Combined effects of predicted climate and land use changes on future hydrological droughts in the Luanhe River basin, China

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Abstract

Drought can be impacted by both climate change and land use change in different ways. Thus, in order to predict future drought conditions, hydrological simulations as an ideal means, can be used to account for both projected climate change and projected land use change. In this study, projected climate and land use changes were integrated with the SWAT (Soil and Water Assessment Tool) model to estimate the combined impact of climate and land use projections on hydrological droughts in the Luanhe River basin. We presented that the measured runoff and the remote sensing inversion of soil water content were simultaneously used to validate the model to ensure the reliability of model parameters. Following the calibration and validation, the SWAT model was forced with downscaled precipitation and temperature outputs from a suite of nine Global Climate Models (GCMs) based on the CMIP5, corresponding to three different representative concentration pathways (RCP 2.6, RCP 4.5 and 8.5) for three distinct time periods: 2011–2040, 2041–2070 and 2071–2100, referred to as early-century, mid-century and late-century, respectively, and the land use predicted by CA-Markov model in the same future periods. Hydrological droughts were quantified using the Standardized Runoff Index (SRI). Compared to the baseline scenario (1961–1990), mild drought occurred more frequently during the next three periods (except the 2080s under the RCP2.6 emission scenario). Under the RCP8.5 emission scenario, the probability of severe drought or above occurring in the 2080s increased, the duration prolonged and the severity increased. Under the RCP2.6 scenario, the upper central region of the Luanhe river in the 2020s and upper reaches of the Luanhe river in the 2080s, were more likely to suffer extreme drought events. And under the RCP8.5 scenario, the middle and lower Luanhe river in the 2080s, were more likely to suffer these conditions.

Highlights

1. The measured runoff and the remote sensing inversion of soil water content were simultaneously used to validate the model to ensure the reliability of model parameters.
2. The meteorological elements obtained from downscaling model and the land use predicted by CA-Markov model in the future period were taken as the input data of the SWAT model to simulate the soil water content and runoff changes in the future period in the Luanhe River basin.
3. The drought characteristics in future scenarios are given.

1. Introduction

Accelerated climate change can affect the water availability globally. According to the International Panel on Climate Change (IPCC), extreme meteorological and hydrological events (e.g. droughts and floods) are expected to be increasingly frequent, which could cause more uncertainties and risks in river basins worldwide in the future (IPCC 2007, 2014; Fang et al., 2018). In addition to the climate change, alterations of land uses driven by anthropogenic activities also lead to changes in water availability in variable ways (Nunes et al., 2011; Li et al., 2014; Wang et al., 2018). Hence, many studies have showed the combined impact of climate changes and human activities on the availability of water resources (Han et al., 2018; Kim et al., 2013; Ceola et al., 2014; Tong et al., 2012). Most of these studies adopted calibrated hydrological models forced with different climate and land use projections to assess hydrological responses under the changing environmental conditions. These hydrological models generally vary from relatively simple lumped models (Liu et al., 2000) to modern process-based distributed models, such as the SWAT model (Shrestha et al., 2017; Serpa, 2015).

The approach most commonly used to evaluate climate change is through the application of General circulation models (GCMs), which are established to forecast future climate characteristics with different emission levels. However, GCM projections have low resolution due to the constraints of mathematical representations of atmospheric dynamics. To capture climate variability in regional hydrological simulations, projected GCM outputs processed by variable downscaling approaches were used to force process-based hydrologic models (Chattopadhyay and Jha, 2016; Stewart et al., 2015; Daggupati et al., 2016; Uniyal et al., 2015), in which statistical downscaling approaches were commonly used, such as the Delta-change method (Tong et al., 2012; Dunn et al. 2012), weather generators (Seung-Hwan et al., 2013), bias correction (Felzer, 2012) or regression-based downscaling. Different downscaling technique selections can lead to varying or even conflicting trends when the processed data are used to force hydrological models (Burger et al., 2012, 2013). Therefore, it is important to choose an appropriate method to characterize future climate scenarios.

It has been reported that decreasing vegetation would cause the annual mean discharge to increase in the context of intensive human activities (Andréassian, 2004; Brown et al., 2005). Some researchers (e.g. Sala, 2000) even believe that influences of land use alterations on hydrological response could outweigh those caused by climate change. Current land use projection methods generally contain generalized assumptions about future conversions (Dunn et al., 2012) and the modeling approach based on socio-economic and geographical driving factors (Kim et al., 2013). Land use models are expected to predict the detailed land use allocation driven by both geographic and socio-economic factors. The variability between different land use scenarios would profoundly influence the projections of hydrological responses (Piras et al., 2014; Sitgter et al., 2014).

