i.e., $P_e = P - \Delta S$, to replace precipitation in the water-energy balance. As a result, using
156 the P_e , the Choudhury and Yang equation (1999) can be extended in short time scale:

$$157 \quad R = P_e - \frac{P_e E_0}{(P_e^n + E_0^n)^{1/n}} \quad (2a)$$

$$158 \quad E = \frac{P_e E_0}{(P_e^n + E_0^n)^{1/n}} \quad (2b)$$

159 Parameter n controls the shape of the Budyko curve and can be calibrated by minimizing the
160 mean absolute error (*MAE*) (Legates and McCabe, 1999; Yang et al., 2007). Parameter n is a
161 catchment characteristic parameter which is mainly related to the underlying conditions (i.e.,
162 topography and soil), climate conditions, and vegetation cover (Liu et al., 2017a; Yang et al.,
163 2009; Zhang et al., 2016c). The underlying characteristics are relatively stable during a short
164 time interval, while climate and vegetation might undergo considerable variations, which can



165 lead to the change of parameter n . As a result, vegetation dynamics and climate variability were
166 applied to simulate n and assess their impact on runoff and evapotranspiration.

167 The vegetation coverage (M), which is the fraction of land surface covered with green
168 vegetation in the region, can be calculated as (Gutman and Ignatov, 1998):

$$169 \quad M = (NDVI - NDVI_{min}) / (NDVI_{max} - NDVI_{min}) \quad (3)$$

170 where $NDVI_{max}$ and $NDVI_{min}$ represent the dense green vegetation and bare soil with
171 $NDVI_{max} = 0.80$ and $NDVI_{min} = 0.05$, respectively (Li et al., 2013; Ning et al., 2017; Yang
172 et al., 2009).

173 3.2 Seasonality and asynchrony of water and energy

174 The seasonality of P and E_0 , which are mainly controlled by solar radiation, follows a sine
175 distribution (Milly, 1994; Woods, 2003):

$$176 \quad P(t) = \bar{P} \left(1 + \delta_P \sin \left(\frac{2\pi}{\tau} \frac{t}{12} \right) \right) \quad (4a)$$

$$177 \quad E_0(t) = \bar{E}_0 \left(1 + \delta_{E_0} \sin \left(\frac{2\pi}{\tau} \frac{t}{12} \right) \right) \quad (4b)$$

178 where t is the time (months), $P(t)$ and $E_0(t)$ are the monthly P and E_0 with the annual mean
179 value of \bar{P} and of \bar{E}_0 , respectively. The quantities δ_P and δ_{E_0} are dimensionless seasonal
180 amplitudes, which can be calibrated by minimizing MAE . The quantity τ is the cycle of
181 seasonality, with half a year in the tropics and one year outside the tropics. The origin of time
182 ($t = 0$) was fixed in April in the previous studies (Milly, 1994; Woods, 2003; Ning et al., 2017).

183 As a result, if the δ_P (δ_{E_0}) was positive, the month with maximum monthly P (E_0) would
184 appear in July, which corresponds to Northern Hemisphere (e.g., Figure 1a); while the southern
185 Hemisphere would show a January maximum with negative δ_P (δ_{E_0}). Considering the
186 difference between seasonal P and E_0 , Wood et al. (2003) defined a climate seasonality index



187 by combining Eq. (4):

$$188 \quad SI = |\delta_P - \delta_{E_0} DI| \quad (5)$$

189 where DI is the dryness index $\left(\frac{\bar{E}_0}{\bar{P}}\right)$.

190 <Figure 1 here please>

191 Equations (4) - (5) were applied to represent the mismatch between water and energy (e.g.,
192 Ning et al., 2017). However, the following two issues still need to be considered: (1) effect of
193 local climate and catchment characteristics, the phase of seasonal P and E_0 may be not entirely
194 consistent with that of solar radiation; and (2) the phases between seasonal P and E_0 cannot
195 always be consistent in a specific basin, such as the Northern Dvina basin (Figure 1b). The
196 values of E for two basins with the same annual mean P , E_0 , δ_P and δ_{E_0} can be different if
197 the phases of seasonal P and E_0 are in mismatch. As a result, the phase shifts of P (S_P) and E_0
198 (S_{E_0}) should be considered in the sine function (Berghuijs and Woods, 2016):

$$199 \quad P(t) = \bar{P} \left(1 + \delta_P \sin \left(\frac{2\pi t - S_P}{\tau} \right) \right) \quad (6a)$$

$$200 \quad E_0(t) = \bar{E}_0 \left(1 + \delta_{E_0} \sin \left(\frac{2\pi t - S_{E_0}}{\tau} \right) \right) \quad (6b)$$

201 As shown in figure 2, Eq. (6) with fitted phase performed much better in simulating monthly P
202 and E_0 than eq. (4) with a fixed phase, with R^2 larger than 0.89 for the former but smaller than
203 0.64 for the latter.

204 <Figure 2 here please>

205 To fully reflect the difference between water and energy, it is necessary to consider not only
206 the seasonal amplitude difference between P and E_0 , but also the phase difference (i.e.,
207 asynchrony) between them (Fig S1b). Therefore, an improved climate index describing the
208 difference between water and energy needs to be developed with the consideration of



209 seasonality and asynchrony of P and E_0 . Based on eq. (6), we further deduced the following
 210 equations to express the difference between P and E_0 :

$$211 \quad \frac{P(t)-E_0(t)}{\bar{P}} = (1 - DI) + \left(\delta_P \sin\left(\frac{2\pi t - S_P}{\tau} \frac{12}{12}\right) - DI \delta_{E_0} \sin\left(\frac{2\pi t - S_{E_0}}{\tau} \frac{12}{12}\right) \right)$$

$$212 \quad = (1 - DI) + (a^2 + b^2)^{1/2} \sin\left(\frac{2\pi t}{\tau} \frac{12}{12} - \varphi\right) \quad (7)$$

213 where $a = \delta_P \cos \delta_P - DI \delta_{E_0} \cos \frac{2\pi S_P}{\tau} \frac{12}{12}$, $b = -\delta_P \sin \delta_P + DI \delta_{E_0} \sin \frac{2\pi S_{E_0}}{\tau} \frac{12}{12}$, $\varphi = \arctan(b/a)$.
 214 Similar to Milly (1994), we defined a seasonality and asynchrony index (SAI) to reflect the
 215 mismatch between water and energy in terms of the magnitude and phase difference between P
 216 and E_0 :

$$217 \quad \text{SAI} = (a^2 + b^2)^{1/2}$$

$$218 \quad = \left(\delta_P^2 - 2\delta_P \delta_{E_0} DI \cos\left(\frac{2\pi S_P - S_{E_0}}{\tau} \frac{12}{12}\right) + (\delta_{E_0} DI)^2 \right)^{1/2} \quad (8)$$

219 The SI value calculated by eq. (5) was an exceptional case for P and E_0 in the same phase
 220 shifts. A larger SAI implies a greater difference between P and E_0 in the year. Besides, SAI
 221 followed the following three scenarios: (1) $\text{SAI} < 1 - DI$, given a wet climate with $P(t) > E_0$
 222 (t) across the whole seasonal cycle; (2) $\text{SAI} < DI - 1$, given a dry climate with $P(t) < E_0$ (t)
 223 across the whole seasonal cycle; (3) $\text{SAI} > |DI - 1|$, given that a larger SAI implies more
 224 surplus of P for the wet season with $P(t) > E_0$ (t).

