

1    **Impacts of climate or vegetation changes on evapotranspiration and**  
2    **streamflow trends in a large water-limited basins?**

3

4                                    Qiang Liu<sup>1,2</sup>, Zhifeng Yang<sup>1,2</sup>, Liqiao Liang<sup>3</sup>, Nan Wang<sup>1,2</sup>

5

6    1 Key Laboratory for Water and Sediment Sciences, Ministry of Education, School of Environment,  
7    Beijing Normal University, Beijing 100875, China

8    2 State Key Laboratory of Water Environment Simulation, School of Environment, Beijing Normal  
9    University, Beijing 100875, China

10   3 Key Laboratory of Tibetan Environment Changes and Land Surface Processes, Institute of Tibetan  
11   Plateau Research, Chinese Academy of Sciences, Beijing 100101, China

12

**Abstract:**

Hydrological processes regulate interactions between climate, vegetation, and soil, particularly in water-limited regions. Causes behind changes in evapotranspiration ( $E$ ) and streamflow ( $Q$ ) in water-limited regions in the Yellow River Basin (YRB), China, were investigated in this study. It was assumed that vegetation type and extent remained fixed and unchanged throughout the study period while the effective rooting depth ( $Z_e$ ) changed under climate change scenarios. The Budyko framework was used to explore climate change and vegetation impacts on  $E$  and  $Q$  on static vegetation and dynamic vegetation rooting depths. Both precipitation ( $P$ ) and potential evapotranspiration ( $E_p$ ) exhibited negative trends, which resulted in decreasing trends in dynamic  $Z_e$  scenarios. Decreasing trends in  $Z_e$  in combination with climatic changes altered the partitioning of  $P$  into  $E$  and  $Q$ . For the dynamic scenario, total  $E$  and  $Q$  were predicted at  $-1.73\%$  and  $28.22\%$ , respectively, greater by comparison to the static scenario. Although climate change regulated changes in  $E$  and  $Q$ ,  $Z_e$  response to climate change had a greater overall contribution to changes in hydrological processes. Results from this study indicated that with the exception of vegetation type and extent, changes in  $Z_e$  scenarios can also affect the partitioning of  $P$  into  $E$  and  $Q$ , which in itself should help regulate climate change impacts on water resources.

**Key words:** ecohydrological processes; evapotranspiration; streamflow; effective rooting depth; water-limited basin

**1. Introduction**

Partitioning of precipitation ( $P$ ) into evapotranspiration ( $E$ ) and streamflow ( $Q$ ) on land surfaces reflects a hydrologic response to land use and climate forcing. Given that this phenomenon impacts water availability globally (Xu et al., 2013), understanding such processes is critical to improve water

resource management practices. A large number of studies have previously been conducted to quantify climate or vegetation change impacts on catchment water balances. Evidence shows that changes in climatic conditions that result from  $P$  and potential evapotranspiration ( $E_p$ ), for example, have a sizeable impact on  $Q$  (e.g., IPCC, 2007; Oudin et al., 2009; Liang et al., 2013). Additionally, changes in land use type can dramatically alter water balances on different scales, such as the reduction in  $Q$  observed in the Loess Plateau, China, that the Grain for Green project (GGP) had identified (McVicar et al., 2010) (GGP is an ecological restoration initiative that was instigated in 1999 by the Chinese Central Government to re-vegetate former farming and grazing land with perennial species). For these reasons, quantifying impacts of climate and vegetation change on  $Q$  remains a challenge for hydrological sciences.

Along with complex, physically-based distributed hydrological models (bottom-up approach), simple coupled water and energy balance models (top-down approach), such as the Budyko framework, have attracted considerable attention in recent years (e.g., Zhang et al., 2001; Yang et al., 2007; Brümmer et al., 2012; Donohue et al., 2012). According to the Budyko framework (1974), available water and energy are the primary factors that determine  $E$  rates, which also control the partitioning of  $P$  into  $E$  and  $Q$ . Because the original version of the Budyko model only included climatic variables, an adjustable parameter has been incorporated into the model to reflect the influence of watershed characteristics (e.g., Fu et al., 1981; Choudhury, 1999; Zhang et al., 2001; Yang et al., 2007). Even though this watershed characteristics parameter ( $n$ ) has been investigated by a number of studies (Zhang et al., 2001; Yang et al., 2009; Donohue et al., 2010), its relation to physical attributes remains obscure (Gerrits et al., 2009; Donohue et al., 2012; Liu and McVicar, 2012). Combining equations by Choudhury (1999) and Porporato et al. (2004), Donohue et al. (2012) deduced relationships between  $n$

and ecohydrological processes, such as storm depth ( $\alpha$ ), the plant-available soil water holding capacity ( $\kappa$ ), and the effective rooting depth ( $Z_e$ ), which offers new insight into understanding the response of hydrological processes to impacts of climate change and vegetation. While numerous studies have investigated impacts of climate and vegetation on hydrological processes (e.g., Liu and McVicar, 2012; Wang and Tang, 2014), few have explored impacts of vegetation on hydrological processes from the point of view of the response of vegetation to climate change. The objectives of this study were: to explore temporal trends in  $E$  and  $Q$  and assess the relative contribution of climate and vegetation changes on  $E$  and  $Q$  in the Yellow River Basin (YRB), a large water-limited basin in China.

## 2. Hydrological model and materials

### 2.1 Hydrological model

This study employed the improved version of the Budyko hydrological model with the addition of an ecohydrological adjustable parameter ( $n$ ) to assess impacts of climate and vegetation changes on  $E$  and  $Q$ . By incorporating this adjustment parameter, the Budyko model can be expressed as follows (e.g., Choudhury's equation (1999)):

$$E = \frac{PE_p}{(P^n + E_p^n)^{(1/n)}}, \quad (1)$$

where  $n$  is a catchment-specific parameter (dimensionless), which reflects the influence of catchment characteristics on the partitioning of  $P$  between  $E$  and  $Q$ . By combining the equation provided by Porporato et al. (2004) and Choudhury (1999), Donohue et al. (2012) used  $Z_e$ , mean depth per storm event ( $\alpha$ ), and the fractional plant-available water holding capacity ( $\kappa$ ) to explain  $n$ .

$$n = 0.21 \frac{\kappa Z_e}{\alpha} + 0.60. \quad (3)$$

Ignoring changes in storage, this steady state water balance model can be expressed as follows (Donohue et al., 2011; Roderick and Farquhar, 2011; Liu and McVicar, 2012):

$$Q = P - E = P - \frac{PE_p}{(P^n + E_p^n)^{(1/n)}}. \quad (3)$$

Equations (2) and (3) constitute the Budyko-Choudhury-Porporato model (BCP model).

