Diagnosis of evapotranspiration controlling factors in the Heihe River basin, northwest China

Linghua Qiu, Dingzhi Peng and Ji Chen

ABSTRACT

Estimation of actual evapotranspiration (ET) and diagnosis of its controlling factors contribute to addressing water scarcity challenges in arid regions. For detecting impacts of vegetation, precipitation, and evaporation capacity on ET, a monthly ET model was proposed on the basis of the three factors and applied in the upstream and midstream of the Heihe River basin, northwest China, an arid and semi-arid basin. Parameter sensitivity analysis, partial correlation analysis, and factor analysis were used to assess the controlling factors of ET. Results demonstrated that the proposed ET model can reconstruct monthly ET processes with satisfying performances and precipitation, evaporation capacity and vegetation are the controlling factors of ET in the study areas. The proposed ET model could be applicable with the three controlling factors to estimate ET in arid regions.

Key words | actual evapotranspiration, ET model, Heihe River basin, vegetation

Linghua Qiu
Dingzhi Peng (corresponding author)
College of Water Sciences,
Beijing Normal University,
Beijing 100875,
China
E-mail: *dzpeng@bnu.edu.cn*

Linghua Qiu
Ji Chen
Department of Civil Engineering,
The University of Hong Kong,
Hong Kong, China

INTRODUCTION

Actual evapotranspiration (ET) is always a critical focus of hydrological cycles, especially in arid regions, which are the most likely places to suffer water shortage and eco-environment issues. In arid regions, ET is the major water loss and can make a distinct difference to hydrological processes. Studies show that ET consumes almost 90% of, or even equals precipitation in arid watersheds (Zhang *et al.* 2001; Wu *et al.* 2005). However, it is still very difficult to monitor ET in fields with current equipment or techniques, so estimation of ET is very important. Many methods have been developed to assess ET (Droogers 2000; Drexler *et al.* 2004; Courault *et al.* 2005; Gao *et al.* 2011; El Tahir *et al.* 2012; Rudd & Kay 2016), for instance, remote sensing technology, Bowen ratio energy balance method, water balance model, complementary relationship method, etc. Areal ET is estimated by CRAE model, AA and GG model in basins with different climatic conditions and their performances in drier regions are poorer than in humid regions (Xu & Singh 2005). More models such as the Penman, Penman–Monteith, Wright–Penman, Blaney–Criddle, radiation balance, and Hargreaves models have been applied to calculate ET in different regions and the results illustrate that different models are applicable for different basins (DehghaniSanij *et al.* 2004). The GG model and Makkink model can estimate ET best out of seven models in Germany (Xu & Chen 2005). However, in Haihe River basin in China, the AA model outperforms the GG model (Gao *et al.* 2011). Nonlinear complementary relationship method is applicable in data-scarce regions like the Tibetan Plateau (Ma *et al.* 2015). In the Blue Nile region, regional ET was estimated by SEBAL model based on MODIS data in the wet season (El Tahir *et al.* 2012). ET was also computed by remote sensing-based methods in arid regions (Li *et al.* 2012).

Although many models have been developed, ET estimation is not an easy thing. What makes these models difficult to use is that most of them require complicated observations to force models or validate model parameters, while available measurements in arid and semi-arid regions are particularly scarce (Allen *et al.* 2011; Sun *et al.* 2011).

doi: 10.2166/nh.2017.156

In addition, estimation reliability is challenging for most methods involving large uncertainties, especially for remote sensing-based models. One advantage of empirical models to estimate ET is the flexibility of data and another advantage is being without the limitations of physical mechanism. It can be a new way to estimate ET by means of statistical models with controlling factors of ET in arid regions according to the close relationship between ET and its controlling factors. Eagleman (1971) developed the relationship by a cubic equation between the relative evapotranspiration (i.e., ET/E_0, and E_0 is evaporation capacity) and soil moisture and the model provided satisfactory estimations. Wang *et al.* (2007) built a multi-variable function between ET and net radiation, vegetation index, and temperature, which could estimate regional or global ET accurately with remote sensing data. Sun *et al.* (2011) and Feng *et al.* (2012) observed that precipitation, vegetation, and evaporation capacity are closely related to ET, especially in arid and semi-arid regions.

Selection of factors is of importance when using statistical methods to estimate ET. Controlling factors of ET could contribute greatly to enhancing model performances. Stephenson (1998) reported that vegetation is closely related to ET. Factors like vegetation, soil water, precipitation, and evaporation capacity, which are closely linked to hydrological processes, probably can be more powerful to deliver solutions of water challenges in the real world. Moreover, these data are more possibly available and meaningful to estimate ET. Zhang *et al.* (2001) suggested that plant-related water controls ET in dry conditions while ET depends on climate, soil, and vegetation in intermediate conditions. The objective of this study is: (1) to propose a possible relationship between ET and its possible controlling factors to estimate ET in arid and semi-arid regions and (2) to evaluate the reliability of these factors.

CASE STUDY

Study area

As the second largest inland river in China, the Heihe River was chosen as a typical case study for assessing ET in an arid and semi-arid region (Li *et al.* 2012). Due to intensive anthropogenic interference and water shortage, the eco-environment is fragile in this basin. Interestingly, the conditions of climate and vegetation are quite different in its upstream and midstream basins. Precipitation, evaporation capacity, and vegetation are chosen as possible controlling factors to estimate ET due to the limitation of data in the basin.

Heihe River mainly supplies water to Gansu, Qinghai Province and the Inner Mongolia Autonomous Region. However, the basin suffers severe water scarcity and even droughts in recent decades (Feng *et al.* 2014; Qiu *et al.* 2016). In the study, the Yingluoxia sub-basin (YLX), the Zhengyixia sub-basin (ZYX), and the basin containing the two sub-basins (YLX&ZYX), were respectively chosen as the study areas (see Figure 1). Therefore, there are three parts of the study area: YLX, ZYX, and YLX&ZYX. The whole study area is nearly 34,000 km^2. The annual average rainfall in YLX is about 300–400 mm, and the pan evaporation is over 800 mm. In ZYX, the annual average rainfall is about 100–200 mm while pan evaporation is close to 1,400 mm.