Previous researches on the influences of climate and land use changes were mainly focused on water availability, but there were few studies further investigating the evolution characteristics of drought. Drought is commonly considered as a complex, multifaceted environmental hazard caused by climate anomalies. It usually arises from precipitation deficits, develops in hydrological systems and eventually threatens the socioeconomic system. Generally, drought is widely accepted to be divided into meteorological, agricultural, hydrological and socio-economical droughts. Among these 4 types of drought, hydrological drought is most highly stressing due to its direct correlation with the inadequate surface and subsurface water resources. In the past years, drought indices have developed into a popular means for drought detection due to the improvement of computational efficiency. To reflect the evolution characteristics of future drought under the changing environment, the selection of drought indices should consider both the ability to quantify drought conditions, and the capability to well depict drought propagation patterns under the same evaluation system. In this study, the Standardized Runoff Index (SRI) (Zhang et al., 2015) was adopted to depict hydrological droughts.

The major objective of the present study is to evaluate the potential impacts of climate change integrated with land use alteration on the evolution of future hydrological drought in the Luanhe River basin of China. The sub-objectives include: (i) making the future projections of the rainfall and minimum and maximum temperature by Statistical Downscaling Model (SDSM); (ii) investigating future land use changes in each catchment using the CA-Markov model; (iii) and quantifying hydrological droughts by using the Standardized Runoff Index (SRI). The findings can inform policy makers and resources managers in taking positive measures to cope with the possible drought in the context of climate and land use changes.

2. Study Sites And Data

The study area extends from 115°30'E to 119°15'E and 39°10'N to 42°30' N. The total area of Luanhe River basin is 44,600 km² (Fig. 1). This basin features a typical temperate continental climate prevails with multi-year average temperature varying from - 0.3 to 11°C and average annual rainfall ranging from 400 to 700 mm/year. The intra-annual rainfall distribution is quite uneven with more than 70% of the rainfall concentrated in summer (June, July, and August). The occurrence of consecutive drought is more frequent due to decreasing runoff generation in the area, becoming an enormous retardant to social economy development. Therefore, it is significant to assess the future drought trends under the rapidly changing environmental conditions.

For downscaling purposes, reanalysis grid point data (2.5°×2.5°) in 1961 ~ 2005 provided by the National Centers for Environmental Prediction/Nation Center for Atmospheric Research (NCEP/NCAR), were used for the study. The multi-model ensemble mean of 9 GCMs for CMIP5 as shown in Table 1 were used in this study to drive the SDSM to project the future climate behavior. The choice of the models was dependent on the availability of GCM simulations for four RCP scenarios namely, RCP2.6, RCP4.5and RCP8.5 scenarios in this study area.

Table 1
Model evaluation statistics of streamflow simulation for the calibration
(1963–2007) and validation (2008–2011) periods at the eight
hydrological stations

Station	Calibration (1963–2007)		Validation (2008–2011)	
	R ²	NSE	R ²	NSE
Xiahenan	0.72	0.68	0.66	0.64
Boluonuo	0.78	0.76	0.73	0.72
Hanjiaying	0.82	0.82	0.74	0.74
Chengde	0.83	0.82	0.75	0.74
Sandaohezi	0.81	0.76	0.72	0.69
Xiabancheng	0.71	0.69	0.65	0.64
Liyang	0.88	0.85	0.79	0.79
Luanxian	0.76	0.70	0.70	0.63

The hydro-meteorological data used to drive the SWAT model include meteorological data, hydrological data and grid data. The information of meteorological, rainfall, hydrological gauges and grids are given in Table 2. The observed runoff from 1961 to 2007 were used to calibrate the SWAT model and the rest of the recorded data (2008–2011) to validate the model. Geographical location of Luanhe River basin and relevant hydro-meteorological stations used in this study are shown in Fig. 1.

Table 2
Precipitation indices used in this study to evaluate the performance of the SDSM model

Indices	Index definition	Units
Mean	Mean monthly values	mm/day
Variance	Variance monthly values	mm/day
90th percentile	90th percentile of the rainy day amount	mm/day
Rx5day	Monthly maximum consecutive 5 day precipitation	mm
Wet-day	Percentage of wet days	%
Cdry	Maximum length of a dry spell	days
Cwet	Maximum length of a wet spell	days

The monthly soil water content data (0.25°×0.25°) of GLDAS(Global Land Data Assimilation Systems)Noah_2.0 covering 1961–2010 were used to validate the established SWAT model.

3. Methodology

The methodology of this study consists of the projection of future climate, hydrological modelling, and land use change modelling (Fig. 2). The SDSM and bias correction methods were applied to project the future climate, the SWAT model was used to simulate the runoff series and the CA- Markov model was used to project the future land use change in the Luanhe River basin.