In order to obtain the ecohydrological parameter ( $n$ ),  $\kappa$  was set to static state as designated by the Harmonized World Soil Database (version 1.0) (FAO/IIASA/ISIRC/ISS-CAS/JRC, 2008). Due to the lack of basin wide, long-term, sub-daily  $P$  data used to calculate  $\alpha$ , the variable was estimated using daily  $P$  throughout 1961–2010 (Porporato et al., 2004). Given that  $Z_e$  is comparatively unobservable on a catchment scale (Gao et al., 2014), it was calculated for YRB by applying the  $Z_e$  model by Guswa (2008) for large water-limited basins. The vegetation fraction for trees and grass was calculated by means of the Normalized Difference Vegetation Index (NDVI), and this was obtained from the NASA Ames Ecological Forecasting Lab website (<http://ecocast.arc.nasa.gov/data/pub/gimms/3g/>), which was used to calculate  $Z_e$ . The fraction of vegetation was also used to reflect the extent of vegetation within the entire basin.

## 2.2 Materials

YRB is approximately 5400 km long with a basin drainage area of  $7.95 \times 10^5 \text{ km}^2$  (Fig. 1). Its headwaters originate in the Tibetan Plateau, flowing through the Loess Plateau and the North China Plain before finally emptying into the Bohai Sea. Since most of the river flows through arid and semiarid regions, increased agricultural and industrial water usage in combination with decreases in  $P$  has led to overall decreases in  $Q$  (Liu et al., 2008; McVicar et al., 2002; Nakayama, 2011). Data from the National Climate Center of the China Meteorological Administration (CMA) were used to investigate impacts of climate change on water resources at 89 meteorological stations. Monthly  $E_p$  was calculated from monthly wind speed, daylight hours, relative humidity, and average air temperature using the Penman equation (Shuttleworth 1993). NDVI data were obtained from the

Global Land Cover Facility (<http://www.glcf.umd.edu/>) and were used to calculate the fraction of photosynthetically active radiation (PAR) absorbed by vegetation ( $f_{PAR}$ ).

For this study, it was assumed that vegetation type and extent were fixed and remained unchanged throughout the study period (1961–2010) while  $Z_e$  changed under the dynamic influence of climatic change. Two scenarios were generated for this study in accordance to the BCP model. For the static  $Z_e$  scenario, 1961  $Z_e$  was fixed for the 1961–2010 simulation period. For the dynamic  $Z_e$  scenario,  $Z_e$  was influenced by specific water and energy conditions of each grid cell in accordance with specific changes in climatic conditions.

(Fig. 1)

### 3. Results

#### 3.1 Changes in ecohydrological processes

YRB  $P$  and  $E_p$  temporal trends (1961–2010) are provided in Fig. 2. On a basin scale, the average slope for  $P$  was  $-0.96 \text{ mm a}^{-2}$  with a range between  $-2.37 \text{ mm a}^{-2}$  and  $1.03 \text{ mm a}^{-2}$  (Fig. 2a) while the average slope for  $E_p$  was  $-0.13 \text{ mm a}^{-2}$  with a range between  $-3.38$  and  $1.47 \text{ mm a}^{-2}$  (Fig. 2b).  $E_p/P$  exhibited increasing trends with an average increase of  $0.004 \text{ mm a}^{-2}$  (Fig. 2).

According to conclusions that stated that the higher the  $P$  (or lower  $E_p/P$ ) the deeper the  $Z_e$  (Schenk and Jackson, 2002; Donohue et al., 2012),  $Z_e$  was calculated for YRB, a large water-limited basin in China (data provided in Fig. 3). Average static  $Z_e$  (Fig. 3a) (1961 was used to set the base condition of  $Z_e$ ) ranged between 89 and 2245 mm (with an average of 381 mm) while average dynamic  $Z_e$  throughout 1961–2010 ranged between 82 and 1818 mm. Dynamic  $Z_e$  was influenced by decreasing  $P$  trends, resulting in an insignificant decreasing trend with a slope of  $-0.12 \text{ mm a}^{-2}$ .

(Fig. 3)

#### 4.2 Changes in streamflow and evapotranspiration

(Fig. 4)

Modeled  $E$  time series using the BCP model incorporating dynamic  $n$  (average  $n$  was 1.81 on a basin scale) are provided in Fig. 4. Results showed similar trends to observed  $E$  (calculated using  $P-Q$ ). Furthermore, the Nash–Sutcliffe model efficiency coefficient ( $NSE$ ) reached up to 0.85 for the dynamic  $Z_e$  scenario while  $NSE$  was 0.83 for the static  $Z_e$  scenario. On account of overestimations of high  $E$  (i.e., during years 1961 and 1964) and the underestimation of high  $E$  (i.e., 2002), modeled  $E$  under the dynamic  $Z_e$  scenario exhibited a negative trend ( $-0.81 \text{ mm a}^{-2}$ ) and was thus in opposition to observations ( $0.23 \text{ mm a}^{-2}$ ). Modeled  $E$  under the static  $Z_e$  scenario also exhibited a negative trend with a slope of  $-0.78 \text{ mm a}^{-2}$ .

(Fig. 5)

Relative differences in modeled annual total  $Q$  and  $E$  between static  $Z_e$  and dynamic  $Z_e$  scenarios are provided in Fig. 5. Results showed that: (i) For the dynamic  $Z_e$  scenario (Fig. 4a), total  $E$  was predicted to be 1.73% less than the static  $Z_e$  scenario while, conversely, total  $Q$  (Fig. 4b) was predicted to be 28.22% greater than the static  $Z_e$  scenario; and (ii) decreasing trends were detected in most areas of the basin for  $E$  while increasing trends were detected in most areas of the basin for  $Q$ .