225 3.3 Contributions of SAI and other factors to R and E

226 From eq. (2), we can redefine the total differential of R and E for any time scale by
 227 introducing effective precipitation (P_e):

$$228 \quad dR = \frac{\partial R}{\partial P_e} dP_e + \frac{\partial R}{\partial E_0} dE_0 + \frac{\partial R}{\partial n} dn \quad (9a)$$

$$229 \quad dE = \frac{\partial E}{\partial P_e} dP_e + \frac{\partial E}{\partial E_0} dE_0 + \frac{\partial E}{\partial n} dn \quad (9b)$$

230 The climatic elasticity of evapotranspiration changes to the changes of precipitation, potential



231 evapotranspiration and n can be separately be expressed as $\varepsilon_{P_e} = \frac{P_e}{E} \frac{\partial f}{\partial P_e}$, $\varepsilon_{E_0} = \frac{E_0}{E} \frac{\partial f}{\partial E_0}$, $\varepsilon_n =$
 232 $\frac{n}{E} \frac{\partial f}{\partial n}$. The climatic elasticity of runoff changes is similar to the climatic elasticity
 233 evapotranspiration changes. The difference operator (d) in eq. (9a) and eq. (9b) refer to the
 234 difference of a variable before and after change points of R and E , respectively. The relative
 235 contribution (C) of P_e , E_0 and n to the R and E changes can be obtained as:

$$236 \quad C_{P_e} = \frac{|I_{P_e}|}{|I_P| + |I_{E_0}| + |I_n|}, \quad C_{E_0} = \frac{|I_{E_0}|}{|I_P| + |I_{E_0}| + |I_n|}, \quad C_n = \frac{|I_n|}{|I_P| + |I_{E_0}| + |I_n|} \quad (10)$$

237 I_{P_e} , I_{E_0} and I_n denote, respectively, the impacts of P_e , E_0 and n on R or E , which can be
 238 expressed by $\frac{\partial E}{\partial P_e} dP_e$, $\frac{\partial E}{\partial E_0} dE_0$ and $\frac{\partial E}{\partial n} dn$, respectively. After getting the contribution of n to the
 239 R and E variations, we can further assess the impacts of M and SAI on the variation of R and E ,
 240 based on the semi-empirical model of n in terms of M and SAI. Following Ning et al. (2017),
 241 the changes of parameter n can be expressed as follows:

$$242 \quad dn = \frac{\partial n}{\partial SAI} dSAI + \frac{\partial n}{\partial M} dM \quad (11)$$

243 Then, the relative contributions of SAI (C_{SAI}) and M (C_M) to the changes of parameter n
 244 can be obtained. Combining with the contribution of n to the R and E changes, the relative
 245 contributions of SAI and M to the variations of R and E can be obtained:

$$246 \quad C_{SAI} = C_n \times C_{SAI}, \quad C_M = C_n \times C_M \quad (12)$$

247

248 **4. Results**

249 **4.1 Performance of the proposed SAI in the Budyko framework**

250 Figure 2 shows that eq. (6) with SAI has a better performance in simulating P and E_0 than
 251 eq. (4) with SI. Here we further assessed the performance of these two indices, by comparing
 252 with the controlling parameter n in the Budyko framework. Parameter n for each year was first



253 calibrated by eq. (2). The calibrated parameter n was called optimized n . For the
254 representativeness of the relation between n and other factors, analysis was done at a larger
255 spatial scale with different climate conditions by combining data from 26 global large basins
256 (Figure 3). The correlation coefficient (r) between SI and optimized n was 0.47 (Figure 3a). If
257 the asynchrony of seasonal P and E_0 was considered in SI, i.e., SAI, r increased to 0.68 (Figure
258 3b). In addition, the accuracy of simulated n using SAI as a predictor was higher than that using
259 SI, i.e., R^2 was 0.46 for the former compared to 0.22 for the latter (Figure 4a and 4b). In short,
260 although SI showed a significant relationship with n , SAI considering both seasonality and
261 asynchrony of P and E_0 was more applicable to represent the difference between water and
262 energy, and better performed in the simulation of n in the Budyko model.

263 <Figure 4 here please>

264 To further assess the impact of SAI on the fluvial water balance, we also analyzed the roles
265 of SAI in Budyko framework and climate elasticity (Figure 3e, Figure 5). As shown in Figure
266 3e, a larger value of n was related to a higher evapotranspiration ratio for a given aridity index,
267 and as SAI increased, the value of controlling parameter n tended to decrease. In other words,
268 catchments with a larger SAI had a lower evapotranspiration ratio given the same aridity index.
269 This result is similar to the finding from Zhang et al (2015), who found that a larger snow ratio
270 caused a higher runoff index for a given dryness index. In contrast, this relationship is not
271 distinct for SI (Figure 3d).

272 Figure 5 shows the spatial patterns of climate elasticities and their relationship with SAI. The
273 climate elasticities of precipitation and parameter n to evapotranspiration increased with SAI,
274 whereas the elasticity of potential evapotranspiration to evapotranspiration decreased with SAI



275 (Figure 5), implying that the variation of evapotranspiration in the catchments with a higher
276 SAI were more sensitive to the changes of precipitation and parameter n , but less sensitive to
277 the changes of potential evapotranspiration.

278 <Figure 5 here please>

279 **4.2 A semi-empirical formula for parameter n**

280 Previous studies have found that vegetation cover is closely related to the spatial variation of
281 n in different regions (e.g., Li et al. 2013). However, the new finding in this study is that
282 vegetation dynamics (M) also has a significant impact on the temporal variation of annual
283 values of parameter n (Figure 3c; Figure 4c) and evapotranspiration ratio (Figure 3f). As shown
284 in Figure 4c, M can explain 67% of spatiotemporal variance of annual n with MAE of 0.28.
285 Nevertheless, the simulation accuracy of n can be further improved, particularly at the high end.
286 As mentioned above, SAI has a significant impact on the variation of n . Therefore, based on
287 the results obtained by Li et al. (2013), it is possible to develop a more dynamic model to capture
288 the spatiotemporal variation of parameter n , and improve the simulation of n by incorporating
289 SAI into the empirical model.

