Identifying separate impacts of climate and land use/cover change on hydrological processes in upper stream of Heihe River, Northwest China

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Abstract
Climate change and land use/cover change (LUCC) are two factors that produce major impacts on hydrological processes. Understanding and quantifying their respective influence is of great importance for water resources management and socioeconomic activities as well as policy and planning for sustainable development. In this study, the Soil and Water Assessment Tool (SWAT) was calibrated and validated in upper stream of the Heihe River in Northwest China. The reliability of the SWAT model was corroborated in terms of the Nash–Sutcliffe efficiency (NSE), the correlation coefficient (R), and the relative bias error (BIAS). The findings proposed a new method employing statistical separation procedures using a physically based modeling system for identifying the individual impacts of climate change and LUCC on hydrology processes, in particular on the aspects of runoff and evapotranspiration (ET).

The results confirmed that SWAT was a powerful and accurate model for diagnosis of a key challenge facing the Heihe River Basin. The model assessment metrics, NSE, R, and BIAS, in the data were 0.91%, 0.95%, and 1.14%, respectively, for the calibration period and 0.90%, 0.96%, and −0.15%, respectively, for the validation period. An assessment of climate change possibility showed that precipitation, runoff, and air temperature exhibited upward trends with a rate of 15.7 mm, 6.1 mm, and 0.38 °C per decade for the 1980 to 2010 period, respectively. Evaluation of LUCC showed that the changes in growth of vegetation, including forestland, grassland, and the shrub area have increased gradually while the barren area has decreased. The integrated effects of LUCC and climate change increased runoff and ET values by 3.2% and 6.6% of the total runoff and ET, respectively. Climate change outweighed the impact of LUCC, thus showing respective increases in runoff and ET of about 107.3% and 81.2% of the total changes. The LUCC influence appeared to be modest by comparison and showed about −7.3% and 18.8% changes relative to the totals, respectively. The increase in runoff caused by climate change factors is more than the offsetting decreases resulting from LUCC. The outcomes of this study show that the climate factors accounted for the notable effects more significantly than LUCC on hydrological processes in the upper stream of the Heihe River.

KEYWORDS
climate change, Heihe River Basin, hydrological processes, LUCC, SWAT

1 INTRODUCTION

It is well known that climate change and land use/cover change (LUCC) are the two critical factors influencing watershed hydrological processes (Piao et al., 2010; Wei, Liu, & Zhou, 2013). Research attention has recently been paid to enhancing the understanding of the relative influences and contributions of the two variables on the hydrological cycles as well as on water resources (Karlsson et al., 2016). Climate change is perceived to have been driven by global warming, in turn, is resulting in the changes in temporal and spatial
distribution of precipitation patterns (IPCC, 2014). The frequency and intensity of floods (Zhang, Lu, Jing, Paul, & Peter, 2008) and the replenishment and discharge of annual water runoff have also been affected (Immerzeel, van Beek, & Bierkens, 2010; Melkonyan, 2015). LUCC, on the other hand, is known to alter the cycle of hydrological processes, including transpiration, interception, and conservation (Tomer & Schilling, 2009). Deforestation, for example, can increase streamflow, which may lead to short-term positive feedbacks. Moreover, the clearing of forests raises the risk of damaging floods and causes increased soil erosion. Reduced precipitation, resulting from decreased evapotranspiration (ET), can also be caused by deforestation (Panday, Coe, Macedo, Lefebvre, & de Almeida Castanho, 2015). Conversely, reforestation and intensive agricultural rehabilitation can dramatically increase ET and continental precipitation. The effects of ET are more likely to lead to changes in surface runoff. On the other hand, vegetation types and distributions may affect air humidity, temperature, precipitation, and consequently, the hydrological cycle. Although the body of scientific literature on this topic appears to be limited, several pioneering studies have explored the interactions of forest change, climate, and hydrological activity (Hoog, 1998; Tague, Grant, Farrell, Choate, & Jefferson, 2008). It is thus important to separate the impacts of the climate change and LUCC factors on hydrological changes in order to accurately quantify their respective roles.

Methods available for analyzing hydrological impacts can be grouped into three categories: catchment paired experiment, statistical analysis, and hydrological models (Li, Zhang, Vaze, & Wang, 2012). The catchment paired experiment is normally applied in small watersheds and is used to separate the climate factor so that the effects of LUCC can be accurately quantified. However, this approach is generally not feasible for large watersheds due to differences in locating two similar catchments in close proximity with the same size, land cover pattern, and soil properties (Serpa et al., 2015). Statistical analysis, on the other hand, is usually easy to access with annual streamflow time series. This method currently in use is frequently misleading in its incapacity to incorporate agronomic and microclimatic effects, and in many cases, particularly egregious in ignoring soil, vadose, and surface storage. Moreover, the experimental and statistical methods treat the study basin as a black box (Wei et al., 2013) and seldom do they consider the complexity and heterogeneity in underlying surface conditions and the relationships between climate change and hydrological processes (Hu, Wang, Wang, Hong, & Zheng, 2015). Hydrological model, such as the Soil and Water Assessment Tool (SWAT), the TOPography based hydrological MODEL (TOPMODEL) and Variable Infiltration Capacity (VIC) is comprehensive and based on physical mechanisms that offer a framework to conceptualize and investigate the relationships between climate, underlying surface, and hydrological processes in various categories in time and space (Jothityangkoon, Sivapalan, & Farmer, 2001; Leavescs, 1994). Hydrological model is more effective as it relates model parameters directly to physically observable land surface characteristics (Legesse, Vallet-Coulemb, & Gasse, 2003). Thus, hydrological models can extract a significant amount of information from limited existing data.