As the headwater of the Heihe River basin, YLX is located in the upstream with mountain topography. Vegetation cover in the sub-basin is relatively abundant with forest, shrub, and grassland (Yin *et al.* 2015). In contrast, ZYX is located in Hexi Corridor in the midstream. It is a main agriculture base and an economic center in the Heihe River basin, with the dominant water consumption of the whole basin. Due to having almost 94% population of the basin (Yin *et al.* 2015), ZYX is intensively interferred with by anthropogenic activities. Artificial oasis and sparse grassland cover the midstream. The land use types (see Figure 2) are shown in Table 1, and provided by the Cold and Arid Regions Science Data Center at Lanzhou, China (http://westdc.westgis.ac.cn). The vegetation cover (forest and grass land) proportion in YLX is doubled in ZYX, and there is a quite difference in farmland between these two sub-basins.

Data

In this study, precipitation, evaporation capacity, and vegetation were applied to build the ET model. Precipitation and pan evaporation at hydrological stations (see Figure 1) were collected from the Hydrology and Water Resources Survey Bureau of Gansu Province. Here, pan evaporation

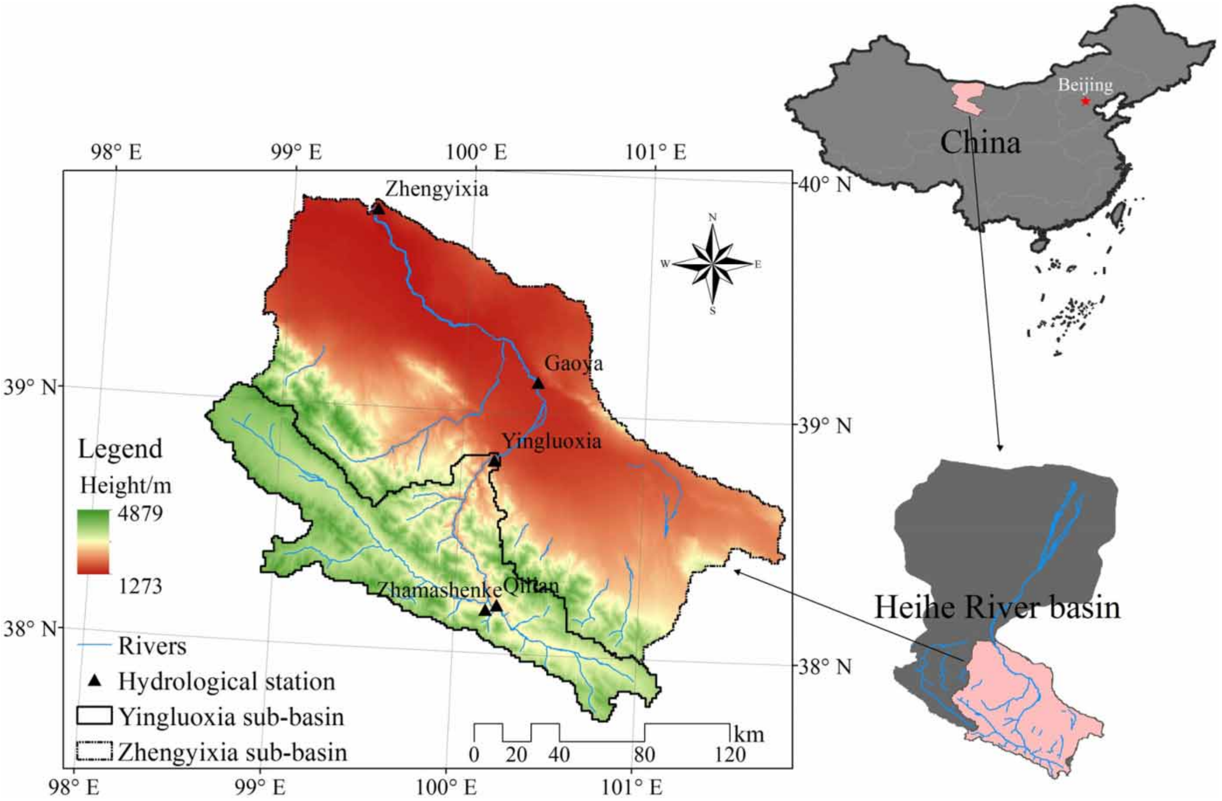

Figure 1 | Study area.

was employed to indicate evaporation capacity. Leaf area index (LAI) can represent vegetation characteristics, so 'Heihe 1 km LAI production' was downloaded from the Cold and Arid Regions Science Data Center at Lanzhou, China (http://westdc.westgis.ac.cn/). The product 'Heihe 1 km monthly ET data', obtained by calculation of the improved ET-Watch model based on multi-source remote sensing data (Wu *et al.* 2012), was also selected from this center as no available observed ET data could be found. The study period was from January 2007 to December 2012. The calibration period was 2007–2010 and validation was 2011–2012.

METHODS

ET model

A hypothesis was assumed that ET could be controlled by factors such as available energy, water, and seasonal vegetation biomass dynamics, and the three elements can be represented by evaporation capacity (E_0), precipitation (P), and vegetation (LAI), respectively (Sun *et al.* 2011):

$$ET = f(P, E_0, LAI) \tag{1}$$

The relationship was explored in over 100 arid and semi-arid regions, and the applicable equation was determined with a nonlinear function as follows (Feng *et al.* 2012):

$$ET = k_1 {*} \mathrm{P} {*} \mathrm{E}_0 + \mathrm{k}_2 {*} \mathrm{P} {*} \mathrm{LAI} + \mathrm{k}_3 {*} \mathrm{E}_0 {*} \mathrm{LAI} + \mathrm{a} \tag{2}$$

where k_1 (mm^{-1}), k_2, k_3 are parameters and a (mm) is the constant.

Evaporative energy and water source play primary roles in ET and vegetation, and are confirmed to be critical factors of ET (Zhang *et al.* 2001; Sun *et al.* 2011). Another reason that these three factors are chosen is that related data are