290 Following the phenomenological considerations and the relationships demonstrated in
291 Figures 3b and 3c, the limiting conditions of SAI and M were achieved: (1) If $SAI \rightarrow +\infty$,
292 which indicates that the match of P and E_0 tends to be the worst, and thus $R \rightarrow P$ and $E \rightarrow$
293 0 , i.e., $n \rightarrow 0$; (2) When $M \uparrow$, then $E \uparrow$, which has been demonstrated by previous studies (i.e.,
294 Yang et al., 2009; Li et al., 2013), and thus $n \uparrow$, which can also be found in Figures 3c and 3f.
295 Based on these limiting conditions, a semi-empirical formula for parameter n was obtained as:

$$296 \quad n = aSAI^bM^c \quad (13)$$



297 where a and b are positive regression coefficients and c is negative. Nonlinear least squares can
298 be used to estimate the values of a , b , and c , based on n calibrated from measured data. Then,
299 the final equation was as follows

$$300 \quad n = 0.27SAI^{-0.30}M^{0.90} \quad (14)$$

301 As shown in Figure 4d, the simulated n calculated by semi-empirical formula match well with
302 the optimized n with R^2 of 0.82 and MAE of 0.2.

303 In addition to the semi-empirical formulae, multiple linear regression (MLR) is often applied
304 to simulate n . For example, taking NDVI, latitude, and topographic index as explanatory
305 variables, Xu et al. (2013) applied MLR to estimate the spatial variation of n for the global large
306 river basins. Accordingly, we also fitted parameter n by MLR. As shown in Figure 4e, the values
307 of R^2 and MAE of the simulated n by using MLR were 0.72 and 0.23, respectively, which was
308 not as good as the performance of the semi-empirical formulae. Therefore, the semi-empirical
309 formula was a better choice not only for simulation but also for explaining the physical meaning.

310 Cross-validation was used to validate the semi-empirical equation. The dataset for one basin
311 was used for validation, and the dataset for the remaining 25 basins were used for calibration.
312 Then the cross-validation process is repeated 26 times, with each of 26 basins used once as
313 validation. Parameter n for the validation basin was simulated by the semi-empirical formula
314 obtained from the other 25 basins. Subsequently, based on annual P_e , E_0 and simulated annual
315 parameter n , simulated annual R and E were calculated using eq. (2). The simulated annual R
316 and E for each validation basin were combined to compare with the observed R and E ,
317 respectively. As shown in Figure 6, the simulated annual R and E showed a remarkable
318 agreement with the observed ones with R^2 larger than 0.96 and MAE smaller than 35 mm. These



319 results indicated that the semi-empirical formula expressed the spatiotemporal variation of
320 parameter n , and the proposed eq. (2) with simulated parameter n was reliable for the simulation
321 of annual R and E .

322 <Figure 6 here please>

323 4.3 Contributions of SAI and other factors to R and E changes

324 To further assess the impact of SAI on the water balance, here we quantified the contributions
325 of SAI and other factors, i.e. P_e , E_0 and M , on the variation of R and E (Figures 7 and 8). As
326 can be seen from Figures 7a and 7c, the P_e changes controlled the variation of R in most basins,
327 with 18 of the 26 selected basins. The contributions of P_e changes to R changes ranged from
328 11% to 96% with the median value at 61% for the 26 basins (Fig 7b). In addition to the P_e
329 changes, the SAI change was also an important factor for the R change with the median
330 contribution at 15%. SAI was the dominant factor with the maximum contribution to R changes
331 in six rivers, such as Yangtze, Yellow, Aral, Northern Dvina, Congo and Mississippi basin. The
332 E_0 changes had a limited impact on the R changes with the median contribution of 8%. However,
333 it is the dominant factor for R changes in Danube River basins.

334 <Figures 7 and 8 here please>

335 The dominant factors of E changes were different from those of R changes (Figure 8). Both
336 the SAI and M changes had remarkable impacts on the E changes, which were the dominant
337 factors for the E changes within eight and five basins, respectively. Also, the contributions of
338 SAI and M changes to E changes were larger than those to R changes with the median
339 contributions of 19% and 21%, respectively. Accordingly, the contribution of P_e to E changes
340 was weaker than that to R changes, the median of which dropped from 61% to 35%.



341 In summary, P_e was the key controlling factor for R and E in most river basins. SAI was the
342 dominant factor for both R and E mainly in East Asian subtropical monsoon zones, such as
343 Yangtze and Yellow River basins. M was the dominant factor for both R and E in the temperate
344 grassland zone of South America, i.e., Parana River basin. E_0 had a limited impact on both R
345 and E , but it is the dominant factor for both R and E changes in temperate maritime climate of
346 Europe, i.e., Danube River basin.

347

348 **5. Discussion**

349 It has been found that both vegetation coverage and climate seasonality have impacts on
350 water balance (Chen et al., 2013; Li et al., 2013; Zeng and Cai, 2016; Abatzoglou and Ficklin,
351 2017; Ning et al., 2017; Zhang et al., 2016a). Li et al. (2013) found that long-term vegetation
352 coverage was closely related to the spatial variation of the calibrated parameter of the Budyko
353 model in global river basins. However, vegetation dynamics also influenced the temporal
354 variation of parameter n , but the relationship remained to be verified over a larger spatial range
355 (Zhang et al., 2016c; Ning et al., 2017). Results of this study confirmed that the vegetation
356 dynamics had a significant impact on both spatial and temporal variations of the controlling
357 parameter n at the global scale.

358 The seasonality index represents the amplitude difference of seasonal P and E_0 , but does not
359 include the phase difference of seasonal P and E_0 . Investigating the water balance across the
360 Loess Plateau in China, Ning et al. (2017) found that seasonal index, SI, was closely related to
361 the controlling parameter. In this study, however, SI showed a worse correlation with the
362 variation of n in the 26 large global river basins than those in Loess Plateau. All catchments



363 selected by Ning et al. (2017) were in the monsoon climate zone, where water and energy are
364 strongly coupled, so the seasonality of P and E_0 in most catchments was in the same phase.
365 Hence, the asynchrony of water and energy was nonexistent and had a limited impact on the
366 variation of n . In contrast, the basins selected in this study covered a large spatial scale with a
367 wide range of climate types. Most basins had different phases between seasonal P and E_0 , such
368 as the Northern Dvina with the phase differences larger than two months. The amplitude
369 difference between seasonal P and E_0 cannot adequately represent the difference between water
370 and energy in the basins with out-of-phase P and E_0 (Hickel and Zhang, 2006). In this case,
371 SAI, considering both amplitude and phase differences between seasonal of P and E_0 , was
372 proposed to reflect the difference between water and energy. Results showed that the proposed
373 SAI had a significant impact on n and evapotranspiration ratio, as well as the sensitively of
374 evapotranspiration to the variation of precipitation, potential evapotranspiration, and
375 catchments characteristics. SAI can also be applied to other studies on water-energy balance.