3.1 SDSM method

The SDSM is a hybrid method of a multivariate linear regression method and a stochastic weather generator. The quantitative statistical relationship F can be described as (Chen 2000):

$$Y = F(x_1, x_1, \dots, x_n) \quad (1)$$

where Y is the local predictand and x_i ($i = 1$ to n) is the i^{th} large-scale atmospheric predictor.

The SDSM determines the precipitation occurrence and the precipitation amount through large-scale atmospheric variables as follows (Wetterhall et al. 2005):

$$\omega_t = \alpha_0 + \sum_{j=1}^n \alpha_j \hat{\mu}_t^{(j)} + \alpha_{t-1} \omega_{t-1} \quad (2)$$

where ω_t is the conditional possibility of precipitation occurrence in the t^{th} day, is the normalized predictor, the regression parameter α_j can be obtained using the LSM method and α_{t-1} is the $t-1$ day regression parameters. The last term of the equation is optional. ω_t is commonly compared to a uniformly distributed random number r_t ($0 \leq r_t \leq 1$) to determine whether the precipitation occurs. The precipitation can be expressed by a z-score as:

$$Z_t = \beta_0 + \sum_{j=1}^n \beta_j \hat{\mu}_t^{(j)} + \beta_{t-1} Z_{t-1} + \varepsilon \quad (3)$$

where Z_t is the z-score on the t^{th} day and β_j is the regression parameter. β_{t-1} and Z_{t-1} are the regression parameter and the z-score on the $(t-1)^{\text{th}}$ day, respectively. ε is a random error term.

Finally, precipitation y_t can be expressed as:

$$y_t = F^{-1}(\phi(Z_t)) \quad (4)$$

where Φ is the normal cumulative distribution function and F is the empirical distribution function of y_t .

3.2 Quantile mapping (QM) of precipitation

The QM method is a non-parametric bias correction method which can be used without any assumption of precipitation distribution and has been widely used in previous studies (Chen et al., 2013; Wilcke et al., 2013). It has been proven effective in correcting bias in the mean, standard deviation and wet-day frequency and quantiles. Eq. (5) shows the precipitation adjustment expressed in the terms of the empirical CDF ($ecdf$) and its inverse ($ecdf^{-1}$) using QM:

$$P_{cor,m,d} = ecdf_{obs,m}^{-1}(ecdf_{raw,m}(P_{raw,m,d})) \quad (5)$$

3.3 Distribution mapping (DM) of temperature

The idea of distribution mapping is to correct the distribution function of the raw data to agree with the observed distribution function. This can be done by creating a transfer function to shift the occurrence distributions of temperature (Sennikovs and Bethers, 2009). It is used to adjust the mean, standard deviation and quantiles. Furthermore, it preserves the extremes (Thiemeßl et al., 2012). For temperature, the Gaussian distribution with a mean μ and a standard deviation σ is usually assumed to fit best (Schoenau and Kehrig, 1990; Deutschbein and Seibert, 2012):

$$f_N(X|\mu, \sigma) = \frac{1}{\sigma\sqrt{2\pi}} \times e^{-\frac{(x-\mu)^2}{2\sigma^2}}; x \in R \quad (6)$$

And similarly, the corrected temperature can be expressed as

$$T_{cor,m,d} = F_N^{-1}(F_N(T_{raw,m,\sigma_{raw,m}})|\mu_{obs,m}, \sigma_{obs,m}) \quad (7)$$

where $F_N(\cdot)$ and $F_N^{-1}(\cdot)$ are the Gaussian CDF and its inverse, $\mu_{raw,m}$ and $\mu_{obs,m}$ are the fitted and observed means of the raw and observed precipitation series in a given month m , and $\sigma_{raw,m}$ and $\sigma_{obs,m}$ are the corresponding standard deviations, respectively.

3.4 CA-Markov method

CA-Markov is the combined Cellular Automata (CA)/Markov Chain/Multi-Criteria/ Multi-Objective Land Allocation (MOLA) land cover prediction method. The Markov model mainly concentrates on quantifying land use changes without detailed allocation of various land use types in terms of the spatial extents (Wickramasuriya et al., 2009),

whereas the CA model has a strong space conception. The CA-Markov model integrates the advantages of these two theories, which can yield a better effect in temporal and spatial land use change simulations (Ji et al., 2009).

The specific procedures of using CA-Markov model to simulate land use changes is as follows: (1) calculating the land use transition probability matrix to serve as the transformation rules adopted in the CA-Markov model; (2) determining the CA filters required to produce a clear sense of the space weighting factor; and (3) determining the starting point and the CA number of iterations.

3.5 Standardized Runoff Index (SRI)

In this study, the hydrological drought is described by SRI, which is calculated similarly to the SPI but is instead applied to the runoff series. The calculation steps are as follows: (1) accumulate the runoff series at a given timescale; (2) fit a probability distribution to the specific runoff series; (3) estimate the cumulative density function (CDF) of an observed cumulative runoff volume; (4) convert the cumulative probability to a standard normal function with zero mean and unit variance. For details about SRI computation, refer to the calculation of the SPI and SRI (Zarch et al. 2015; Ahmadi et al. 2017).