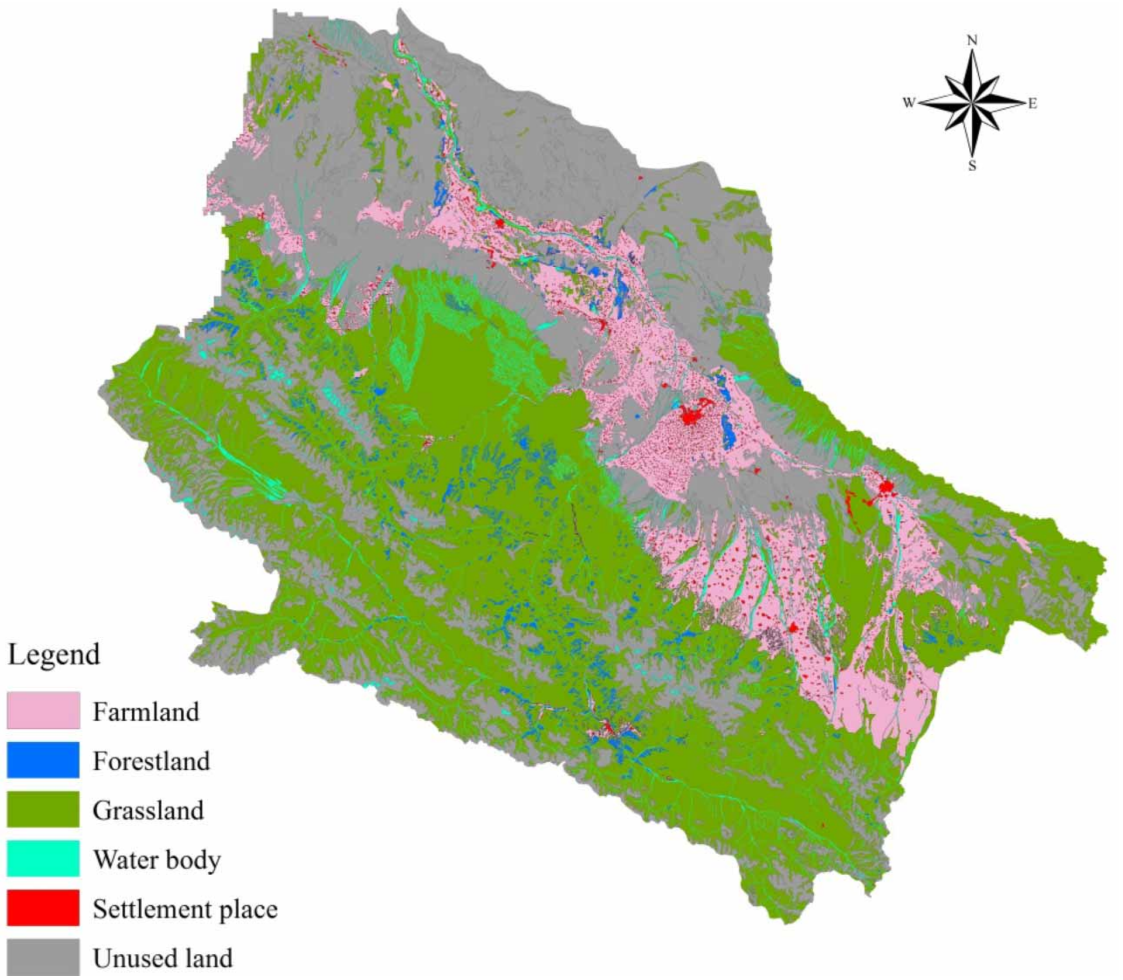

Figure 2 | Land use in the study area.

Table 1 | Proportion of different land use types in YLX and ZYX

	Proportion/%	
	YLX	**ZYX**
Farmland	0.5	21.0
Forestland	2.7	1.9
Grassland	68.0	33.4
Water body	3.2	3.4
Settlement place	0.1	1.0
Unused land	25.5	39.3

available in most regions, although with a sparse resolution in some regions. To find an applicable equation to further estimate ET in arid and semi-arid regions, a new equation is proposed by the relationship in Equation (1) with different possible linear or nonlinear combinations:

$$ET = a_1 \cdot P + a_2 \cdot E_0 + a_3 \cdot LAI + a_4 \cdot P \cdot E_0 + a_5 \cdot P \cdot LAI + a_6 \cdot E_0 \cdot LAI + a_7 \cdot P \cdot E_0 \cdot LAI + b \qquad (3)$$

where a_1, a_2, a_3 (mm), a_4 (mm^{-1}), a_5, a_6, a_7 (mm^{-1}) are parameters and b (mm) is the constant. This model was employed to estimate ET in the study areas. Here, the SCE-UA algorithm (Duan *et al.* 1994) was applied to determine the parameters.

Nash coefficient (*NS*) (Nash & Sutcliffe 1970), relative error (*RE*), and normalized root-mean-square error (*NRMSE*) are employed to estimate performances of the proposed model:

$$NS = 1 - \frac{\sum_{\mathrm{i}=1}^{n}(ET_i - ET_i')^2}{\sum_{i=1}^{n}(ET_i - \overline{ET})^2} \tag{4}$$

$$RE = \frac{\sum_{\mathrm{i}=1}^{n} ET_i - \sum_{\mathrm{i}=1}^{n} ET_i'}{\sum_{i=1}^{n} ET_i} \times 100\% \tag{5}$$

$$NRMSE = \frac{\sqrt{\sum_{\mathrm{i}=1}^{n}(ET_i - ET_i')^2/n}}{\overline{ET}} \tag{6}$$

where ET_i and ET_i' indicate the measured and simulated ET in i time, respectively, while $\overline{ET}$ is the average measured ET during the whole study period.

Partial correlation analysis

The correlation coefficient r_{1-2} between variable 1 and 2 is calculated as:

$$r_{1-2} = \frac{\sum_{\mathrm{i}=1}^{n}(x_{1i} - \overline{x_1})(x_{2i} - \overline{x_2})}{\sqrt{\sum_{i=1}^{n}(x_{1i} - \overline{x_1})^2 \times \sum_{i=1}^{n}(x_{2i} - \overline{x_2})^2}} \tag{7}$$

where x_{1i} and x_{2i} is the value of variable 1 and 2 in i time, respectively. $\overline{x_1}$ and $\overline{x_2}$ is the mean value of variable 1 and 2 during the entire periods, respectively.

The partial correlation coefficient $R_{1-2,3}$ between variable 1 and 2 after removing the effect of variable 3 is as follows (Bethune *et al.* 2008):

$$R_{1-2,3} = \frac{r_{1-2} - r_{1-3} \cdot r_{2-3}}{\sqrt{1 - r_{1-3}^2} \cdot \sqrt{1 - r_{2-3}^2}} \tag{8}$$

The partial correlation coefficient $R_{1-2,3-4}$ between variable 1 and 2 after eliminating the effects of variable 3 and 4 is computed as:

$$R_{1-2,3-4} = \frac{r_{1-2,3} - r_{1-4,3} \cdot r_{2-4,3}}{\sqrt{1 - r_{1-4,3}^2 \cdot \sqrt{1 - r_{2-4,3}^2}}} \tag{9}$$

In this study, partial correlation analysis is applied to validate the controlling capacity of the three factors for ET and the relationship of them.