376 In small-size catchments, interactions between climate variability, vegetation dynamics, and
377 water balance are more complex (Li et al., 2013). Many other factors, such as basins area,
378 latitude, slope gradient, compound topographic index, and so on (Abatzoglou and Ficklin, 2017;
379 Xu et al., 2013; Yang et al., 2009), have been identified to play a role in the spatial distribution
380 of n for small-size catchments. However, in this study, these factors had little changes at the
381 annual time scale, so they were not considered in determining the annual variation of n . This
382 study demonstrated that SAI and M play an important role in the spatiotemporal variation of n
383 in large river basins, nevertheless, other factors should also be considered in the simulation of
384 spatial variation of n for small-size catchments.



385 SAI was identified to have a great influence on the changes of R and E . Especially, the
386 changes of both R and E for the two major rivers (i.e., Yangtze and Yellow River basins) in East
387 Asian monsoon zone is mainly controlled by SAI. Hoyos and Webster, (2007) found that the
388 variation of monsoon systems remarkably affects the climate seasonal pattern (Hoyos and
389 Webster, 2007). Using the covariance of P and E_0 as an explanatory variable, Zeng and Cai
390 (2016) indicated that the seasonality of P and E_0 had a significant impact on the E variation,
391 such as the Yangtze River basin. Their results are generally consistent with ours. To assess the
392 impact of ecological restoration on runoff in the Loess Plateau of China, Liang et al. (2015)
393 regarded the ecological restoration, i.e., vegetation dynamics, as the cause of changes in n .
394 However, our results showed that SAI also played an important role in the changes of n ,
395 particularly for the East Asian subtropical monsoon zone.

396 E_0 is the mainly controlling factor for the changes of both R and E in Danube river. The
397 increased air temperature (Busuioc et al, 2010) increase the potential evapotranspiration
398 significantly for the Danube river, which make a deficit increase and a decrease of excess water
399 from precipitation (Bandoc et al., 2012). As a result, the R and E in Danube river was
400 significantly affected by the E_0 .

401 Although SAI combined with M can well capture the changes of n (Figure 4d), the impact of
402 n on the water balance not only includes SAI and M , but also the human influence, which has
403 been verified by our previous study (Liu et al., 2017a). As a result, this may cause uncertainty
404 in our findings. The human influences on R and E need to be further investigated.

405



406 **6. Conclusions**

407 In this study, a semi-empirical formula was developed to simulate the spatiotemporal
408 variation of the controlling parameter n in the Budyko model. Influences of climate-vegetation
409 factors on water balance were evaluated. The Choudhury-Yang equation modified by the
410 effective precipitation is recommended to calibrate the controlling parameter n and to simulate
411 evapotranspiration (E) and runoff (R), and their variation.

412 A climate seasonality and asynchrony index, i.e., SAI, is proposed to reflect the difference
413 between water and energy. Results show that the optimized n has a much higher correlation
414 with SAI than the existing SI, implying that the phase mismatch between seasonal water and
415 energy should be considered in the impact assessment of water balance. In general, our results
416 suggest that the catchments with a larger SAI usually have a larger evapotranspiration ratio
417 given the same climatic and underlying condition, and the variation of evapotranspiration tends
418 to be more sensitive to the changes of precipitation and landscape properties (parameter n),
419 whereas less sensitive to the potential evapotranspiration in the catchments with larger SAI.
420 Furthermore, this study confirms that vegetation dynamics (M) also plays an important role in
421 modifying the temporal variation of n at the annual scale. Based on SAI and M , a semi-empirical
422 formula for the spatiotemporal variation of parameter n has been developed, and it performs
423 well in the prediction of annual evapotranspiration and runoff.

424 Employing the developed semi-empirical formula, the contributions of SAI and M , as well
425 as P_e and E_0 , to the variation of E and R were assessed. Results show that precipitation is the
426 first-order control on the R and E changes, and, secondly, SAI was found to control the changes
427 of R and E in the subtropical monsoon regions of East Asian. SAI, M and E_0 have large impacts



428 on E than on R , whereas P_e has larger impacts on R .

429 The study assesses the influence of climate variability and vegetation dynamics on water
430 balance, which highlights the role of climate seasonality and asynchrony as well as vegetation
431 dynamics in the annual variation of n , and sheds new light on the difference in the contributions
432 of climate-vegetation factors to the changes in R and E . This study can be useful for water-
433 energy modelling, hydrological forecasting, and water management.

434

435 **Acknowledgments:** This work is financially supported by the National Science Foundation for
436 Distinguished Young Scholars of China (Grant No.: 51425903), the Fund for Creative Research
437 Groups of National Natural Science Foundation of China (Grant No.: 41621061), National
438 Natural Science Foundation of China (No. 41771536) and by Key Project of National Natural
439 Science Foundation of China (Grant No.: 51190091), National Natural Science Foundation of
440 China under Grant No. 41401052. We would like to thank Ming Pan (mpan@princeton.edu),
441 Dan Li (danl@princeton.edu) at Princeton University and Xianli Xu (xuxianliww@gmail.com)
442 at Chinese Academy of Sciences for sharing basin data set. Information of the data were
443 provided with great details in the Data section and further message concerning data please write
444 to zhangq68@bnu.edu.cn.

445

446 **References**

447 Abatzoglou, J. T., and Ficklin, D. L.: Climatic and physiographic controls of spatial variability
448 in surface water balance over the contiguous United States using the Budyko relationship,
449 Water Resour. Res., 10.1002/2017wr020843, 2017.