#### 4.3 Relative contribution of climatic and vegetation changes on $E$ and $Q$

Temporal trends in  $E$  calculated from both static and dynamic  $Z_e$  scenarios are respectively provided in Fig. 6a and b. Results showed that: (i) Temporal trends for both static and dynamic  $Z_e$  scenarios exhibited similar spatial patterns, i.e., most areas of the basin contributed to negative (decreasing)  $E$  trends and only the northwestern region contributed to positive (increasing)  $E$  trends; (ii) temporal trends in  $E$  under the static  $Z_e$  scenario ranged between  $-2.70$  and  $1.41 \text{ mm a}^{-2}$  with an average increase of  $-0.81 \text{ mm a}^{-2}$  (Fig. 6a) while temporal trends in  $E$  under the dynamic  $Z_e$  scenario ranged between  $-2.86$  and  $1.41 \text{ mm a}^{-2}$  with an average increase of  $-0.80 \text{ mm a}^{-2}$  (Fig. 6b); and (iii) significant trends

( $P < 0.05$ ) in  $E$  under static (Fig. 6c) and dynamic (Fig. 6d)  $Z_e$  scenarios showed similar patterns for YRB while the extent of these increasing trends per area were significant under the static  $Z_e$  scenario (Fig. 6d).

(Fig. 6)

(Fig. 7)

The relative contribution of climate and vegetation (Fig. 7a and 7b) were calculated for each grid cell. Results showed that climate regulated temporal trends in  $E$  while changes in  $Z_e$  only contributed slightly to changes in  $E$ . Using the differential of  $E$  or  $Q$  to variables (e.g.,  $\partial E/\partial P$ ) multiplied by changes in variables (e.g.,  $dP$ ), contributions of different variables can be obtained ( $\partial E/\partial P * dP$ ). For example, following Donohue et al. (2012), the “typical variability” observed for each variable between 1961 and 2010 was determined (represented by the standard deviation of annual values). Results showed that: (i) Changes in  $P$  caused the greatest variability in  $E$  (or  $Q$ ), generally followed by variability in  $Z_e$ ,  $\alpha$ , and  $E_p$ ; (ii) changes in  $P$  contributed greater to changes in  $E$  (when compared to  $Q$ ); and (iii) summed contributions of climatic variables ( $P$ ,  $E_p$ , and  $\alpha$ ) to  $E$  and  $Q$  were greater than  $Z_e$ , especially for  $E$ .

(Table 1)

## 5. Discussion

As demonstrated by this study (Fig. 1), both  $P$  and  $E_p$  showed decreasing trends while  $E_p/P$  showed a slight increasing trend ( $0.004 \text{ mm a}^{-2}$ ) throughout 1961–2010. Results were consistent with those reported by Liu and McVicar (2012). Decreasing trends in  $P$  (with an average trend of  $-0.96 \text{ mm a}^{-2}$ ) or increasing trends in  $E_p/P$  resulted in decreasing trends in  $Z_e$  (data provided in Fig. 2). Strong interactions are known to exist between climate, vegetation, and soil properties that subsequently result



in specific hydrologic partitioning on a catchment scale (Troch et al., 2013). Inevitably, it is available water ( $P$ ) and energy (represented by  $E_p$ ) that regulate vegetation patterns. Degradation in vegetation caused by decreasing  $P$  has been previously reported in YRB (e.g., Xin et al., 2008). In particular, changes in vegetation extent and type (mainly resulting from human activity) are major causes of  $Q$  change (Li et al. 2007; Liu et al., 2009). For example, changes in vegetation patterns prompted by land use changes (e.g., such as those determined by the Grain for Green project in the Loess Plateau) inevitably alter hydrological processes and result in a decrease in  $Q$  (McVicar et al. 2007; Cao et al., 2011). On the one hand, numerous studies have concluded that vegetation change was the main cause for changes in hydrological processes, such as observed changes in  $Q$  in the Yiluo River basin (Liu et al., 2009). On the other hand, other studies reported that climate variability in certain regions have had a greater influence on surface hydrology than land use changes, such as that observed in the Heihe River basin, China (Li et al., 2009), as well as the upper Mississippi River basin (Frans et al., 2013) .

In combination with climate change, this study explored how vegetation impacts hydrological processes from an alternative aspect, i.e., assessing  $Z_e$  response to climate change and its impacts on  $Q$  and  $E$ . According to the Budyko framework, the greater the  $P$  the deeper the rooting depth (Schenk and Jackson, 2002). Furthermore, modeled  $E$  under dynamic and static  $Z_e$  scenarios exhibited negative trends while observed  $E$  exhibited positive trends (Fig. 3). Vegetation structure profoundly regulates the annual surface hydrological cycle and is a cause and consequence of surface water balances (Gentine et al., 2012). For this study, following Donohue et al. (2012),  $Z_e$  in combination with  $\alpha$  and  $\kappa$  were used to calculate  $n$  (1.81 average). Results were similar to  $n$  ( $n = 1.76$ ) calculated from a nonlinear fitted model by Liu and McVicar (2012). Given the scarcity of  $Z_e$  data, validation of modeled  $Z_e$  is difficult to obtain for larger basins (Donohue et al., 2012). From the  $n$  calculated for each grid cell, it was shown that

simulated  $E$  and  $Q$  fitted well with observed values (data provided in Fig. 3).  $Z_e$  alteration contributed greater to changes in  $Q$  and  $E$  (Fig. 4 and Table 1), which indicated that the response of vegetation to climatic change can alter the partition of  $P$  into  $E$  and  $Q$ . The BCP model with the addition of ecohydrological parameters (such as  $Z_e$ ,  $\alpha$ , and  $\kappa$ ) captured effects of watershed characteristics on partitioning of  $P$  into  $E$  and  $Q$ . Results can also reflect relative contributions (provided in Fig. 5 and Fig. 6). For example, Fig. 5c and Fig. 5d show that significant temporal trends in  $E$  yielded different results between static and dynamic  $Z_e$  scenarios. Fig. 6 shows that climate change regulates temporal trend changes in  $E$ , which is consistent with data provided in Table 1. Furthermore, given that soil, topography, vegetation, and climate are intrinsically interconnected, Gentile et al. (2012) attempted to use the Budyko curve to explain ecohydrological controls of soil water balances. Further research should focus more attention on mechanisms of watershed parameters and improve accuracy of the Budyko framework as it relates to different temporal and spatial scales.