Factor analysis

Factor analysis (Andrew & Howard 2013) is applied to explore the interrelationships among the possible controlling factors of ET. In the factor analysis model, underlying factors, which act as the common factors affecting all the original variables, are assumed to reveal the nature of original datasets. In the study, LAI, P, and E_0 are all considered as the original variables. The model is:

$$X_{\mathrm{j}} = \sum_{i=1}^{p} a_{ji}F_i + \varepsilon_j \tag{10}$$

where X_j and F_i is the j^{th} original variable and the i^{th} common factor, respectively. p is the number of common factors, and $\mathcal{E}_j$ is the random variation of X_j. a_{ji} is the factor loading, which indicates the correlation between X_j and F_i. If $a_{ji} > 0.3$, it is significant. If $a_{ji} > 0.5$, it is very significant (Panagopoulos 2014). Communality of X_i could be calculated as $\sum_{i=1}^{p} a_{ji}^2$, which illustrates the contribution of all common factors to the original variable, and the cumulative variance of F_i is $\sum_{j=1} a_{ji}^2$.

RESULTS

Simulated results

The variation of P, LAI, E_0, and measured ET presented similar fluctuations during the study period, and the variation in YLX is shown in Figure 3. It also can be seen from the figure that the differences of different variables in the crests are much larger than in the troughs, particularly for the difference between E_0 and ET.

Here, the period of 2009–2012 was selected for calibration and 2007–2008 for validation. Figure 4 shows the measured and simulated ET by the ET model and the simulated process could match the measured one with a satisfying performance. However, some simulated peak values were underestimated while some were overestimated. The unmatched peak values may ascribe to the uncertainties of the measured ET data (Wu *et al.* 2012). Also, it was interesting that the overestimated ET somehow matched the rough variations of ET/E_0 ratio in

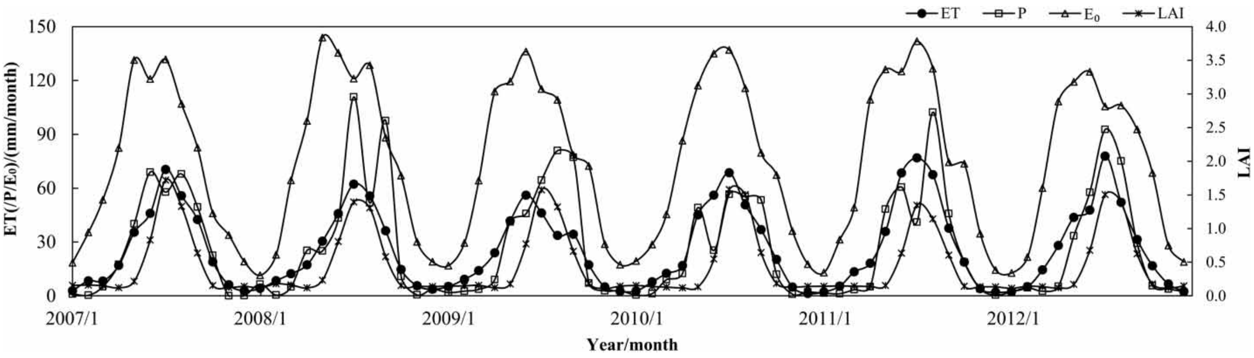

Figure 3 | *P*, *LAI*, E_0, and ET in YLX for 2007–2012.

Figure 5, particularly in YLX. The phenomenon may be due to intensive human disturbances (Qiu *et al.* 2016). Additionally, it can be seen from Figure 4 that performances in YLX&ZYX and ZYX were better than those in YLX.

In Table 2, *NS* were almost all over 0.90 except in YLX. *RE* in YLX&ZYX for validation and YLX for calibration were 7% and 12%, respectively, while the absolute values of other *RE*s were all 2%. *NRMSE* in all three basins was below 0.3. All the estimators described satisfying performances of ET simulation in the study areas, implying the applicability of the ET model in the study areas. The estimation of ET by means of the ET model in the study is more accurate than that by the evaporative fraction model in the middle reaches of the Heihe River basin (Li *et al.* 2012).

Table 3 shows the proposed ET models for all study areas. The parameters of $P^*E_0{}^*LAI$ term in the three study areas were all zero. The parameter for P^*E_0 part in ZYX was also zero.

The proposed ET model contributes to reconstructing ET processes with satisfying performances in the Heihe River basin. Due to water shortages, in many basins, intensive human activities intervene in utilization of the river flow and groundwater (Peng *et al.* 2016; Qiu *et al.* 2016), resulting in difficulties to simulate the processes of streamflow. Thus, rebuilding ET processes is of significance in unfolding the mechanism of hydrological processes. By means of the possible controlling factors related to the hydrological regime, the ET model provides a new approach to study hydrological processes in arid regions.

Parameters' sensitivity analysis

A simple method based on local parameter techniques (Qiu *et al.* 2013), by adding linear increments to the parameter estimated while keeping other parameters unchanged, was used to analyze the sensitivity of parameters in the proposed ET model. Parameters from a_1 to a_6 were estimated and *NS* acted as the performance indicator (Table 4).

The results showed that the sensitivity of parameters had the same rankings of $a_4 > > a_2 > a_6 > a_5 > a_1 > a_3$ when the increment was 0.1 and 0.01. The parameter a_4 was always much more sensitive than the others, indicating the strong effect of the item P^*E_0 on ET. When the increment was 0.1 or 0.01, the sensitivity of parameters related to E_0 was always remarkable, then *P*, and finally *LAI*. However, when the increment decreased to 0.001, the sensitivity of a_1, a_3, and a_5 changed in the study areas: the sensitivity of a_1 was almost the same as a_5 and both of them were less sensitive than a_3 in YLX&ZYX, but more sensitive than a_3 in ZYX. Except for a_4, the sensitivity of other parameters was almost the same when the increment was 0.0001.