The interactive, yet, overlapping relationship between climate change and LUCC is at a juxtaposition of separating their impacts challenging (Lin et al., 2015). Recent research in understanding these has been based on distributed hydrological models. In general, the one-factor-at-a-time approach (OFAT) has been widely applied to understand the relationship between climate change and LUCC (Chang et al., 2015; Natkhin, Dietrich, Schäfer, & Lischeid, 2015; Zhao et al., 2015). However, in accordance with literature, an accurate identification of their separate effects on hydrological processes cannot be accomplished with this method since the overall contribution do not, in fact, total to 100%. Notably, Li, Liu, Zhang, and Zheng (2009a) studied an agricultural catchment area on the Loess Plateau in China during the period 1981 to 2000 and identified the separate impacts of climate change and LUCC on decreasing river flow amounting to about 95.8% and 9.6%, respectively. The results indicated that other factors were apparently involved. A basic flaw of the OFAT method, however, is its inherent assumption that in the course of evaluating the influence of a given factor (e.g., climate change) on hydrological processes, the other factor (e.g., land use/cover) does not change from baseline to the affected period. For instance, separating the influence of climate change on hydrological processes warrants the inputting of only status of land cover for the baseline as a factor applicable to the entire study period. Transformation of land use from the baseline to the observation period is a variable that is ignored. In fact, LUCC is known to interact with climate factor, which in turn, impacts the hydrological processes and is concurrently changing and impacting on the first extent over the entire period of observation. Thus, a new method that combines statistical analysis and hydrological tools should be applied to unveil the interactions of climate change and LUCC in order to fully separate the contribution of the two interconnected factors. Furthermore, regional impacts of climate change and LUCC on hydrology can vary according to the place and time, so an investigation needs to be focus on local rather than on regional and continental level.

The primary area of focus in this paper entails Heihe River, which has attracted significant attention in China due to increasing pressures on water supply and the natural environment at this location (Feng, Ma, Jiang, Wang, & Cao, 2015; Li, Xu, Shao, & Yang, 2009b). The upper Heihe River (Yingluoxia catchment) is located in the middle of the Qilian Mountain, which is situated on northeastern Tibetan Plateau. This region is among the most sensitive zones in terms of climate change (Zhang, Zheng, Wang, & Yao, 2015a; Zhang, Nan, Yu, & Ge, 2015b). More than 1.3 million people live in this region, which also has about 266,000 ha of irrigated agricultural land located in the middle and lower stream that relies on the runoff emanating from its upper stream (Zhang, Fu, Sun, Zhang, & Men, 2015c). This flow is crucial for maintaining the climatic oasis functions and agricultural ecosystems in the middle and lower stream areas. The objectives of this study are threefold: (a) to define a conceptual framework and propose a new method combined statistical analysis and hydrological model, (b) to improve the modeling accuracy reached in separating the contributions of climate change and LUCC to streamflow, and (c) to understand and identify the dominating factors affecting hydrological processes in this ecologically sensitive zone. Results can serve as a baseline for assessment and management of water resources in the middle and lower sections of the Heihe River.
2 | STUDY AREA AND DATA COLLECTION

2.1 | Study area

The Heihe River Basin (HRB) is located in the middle reach of the Hexi Corridor in Gansu Province (China), lying between about 98° to 101°E and 38° to 42°N. It is the second-largest inland river basin in the arid region of China (Zhu, Su, Huang, Feng, & Liu, 2010). Altitudinal landscape zonation and related socioeconomic features allow the designation of four distinctive zones in the Hexi Corridor: alpine ice-snow and permafrost, water conservation forest, piedmont oasis, and desert oasis (Feng, Liu, Su, Zhang, & Si, 2004).

The primary section of upper stream, the Yingluoxia catchment, was selected as the study area (Figure 1). The elevation varies significantly from 5120 m to 1674 m, and the area is the main source of water flow for the entire river basin. Approximately 90% of water in the middle and lower stream is replenished from the Qilian Mountain. The climate in this watershed zone is mainly cold and dry in winter and warm and wet in summer period with significant spatial and temporal variations (Yin et al., 2014). Total annual average precipitation exceeds 450 mm and generally increases by 15.5–16.4 mm for every 100-m increase in elevation. At higher altitudes as much as 600 to 700 mm of precipitation can be observed. Nearly 70% of the total precipitation occurs between June and September with only 3.5% falling between December and February (Li et al., 2009b) while the annual mean temperature varies from −5 °C to 4 °C. The average annual runoff is about 16.05 × 10^8 m^3 with remarkable variability during the course of the year (Zhang, Zheng et al., 2015a). Predominant land-use activities within the watershed region are grassland, while the primary soil types are alpine meadow soil, alpine frost desert soil, and chestnut soil.

2.2 | Data

In order to investigate the separate impacts of climate change and LUCC on hydrological processes in upper stream of Heihe river, topographic, land use and land cover, and soil and hydro-meteorological data were collected for analysis. A digital elevation model (1:250,000) of soil type (1:500,000) and land-use maps (1:100,000) for 1980s and 2000s was provided by the Environmental and Ecological Science Data Center for West China. Soil properties were obtained from the Chinese Soil Database of the Institute of Soil Science, while land-use properties were sourced directly from the SWAT model database. Runoff data in the Heihe River were acquired from the Scientific Database of the Yellow River Hydrology Service, including monthly series for the period 1980–2010. Meteorological data for the 1980–2010 period were collected from China Meteorological Administration. The latter provided information on daily precipitation, maximum and minimum temperature, sunshine hours, humidity, wind speed, and wind directions. The meteorological time series had already been analyzed for homogeneity using the standard normal homogeneity test (Yang & Li, 2014). The station gauged precipitation series were adjusted using bias-correction methods according to Ye, Yang, Ding, and Han (2004) and Karlsson, Sonnenborg, Jensen, and Refsgaard (2014). Air temperature and precipitation records for a total of 30 years and the daily dataset were used to determine monthly values. Regional precipitation and air temperature levels were acquired by spatial interpolation methods applied in combination with the topographical corrective methods (Liu & Zou, 2006). The regional data was based on statistical relationship between meteorological and topographical factors. This relationship in fact reflected the main characteristics of the spatial pattern of alpine meteorology (Li et al., 2015).