## 5. Conclusions

Climate change and vegetation impacts on  $Q$  and  $E$  can be explored using the BCP model with the addition of adjustable ecohydrological parameters (such as  $Z_e$ ,  $\alpha$ , and  $\kappa$ ). According to the “typical variability” of different variables, climate change and vegetation impacts were obtained for the static and dynamic  $Z_e$  scenarios investigated for this study. The following conclusions can be drawn from this study:

- (i) The BCP model in combination with simulated static and dynamic  $Z_e$  scenarios captured effects of changes in climate and vegetation on  $E$  or  $Q$ . In this study, simulated  $E$  under static and dynamic  $Z_e$  scenarios exhibited negative trends with an average increase of  $-0.78$  and  $-0.81 \text{ mm a}^{-2}$ , respectively. For the dynamic scenario, total  $E$  and  $Q$  were respectively predicted to be  $-1.73\%$  and  $28.22\%$  greater

than the static scenario, which exhibited obvious spatial variation.

(ii) As predicted, although climate change regulates changes in  $E$  and  $Q$ ,  $Z_e$  response to climate change contributed greater to changes in  $E$  and  $Q$  in the water-limited region investigated. Results indicated that with the exception of vegetation type and extent,  $Z_e$  scenarios were able to alter the partitioning of  $P$  into  $E$  and  $Q$ . These results should help our understanding of interactions between climate, vegetation, and hydrological processes, and help to regulate water resources over basin scales.

#### **Acknowledgement:**

This study was supported by the National Science Foundation for Innovative Research Group (no. 51121003), the Fundamental Research Funds for the Central Universities (no. 2012LYB12), and the Beijing Higher Education Young Elite Teacher Project (no. YETP0259). We would like to thank the National Meteorological Information Center, the China Meteorological Administration, and the Yellow River Conservancy Commission for providing meteorological and streamflow data.

#### **References:**

- Allen, R.G., L.S. Pereira, D. Raes, and M. Smith (1988), Crop evapotranspiration: Guidelines for computing crop water requirement. *FAO Irrig. and Drain. Paper No.56*. FAO: Rome, Italy.
- Bonan, G.B. (2001), Observational evidence for reduction of daily maximum temperature by croplands in the Midwest United States, *J. Climate*, 14, 2430–2442.
- Brümmer, C., T.A. Black, R.S. Jassal, N.J. Grant, D.L. Spittlehouse, B. Chen, Z. Nesic, B.D. Amiro, M.A. Arain, A.G. Barr, C.P.A. Bourque, C. Coursolle, A.L. Dunn, L.B. Flannagan, E.R. Humphreys, P.M. Lafleur, H.A. Margolis, J.H. McCaughey, and S.C. Wofsy (2012), How climate

236 and vegetation type influence evapotranspiration and water use efficiency in Canadian forest,  
 237 peatland and grassland ecosystems, *Agr. Forest Meteorol.*, 153, 14–30.

238 Budyko, M. I. (1974), *Climate and Life*, *Acad. Pr.*, 508 pp.

239 Cao, S.X., L. Chen, D. Shankman, C. Wang, X. Wang, and H. Zhang (2011), Excessive reliance on  
 240 afforestation in China's arid and semi-arid regions: Lessons in ecological restoration, *Earth-Sci.*  
 241 *Rev.*, 104, 240–245.

242 Choudhury, B.J. (1999), Evaluation of an empirical equation for annual evaporation using field  
 243 observations and results from a biophysical model, *J. Hydrol.*, 216, 99–110.

244 Donohue, R.J., M.L. Roderick, and T.R. McVicar (2010), Can dynamic vegetation information improve  
 245 the accuracy of Budyko's hydrological model? *J. Hydrol.*, 390 (1-2), 23–34.

246 Donohue, R.J., M.L. Roderick, and T.R. McVicar (2011), Assessing the differences in sensitivities of  
 247 runoff to changes in climatic conditions across a large basin, *J. Hydrol.*, 406, 234–244.

248 Donohue, R.J., M.L. Roderick, and T.R. McVicar (2012), Roots, storms and soil pores: incorporating  
 249 key ecohydrological processes into Budyko's hydrological model, *J. Hydrol.*, 436–437, 35–50.

250 Frans, C., E. Istanbuluoglu, V. Mishra, F. Munoz-Arriola, and D.P. Lettenmaier (2013), Are climatic or  
 251 land cover changes the dominant cause of runoff trends in the Upper Mississippi River Basin?  
 252 *Geophys. Res. Lett.*, 40, 1104–1110, doi:10.1002/grl.50262.

253 Fu, B.P. (1981), On the calculation of the evaporation from land surface (in Chinese), *Scientia.*  
 254 *Atmosp.Sinica*, 5, 23–31.

255 Gentine, P., P. D'Odorico, B.R. Lintner, G. Sivandran, and G. Salvucci (2012), Interdependence of  
 256 climate, soil, and vegetation as constrained by the Budyko curve, *Geophys. Res. Lett.*, 39, L19404,  
 257 doi: 10.1029/2012GL053492.

258 Gerrits, A.M.J., H.H.G. Savenije, E.J.M. Veling, and L.P. Fister (2009), Analytical derivation of the  
 259 Budyko curve based on rainfall characteristics and a simple evaporation model, *Water Resour.*  
 260 *Res.*, 45, W04403, doi:10.1029/2008WR007308.

261 IPCC (2007), Climate Change 2007: The Physical Science Basis. Contribution of Working Group I to  
 262 the Fourth Assessment, *Camb. U. Pr.*, New York.