Control factors

A three-common factor model for factor analysis was developed and the results are shown in Table 5. All original variables have one very significant factor loading at least. In YLX&ZYX, F_1, F_2, and F_3 have the closest relationship with *LAI*, E_0, and *P*, respectively. In YLX, F_1 has a significant relationship with *LAI*, F_1 and F_2 with *P*, and F_2 with E_0. In ZYX, F_1-*LAI*, F_2-*P* and F_1-E_0 have the most

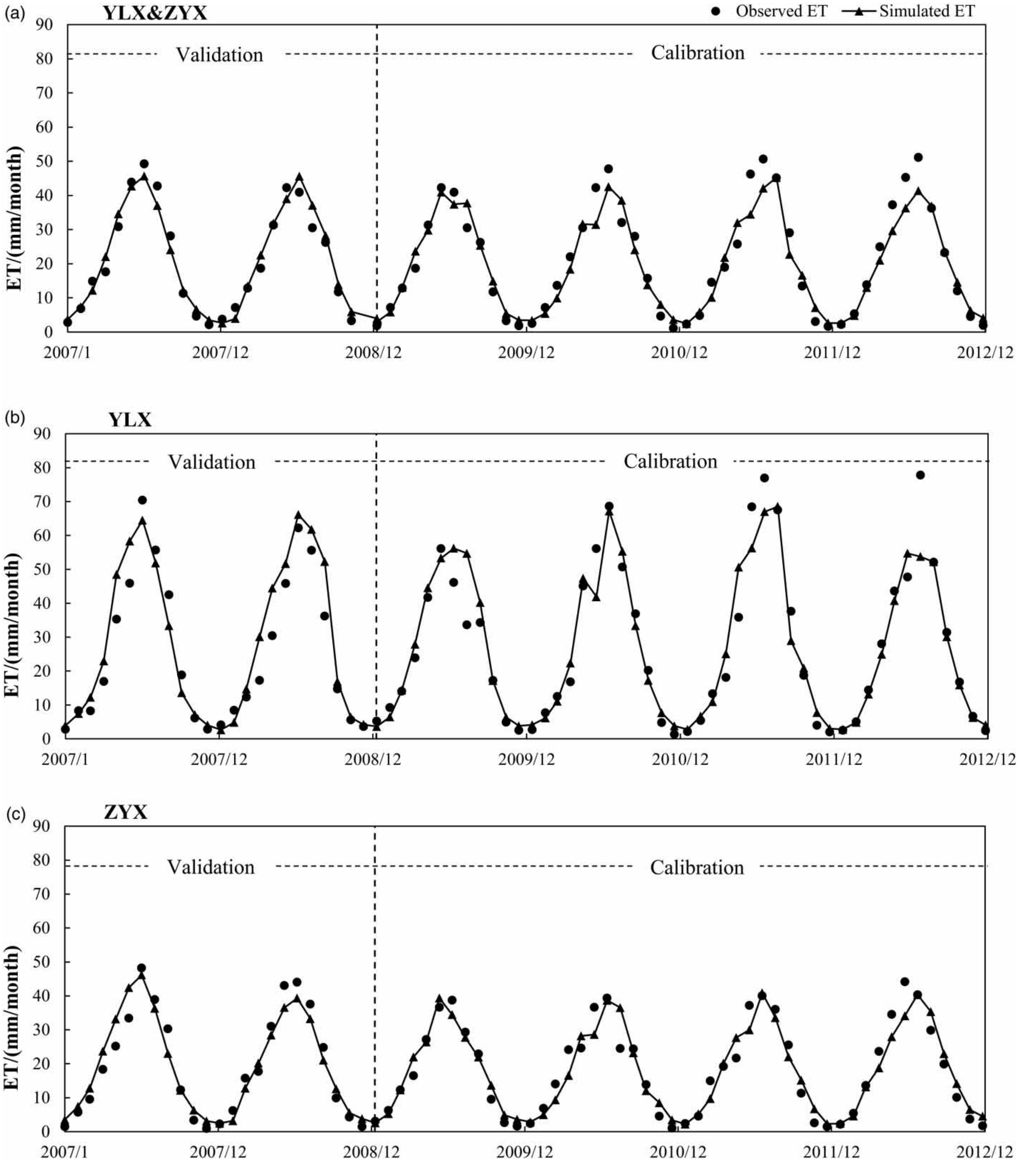

Figure 4 | Measured and simulated ET in (a) YLX&ZYX, (b) YLX, and (c) ZYX.

remarkable relationships. All factor loadings of F_3 are not significant in YLX or ZYX, but are significant in YLX&ZYX. All communalities are larger than 0.680, indicating that the three common factors could explain the three original variables well. The same conclusion can be found by the cumulative variance.

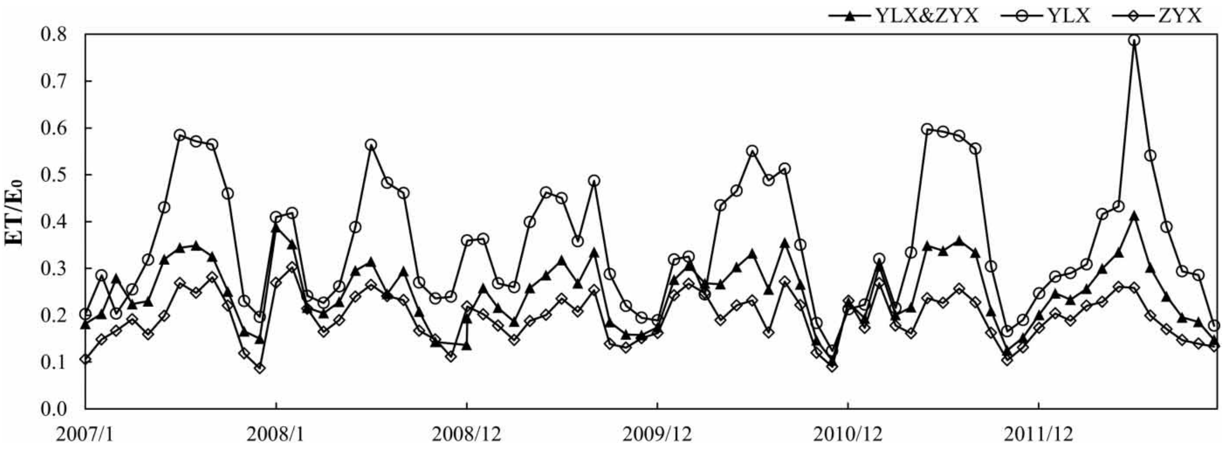

Figure 5 | Variation of ET/E_0.