3.6 Performance evaluation criteria for downscaling model

In this study, the coefficient of determination (R^2), Root Mean Square Error ($RMSE$) and Nash-Sutcliffe coefficient (NSE) (Nash and Sutcliffe, 1970) were used to measure the performance of the SDSM (Fang et al. 2018). R^2 is the square of the correlation coefficient and describes how much of the variance between the observed and simulated variables can be explained through a linear fit. The $RMSE$ explains the difference between the observed and simulated variables. In other words, it describes the spread of error or the performance of the model. The $RMSE$ is measured in the same unit used for the simulation or observed data. The NSE quantitatively describes the accuracy of the model output for hydrological variables. The NSE value can range between -1 and 1.

$$R^2 = \frac{(\sum_{i=1}^n (x_{obs,i} - \bar{x}_{obs})(x_{sim,i} - \bar{x}_{sim}))^2}{\sum_{i=1}^n (x_{obs,i} - \bar{x}_{obs})^2 \sum_{i=1}^n (x_{sim,i} - \bar{x}_{sim})^2} \quad (8)$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^n (x_{sim,i} - x_{obs,i})^2}{n}} \quad (9)$$

$$NSE = 1 - \frac{\sum_{i=1}^n (x_{sim,i} - x_{obs,i})^2}{\sum_{i=1}^n (x_{obs,i} - \bar{x}_{obs})^2} \quad (10)$$

where $x_{obs,i}$ is the i^{th} observed precipitation or temperature (monthly), $x_{sim,i}$ is the i^{th} simulated (raw GCM or downscaled) precipitation or temperature (monthly), and n is the number of data.

4. Results And Discussion

4.1. Calibration and validation of the SWAT model

The SWAT model is a semi-distributed and physically-based model. The simulations for SWAT was run from 1961 to 2011 (warm-up period: 1961–1962; calibration period: 1963–2007; validation period: 2008–2011) for eight hydrological stations (Fig. 1). The model was calibrated by the SWAT-CUP. This program includes five methods,

from which the Sequential Uncertainty Fitting (SUFI-2) method was chosen. The determination coefficient (R^2) and Nash-Sutcliffe coefficient of efficiency (NSE) were used as the performance metrics. As shown in Table 3 the evaluation index R^2 values for the calibration period were all greater than 0.71, and for the validation period, the values were all greater than 0.65 in the eight catchments. The evaluation index NSE value for the calibration and validation periods were all greater than 0.64, with the maximum value reaching 0.85 (obtained at the LY station).

Table 3
Transfer matrix of land use area in the Luanhe River basin from 1990 to 2000 (km²)

Type	Dry land	Paddy field	Forest	Grassland	Water body	Construction land	Unutilized land	Total
Dry land	4056	91	1725	2561	199	223	224	9079
Paddy field	102	215	34	51	28	39	5	474
Forest	1897	42	11994	2612	110	54	57	16766
Grassland	2110	36	2898	7542	131	94	404	13215
Water body	216	21	127	115	127	17	13	636
Construction land	212	38	48	97	17	92	17	521
Unutilized land	211	13	44	458	7	17	562	1312
Total	8804	456	16870	13436	619	536	1282	42003

To intuitively evaluate the model performance, the comparison of the observed and simulated streamflow at the stations for the period from 1961 to 2011 was shown. Due to limited space, only the results of three hydrological stations (Chengde, Liying and Luanxian) are shown in Fig. 3. The fitting between the observed and simulated time series is very good both in quantity and trend, as underlined by the high R^2 and NSE values. All three runoff time series show some underestimation of the peak flows in summer. There are two possible reasons for the difference: the water released from reservoirs in summer not being considered by the model and an inefficient calibration of the parameters. The results of a satisfying fitting of the streamflow at eight hydrological stations (Table 3 and Fig. 3) indicates that it is feasible to use the SWAT model to simulate the hydrologic processes in the Luanhe River basin, and this model can be used to construct a drought evaluation model for study region.

By calculating the Spearman correlation coefficients for all sub-basins between the soil moisture content of GLDAS Noah 2.0 and the soil moisture content simulated by the SWAT model, the simulation effect of the soil moisture content of the SWAT model was evaluated. The results of correlation analysis are shown in Fig. 4. As can be seen from Fig. 4, the correlation coefficient between the assimilated soil moisture content and simulated soil moisture content in each sub-basin is greater than 0.58, with the maximum correlation coefficient of 0.86, which appears in the 19[#] sub-basin. In general, the simulation accuracy in the upstream of Luanhe river is significantly higher than that of the downstream. The results of correlation analysis show that the SWAT model can well depict the variation characteristics of soil moisture content in the Luanhe River basin from 1961 to 2010.