**FIGURE 1** Location of the Yingluoxia catchment with weather stations, river gauging stations, and digital elevation map (DEM)
3 | METHODOLOGY

3.1 | Mann–Kendall trend test

The Mann–Kendall (M–K) test was applied to assess any pertinent trends in datasets based on nonparametric testing procedure according to the work of Mann (1945) and Kendall (1975). This method is widely used in hydro-meteorological trend detection studies and utilizes the notion that for a time-ordered sample of data $x_i (i = 1, 2, ..., n)$, $x_i$ is independent and identically distributed. The test statistic $S$ is given by (Deo, McAlpine, Syktus, McGowan, & Phinn, 2007; Kendall, 1975; Mann, 1945):

$$S = \sum_{i,j} a_{ij},$$  

where

$$a_{ij} = \text{sgn}(x_j - x_i) = \begin{cases} 
1 & x_i < x_j \\
0 & x_i = x_j \\
-1 & x_i > x_j 
\end{cases} \quad (2)$$

It should be noted that the statistic $S$ only depends on the rank of observations rather than their actual value and therefore, yields a result based on a distribution-free metric. This provides a distinct advantage of applying M–K test since the results are unaffected by actual distribution of considered dataset (Hamed, 2008). Following an assumption that the tested data are independent and identically distributed, the mean and variances are given by

$$\begin{align*} 
E(S) &= 0 \\
\text{Var}(S) &= n(n-1)(2n+5)/18 - \frac{a}{2} \sum_{i=1}^n t_i(t_i-1)(2t_i + 5)/18. 
\end{align*}$$  

(3)

In Equation 4, $t_i$ is the number of ties of extent $i$, and significance of a trend, if any, is tested by comparing the standardized variable $Z_c$ with the standardized normalized variance $Z_{1-a/2}$ at a desired significance level $\alpha$ (Karlsson et al., 2014):

$$Z_c = \begin{cases} 
\frac{S - 1}{\sqrt{\text{Var}(S)}} & S > 0 \\
0 & S = 0 \\
\frac{S + 1}{\sqrt{\text{Var}(S)}} & S < 0 
\end{cases} \quad (5)$$

Notably, the null hypothesis that the investigated data are trend free is rejected when the Mann–Kendall statistics $|Z_c| > Z_{1-a/2}$ corresponds to a $1-\alpha/2$ quantile of the standard normal distribution. Hence, the alternative hypothesis that there is a trend in data series is accepted at a significance level of $\alpha$ (Hisdal, Stahl, Tallaksen, & Demuth, 2001; Karlsson et al., 2014).

3.2 | Sen slope

The magnitudes of estimated changes in the trend of meteorological variables in this study were estimated by an application of the Sen slope method. This technique calculates the gradient as a change in the measurements correlated with units of temporal change. The advantages of this method are the allowances for missing data, avoidance of assumptions on distributions of tested data, and the averting of the effects of gross data errors and outliers (Sen, 1968). Therefore, this method alleviates the consequences of missing data and/or anomalous trends therein by using the median values of the time series of various slopes that were detected as a judgmental tool viz (Deo et al., 2007; Sen, 1968):

$$\beta = \text{median} \left( \frac{x_j - x_i}{j-i}, \forall j>i \right).$$  

(6)

Note that in Equation 6, $1 < j < i < n$. The estimator $\beta$ is the median overall combinations of the recorded pairs for the entire dataset where trend analysis is performed and a positive $\beta$ is expected to exhibit an “increasing trend” while a negative value indicates a “decreasing trend” (Deo et al., 2007; Zhang et al., 2008).

3.3 | The SWAT model

The SWAT is a physically and mathematically based semidistributed hydrological model (Arnold, Srinivasan, Muttiah, & Williams, 1998). The SWAT model is capable of processing hydrological simulations by applying the principle of water balance (Jung et al., 2012) in each hydrologic response units, which defines the areas with identical combinations of surface slope, land use, and soil type (Karlsson et al., 2016). The water balance equation is given as (Arnold et al., 1998)

$$SW_t = SW_0 + \sum_{i=1}^n \left( P_{\text{day}} - Q_{\text{surf}} - E_a - W_{\text{seep}} - Q_{\text{gw}} \right).$$  

(7)

where $SW_t$ is the final soil moisture (mm), $SW_0$ is the initial soil moisture at the time of $i$ (mm), $P_{\text{day}}$ is the precipitation at the time of $i$ (mm), $Q_{\text{surf}}$ is the surface runoff at the time of $i$ (mm), $E_a$ is the evapotranspiration at the time of $i$ (mm), $W_{\text{seep}}$ is the water flow to the unsaturated zone from the soil profile at the time of $i$ (mm), and $Q_{\text{gw}}$ is the water flow from the watershed from underground at the time of $i$ (mm).

In this study, we have used the model version denoted as SWAT2009.10.1. To apply this model, we partitioned the study area into 43 of subwatersheds with 2641 HRUs. The Soil Conservation Service curve number method was used for computing surface runoff volume (Li et al., 2009b) while Muskingum and Penman–Monteith schemes were used for flow routing and estimating the potential ET.
3.4 Framework for separating effects of climate change and LUCC

In a given river basin, changes in hydrological processes are caused by climate change and LUCC, which are assumed to be independent factors (Zhang et al., 2008). In this study, hydrological processes were treated as a function of the two variables. To separate the discrete effects of climate change on hydrological processes, we created a schematic sketch map that represented the variations of hydrological processes along with climate change factors under differing LUCC scenarios (Figure 2).