- 450 Arnell, N. W., and Gosling, S. N.: The impacts of climate change on river flow regimes at the
451 global scale, *J. Hydrol.*, 486, 351-364, 2013.
- 452 Bandoc, G.: Estimation of the annual and interannual variation of potential evapotranspiration,
453 *Evapotranspiration-Remote Sensing and Modeling*, InTech, 251-272, 2012.
- 454 Berghuijs, W. R., & Woods, R. A.: A simple framework to quantitatively describe monthly
455 precipitation and temperature climatology, *Int. J. Climatology*, 36(9), 3161-3174, 2016.
- 456 Biswal, B.: Dynamic hydrologic modeling using the zero-parameter Budyko model with
457 instantaneous dryness index, *Geophys. Res. Lett.*, 43, 9696-9703, 10.1002/2016gl070173,
458 2016.
- 459 Buermann, W.: Analysis of a multiyear global vegetation leaf area index data set, *J. Geophys.*
460 *Res.-Atmos.*, 107, 10.1029/2001jd000975, 2002.
- 461 Busuioc, A.; Caian, M.; Cheval, S.; Bojariu, R.; Boroneant, C.; Baciu, M.; Dumitrescu, A.:
462 *Climate variability and change in Romania*, Ed. ProUniversitaria, 59-72, ISBN 978-973-
463 129-549-7, București, România 2010.
- 464 Cai, D., Fraedrich, K., Sielmann, F., Guan, Y., Guo, S., Zhang, L., and Zhu, X.: Climate and
465 vegetation: An ERA-interim and GIMMS NDVI analysis, *J. Climate*, 27, 5111-5118, 2014.
- 466 Chen, X., Alimohammadi, N., and Wang, D.: Modeling interannual variability of seasonal
467 evaporation and storage change based on the extended Budyko framework, *Water Resour.*
468 *Res.*, 49, 6067-6078, 10.1002/wrcr.20493, 2013.
- 469 Choudhury, B.: Evaluation of an empirical equation for annual evaporation using field
470 observations and results from a biophysical model, *J. Hydrol.*, 216, 99-110, 1999.
- 471 Dagon, K., and Schrag, D. P.: Exploring the effects of solar radiation management on water



- 472 cycling in a coupled land–atmosphere model. *J. Climate*, 29, 2635–2650, 2016.
- 473 Donohue, R. J., Roderick, M. L., and McVicar, T. R.: Roots, storms and soil pores:
474 Incorporating key ecohydrological processes into Budyko’s hydrological model, *J. Hydrol.*,
475 436–437, 35–50, 10.1016/j.jhydrol.2012.02.033, 2012.
- 476 Fu, B. P.: On the calculation of the evaporation from land surface, *Sci. Atmos. Sin.*, 5, 23–31,
477 1981 (in Chinese).
- 478 Gentine, P., D’Odorico, P., Lintner, B. R., Sivandran, G., and Salvucci, G.: Interdependence of
479 climate, soil, and vegetation as constrained by the Budyko curve, *Geophys. Res. Lett.*, 39,
480 n/a–n/a, 10.1029/2012gl053492, 2012.
- 481 Greve, P., Gudmundsson, L., Orlowsky, B., and S. I. Seneviratne: The Budyko framework
482 beyond stationarity, *Hydrol. Earth Syst. Sci. Discuss*, 12, 6799–6830, 2015.
- 483 Gutman, G., and Ignatov, A.: The derivation of the green vegetation fraction from
484 NOAA/AVHRR data for use in numerical weather prediction models, *Int. J. Remote*
485 *Sens.*, 19, 1533–1543, 1998.
- 486 Hickel, K., and Zhang, L.: Estimating the impact of rainfall seasonality on mean annual water
487 balance using a top-down approach, *J. Hydrol.*, 331, 409–424, 2006.
- 488 Hoyos, C. D., and Webster, P. J.: The role of intraseasonal variability in the nature of Asian
489 monsoon precipitation, *J. Climate*, 17, 4402–4424, 2007.
- 490 Koster, R. D. and Suarez, M. J.: A simple framework for examining the interannual variability
491 of land surface moisture fluxes, *J. Climate*, 12, 1911–1917, 1999.
- 492 Legates, D. R., and McCabe, G. J.: Evaluating the use of “goodness - of - fit” measures in
493 hydrologic and hydroclimatic model validation, *Water Resour. Res.*, 35, 233–241, 1999.



- 494 Li, D., Pan, M., Cong, Z., Zhang, L., and Wood, E.: Vegetation control on water and energy
495 balance within the Budyko framework, *Water Resour. Res.*, 49, 969-976,
496 10.1002/wrcr.20107, 2013.
- 497 Liang, W., Bai, D., Wang, F., Fu, B., Yan, J., Wang, S., Yang, Y., Long, D., and Feng, M.:
498 Quantifying the impacts of climate change and ecological restoration on streamflow
499 changes based on a Budyko hydrological model in China's Loess Plateau, *Water Resour.*
500 *Res.*, 51, 6500-6519, 2015.
- 501 Liu, J., Zhang, Q., Singh, V. P., and Shi, P.: Contribution of multiple climatic variables and
502 human activities to streamflow changes across China, *J. Hydrol.*, 545, 145-162, 2017a.
- 503 Liu, J., Zhang, Q., Zhang, Y., Chen, X., Li, J., and Aryal, S. K.: Deducing climatic elasticity to
504 assess projected climate change impacts on streamflow change across China, *J. Geophys.*
505 *Res.-Atmos.*, 2017b.
- 506 Milly, P. C. D.: Climate, soil water storage, and the average annual water balance, *Water Resour.*
507 *Res.*, 30, 2143-2156, 1994.
- 508 Ning, T., Li, Z., and Liu, W.: Vegetation dynamics and climate seasonality jointly control the
509 interannual catchment water balance in the Loess Plateau under the Budyko framework,
510 *Hydrol. Earth Syst. Sci.*, 21, 1515-1526, 10.5194/hess-21-1515-2017, 2017.
- 511 Pan, M., Sahoo, A. K., Troy, T. J., Vinukollu, R. K., Sheffield, J., and Wood, E. F.: Multisource
512 Estimation of Long-Term Terrestrial Water Budget for Major Global River Basins, *J.*
513 *Climate*, 25, 3191-3206, 10.1175/jcli-d-11-00300.1, 2012.
- 514 Potter, N. J., Zhang, L., Milly, P. C. D., McMahon, T. A., and Jakeman, A. J.: Effects of rainfall
515 seasonality and soil moisture capacity on mean annual water balance for Australian