4.2. Evaluation of the SDSM model for the calibration and validation periods

The 45-year observed data was used for the calibration (1961–1990) and validation (1991–2005) of the SDSM. For the sake of evaluating the performance of the downscaling results, a total of seven precipitation indices and two temperature indices were employed. The indices provide detailed information about the intensity, duration and frequency of the time series rather than carrying out simple statistical mean values. Table 4 tabulates the description of the precipitation indices used in this study. They are labeled as Mean, Variance, 90th percentile, Rx5day, Wet-day, Cday and Cwet. Although the calibration and validation phases were performed for each of the 45 sub-basins of the Luanhe River basin individually, here, only the calibration and validation results of Boluonuo station are presented graphically as a representative example.

Table 4
Forecast simulation accuracy for land use types in 2005 and 2010

Type	2005				2010			
	Current	Simulated	Area	Space	Current	Simulated	Area	Space
	Area	Area	Accuracy	Accuracy	area	Area	Accuracy	accuracy
	/km ²	/km ²	/%	/%	/km ²	/km ²	/%	/%
Dry land	9083	9350	97.06	90.46	9068	9323	97.19	88.21
Paddy field	466	434	93.13	83.23	459	424	92.37	78.40
Forest	16792	16279	96.94	93.09	16788	16399	97.68	91.72
Grassland	13166	13345	98.64	91.83	13287	13358	99.47	88.73
Water body	652	716	90.18	87.65	657	696	94.06	88.81
Construction land	580	588	98.62	82.82	610	565	92.62	76.79
Unutilized land	1343	1373	97.77	86.45	1213	1322	91.01	81.92

Figures 5 and 6 present the monthly, seasonal and annual average values of the 7 precipitation indices for Boluonuo station during the calibration and validation period. It is obvious that, the model showed good performance in the calibration as well as validation periods by means of the Mean, Variance, Wet-day and Cday indices, the Cwet and, especially, the 90th percentile and Rx5day indices are poorly matched between the observation and simulation data. The performance of the downscaling models were also assessed using standard statistical approaches, namely, the coefficient of determination (R^2), root mean squared error ($RMSE$) and Nash-Sutcliff efficiency (NSE). Figure 7 shows the ensemble average of R^2 , NSE and $RMSE$ between the observed and simulated data evaluated daily for each station during the calibration and validation periods. It is obvious that the values of R^2 and NSE for the 45 sub-basins are all larger than 0.35 for the calibration period, and all larger than 0.3 for the validation period. In addition, the values of $RMSE$ are all smaller than 9 for the calibration and validation period. These results indicate that the reproducibility of precipitation data by the SDSM is relatively low, which may be explained as follows. The complexity of the stochastic processes which contribute to precipitation formation is greater than those which contribute to the air temperature distribution and other meteorological phenomena. Accordingly, even a GCM model with the highest possible resolution would be inadequate for use by the SDSM to accurately represent precipitation, resulting in difficulty in representing the amount and location of precipitation in

an accurate manner. The values of R^2 obtained in other studies for downscaling daily precipitation were between 0.1 and 0.3 (Wilby et al. 2002; Hessami et al. 2008), and the simulation results in the Luanhe River basin were closer to these values. Therefore, the ability of the downscaling model to reproduce rainfall as revealed by the R^2 values is sufficient. However, the accuracy simulated in this study cannot meet the requirements of hydrological model. Therefore, bias correction is necessary before the output results of the SDSM model are used for hydrological simulations. In this study, the bias correction method of QM was performed on rainfall data downscaled using the SDSM model. The results of the bias correction of precipitation are presented in Fig. 8. As shown in the Fig. 8, the correction methods adjusted the biases in the output precipitation of the SDSM model and the corrected precipitation has similar quantile values to those of the observations.

Figures 9 and 12 present the mean and variance values of the maximum and minimum daily temperature at Boluonuo station during the calibration and validation periods. As shown in Fig. 9 and Fig. 12, the mean value and variation of the maximum and minimum daily temperature can be accurately simulated by the SDSM for the calibration period. For the validation period, the mean of the maximum temperature was slightly underestimated and the variation was slightly overestimated for four seasons, the mean of the minimum temperature was slightly underestimated for summer, and slightly overestimated for the other seasons, and the variation was slightly overestimated for four seasons. Figure 10 and Fig. 13 show the ensemble averages of R^2 , NSE and $RMSE$ between the observed and simulated maximum and minimum daily temperature at each station during the calibration and validation period. It is obvious that the values of R^2 and NSE for the 45 sub-basins are all larger than 0.95 and the values of $RMSE$ are all smaller than 3, which indicates that the statistical downscaling procedure performed well for the maximum and minimum temperatures. To improve the simulated accuracy of the SDSM, the DM method was used for the maximum and minimum temperatures downscaled using the SDSM model. The corrected results are shown in Fig. 11 and Fig. 14. From Fig. 11 and Fig. 14, it is obvious that the temperature correction method adjusts the biases in the maximum and minimum temperatures and that mean of the corrected temperature is closer to the values of the observations. The bias correction factors seem to provide a good improvement in the correction of the maximum and minimum temperature from the SDSM model prior to their use in hydrological models.