The separate impacts of climate factors on hydrological processes under LUCC, L1, and L2 are applied to calculate ΔQC1 and ΔQC2 (Figure 2a), respectively. In general, the smaller the change in land use (ΔL), the closer is the ΔQC1 to ΔQC2. Thus, we utilized an average of the ΔQC1 and ΔQC2 values to denote the separate impacts of climate change on hydrological elements (ΔQC):

\[
\Delta Q_C = \frac{1}{2}(\Delta Q_{C1} + \Delta Q_{C2}) = \frac{1}{2}\left[(Q_{C1}^2 - Q_{C1}^1) + (Q_{C2}^2 - Q_{C2}^1)\right].
\]

Similarly, the effects of LUCC on hydrological processes were calculated by applying the difference of hydrological component values under land-use conditions L1 and L2, which are denoted as ΔQL1 and ΔQL2 (Figure 2b). The smaller the moderation in climate change (ΔC), the closer is ΔQL1 to ΔQL2. Thus, we applied the arithmetic mean of ΔQL1 and ΔQL2 as the separate impacts of LUCC to the hydrological processes (ΔQL):

\[
\Delta Q_L = \frac{1}{2}(\Delta Q_{L1} + \Delta Q_{L2}) = \frac{1}{2}\left[(Q_{L1}^2 - Q_{L1}^1) + (Q_{L2}^2 - Q_{L2}^1)\right].
\]

At the same time, we must note that the total changes in hydrological processes are equal to the sum of the two impacts. The changes also can be estimated by the differences in the observed hydrological elements within the baseline period and period in which the effects were recorded:

\[
\Delta Q = \Delta Q_L + \Delta Q_C = Q_{L2}^2 - Q_{L1}^1.
\]

In Equation 10, ΔQ represents the total changes in hydrological processes, where the hydrological elements can serve as statistic mean value over annual, seasonal, or monthly time scales. We used the above method to recalculate the relative contributions of climate change and LUCC to runoff as reported by Li et al. (2009a). Therefore, the revised analysis was based on the outcomes of their SWAT-based modeling. According to our method, it was evident that climate change and LUCC had influenced the decrease of runoff by about 93.3% and 6.7%, respectively. The latter results differed from those obtained prior to the recalculation process, which were, respectively, 95.8% and 9.6%.

Meteorological data for the periods 1982–1995 and 1996–2010 were selected in this study, with land use for each period reflected on separate map. The land-use maps for the 1980s and 2000s were used to represent the land-use patterns for the two periods. A calibrated SWAT model was then applied to each of the four permutations derived from the two time periods and the two land-use maps. Herein- after, these are denoted as four different scenarios where the influence of LUCC and climate change can be quantified by comparing the SWAT model outputs of the four scenarios:


3.5 Model calibration and validation

The SWAT model was calibrated using historical data from January 1982 to December 1995 collected at Yingluoxia hydrological station. The validation period was based on information from January 1996 to December 2010. In addition to the foregoing, the warming-up period was January 1980 to December 1982. The model was auto-calibrated with the sequential uncertainty fitting algorithm (SUFI2) implemented in SWAT Calibration and Uncertainty Procedures by Abbaspour, Vejdani, and Haghighat (2007). It was also auto-calibrated repeatedly 12 times including 100 simulations each time. We
considered three parallel ancillary tools, including the correlation coefficient (R), the relative bias error (BIAS) and the Nash–Sutcliffe coefficient (NSE; Nash & Sutcliffe, 1970). We also considered the relative (%) Bias error (BIAS) to evaluate the performance of the SWAT model during calibration and validation phases (LaFontaine, Hay, Viger, Regan, & Markstrom, 2015; Lin et al., 2015). Thus, the following equations were applied as performance measures:

\[
R = \frac{\sum_{i=1}^{N} (Q_{obs}(i) - \bar{Q}_{obs})(Q_{sim}(i) - \bar{Q}_{sim})}{\left(\sum_{i=1}^{N} (Q_{obs}(i) - \bar{Q}_{obs})^2\right)^{1/2} \left(\sum_{i=1}^{N} (Q_{sim}(i) - \bar{Q}_{sim})^2\right)^{1/2}},
\]

\[
BIAS = \frac{\sum_{i=1}^{N} (Q_{obs}(i) - Q_{sim}(i))}{\sum_{i=1}^{N} Q_{obs}(i)} \times 100\%,
\]

\[
NSE = 1 - \frac{\sum_{i=1}^{N} (Q_{obs}(i) - Q_{sim}(i))^2}{\sum_{i=1}^{N} (Q_{obs}(i) - \bar{Q}_{obs})^2}.
\]

where \(N\) is the number of data points, \(Q_{obs}\) is the observed runoff at time step \(i\), \(Q_{sim}\) is the simulated runoff at time step \(i\), and \(\bar{Q}_{obs}\) and \(\bar{Q}_{sim}\) are the respective mean values of the observed and simulated runoff.

### 4 | RESULTS AND DISCUSSION

#### 4.1 | Changes in hydro-meteorological processes

Three hydro-meteorological elements, annual precipitation, runoff, and mean air temperature, were either aggregated or averaged based on monthly data series. Results of the Sen slope method examining the temporal trends in annual hydro-meteorological factors per decade over the course of entire data series are shown in Figure 3. It is evident that all trends of decadal durations in the three hydro-meteorological elements appear to exhibit an increasing trend and reflect different levels of significance. Increased trends in precipitation and runoff data during the 2000–2010 period (with estimated magnitudes (\(\beta\)) of 172.4 mm and 59.2 mm per decade, respectively) were generally higher compared to those of the 1980–1989 (65.6 and 13.2 mm per decade, respectively) and 1990–1999 periods (65.1 and 27.2 mm per decade, respectively). However, the trends in average annual air temperature over the 3 decades considered in this work were similar, with a rate of increase of approximately 0.5 °C every 10 years. Overall, the three variables exhibited an upward trend, with positive gradients of about 15.7 mm, 6.1 mm, and 0.38 °C per decade, respectively, during the last 3 decades.