- 516 catchments, *Water Resour. Res.*, 41, 10.1029/2004wr003697, 2005.
- 517 Wang, D., and Alimohammadi, N.: Responses of annual runoff, evaporation, and storage
518 change to climate variability at the watershed scale, *Water Resour. Res.*, 48,
519 doi:10.1029/2011WR011444, 2012.
- 520 Weiss, M., and Coauthors: Contribution of dynamic vegetation phenology to decadal climate
521 predictability, *J. Climate*, 27, 8563-8577, 2014.
- 522 Woods, R.: The relative roles of climate, soil, vegetation and topography in determining
523 seasonal and long-term catchment dynamics, *Adv. Water Resour.*, 26, 295-309, 2003.
- 524 Woods, R. A.: Analytical model of seasonal climate impacts on snow hydrology: Continuous
525 snowpacks. *Adv. Water Resour.*, 32, 1465-1481, doi:10.1016/j.advwatres.2009.06.011,
526 2009.
- 527 Xu, X., Liu, W., Scanlon, B. R., Zhang, L., and Pan, M.: Local and global factors controlling
528 water-energy balances within the Budyko framework, *Geophys. Res. Lett.*, 40, 6123-6129,
529 10.1002/2013gl058324, 2013.
- 530 Yan, J. W. and Coauthors: Changes in the land surface energy budget in eastern China over the
531 past three decades: Contributions of land-cover change and climate change. *J. Climate*, 27,
532 9233-9252, 2014.
- 533 Yang, D., Sun, F., Liu, Z., Cong, Z., Ni, G., and Lei, Z.: Analyzing spatial and temporal
534 variability of annual water-energy balance in nonhumid regions of China using the Budyko
535 hypothesis, *Water Resour. Res.*, 43, , 10.1029/2006wr005224, 2007.
- 536 Yang, D., Shao, W., Yeh, P. J. F., Yang, H., Kanae, S., and Oki, T.: Impact of vegetation coverage
537 on regional water balance in the nonhumid regions of China, *Water Resour. Res.*, 45,



- 538 10.1029/2008wr006948, 2009.
- 539 Yang, H., Yang, D., Lei, Z., and Sun, F.: New analytical derivation of the mean annual water-
540 energy balance equation, *Water Resour. Res.*, 44, n/a-n/a, 10.1029/2007wr006135, 2008.
- 541 Yang, H., Lv, H., Yang, D., and Hu, Q.: Seasonality of precipitation and potential
542 evaporation and its impact on catchment water energy balance, *Journal of Hydroelectric
543 Engineering, Journal of Hydroelectric Engineering*, 31, 54-59, 2012 (in Chinese).
- 544 Ye, S., Li, H.-Y., Li, S., Leung, L. R., Demissie, Y., Ran, Q., and Blöschl, a. G.: Vegetation
545 regulation on streamflow intra - annual variability through adaption to climate variations,
546 *Geophys. Res. Lett.*, 42, 10.1002/, 2015.
- 547 Zeng, R., and Cai, X.: Climatic and terrestrial storage control on evapotranspiration temporal
548 variability: Analysis of river basins around the world, *Geophys. Res. Lett.*, 43, 185-195,
549 10.1002/2015gl066470, 2016.
- 550 Zhang, D., Cong, Z., Ni, G., Yang, D., and Hu, S.: Effects of snow ratio on annual runoff within
551 the Budyko framework. *Hydrol. Earth Syst. Sci.*, 19, 1977-1992, 2015.
- 552 Zhang, D., Liu, X., Zhang, Q., Liang, K., and Liu, C.: Investigation of factors affecting intra-
553 annual variability of evapotranspiration and streamflow under different climate conditions,
554 *J. Hydrol.*, 543, 759-769, 10.1016/j.jhydrol.2016.10.047, 2016a.
- 555 Zhang, Q., Liu, J., Singh, V. P., Gu, X., and Chen, X.: Evaluation of impacts of climate change
556 and human activities on streamflow in the Poyang Lake basin, China, *Hydrol. Process.*, 30,
557 2562-2576, 10.1002/hyp.10814, 2016b.
- 558 Zhang, S., Yang, H., Yang, D., and Jayawardena, A. W.: Quantifying the effect of vegetation
559 change on the regional water balance within the Budyko framework, *Geophys. Res. Lett.*,



560 43, 1140-1148, 10.1002/, 2016c.
561



562 Table 1. Long-term annual mean meteorological and hydrological characteristics and vegetation coverage

563 (1984-2006) for the 26 large river basins around the world.

Number	Basins	P (mm)	E_0 (mm)	ΔS (mm)	E (mm)	R (mm)	M	SAI	n
1	Amazon	2173	1284	6	1145	1022	9.2	0.5	2.3
2	Amur	411	756	-5	282	134	3.8	0.9	1.1
3	Aral	255	1129	-22	209	68	2.4	0.8	0.9
4	Columbia	566	916	-20	318	268	4.7	1.9	0.9
5	Congo	1371	1175	9	1008	354	8.8	0.2	3.3
6	Danube	733	742	-14	498	249	6.7	0.7	1.8
7	Indigirka	223	345	6	73	144	2.4	1.6	0.5
8	Indus	450	1315	-6	293	163	2.5	1.3	0.8
9	Kolyma	267	355	6	125	137	2.6	1.2	0.8
10	Lena	352	436	4	180	168	3.6	1.0	0.9
11	Mackenzie	392	462	2	212	178	4.4	1.0	1.0
12	Mississippi	776	1104	-3	578	201	6.1	0.7	1.6
13	Niger	616	1958	-10	423	202	3.2	1.5	0.8
14	Nile	543	1863	-2	421	124	3.7	0.7	1.0
15	Northern Dvina	588	479	-10	267	330	6.3	0.9	1.0
16	Ob	474	597	-2	275	200	4.7	1.1	1.1
17	Olenek	277	370	-2	113	166	2.5	1.4	0.7
18	Parana	1242	1307	-14	982	274	8.4	0.5	2.6
19	Pearl	1424	967	-7	627	804	6.1	0.7	1.2
20	Pechora	544	394	2	186	356	3.8	0.8	0.8
21	Senegal	318	2014	-8	284	41	2.0	2.2	1.0
22	Volga	568	651	-11	354	225	5.6	1.2	1.3
23	Yangtze	1000	857	-3	378	625	5.4	0.5	0.8
24	Yellow	424	919	-5	324	105	3.4	0.8	1.2
25	Yenisei	430	468	-6	227	209	4.3	0.8	1.0
26	Yukon	268	383	16	86	166	3.7	1.1	0.5

564



565 **Figure captions**

566 **Figure 1.** Two examples showing the mismatch between precipitation (P) and potential
567 evapotranspiration (E_0), in terms of (a) seasonal amplitudes (δ_P , δ_{E_0}) and (b) phase shift
568 (S_P , S_{E_0}).

569 **Figure 2.** Comparing the observed and simulated monthly precipitation and potential
570 evapotranspiration, using the sine function with fixed phase (i.e., Eq. (4)) and fitted phase
571 (i.e., Eq. (6)).

572 **Figure 3.** Relationship between optimized n and (a) SI, (b) SAI and (c) M. (d-f) Distribution of
573 evapotranspiration ratio (E/P_e) as a function of the aridity index (E_0/P_e) classified by 26
574 global large river basins at annual scale. The Budyko curves from the top down are derived
575 from eq. (2b) with $n=\infty$, $n=5$, $n=2$, $n=1$, $n=0.6$ and $n=0.4$, respectively. Noted that each
576 point represents one year based on the combined dataset from 26 global large basins.