4.3. Land Use Change Projection Using the CA-Markov Model

The transfer probability matrix of land use change can not only quantitatively explain the conversion between land use types, but can also reveal the transfer rate among different types. The transfer matrix of land use area in the Luanhe River basin from 1990 to 2000 can be obtained by applying the CA-Markov model, as shown in Table 5. It can be seen that from 1990 to 2000, the major land use types in the Luanhe River basin underwent complex mutual transformation. The area of dry land, paddy field, water body and unutilized land decreased by 3.03%, 3.80%, 2.67% and 2.29%, respectively, and the area of grassland and forest and construction land increased by 0.62%, 1.67% and 2.87%, respectively. Therefore, the dry land area decreased the most, and the most of the land transferred out was forest and grassland, which was the result of returning farmland to forest and grassland under the guidance of government policies. Affected by the rapid development of economic construction and urbanization, the area of construction land increases rapidly, and the main sources of transfer were dry land and grassland. The water body areas decreased by 17 km² from 1990 to 2000. On one hand, this reflects that with the increase of urban expansion and agricultural intensification, the amount of surface water absorbed become large, leading to lake and river reclamation. On the other hand, it is mainly affected by climate change. Wang et al., (2015) found that the Luanhe River basin over the past 50 years has had a drying tendency, especially since the 1980s. The drought index in the Luanhe River basin has presented continuous negative values for many times, and after 1999, this basin suffered

more severe drought. This is roughly consistent with the change trend of the water area in this paper, showing that the impact of climate change on the water area is significant (Yinglan et al., 2019).

The land use in 2005 and 2010 were projected using the CA-Markov model and compared to the actual land use maps of 2005 and 2010 (Table 6 and Fig. 15). It was found that the simulated land use maps of 2005 and 2010 were very similar to the observed land use map of 2005 and 2010, which reflects that the results simulated by the CA-Markov model have a good reliability and applicability. The relative error of area and spatial distribution of each land use category for the calibration period were less than 10% and 20%, and for the validation period, the relative errors of the area and spatial distribution were less than 10% and 25%, respectively, showing the total accuracy of the land use simulation to be reliable, hence, the CA-Markov model was used to simulate land use changes in the Luanhe River basin in the 2020s, 2050s and 2080s.

On the premise of proving the feasibility and accuracy of the model, the land use in 2010 was taken as the initial state, and the transfer probability matrix of land use from 1900 to 2000 was adjusted based on the land use types in 2005 and 2010. The land use structure in the next 25 years, 55 years and 85 years was predicted by the model, and the results are shown in Fig. 16.

According to the predicted results, the changes of major land use types in the Luanhe River basin in the future period (2020s, 2050s and 2080s) were basically consistent with the change trends in 1990–2000. The dry land, paddy fields, water body and unutilized land continued to decrease, the reduction rates of dry land, water body and unutilized land were faster, and the amounts of forest and grassland continued to grow slowly (Fig. 16). Compared with 2010, the forest area increased the most, followed by grassland in 2025, and forest accounted for 40.27%, 40.48 and 40.65% of the total area in 2025, 2055 and 2085, respectively. Dry land decreased the most, followed by unutilized land, and dry land accounted for 21.02%, 21.00 and 20.96% of the total area in 2025, 2055 and 2085, respectively. The largest annual increase was in construction land. In contrast, the largest annual decrease was in the unutilized land. In addition, the change range of forest, grassland and paddy field area were small and basically stable.

4.4. Impacts of Climate Change and Land Use Changes on hydrological drought

The daily climate data obtained through the downscaling method and the land use data obtained through the CA-Markov method in the future periods were substituted into the calibrated SWAT model to simulate the runoff series of each sub-basin under the future climate scenarios. On this basis, the SRI was calculated, and then the characteristics of drought variation in the future periods were identified using the run theory. Figure 17 gives the variation of the drought duration, drought severity and drought frequency in the Luanhe River basin during the baseline period and future periods. In both periods, the higher is the drought level, the smaller will be the drought duration and drought frequency, indicating that the duration of severe drought is short and the probability of occurrence is low. The duration of mild drought in the 2020s under the three emission scenarios and in the 2050s under the RCP2.6 and RCP4.5 emission scenarios is higher than that in the baseline period. The severity of mild drought in the 2020s under the RCP2.6 emission scenario and in the 2020s and 2050s under the RCP4.5 emission scenario are all higher than that in the historical baseline period. Under the three emission scenarios, mild drought occurred more frequently in the next three periods (except in the 2080s under the RCP2.6) than that in the historical baseline period, indicating that the probability of mild drought increased in the future. Under the RCP2.6 emission scenario, the moderate drought duration in the 2020s and under RCP8.5 emission scenario in the 2080s were higher than that in the baseline period. Under the RCP8.5 emission scenario, the moderate drought severity at the time of