In order to establish a statistical veracity, M–K test was performed to test the significance of the trends presented in Figure 4. This testing was able to detect various trends in the three variables including a demarcation of the statistically significant trends for specific months analyzed in the study period (Table 1). The trend in precipitation was, with the exception of June and September, nearly insignificant at a confidence level of 10%. In June and September, there was a decreasing trend of about 12.8 mm per decade and an increasing trend of about 19.1 mm per decade, respectively. The increase in annual precipitation was attributable to mainly large rise of precipitation in the month of September.

With the exception of April and October, air temperature data exhibited a rising trend during the remaining months. The trends were modestly significant at above 10% confidence interval, except for January, October, and November. The average rate of air temperature increase from December to March (1.19 °C/decade) was four times higher than the rise from June to October (0.26°C/decade). These trends were similar to results reported by Piao et al. (2010), which also showed that the warming during the winter period was more evident than that during the summer period in the same study area.

Influenced by climate change and LUCC factors, the runoff trends in this study reflected the interaction of two factors with the environment. A variation in the trends of monthly runoff apparently occurred
Based on the analyses of spatial distribution and statistical data, the composition of land use in the Yingluoxia catchment exhibited changes since the early 1980s (as shown in Figure 5 and Table 2). The leading type of land use was pasture, which accounted for more than 51% of the entire expanse (51.66% and 52.73% for 1980s and 2000s, respectively). The second largest use type was barren land, including areas of the SWAT model for annual runoff did not meet a very high correlation with the observed data series in both calibration and validation periods (Figure 6). Meanwhile, the result also showed an increase in pasture, woodland, shrub, water, arable land, and urbanized areas of rock and sparse grassland, accounting for more than 21%. These land uses were followed by shrub (12.13% and 12.30%), woodland (9.44% and 10.11%), and water (1.72% and 2.53%). We also observed an increase in pasture, woodland, shrub, water, arable land, and urbanized area (combined residential, transportation, and industrial uses) and a decrease in barren land as well as glacier. Compared with land-use area in 1980s, the pasture, woodland, shrub, and water in the 2000s had increased in areal extent, by respective amounts of 100.09, 62.44, 15.67, and 75.63 km². In contrast, the barren land and glaciers exhibited a decrease by 240.03 and 31.35 km², respectively, while the arable land and urbanized areas showed modest changes compared to their 1980 baselines. In general, these results indicated that the expansion of vegetation coverage had in fact increased, and the natural environment had improved over the period of study.

Table 3 shows a land-use transformation matrix for the Yingluoxia catchment used to reflect the direction of change in the various land-use types. Overall, it was evident that about 913 km² of land has changed from 1980s to 2000s, which comprised of approximately 1.1%, 3.35 km² and 3.85 km². These changes were caused by climate change, which in turn, led to the extension of pasture into high altitudes and desertification (Feng et al., 2015). In order to compare the net transformation according to different land-use types, Table 4 shows the predominating forms of changes. For a certain pair of land-use patterns, its net quantitative change was dependent on the differences between transformations from and into the certain other land-use patterns. There were six changeovers that exceeded 10 km², which can be classified into three groups: barren land transformed into pasture (48.89 km²) and barren land (7.46 km²). Shrub area had increased by the transformation from pasture (17.12 km²), which was attributable to large-scale reforestation and ecological restoration programs in the Qilian Mountain launched in the early 2000s (Liang et al., 2015). Changes in pasture areas also occurred as result of transformation both from and into barren land (797.53 and 571.5 km², respectively). These changes were caused by climate change, which in turn, led to the extension of pasture into high altitudes and desertification (Feng et al., 2015). In order to compare the net transformation according to different land-use types, Table 4 shows the predominating forms of changes. For a certain pair of land-use patterns, its net quantitative change was dependent on the differences between transformations from and into the certain other land-use patterns. There were six changeovers that exceeded 10 km², which can be classified into three groups: barren land transformed into pasture, glacier into barren land, and pasture into other types of land use. Except for the transformation of pasture into water, other changes resulted in increase in the vegetation coverage. This may, in turn, lead to an increase in canopy interception and transpiration through vegetation, while decreasing the surface runoff in a reciprocating manner.

### 4.3 Calibration and validation of measurement models

Simulated monthly runoff of the Yingluoxia catchment showed a positive correlation with the observed data series in both calibration and validation periods (Figure 6). Meanwhile, the result also showed examples of overestimate or underestimate can be observed from certain runoff during peak periods. There was also a strong correlation between the observed and simulated runoff at monthly and annual scales (Figure 7 and Table 5). Importantly, the BIAS value was about 1.14% and −0.15% for the model calibration and validation periods, respectively. This concurred with a value of R and NSE of 0.95 and 0.91, respectively, for the monthly runoff, and about 0.94 and 0.88, respectively, for the annual runoff in the calibration period. During the validation period, the value of R and NSE were about 0.96 and 0.90, respectively, for monthly runoff, and about 0.96 and 0.76, respectively, for annual runoff (Table 5). Results of the study also showed no evidence of systematic bias in the simulated streamflow in model calibration and validation phases. Although the performance of the SWAT model for annual runoff did not meet a very high