577 **Figure 4.** Optimized (calibrated) n versus simulated n modeled by (a) SI, (b) SAI, (c) M, (d) M
578 and SAI using the semi-empirical formula (SEF, eq. (14)), and (e) M and SAI using the
579 multiple linear regression (MLR). Noted that each point represents one year based on the
580 combined dataset from 26 global large basins.

581 **Figure 5.** The climatic elasticity of evapotranspiration to the changing precipitation, potential
582 evaporation and other factors represented by controlling parameter n in the 26 global large
583 river basins, and its relations with the climate seasonality and asynchrony index (SAI).
584 Noted that each point represents one of the 26 global large basins.

585 **Figure 6.** Simulation versus observation for (a) annual evapotranspiration and (b) annual runoff
586 by using Eq. (2) with the simulated parameter n regarding M and SAI as predictor using

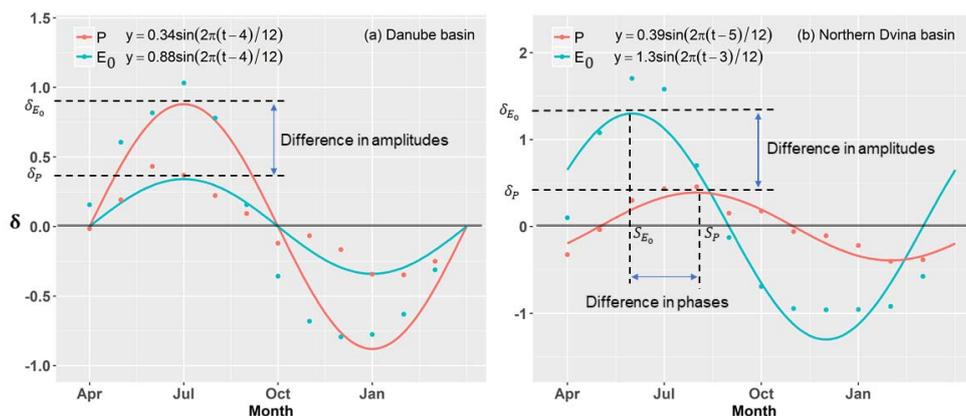


587 the semi-empirical formula (i.e., eq. (14).

588 **Figure 7.** Relative contributions to the long-term mean changes of Runoff (before and after
589 changepoint) from P_e , SAI, M) and E_0 changes. The distribution ranges of relative
590 contribution for each factor are shown in (b) and the number of basins dominated by each
591 factor with the largest relative contribution is summarized in (c).

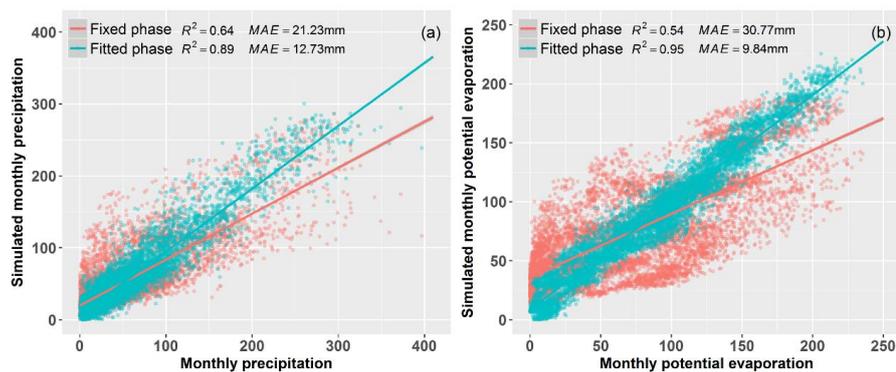
592 **Figure 8.** The same as Figure 7 but for relative contribution to the changes of evapotranspiration.

593



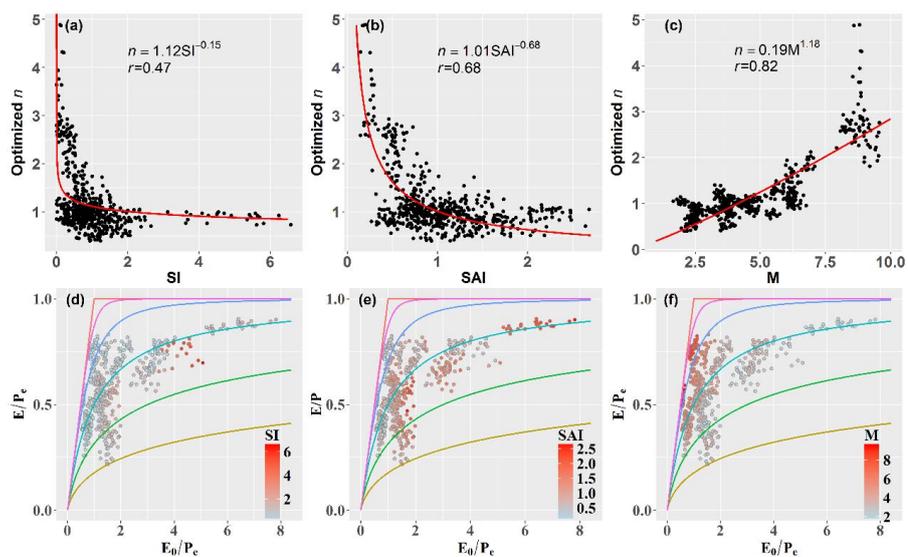
594

595 **Figure 1.** Two examples showing the mismatch between long-term monthly precipitation (P) and potential
 596 evapotranspiration (E_0), in terms of (a) seasonal amplitudes (δ_P , δ_{E_0}) and (b) phase shift (S_P , S_{E_0}).
 597