the 2080s was greater than that in the baseline period. Under the three emission scenarios, the frequency of drought during the next three periods was less than that in the historical baseline period, that is, the probability of drought in the future period decreased. Under the RCP8.5 emission scenario, the extreme drought duration of the 2080s was longer than that of the baseline period, and the drought severity and frequency increased. In general, the drought characteristics of light drought changed more greatly compared to the baseline period. Under the RCP8.5 emission scenario, the probability of severe drought or above occurring in the 2080s increased, and the duration prolonged and the severity increased.

Figures 18–20 show the spatial distribution of the drought duration, drought severity and drought frequency of extreme drought in the future under three emission scenarios for the Luanhe River basin. From Fig. 18 and Fig. 19, it can be seen that under the RCP2.6 and RCP4.5 scenarios, the duration of extreme drought in the 2050s is shorter and the drought severity is smaller. Under the RCP2.6 and RCP8.5 scenarios, the duration of extreme drought was longer and the drought severity was greater in the 2080s. The long drought duration and large drought severity during the historical baseline period were mainly distributed in the upper reaches and the eastern region of the lower reaches. Under the RCP2.6 scenario, the long drought duration and great drought severity in the 2020s, 2050s and 2080s periods were mainly distributed in the upper central region, the western region of the lower reaches, the upstream region and the western region of the lower reaches of the Luanhe river, respectively. Under the RCP4.5 scenario, the long drought duration and great drought severity in the 2020s, 2050s and 2080s periods were mainly distributed in the middle and upper reaches, the western region of the middle reaches and the western region of the lower reaches, respectively. Under the RCP8.5 scenario, the long drought duration and great drought severity in the 2020s, 2050s and 2080s periods were mainly distributed in the middle reaches, the upper central region and the western region of the lower reaches, and the middle reaches of the Luanhe river, respectively. Under the RCP2.6 scenario for the 2080s and the RCP4.5 scenario for the 2020s, the Luanhe river upstream was prone to extreme droughts, with a longer drought duration than that in the historical baseline period. Under the RCP8.5 for the 2080s, the middle and lower reaches of the Luanhe river was prone to extreme droughts which has longer drought duration and greater drought severity. It can be seen from Fig. 20 that under the RCP2.6 scenario in the 2020s, the upper central region of the Luanhe River was more likely to experience extreme drought events than during the historical baseline period, and in the 2080s the upper reaches were more likely to experience these effects. Under the RCP8.5 scenario in the 2080s, the middle and lower reaches were more likely to experience extreme drought events.

5. Conclusions

This paper investigated the combined impacts of future climate change and land use change on hydrological drought in the Luanhe River basin, China. To obtain reliable T_{max} , T_{min} and precipitation series under various climate change scenarios, we employed the SDSM model to downscale future climate variables, and the QM and DM methods were used to correct the output precipitation and temperature of the SDSM model. The CA-Markov model was used to simulate the land use conditions in the 2020s, 2050s and 2080s. The future climate scenarios and land use change scenarios were fed into a well calibrated and validated hydrological model, SWAT, to simulate future hydrological processes. Based on the simulated runoff series, the SRI was used to characterize the hydrological drought in the 2020s, 2050s and 2080s under the RCP2.6, RCP4.5 and RCP8.5 scenarios. The most notable conclusions of this study can be summarized as follows:

(1) The SWAT model was calibrated and validated by simulating the observed continuous streamflows over the period of 1961–2011. The good agreement between the observed and simulated values indicated that the

calibrated model with the set of optimized parameters could be applied to examine the responses of hydrological drought to climate and land use changes in the Luanhe River basin.

(2) The SDSM can well capture the statistical relationships between the large-scale climate variables and the observed weather at the regional scale, except for a less satisfactory performance for precipitation. The bias correction factors seem to provide good improvement in the correction of the precipitation, maximum and minimum temperature from the SDSM model. Hence, the results were acceptable for practical use.

(3) Land use change analysis with the CA-Markov model have projected that forest would increase most, followed by grassland, and that dry land would decrease most, followed by unutilized land. The largest annual increase was in construction land. In contrast, the largest annual decrease was in unutilized land, and the change range of forest, grassland and paddy field were small and basically stable.