Table 2 | Performances for calibration (2009–2012) and validation (2007–2008)

	Calibration			**Validation**		
Study area	***NS***	***RE***	***NRMSE***	***NS***	***RE***	***NRMSE***
YLX&ZYX	0.94	−1%	0.19	0.91	7%	0.23
YLX	0.88	−12%	0.25	0.90	−2%	0.29
ZYX	0.91	−1%	0.21	0.92	1%	0.25

According to the correlation coefficient between ET and different variables (see Figure 6), it can be known that E_0 always had the closest relation with ET in all the study areas. P and LAI had a similar relation with ET in YLX&ZYX and YLX, while LAI had a much closer relation with ET than P in ZYX. Figure 6 demonstrates that ET was closely associated with P, E_0, and LAI in the study areas. Then, partial correlation coefficients between ET and the three factors were calculated to estimate the independent effect of the individual factors (see Figure 7). It can be seen that the partial correlation coefficients were much smaller than the corresponding correlation coefficients, especially for P and LAI. By comparison of Figures 6 and 7, it is clear that the three factors had interaction among themselves, especially P and LAI. Results showed that in all the three study areas, independent E_0 had the strongest effect on ET, then independent LAI, and finally independent P, demonstrating the controlling roles of the three factors.

DISCUSSION

During the study period, the proposed ET model is applicable to simulate monthly ET with good performances. The ET model is rather easy to operate and data requirements are easy to match. Another advantage of the model is the flexibility and augmentability by means of adding to the model possible controlling factors adapted to a certain region to enhance model performances. Thus, it is of value in generalizing the model in arid regions.

The big flaw of the ET model is the requirement of measured ET data to calibrate the model, which is similar to most hydrological models. Another deficiency is no basis of physical mechanism. The controlling factors

Table 3 | Proposed ET model in the three study areas

Study area	**ET model**
YLX&ZYX	$ET = 0.115 \cdot P + 0.166 \cdot E_0 + 0.003 \cdot LAI + 0.001 \cdot P \cdot E_0 + 0.0003 \cdot P \cdot LAI + 0.032 \cdot E_0 \cdot LAI$
YLX	$ET = 0.110 \cdot P + 0.238 \cdot E_0 + 0.048 \cdot LAI + 0.002 \cdot P \cdot E_0 + 0.00002 \cdot P \cdot LAI + 0.051 \cdot E_0 \cdot LAI + 0.007$
ZYX	$ET = 0.178 \cdot P + 0.127 \cdot E_0 + 1.991 \cdot LAI + 0.005 \cdot P \cdot LAI + 0.022 \cdot E_0 \cdot LAI + 0.003$

Table 4 | Sensitivity analysis of ET model parameters a_1–a_6 with different individual parameter increments

Study area	Sensitivity of parameters Increment of 0.1	Increment of 0.01	Increment of 0.001	Increment of 0.0001
YLX&ZYX	$a_4 > > a_2 > a_6 > a_5 > a_1 > a_3$	$a_4 > > a_2 > a_6 > a_5 > a_1 > a_3$	$a_4 > > a_2 > a_6 > a_3 > a_5 \approx a_1$	$a_4 > > a_1 \approx a_2 \approx a_3 \approx a_5 \approx a_6$
YLX	$a_4 > > a_2 > a_6 > a_5 > a_1 > a_3$	$a_4 > > a_2 > a_6 > a_5 > a_1 > a_3$	$a_4 > > a_3 > a_2 > a_1 > a_5 > a_6$ or $a_4 > > a_2 > a_6 > a_1 > a_3 > a_5$	$a_4 > > a_1 \approx a_2 \approx a_3 \approx a_5 \approx a_6$
ZYX	$a_4 > > a_2 > a_6 > a_5 > a_1 > a_3$	$a_4 > > a_2 > a_6 > a_5 > a_1 > a_3$	$a_4 > > a_2 > a_6 > a_1 \approx a_5 > a_3$	$a_4 > > a_2 > a_6 > a_1 \approx a_5 > a_3$

considered and the nonlinear relationships between different factors in the model solve the problem to some degree.

The reason for the three factors considered in the study, rather than other factors, is that these three factors are not only possible controlling factors of ET but are also closely linked to hydrological processes. ET processes based on these factors have the potential to reveal hydrological processes in study areas. Although it is difficult to tell the dominant factor for ET in the study areas by the sensitivity analysis of the model parameters and the partial correlation analysis, it can be determined that E_0, P, and LAI are the controlling factors for ET in the Heihe River basin in the monthly time scale.

In YLX&ZYX, the total amount of P (1,478 mm) during the study period is nearly equal to that of ET (1,473 mm); the amount of P (1,975 mm) is slightly larger than that of ET (1,900 mm) in YLX. However, the situation is opposite in that the amount of ET (1,334 mm) is much larger than P (986 mm) in ZYX. The lesser amount of P than ET in ZYX implies that water availability derives far more from P in the basin. In fact, most water sources in ZYX come from the upper midstream. For YLX, although P provides most of the water source, other sources like snowmelt water contribute to its water availability. It has been

Table 5 | Results of factor analysis

Variable	YLX&ZYX F_1	F_2	F_3	Communalities	YLX F_1	F_2	F_3	Communalities	ZYX F_1	F_2	F_3	Communalities
LAI	**0.685**	0.402	0.439	0.823	**0.835**	0.356	0.021	0.825	**0.757**	−0.402	−0.263	0.804
P	0.466	0.408	**0.665**	0.825	**0.746**	**0.518**	−0.189	0.860	0.361	**−0.739**	−0.066	0.680
E_0	0.366	**0.716**	0.358	0.774	0.418	**0.763**	−0.032	0.757	**0.832**	−0.296	0.024	0.780
Cumulative variance	0.820	0.841	0.763		1.428	0.977	0.037		1.396	0.795	0.074	

Note: The significant level is denoted in bold ($a_{ij} > 0.5$).

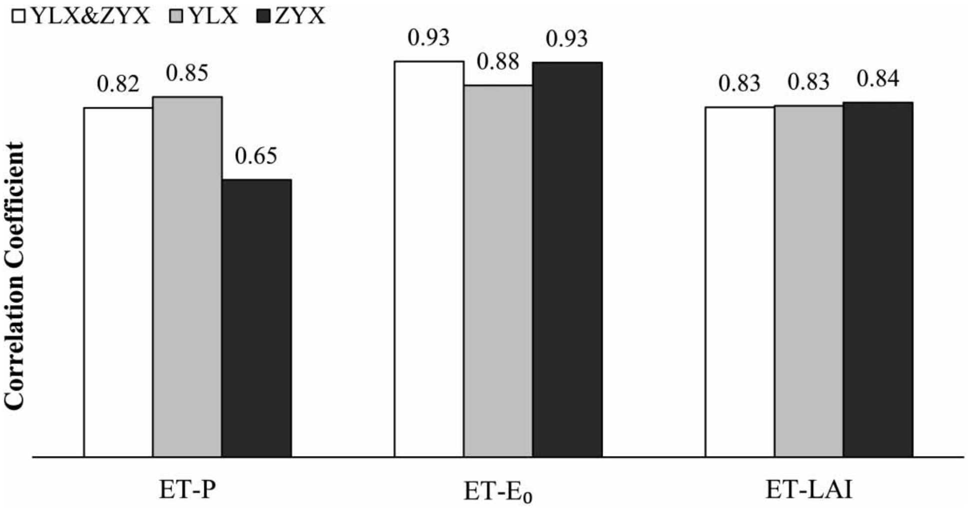

Figure 6 | Correlation coefficients between ET and the three factors in the study areas.