### TABLE 1 Trend analysis results of hydro-meteorological variables based on Sen slope (per decade) and the M-K tests

<table>
<thead>
<tr>
<th>Month</th>
<th>Precipitation</th>
<th>Temperature</th>
<th>Runoff</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Test Z</td>
<td>Sig.</td>
<td>β</td>
</tr>
<tr>
<td>Jan.</td>
<td>1.11</td>
<td>0.34</td>
<td>1.50</td>
</tr>
<tr>
<td>Feb.</td>
<td>0.29</td>
<td>0.24</td>
<td>2.36</td>
</tr>
<tr>
<td>Mar.</td>
<td>−0.39</td>
<td>−0.32</td>
<td>2.25</td>
</tr>
<tr>
<td>Apr.</td>
<td>0.82</td>
<td>1.84</td>
<td>−2.60</td>
</tr>
<tr>
<td>May.</td>
<td>0.43</td>
<td>2.75</td>
<td>1.82</td>
</tr>
<tr>
<td>Jun.</td>
<td>−1.82</td>
<td>−12.79</td>
<td>3.35</td>
</tr>
<tr>
<td>Jul.</td>
<td>0.12</td>
<td>1.55</td>
<td>3.85</td>
</tr>
<tr>
<td>Aug.</td>
<td>0.23</td>
<td>1.65</td>
<td>3.14</td>
</tr>
<tr>
<td>Sep.</td>
<td>2.34</td>
<td>b 19.09</td>
<td>3.82</td>
</tr>
<tr>
<td>Oct.</td>
<td>0.37</td>
<td>0.85</td>
<td>−1.53</td>
</tr>
<tr>
<td>Nov.</td>
<td>0.59</td>
<td>0.20</td>
<td>0.71</td>
</tr>
<tr>
<td>Dec.</td>
<td>−0.55</td>
<td>−0.10</td>
<td>1.68</td>
</tr>
</tbody>
</table>

Note. Positive values in the table indicate an increase and negative values indicate a decrease.

*a* indicates a significance level of 0.1.

*b* indicates a significance level of 0.05.

*c* indicates a significance level of 0.01.
accuracy since R and NSE were much lower compared to the monthly runoff data, the basic rainfall–runoff relationship and water balance were still well captured, as was their intra-annual distributions. In spite of this lower performance, the present results were still within the range of “good performance” according to the performance classification of Moriasi et al. (2007). These results show that the SWAT model is indeed a robust simulation tool that can be embraced for estimating the effects of climate change and LUCC in the Yingluoxia catchment of the Heihe River. The optimal values and range of parameters during the last repetitions are presented in Table 6.

**FIGURE 5** Distribution of land use for 1980s and 2000s in the Yingluoxia catchment area

**TABLE 2** Change of land-use structure in the Yingluoxia catchment during 1980s–2000s

<table>
<thead>
<tr>
<th>Land-use type</th>
<th>1980s Area (km²)</th>
<th>1980s Area (%)</th>
<th>2000s Area (km²)</th>
<th>2000s Area (%)</th>
<th>Change Area (km²)</th>
<th>Change Area (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Arable land</td>
<td>31.01</td>
<td>0.33</td>
<td>42.60</td>
<td>0.45</td>
<td>11.59</td>
<td>0.12</td>
</tr>
<tr>
<td>Woodland</td>
<td>884.74</td>
<td>9.44</td>
<td>947.18</td>
<td>10.11</td>
<td>62.44</td>
<td>0.67</td>
</tr>
<tr>
<td>Shrub</td>
<td>1137.02</td>
<td>12.13</td>
<td>1152.69</td>
<td>12.30</td>
<td>15.67</td>
<td>0.17</td>
</tr>
<tr>
<td>Pasture</td>
<td>4841.93</td>
<td>51.66</td>
<td>4942.02</td>
<td>52.73</td>
<td>100.09</td>
<td>1.07</td>
</tr>
<tr>
<td>Water</td>
<td>161.45</td>
<td>1.72</td>
<td>237.08</td>
<td>2.53</td>
<td>75.63</td>
<td>0.81</td>
</tr>
<tr>
<td>Residential</td>
<td>9.32</td>
<td>0.10</td>
<td>15.28</td>
<td>0.16</td>
<td>5.96</td>
<td>0.06</td>
</tr>
<tr>
<td>Barren land</td>
<td>2249.74</td>
<td>24.00</td>
<td>2009.71</td>
<td>21.44</td>
<td>−240.03</td>
<td>−2.56</td>
</tr>
<tr>
<td>Glacier</td>
<td>59.39</td>
<td>0.63</td>
<td>28.04</td>
<td>0.30</td>
<td>−31.35</td>
<td>−0.33</td>
</tr>
</tbody>
</table>
Effects of climate change and LUCC on runoff and evapotranspiration

In this paper, simulated results were adopted instead of the measured data, to compare the hydrological outcomes in upper stream of the Heihe River. Table 7 shows the results for runoff and ET data simulated by the SWAT model under the four hypothetical scenarios presented in Section 3.4. Compared with scenario S1, simulated runoff and ET in S4 increased by about 5.6 and 17.5 mm, respectively. Thus, the combined impacts of climate change and LUCC from 1980s to 2000s were clearly evident. The magnitude of these changes was about 3.2% and 6.6% for the total runoff and ET, respectively. Interestingly, the contrasting values obtained between S1 and S2 and those of S3 and S4 concurred the influence of land-use change during the two subjected periods. We therefore applied the separation equation (Equation 9) to assess the impacts of land-use change. The results suggested that LUCC appears to have contributed to a decrease in runoff by about 0.4 mm, which in turn, accounted for 7.3% of the change in runoff values. It should also be noted that the land-use factor contributed to an increase in ET by about 3.3 mm, thus accounting for almost 18.8% of the change in total ET.

The influence of climate change on runoff and ET data during the two subjected periods were calculated by measuring the difference between scenarios S1 and S3 as well as those between S2 and S4. The results showed that climate variations appeared to have increased the runoff values by about 6.0 mm, thus accounting for about 107.3% of the total runoff change. The climate factor also increased ET value by about 14.2 mm, which comprised of about 81.2% of the total ET change. In light of these results, it is construed that, while LUCC and climate change appeared to increase the ET values during the 1980s to 2000s, the impact of climate factors exceeded by far that the impact of LUCC factors. At the same time, increase in runoff appeared to have been caused by climate change more than the offset, which led a decrease caused by LUCC factors. According to this finding, this result about 3.2% and 6.6% for the total runoff and ET, respectively. Interestingly, the contrasting values obtained between S1 and S2 and those of S3 and S4 concurred the influence of land-use change during the two subjected periods. We therefore applied the separation equation (Equation 9) to assess the impacts of land-use change. The results suggested that LUCC appears to have contributed to a decrease in runoff by about 0.4 mm, which in turn, accounted for 7.3% of the change in runoff values. It should also be noted that the land-use factor contributed to an increase in ET by about 3.3 mm, thus accounting for almost 18.8% of the change in total ET.