263 Li, L.J., L. Zhang, H. Wang, J. Wang, J.W. Yang, D.J. Jiang, J.Y. Li, and D.Y. Qin (2007), Assessing the  
 264 impact of climate variability and human activities on streamflow from the Wuding River basin in  
 265 China, *Hydrol. Processes.*, 21, 3485–3491.

266 Li, Z., W.Z. Liu, X.C. Zhang, and F.L. Zheng (2009), Impacts of land use change and climate  
 267 variability on hydrology in an agricultural catchment on the Loess Plateau of China, *J. Hydrol.*,  
 268 377, 35–42.

269 Liang, L.Q., and Q. Liu (2013), Streamflow sensitivity analysis to climate change for a large  
 270 water-limited basin, *Hydrol. Processes*, doi: 10.1002/hyp.9720.

271 Liu, Q., and T.M. McVicar (2012), Assessing climate change induced modification of Penman potential  
 272 evaporation and runoff sensitivity in a large water-limited basin, *J. Hydrol.*, 464–465, 352–262.

273 Liu, Q., and Z.F. Yang (2010), Quantitative estimation of the impact of climate change on actual  
 274 evapotranspiration in the Yellow River Basin, China, *J. Hydrol.*, 395, 226–234.

275 Liu, Q., Z.F. Yang, and B.S. Cui (2008), Spatial and temporal variability of annual precipitation during  
 276 1961–2006 in Yellow River Basin, China, *J. Hydrol.*, 361, 330–338.

277 Liu, Q., Z.F. Yang, B.S. Cui, T. Sun (2009), Temporal trends of Hydro-climatic variables and runoff  
 278 response to climatic variability and vegetation changes in the Yiluo River basin, China, *Hydrol.*  
 279 *Processes.*, 23(21), 3030–3039.

280 McVicar, T.R., L.T. Li, T.G. Van Niel, L. Zhang, R. Li, Q.K. Yang, X.P. Zhang, X.M. Mu, Z.M. Wen,  
 281 W.Z. Liu, Y.A. Zhao, Z.H. Liu, and P. Gao (2007a), Developing a decision support tool for  
 282 China's re-vegetation program: Simulating regional impacts of afforestation on average annual  
 283 streamflow in the Loess Plateau, *Forest Ecol. and Manag.*, 251 (1–2), 65–81.

284 McVicar, T.R., G.L. Zhang, A.S. Bradford, H.X. Wang, W.R. Dawes, L. Zhang, and L.T. Li (2002),  
 285 Monitoring regional agricultural water use efficiency for Hebei Province on the North China Plain,  
 286 *Aust. J. Agr. Res.*, 53, 55–76.

287 McVicar, T.R., T.G. Van Niel, L.T. Li, Z.M. Wen, Q.K. Yang, R. Li, F. Jiao (2010), Parsimoniously  
 288 modelling perennial vegetation suitability and identifying priority areas to support China's  
 289 re-vegetation program in the Loess Plateau: Matching model complexity to data availability,  
 290 *Forest Ecol Manag.*, 259 (7), 1277–1290.

291 Nakayama, T. (2011), Simulation of the effect of irrigation on the hydrologic cycle in the highly  
 292 cultivated Yellow River Basin, *Agr. Forest Meteorol.*, 151, 314–327.

293 Oudin, L., V. Andreassian, J. Lerat, and C. Michel (2008), Has land cover a significant impact on mean  
 294 annual streamflow? An international assessment using 1508 catchments, *J. Hydrol.*, 357 (3–4),  
 295 303–316.

296 Porporato, A., E. Daly, and I. Rodriguez-Iturbe (2004), Soil water balance and ecosystem response to  
 297 climate change, *Am. Nat.*, 164 (5), 625–632.

298 Roderick, M.L., and G.D. Farquhar (2011), A simple framework for relating variations in runoff to  
 299 variations in climatic conditions and catchment properties, *Water Resour. Res.*, 47, W00G07,  
 300 doi:10.1029/2010WR009826.

301 Schenk, H.J., and R.B. Jackson (2002), Rooting depths, lateral root spreads and

302 below-ground/above-ground allometries of plants in water-limited ecosystems, *J. Ecol.*, 90,  
 303 480–494.

304 Shuttleworth, W.J. (1993), Evaporation. In: D.R. Maidment (Editor), *Handbook Hydrol.*, McGraw-Hill,  
 305 Sydney.

306 Troch, P.A., G. Garrllo, M. Sivapalan, T. Wagener, and K. Sawicz (2013), Climate-vegetation-soil  
 307 interactions and long-term hydrologic partitioning: signatures of catchment co-evolution, *Hydrol.*  
 308 *Earth Syst. Sc.*, 10, 2927–2954.

309 Xin, Z.B., J.X. Xu, and Z. Wei (2008), Spatiotemporal variations of vegetation cover on the Chinese  
 310 Loess Plateau (1981–2006): Impacts of climate changes and human activities, *Sci China Ser. D:*  
 311 *Earth Sc*, 51, 67–78.

312 Xu, X.L., W. Liu, B.R. Scanlon, L. Zhang, and M. Pan (2013), Local and global factors controlling  
 313 water-energy balances within the Budyko framework, *Geophys. Res. Lett.*, 40, 6123–6129.

314 Yang, D.W., F.B. Sun, Z.Y. Liu, Z.T. Cong, G.H. Ni, and Z.D. Lei( 2007), Analyzing spatial and  
 315 temporal variability of annual water-energy balance in non-humid regions of China using the  
 316 Budyko hypothesis, *Water Resour. Res.*, 43, W04426, <http://dx.doi.org/10.1029/2006WR005224>.

317 Yang, D.W., W.W. Shao, P.J.F. Yeh, H.B. Yang, S. Kanae, and T. Oki (2009), Impact of vegetation  
 318 coverage on regional water balance in the non-humid regions of China, *Water Resour. Res.*, 45,  
 319 W00A14, doi:10.1029/2008WR006948.