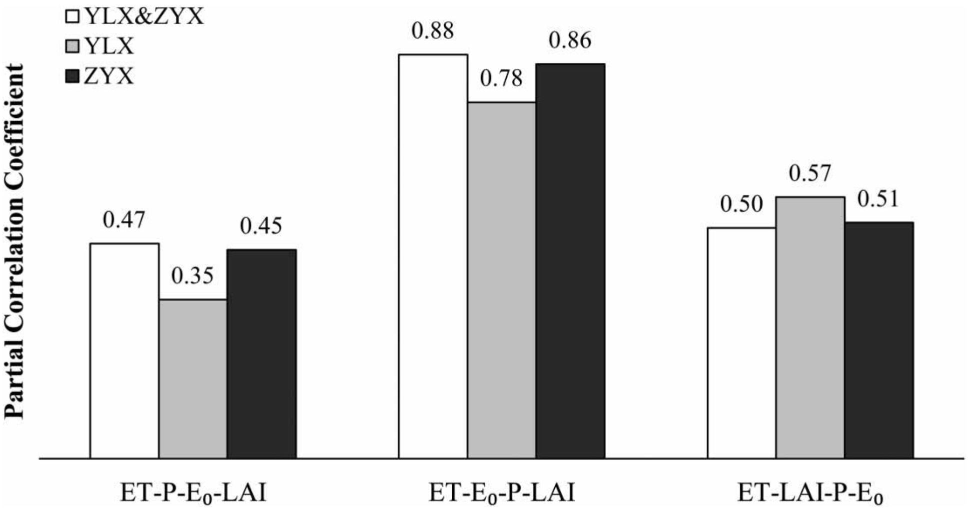

Figure 7 | Partial correlation coefficients between ET and the three factors in the study areas.

proposed that potential evaporation in ZYX is larger than in YLX, but ET in YLX is larger than in ZYX, which attributes to the larger water availability of YLX than ZYX. However, ET in both YLX and ZYX is much less than their potential evaporation, indicating water shortages in the study areas. Although *P* here does not denote the total water availability and whether the requirement of E_0 is matched or not, the two factors present critical controls on ET in the study areas.

According to Figure 1 and Table 1, YLX is about 70% covered and located near rivers. ZYX is half covered and half unused, of which, the half-covered ZYX is almost half covered by farmland, most of which is irrigated with large amounts of water consumption (Nian *et al.* 2013). Thus, vegetation cover in the study areas remarkably relates to ET.

CONCLUSIONS

ET is the most important form of water loss in arid regions and diagnosis of its controlling factors may be appropriate for reaching better water resources management. An ET model with precipitation, evaporation capacity, and vegetation and optimized by SCE-UA was proposed and applied to simulate ET in the upper and middle regions of the Heihe River basin. The controlling factors of ET were diagnosed by parameter sensitivity analysis and partial correlation analysis. The following conclusions can be drawn:

1. The proposed ET model with the three factors can reconstruct the actual ET in the upstream and midstream of the Heihe River basin properly. Additionally, the ET model is flexible to be applicable to other arid regions by adding more controlling factors to the model.
2. Evaporation capacity, precipitation, and vegetation are the control factors on ET in the upstream and midstream of the Heihe River basin.

ACKNOWLEDGEMENTS

This study was financially supported by the State Key Program of National Natural Science of China (91647202). Sincere thanks are due to two reviewers for their very helpful comments and suggestions.

REFERENCES

Allen, R. G., Pereira, L. S., Howell, T. A. & Jensen, M. E. 2011 Evapotranspiration information reporting: I. Factors governing measurement accuracy. *Agricultural Water Management* **98** (6), 899–920. doi: 10.1016/j.agwat.2010.12.015.

Andrew, L. C. & Howard, B. L. 2013 *A First Course in Factor Analysis*. Psychology Press, Hove, UK.

Bethune, M. G., Selle, B. & Wang, Q. J. 2008 Understanding and predicting deep percolation under surface irrigation. *Water Resources Research* **44** (12), W12430. doi: 10.1029/2007wr006380.

Courault, D., Seguin, B. & Olioso, A. 2005 Review on estimation of evapotranspiration from remote sensing data: from empirical to numerical modeling approaches. *Irrigation and Drainage Systems* **19** (3–4), 223–249. doi: 10.1007/s10795-005-5186-0.

DehghaniSanij, H., Yamamoto, T. & Rasiah, V. 2004 Assessment of evapotranspiration estimation models for use in semi-arid environments. *Agricultural Water Management* **64** (2), 91–106. doi: 10.1016/s0378-3774(03)00200-2.

Drexler, J. Z., Snyder, R. L., Spano, D. & Paw, U. K. T. 2004 A review of models and micrometeorological methods used to estimate wetland evapotranspiration. *Hydrological Processes* **18** (11), 2071–2101. doi: 10.1002/hyp.1462.

Droogers, P. 2000 Estimating actual evapotranspiration using a detailed agro-hydrological model. *Journal of Hydrology* **229** (1–2), 50–58. doi: 10.1016/s0022-1694(99)00198-5.

Duan, Q., Sorooshian, S. & Gupta, V. K. 1994 Optimal use of the SCE-UA global optimization method for calibrating watershed models. *Journal of Hydrology* **158** (3–4), 265–284. doi: 10.1016/0022-1694(94)90057-4.

Eagleman, J. R. 1971 An experimentally derived model for actual evapotranspiration. *Agricultural Meteorology* **8**, 385–394. doi: 10.1016/0002-1571(71)90124-5.