TABLE 3 Matrix of land-use transformation in the Yingluoxia catchment area during 1980s–2000s (km²)

<table>
<thead>
<tr>
<th>Transformation Matrix</th>
<th>Arable land</th>
<th>Woodland</th>
<th>Shrub</th>
<th>Pasture</th>
<th>Water</th>
<th>Residential</th>
<th>Barren land</th>
<th>Glacier</th>
</tr>
</thead>
<tbody>
<tr>
<td>1980s</td>
<td>9.67</td>
<td>1.12</td>
<td>1.01</td>
<td>15.83</td>
<td>1.43</td>
<td>1.92</td>
<td>0.03</td>
<td>0</td>
</tr>
<tr>
<td>Woodland</td>
<td>0</td>
<td>883.96</td>
<td>0</td>
<td>0.42</td>
<td>0</td>
<td>0</td>
<td>0.36</td>
<td>0</td>
</tr>
<tr>
<td>Shrub</td>
<td>0</td>
<td>0.07</td>
<td>1123.51</td>
<td>1.94</td>
<td>0.01</td>
<td>0</td>
<td>1.48</td>
<td>0.01</td>
</tr>
<tr>
<td>Pasture</td>
<td>29.13</td>
<td>48.89</td>
<td>17.12</td>
<td>4042.70</td>
<td>127.58</td>
<td>3.45</td>
<td>571.50</td>
<td>1.56</td>
</tr>
<tr>
<td>Water</td>
<td>3.72</td>
<td>5.68</td>
<td>1.05</td>
<td>79.15</td>
<td>59.32</td>
<td>0.59</td>
<td>11.94</td>
<td>0</td>
</tr>
<tr>
<td>Residential</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>9.32</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Barren land</td>
<td>0.08</td>
<td>7.46</td>
<td>0</td>
<td>797.53</td>
<td>48.64</td>
<td>0</td>
<td>1388.09</td>
<td>7.94</td>
</tr>
<tr>
<td>Glacier</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>4.45</td>
<td>0.10</td>
<td>0</td>
<td>36.31</td>
<td>18.53</td>
</tr>
</tbody>
</table>

TABLE 4 Major transformations of land use in the Yingluoxia catchment during 1980–2000. The percent change of converted land use is the percentage of changed area on the primary land-use pattern area

<table>
<thead>
<tr>
<th>Predominating transformation types</th>
<th>Net changed Area (km²)</th>
<th>Percent change of converted land use (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Barren land to pasture</td>
<td>226.03</td>
<td>10.05</td>
</tr>
<tr>
<td>Pasture to woodland</td>
<td>48.47</td>
<td>1.00</td>
</tr>
<tr>
<td>Pasture to water</td>
<td>48.43</td>
<td>1.00</td>
</tr>
<tr>
<td>Glacier to barren land</td>
<td>28.37</td>
<td>47.77</td>
</tr>
<tr>
<td>Pasture to shrub</td>
<td>15.18</td>
<td>0.31</td>
</tr>
<tr>
<td>Pasture to arable land</td>
<td>13.30</td>
<td>0.27</td>
</tr>
</tbody>
</table>

4.4 Effects of climate change and LUCC on runoff and evapotranspiration

In this paper, simulated results were adopted instead of the measured data, to compare the hydrological outcomes in upper stream of the Heihe River. Table 7 shows the results for runoff and ET data simulated by the SWAT model under the four hypothetical scenarios presented in Section 3.4. Compared with scenario S1, simulated runoff and ET in S4 increased by about 5.6 and 17.5 mm, respectively. Thus, the combined impacts of climate change and LUCC from 1980s to 2000s were clearly evident. The magnitude of these changes was about 3.2% and 6.6% for the total runoff and ET, respectively. Interestingly, the contrasting values obtained between S1 and S2 and those of S3 and S4 concurred the influence of land-use change during the two subjected periods. We therefore applied the separation equation (Equation 9) to assess the impacts of land-use change. The results suggested that LUCC appears to have contributed to a decrease in runoff by about 0.4 mm, which in turn, accounted for 7.3% of the change in runoff values. It should also be noted that the land-use factor contributed to an increase in ET by about 3.3 mm, thus accounting for almost 18.8% of the change in total ET.

The influence of climate change on runoff and ET data during the two subjected periods were calculated by measuring the difference between scenarios S1 and S3 as well as those between S2 and S4. The results showed that climate variations appeared to have increased the runoff values by about 6.0 mm, thus accounting for about 107.3% of the total runoff change. The climate factor also increased ET value by about 14.2 mm, which comprised of about 81.2% of the total ET change. In light of these results, it is construed that, while LUCC and climate change appeared to increase the ET values during the 1980s to 2000s, the impact of climate factors exceeded by far that the impact of LUCC factors. At the same time, increase in runoff appeared to have been caused by climate change more than the offset, which led a decrease caused by LUCC factors. According to this finding, this result...
indicates that climate change was the predominant factor that affected the runoff while the influence of LUCC was relatively smaller.

Figure 8 presents the intra-annual ET and runoff changes that result from both climate change and LUCC. The remarkable variation of ET and runoff data impacted by climate change became particularly evident in different months (Figure 8a), where the combined influence of meteorological factors were reflected. It should be made clear that the change contributed by climate change factors occurs during the wet season from April to October when both the precipitation and air temperature values are generally higher in the present study site. Changes in runoff correlated positively with the variations and delays in precipitation, especially during the months of June and September.