320 Yang, H., D. Yang, Z. Lei, and F. Sun (2008), New analytical derivation of the mean annual water  
 321 balance equation, *Water Resour. Res.*, 44, W03410, doi:10.1029/2007WR006135. Zhang, L., W.R.  
 322 Dawes, and G.R. Walker (2001), The response of mean annual evapotranspiration to vegetation  
 323 changes at catchment scale, *Water Resour. Res.*, 37 (3), 701–708

324 Gao, H., Hrachowitz, M., Schymanski, S.J., Fenicia, F., Sriwongsitanon, N., Savenije, H.H.G., 2014.  
325 Climate controls how ecosystems size the root zone storage capacity at catchment scale, *Geophys.*  
326 *Res. Lett.*, DOI: 10.1002/2014GL061668.

327 FAO/IIASA/ISIRC/ISS-CAS/JRC, 2008. Harmonized World Soil Database (version 1.0) FAO, Rome,  
328 Italy and IIASA, Laxenburg, Austria.

329 Wang, D.B., Y, Tang (2014). A one-parameter Budyko model for water balance captures emergent  
330 behavior in darwinian hydrologic models, *Geophys. Res. Lett.*, 41, 4569-4577.

331



**Table and Figure captions:**

Table 1 Summaries of  $E$  and  $Q$  sensitivity to changes in ecohydrological conditions throughout the study period (1961–2010). Shown for each variable and zone are  $E$  and  $Q$  sensitivity coefficients, observed variability per variable, and typical variability in  $E$  caused by driving variables.  $dZ_e$  is the difference between tree and grass  $Z_e$  modeled for the basin.

Fig. 1 Location of the Yellow River.

Fig. 2 Temporal trends in  $P$  (a) and  $E_p$  (b) ( $\text{mm a}^{-2}$ ) for the Yellow River basin.

Fig. 3 Static  $Z_e$  (1961) (a) and average dynamic  $Z_e$  (b) (1961–2010) for the Yellow River basin.

Fig. 4 Observed and modeled annual  $E$  for the Yellow River basin.

Fig. 5 Modeled percentage differences in mean annual total  $E$  (a) and  $Q$  (b) between static  $Z_e$  ( $Z_e$  determined for 1961 was fixed throughout the 1961–2010 simulation period) and dynamic  $Z_e$  ( $Z_e$  was influenced by specific water and energy conditions for each grid cell in accordance with specific climate change conditions).  $E_{change} = \left( (E_d - E_s) / E_d \right) \times 100\%$ , where  $E_{change}$  is the percentage difference in mean annual total  $E$ , and  $E_d$  and  $E_s$  are mean annual total  $E$  between static  $Z_e$  and dynamic  $Z_e$  project.  $Q_{change} = \left( (Q_d - Q_s) / Q_d \right) \times 100\%$ , where  $Q_{change}$  is the percentage difference in mean annual total  $Q$ , and  $Q_d$  and  $Q_s$  are mean annual total  $E$  between static  $Z_e$  and dynamic  $Z_e$  scenarios.

Fig. 6 Temporal trends in  $E$  under static  $Z_e$  (Fig. 5a) and dynamic  $Z_e$  (Fig. 5b) scenarios, and regions exhibiting significant  $E$  slopes ( $p < 0.05$ ) for static  $Z_e$  (Fig. 5c) and dynamic  $Z_e$  (Fig. 5d) scenarios as determined by the Mann–Kendall method.

Fig. 7 Relative contributions of climate (a) and vegetation (b) to changes in  $E$  for YRB (areas void of significant trends are showed in white). Relative contributions can be expressed as:

$E_c = (S_{sz} / S_{dy}) \times 100\%$ ,  $E_v = ((S_{dz} - S_{sz}) / S_{dz}) \times 100\%$ , where  $E_c$  is the relative contribution resulting from climate on  $E$ ;  $E_v$  is the relative contribution resulting from vegetation on  $E$ ; and  $S_{sz}$  and  $S_{dz}$  are trends ( $p < 0.05$ ) of modeled  $E$  under static  $Z_e$  and dynamic scenarios, respectively.

Table 1 Summaries of  $E$  (left) and  $Q$  (right) sensitivity to changes in ecohydrological conditions throughout the study period (1961–2010). Shown for each variable and zone are  $E$  and  $Q$  sensitivity coefficients, observed variability per variable, and typical variability in  $E$  caused by driving variables.  $dZ_e$  is the difference between tree and grass  $Z_e$  modeled for the basin.

Sensitivity for $E$	unit	YRB	Sensitivity for $Q$	unit	YRB
$\partial E/\partial P$	mm a <sup>-1</sup> / mm a <sup>-1</sup>	0.73	$\partial Q/\partial P$	mm a <sup>-1</sup> / mm a <sup>-1</sup>	0.17
$dP$	mm a <sup>-1</sup>	59	$dP$	mm a <sup>-1</sup>	59
$\partial E/\partial P * dP$	mm a <sup>-1</sup>	41.9	$\partial Q/\partial P * dP$	mm a <sup>-1</sup>	10.1
$\partial E/\partial E_p$	mm a <sup>-1</sup> / mm a <sup>-1</sup>	0.05	$\partial Q/\partial E_p$	mm a <sup>-1</sup> / mm a <sup>-1</sup>	-0.05
$dE_p$	mm a <sup>-1</sup>	42	$dE_p$	mm a <sup>-1</sup>	42
$\partial E/\partial E_p * dE_p$	mm a <sup>-1</sup>	2.1	$\partial Q/\partial E_p * dE_p$	mm a <sup>-1</sup>	-2.1
$\partial E/\partial \alpha$	mm a <sup>-1</sup> / mm	-10.6	$\partial Q/\partial \alpha$	mm a <sup>-1</sup> / mm	10.6
$d\alpha$	mm	0.39	$d\alpha$	mm	0.39
$\partial E/\partial \alpha * d\alpha$	mm a <sup>-1</sup>	-4.2	$\partial Q/\partial \alpha * d\alpha$	mm a <sup>-1</sup>	4.2
$\partial E/\partial Z_e$	mm a <sup>-1</sup> / mm	0.17	$\partial Q/\partial Z_e$	mm a <sup>-1</sup> / mm	-0.17
$dZ_e$	mm	30	$dZ_e$	mm	30
$\partial E/\partial Z_e * dZ_e$	mm a <sup>-1</sup>	5	$\partial Q/\partial Z_e * dZ_e$	mm a <sup>-1</sup>	-5