El Tahir, M. E. H., Wang, W. Z., Xu, C. Y., Zhang, Y. J. & Singh, V. P. 2012 Comparison of methods for estimation of regional actual evapotranspiration in data scarce regions: Blue Nile region, Eastern Sudan. *Journal of Hydrologic Engineering* **17** (4), 578–589. doi:10.1061/(asce)he.1943-5584.0000429.

Feng, X. M., Sun, G., Fu, B. J., Su, C. H., Liu, Y. & Lamparski, H. 2012 Regional effects of vegetation restoration on water yield across the Loess Plateau, China. *Hydrology and Earth System Sciences* **16** (8), 2617–2628. doi: 10.5194/hess-16-2617-2012.

Feng, J., Yan, D., Li, C., Gao, Y. & Liu, J. 2014 Regional frequency analysis of extreme precipitation after drought events in the Heihe River basin, Northwest China. *Journal of Hydrologic Engineering* **19** (6), 1101–1112. doi: 10.1061/(asce)he.1943-5584.0000903.

Gao, G., Xu, C. Y., Chen, D. & Singh, V. P. 2011 Spatial and temporal characteristics of actual evapotranspiration over Haihe River basin in China. *Stochastic Environmental Research and Risk Assessment* **26** (5), 655–669. doi:10.1007/s00477-011-0525-1.

Li, X., Lu, L., Yang, W. & Cheng, G. 2012 Estimation of evapotranspiration in an arid region by remote sensing – a case study in the middle reaches of the Heihe River basin. *International Journal of Applied Earth Observation and Geoinformation* **17**, 85–93. doi: 10.1016/j.jag.2011.09.008.

Ma, N., Zhang, Y., Xu, C. Y. & Szilagyi, J. 2015 Modeling actual evapotranspiration with routine meteorological variables in the data-scarce region of the Tibetan Plateau: comparisons and implications. *Journal of Geophysical Research: Biogeosciences* **120** (8), 1638–1657. doi: 10.1002/2015jg003006.

Nash, J. E. & Sutcliffe, J. V. 1970 River flow forecasting through conceptual models part I – A discussion of principles. *Journal of Hydrology* **10** (3), 282–290. doi: 10.1016/0022-1694(70)90255-6.

Nian, Y., Li, X., Zhou, J. & Hu, X. 2013 Impact of land use change on water resource allocation in the middle reaches of the Heihe River basin in northwestern China. *Journal of Arid Land* **6** (3), 273–286. doi: 10.1007/s40333-013-0209-4.

Panagopoulos, G. P. 2014 Assessing the impacts of socio-economic and hydrological factors on urban water demand: a multivariate statistical approach. *Journal of Hydrology* **518**, 42–48. doi: 10.1016/j.jhydrol.2013.10.036.

Peng, D. Z., Qiu, L. H., Fang, J. & Zhang, Z. Y. 2016 Quantification of climate changes and human activities that impact runoff in the Taihu Lake basin, China. *Mathematical Problems in Engineering* 1–7. doi: 10.1155/2016/2194196.

Qiu, L. H., You, J. J., Qiao, F. & Peng, D. Z. 2013 Simulation of snowmelt runoff in ungauged basins based on MODIS: a case study in the Lhasa River basin. *Stochastic Environmental Research and Risk Assessment* **28** (6), 1577–1585. doi: 10.1007/s00477-013-0837-4.

Qiu, L. H., Peng, D. Z., Xu, Z. X. & Liu, W. F. 2016 Identification of the impacts of climate changes and human activities on runoff in the upper and middle reaches of the Heihe River basin, China. *Journal of Water and Climate Change* **7** (1), 251–262. doi: 10.2166/wcc.2015.115.

Rudd, A. C. & Kay, A. L. 2016 Use of very high resolution climate model data for hydrological modelling: estimation of potential evaporation. *Hydrology Research* **47** (3), 660–670.

Stephenson, N. 1998 Actual evapotranspiration and deficit: biologically meaningful correlates of vegetation distribution across spatial scales. *Journal of Biogeography* **25** (5), 855–870. doi: 10.1046/j.1365-2699.1998.00233.x.

Sun, G., Alstad, K., Chen, J., Chen, S., Ford, C. R., Lin, G., Liu, C., Lu, N., McNulty, S. G., Miao, H. & Noormets, A. 2011 A general predictive model for estimating monthly ecosystem evapotranspiration. *Ecohydrology* **4** (2), 245–255. doi: 10.1002/eco.194.

Wang, K., Wang, P., Li, Z., Cribb, M. & Sparrow, M. 2007 A simple method to estimate actual evapotranspiration from a combination of net radiation, vegetation index and temperature. *Journal of Geophysical Research* **112**, D15107. doi: 10.1029/2006jd008351.

Wu, J. K., Ding, Y. J., Wang, G. X., Shen, Y. P., Yusuke, Y. & Jumpei, K. 2005 Evapotranspiration of low-lying prairie wetland in middle reaches of Heihe River in Northwest China. *Chinese Geographical Science* **15** (4), 325–329. doi: 10.1007/s11769-005-0020-z.

Wu, B., Yan, N., Xiong, J., Bastiaanssen, W. G. M., Zhu, W. & Stein, A. 2012 Validation of ETWatch using field measurements at diverse landscapes: a case study in Hai basin of China. *Journal of Hydrology* **436**, 67–80. doi: 10.1016/j.jhydrol.2012.02.043.

Xu, C. Y. & Chen, D. 2005 Comparison of seven models for estimation of evapotranspiration and groundwater recharge using lysimeter measurement data in Germany. *Hydrological Processes* **19** (18), 3717–3734. doi: 10.1002/hyp.5853.

Xu, C. Y. & Singh, V. P. 2005 Evaluation of three complementary relationship evapotranspiration models by water balance approach to estimate actual regional evapotranspiration in different climatic regions. *Journal of Hydrology* **308** (1–4), 105–121. doi: 10.1016/j.jhydrol.2004.10.024.

Yin, D. Q., Li, X., Huang, Y. F., Si, Y. & Bai, R. 2015 Identifying vegetation dynamics and sensitivities in response to water resources management in the Heihe River basin in China. *Advances in Meteorology*. doi: 10.1155/2015/861928.

Zhang, L., Dawes, W. R. & Walker, G. R. 2001 Response of mean annual evapotranspiration to vegetation changes at catchment scale. *Water Resources Research* **37** (3), 701–708. doi: 10.1029/2000wr900325.

First received 31 March 2017; accepted in revised form 18 July 2017. Available online 11 September 2017