However, the change in ET values caused by climate change correlated with the change in runoff caused by the climate factor in most of the months between April and October. We also saw the relative complexity in ET and the influence of both water and energy supplies. Increased air temperatures could potentially lead to higher values of ET. Consequently, if there was an adequate water supply, the ET values are expected to increase accordingly during the months of May and July.

Figure 8b shows the reflected influences of LUCC on ET and runoff over a monthly scale. It is noticeable that the impacts of LUCC on ET exhibited a peak in the month of May and displayed the lowest point in the months of January and December. The single peak approximately corresponded to the intra-annual distribution of the changes in vegetation. According to our analysis of LUCC, the transformation of vegetation coverage from low to high can lead to an increase in ET by elevating both the intercepted evaporation and vegetation transpiration. This effect is normally evident during the growing season. Compared with the variations in ET, the impact of LUCC on runoff was relatively small. However, it is reasonable to argue that the value of runoff decreased during the growing period of April to October, which was mainly due to the increase in vegetation growth in the study region. This reduction possibly led to a higher canopy interception and regulation capability, which in turn, may have caused the changes to be stored at the root zone. It is interesting to note that the streamflow exhibited an increase from the month of November to March, which was probably attributable to an increased base flow resulting from a higher soil storage. Compared to the impact of climate change (Figure 8a), the influence arising from LUCC was significantly smaller, ranging from −0.3 to 0.5 mm. It is therefore conclusive that the impacts of climate change on hydrological processes were larger than the impacts of LUCC.

Recently, a number of studies were dedicated to the investigation of the impacts of climate change and LUCC on hydrological processes, but a careful examination of these studies shows that the contribution of the two factors considered in this paper can vary along with the different study areas (Hu et al., 2015; Karlsson et al., 2016; Tomer & Schilling, 2009). Ma, Xu, Luo, Prasad Aggarwal, and Li (2009) reported that LUCC can play a dominant role on the changes in streamflow in subtropical watersheds, where the LUCC was mainly driven by anthropogenically induced activities. Chung, Park, and Lee (2011) identified
that climate change had a more significant influence on runoff compared to land-use changes in a Korean urban watershed. Li et al. (2012) confirmed that the impacts of LUCC on streamflow were more obvious than that of climate change. The different impacts of the two factors among the different study areas therefore reflect the spatial heterogeneity of climate change and LUCC. It is important to note that our study has captured an increase in runoff caused by climate change that was relatively larger in magnitude than the offsetting decrease caused by LUCC in the upper Heihe River, which indicated that the climate change was the predominant factor impacting streamflow. This conclusion is similar to the studies of Zhang and Nan et al. (2015b) and Zhang et al., (2015c), who demonstrated that climate change rather than LUCC was primarily responsible for hydrological variations, although these results were acquired from the projection of future climate and land use/cover. However, the projected future land-use patterns were not appreciably different from the actual map for the year 2000 (Zhang, Nan et al., 2015b), which indicated that LUCC in study area was not apparent compared to climate change. The findings of hydrological impacts of climate change imply that better management hints are necessary for the upper HRB where few human activities have occurred (Zhang, Zheng et al., 2015a).

From this study, it is also evident that there is a critical need for an integrated approach that combines the effects of climate change and LUCC for an accurate assessment of hydrological processes. Compared to the OFAT method, a new combined statistical analysis and hydrological modeling methods consider the interactive impacts of climate change and LUCC on hydrological processes over the entire period of study. The separation results were more reasonable and accurate than the traditional OFAT and other statistical methods (Hu et al., 2015; Lin et al., 2015; Wei et al., 2013).

It is acknowledged that even though this paper has attempted to separate the impacts of climate change and LUCC, there is a room for improvement. For instance, the uncertainties may influence the modeling results and separation of impacts. The choice of the parameter is also a key source of uncertainty in most hydrological model, which may influence the separation of results (Li et al., 2009b). Furthermore, the choice of hydrological model is expected to affect the separation of results in an indirect way as well (Karlsson et al., 2016). Considering these pertinent issues, there is a need to apply multiple models to validate the separation of results in another independent study.

5 CONCLUSIONS

The growing deficit in water resources in China has raised the importance of understanding the causality of changes in hydrological processes. It had been widely accepted that these processes are controlled mainly by climatic conditions. At the same time, it was believed that they are strongly influenced by LUCC. The latter is produced by anthropogenic activities, which in part, are the causes of climate change. In the present study, the SWAT method was successfully applied in the Yingluoxia catchment area of the upper HRB.
research confirmed the usefulness of the new method combined with statistical analysis and hydrological models for accurately separating the impacts of climate change from LUCC on streamflow and ET data.

The results of the case study concluded that the atmospheric temperature and water vapor were raising with precipitation, runoff, and air temperature values with an upward trend during the period of 1980 to 2010. LUCC also showed an increasing variation in vegetation growth in nearly 9.7% of the entire catchment area. Changes in land use showed an increase in forestland, grassland, and shrub. The combined effects of LUCC and climate change appeared to have increased the runoff and ET by about 5.6 and 17.5 mm, respectively, comprising of 3.2% and 6.6% of the total runoff and ET in the study period. The impact of climate change on the increase of runoff and ET, established respectively at 6.0 and 14.2 mm, outweighed the influence of LUCC. The latter delivered changes of about -0.4 and 3.2 mm for runoff and ET, respectively. These outcomes were based on analysis of data collected over the last 30 years. The increase in runoff was also caused by climate change more than that offsetting decreases produced by LUCC. The results showed that the climate change had higher impact than LUCC on hydrological processes in the study region. As a key strategic outcome, this research provides potentially important pathways to be adopted by various decision makers for designing adaptive measures to climate change and for planning the sustainable development of ecological systems of the HRB.

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REFERENCES