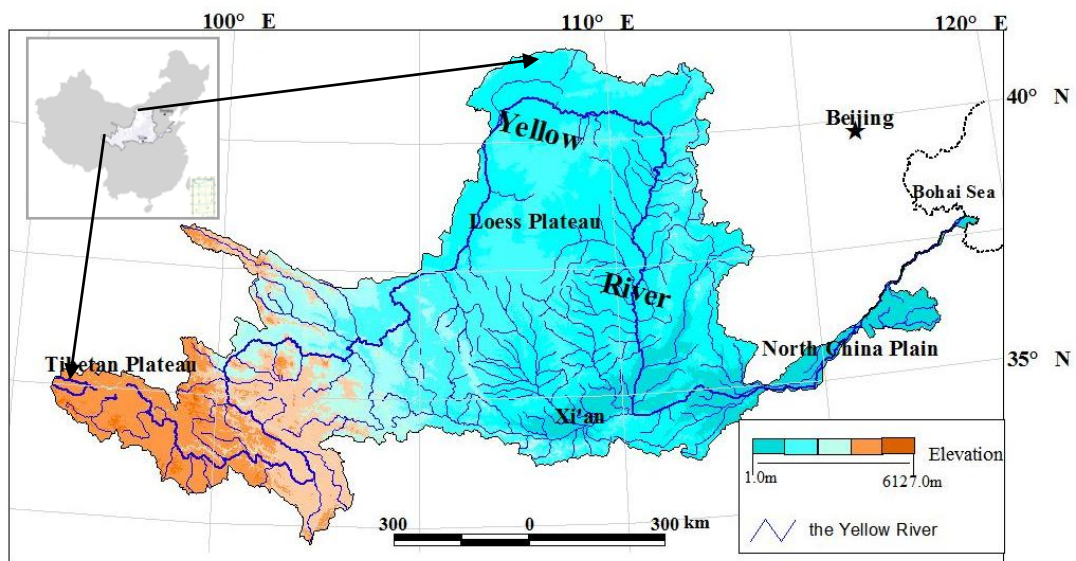


Fig. 1 Location of Yellow River.

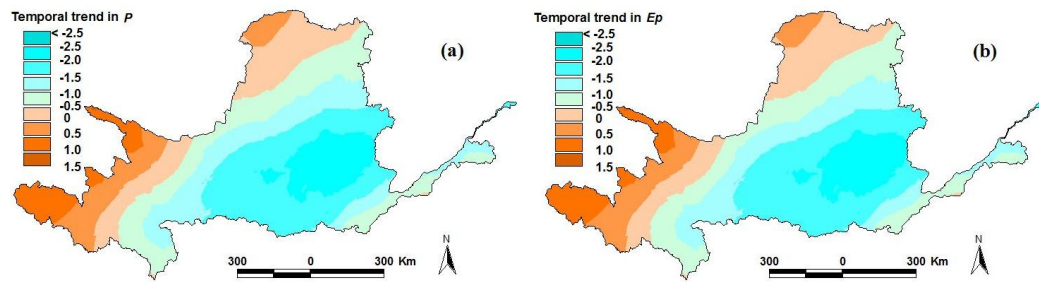


Fig. 2 Temporal trends in  $P$  (a) and  $E_p$  (b) ( $\text{mm a}^{-2}$ ) for the Yellow River basin.

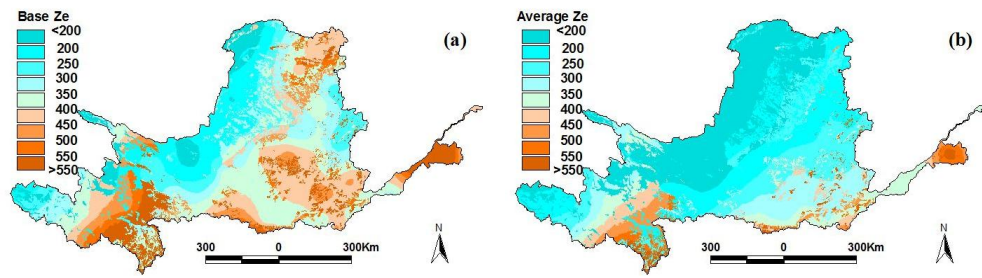


Fig. 3 Static  $Z_e$  (1961) (a) and average dynamic  $Z_e$  (b) (1961–2010) for the Yellow River basin.

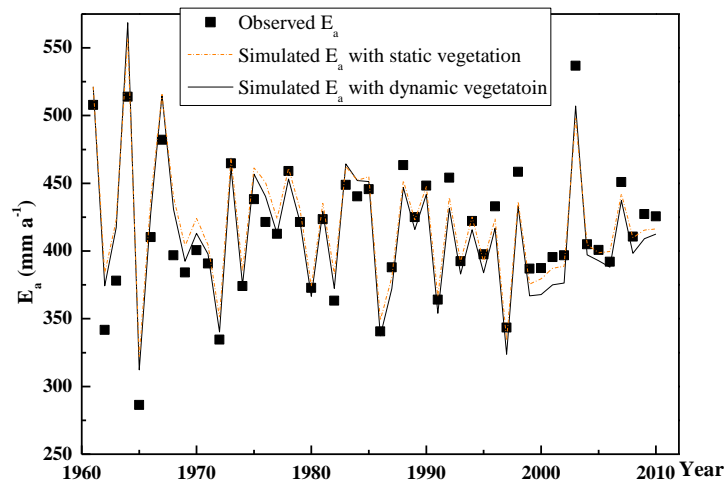


Fig. 4 Observed and modeled annual  $E$  for the Yellow River basin.