598
599
600
601
602

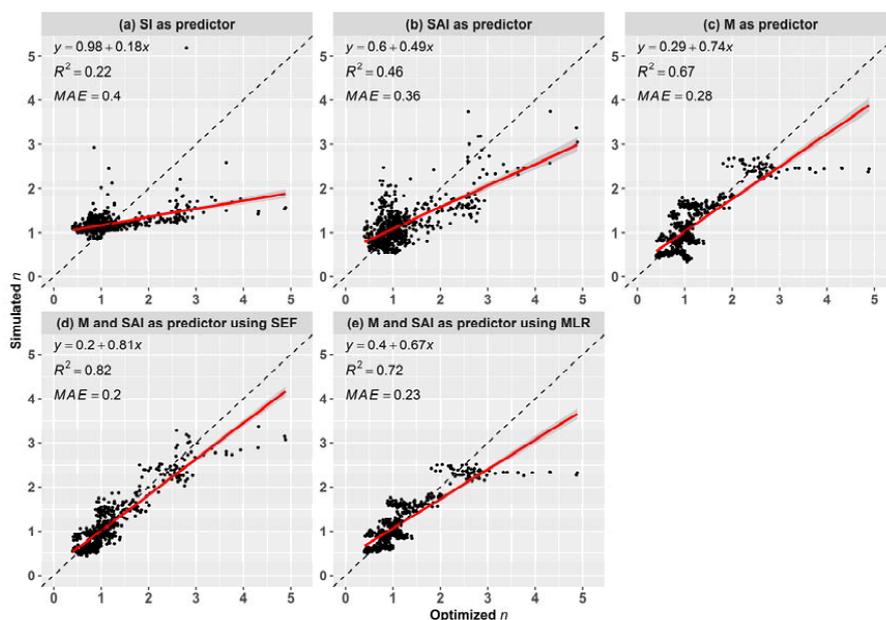
Figure 2. Comparing the observed and simulated monthly precipitation and potential evapotranspiration, using the sine function with fixed phase (i.e., Eq. (4)) and fitted phase (i.e., Eq. (6)). Noted that each point represents one-month data based on the combined dataset from 26 global large basins.



603

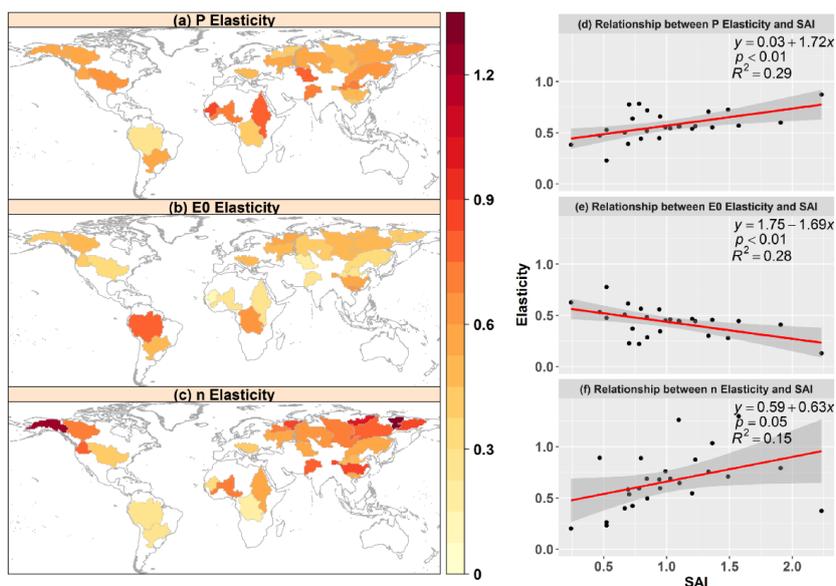
604 **Figure 3.** Relationship between optimized n and (a) SI, (b) SAI and (c) M. (d-f) Distribution of
 605 evapotranspiration ratio (E/P_c) as a function of the aridity index (E_0/P_c) classified by 26 global large river
 606 basins at annual scale. The Budyko curves from the top down are derived from eq. (2b) with $n=\infty$, $n=5$,
 607 $n=2$, $n=1$, $n=0.6$ and $n=0.4$, respectively. Noted that each point represents one year based on the combined
 608 dataset from 26 global large basins.

609



610
611
612
613
614
615

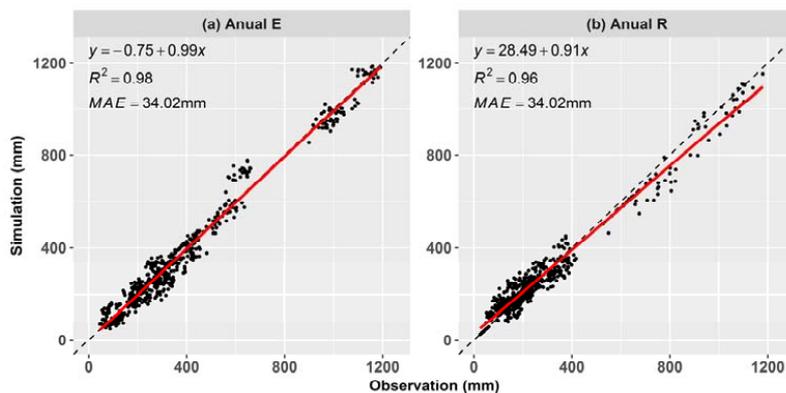
Figure 4. Optimized (calibrated) n versus simulated n modeled by (a) SI, (b) SAI, (c) M, (d) M and SAI using the semi-empirical formula (SEF, eq. (14)), and (e) M and SAI using the multiple linear regression (MLR). Noted that each point represents one year based on the combined dataset from 26 global large basins.



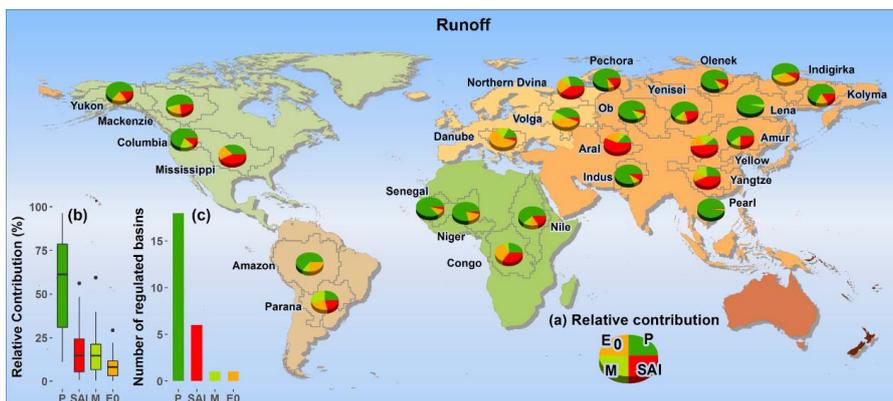
616

617 **Figure 5.** The climatic elasticity of evapotranspiration to the changing precipitation, potential evaporation
618 and other factors represented by controlling parameter n in the 26 global large river basins, and its relations
619 with the climate seasonality and asynchrony index (SAI). Noted that each point represents one of the 26
620 global large basins.

621



622
623 **Figure 6.** Simulation versus observation for (a) annual evapotranspiration and (b) annual runoff by using
624 Eq. (2) with the simulated parameter n regarding M and SAI as predictor using the semi-empirical formula
625 (i.e., eq. (14)).



626
 627 **Figure 7.** Relative contributions to the long-term mean changes of Runoff (before and after changepoint)
 628 from P_e , SAI, M and E_0 changes. The distribution ranges of relative contribution for each factor are shown
 629 in (b) and the number of basins dominated by each factor with the largest relative contribution is summarized
 630 in (c).