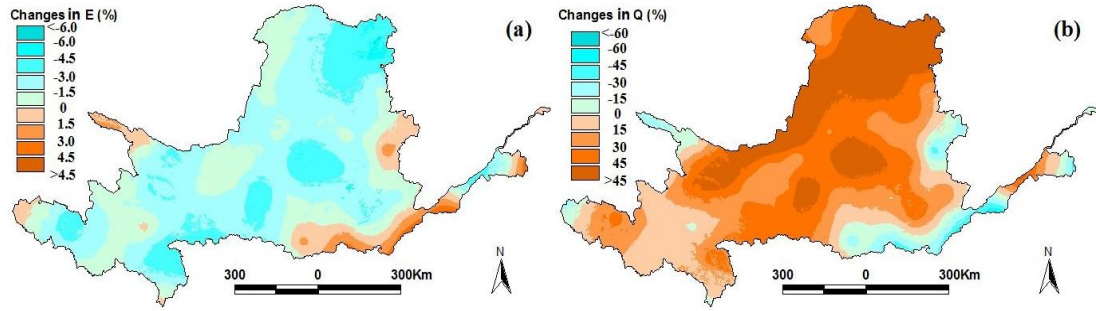


Fig. 5 Modeled percentage differences in mean annual total  $E$  (a) and  $Q$  (b) between static  $Z_e$  ( $Z_e$  determined for 1961 was fixed throughout the 1961–2010 simulation period) and dynamic  $Z_e$  ( $Z_e$  was influenced by specific water and energy conditions for each grid cell in accordance with specific climate change conditions).  $E_{change} = \left( \frac{E_d - E_s}{E_d} \right) \times 100\%$ , where  $E_{change}$  is the percentage difference in mean annual total  $E$ , and  $E_d$  and  $E_s$  are mean annual total  $E$  between static  $Z_e$  and dynamic  $Z_e$  scenarios.  $Q_{change} = \left( \frac{Q_d - Q_s}{Q_d} \right) \times 100\%$ , where  $Q_{change}$  is the percentage difference in mean annual total  $Q$ , and  $Q_d$  and  $Q_s$  are mean annual total  $E$  between static  $Z_e$  and dynamic  $Z_e$  scenarios.

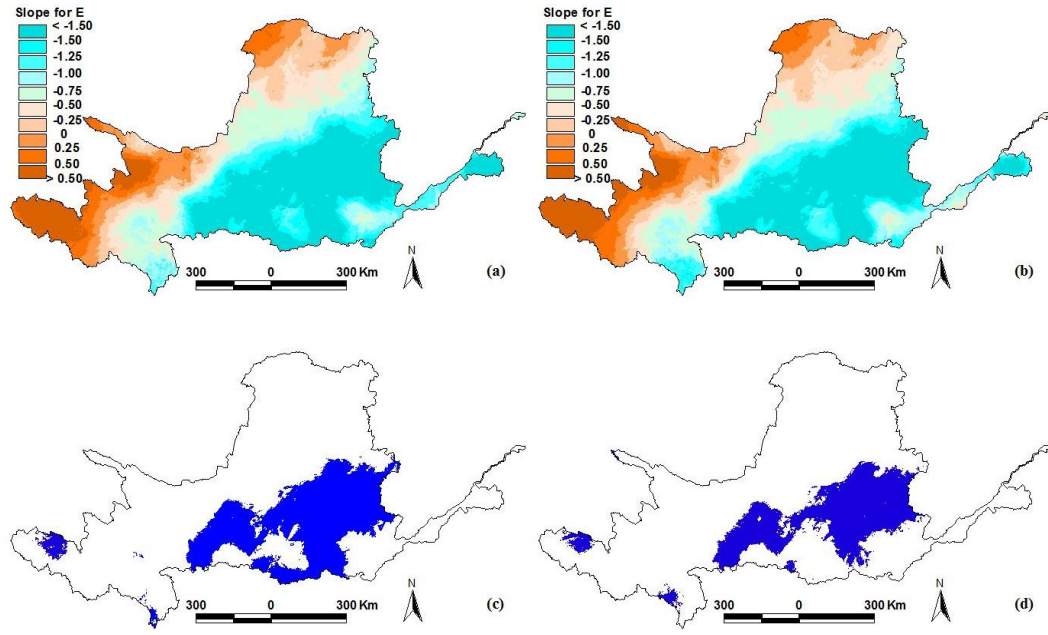


Fig. 6 Temporal trends in  $E$  under static  $Z_e$  (Fig. 5a) and dynamic  $Z_e$  (Fig. 5b) scenarios, and regions exhibiting significant  $E$  slopes ( $p < 0.05$ ) for static  $Z_e$  (Fig. 5c) and dynamic  $Z_e$  (Fig. 5d) scenarios as determined by the Mann–Kendall method.



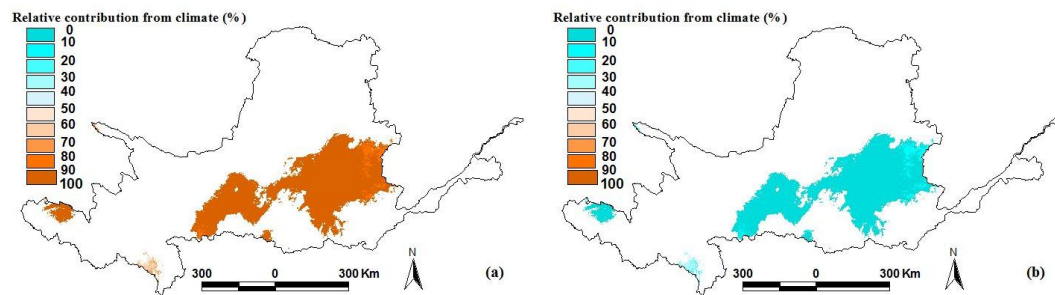


Fig. 7

Relative contributions of climate (a) and vegetation (b) to changes in  $E$  for YRB (areas void of significant trends are showed in white). Relative contributions can be expressed as:

$E_c = (S_{sz} / S_{dy}) \times 100\%$ ,  $E_v = ((S_{dz} - S_{sz}) / S_{dz}) \times 100\%$ , where  $E_c$  is the relative contribution resulting from climate on  $E$ ;  $E_v$  is the relative contribution resulting from vegetation on  $E$ ; and  $S_{sz}$  and  $S_{dz}$  are trends ( $p < 0.05$ ) of modeled  $E$  under static  $Z_e$  and dynamic scenarios, respectively.