(4) Under the three emission scenarios, mild drought occurred more frequently during the next three periods (except in the 2080s under the RCP2.6) than that during the historical baseline period, indicating that the probability of mild drought increased in the future period. Under the RCP8.5 emission scenario, the probability of severe drought or above in the 2080s increased, and the duration prolonged and the severity increased. Under the RCP2.6 scenario in the 2020s, the upper central region of the Luanhe River was more likely to suffer extreme drought events, and in the 2080s, the upper reaches were more likely to suffer these conditions. Under the RCP8.5 scenario in the 2080s, the middle and lower reaches were more likely to suffer extreme drought events.

From the present work, it becomes evident that an integrated approach combining the effects of climate and land use change is crucial for the realistic evaluation of the future state of drought. In addition to being a starting point towards a better understanding of the direct and indirect impacts of climate change and land use on the hydrological drought in the Luanhe River basin, this study provides important information that can be useful for decision-makers to design adaptive measures for climate changes. Future work should address the range of foreseeable scenarios for the study area to take into account the uncertainty inherent in climate and land use change predictions.

Declarations

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Tables

Tables 5 and 6 are not available with this version:

Table 5 Transfer matrix of land use area in the Luanhe River basin from 1990 to 2000

Table 6 Forecast simulation accuracy for land use types in 2005 and 2010

Figures

Figure 1

Location of the Luanhe River basin and relevant hydro-meteorological stations. Note: The designations employed and the presentation of the material on this map do not imply the expression of any opinion whatsoever on the part of Research Square concerning the legal status of any country, territory, city or area or of its authorities, or concerning the delimitation of its frontiers or boundaries. This map has been provided by the authors.

Figure 2

Flowchart of the modeling work

(a) Chengde

(b) Liying

(c) Luanxian

Figure 3

Comparison of observed and simulated monthly streamflow at three hydrological stations

Figure 4

Spearman correlation coefficients for all sub-basins between the soil moisture content of GLDAS Noah 2.0 and the soil moisture content simulated by the SWAT model. Note: The designations employed and the presentation of the material on this map do not imply the expression of any opinion whatsoever on the part of Research Square concerning the legal status of any country, territory, city or area or of its authorities, or concerning the delimitation of its frontiers or boundaries. This map has been provided by the authors.

Figure 5

Precipitation indices of observation and simulation for the calibration period at the representative station of Boluonuo

Figure 6

Precipitation indices of observation and simulation for the validation periods at the representative station of Boluonuo

Figure 7

Performance statistics of the downscaled daily precipitation from the SDSM model for the calibration and validation periods at 52 precipitation stations

(a) Calibration period

(b) Validation period

Figure 8

Q-Q plots of the observed and simulated precipitation before and after bias correction for the calibration and validation periods at the representative station of Boluonuo

Figure 9

Mean and variance of the observed and simulated maximum temperature for the calibration and validation periods at the representative station of Duolun

Figure 10

Performance statistics of the downscaled daily maximum temperature from the SDSM model for the calibration and validation periods at 40 meteorological stations

(a) Calibration period

(b) Validation period

Figure 11

Q-Q plots of the observed and simulated maximum temperature before and after bias correction for the calibration and validation periods at the representative station of Duolun

Figure 12

Mean and variance of the observed and simulated minimum temperature for the calibration and validation periods at the representative station of Duolun

Figure 13

Performance statistics of the downscaled daily minimum temperature of the SDSM model for the calibration and validation periods at 40 meteorological stations

(a) Calibration period

(b) Validation period

Figure 14

Q-Q plots of the observed and simulated minimum temperature before and after bias correction for the calibration and validation periods at the representative station of Duolun

Figure 15

Verification of the forecast accuracy for land use types in 2005 and 2010. Note: The designations employed and the presentation of the material on this map do not imply the expression of any opinion whatsoever on the part of Research Square concerning the legal status of any country, territory, city or area or of its authorities, or concerning the delimitation of its frontiers or boundaries. This map has been provided by the authors.

(a) Predicted land use map in future periods

(b) Area statistics of land use in thw baseline and future periods

Figure 16

Predicted land use maps and their area statistics in 2025, 2025 and 2085. Note: The designations employed and the presentation of the material on this map do not imply the expression of any opinion whatsoever on the part of Research Square concerning the legal status of any country, territory, city or area or of its authorities, or concerning the delimitation of its frontiers or boundaries. This map has been provided by the authors.

Figure 17

Drought duration, severity and frequency in the Luanhe River basin in the baseline period and future periods

Figure 18

Spatial distribution of the drought duration of extreme drought in the 2020s, 2050s and 2080s under RCP 2.6, 4.5 and 8.5, respectively. Note: The designations employed and the presentation of the material on this map do not imply the expression of any opinion whatsoever on the part of Research Square concerning the legal status of any country, territory, city or area or of its authorities, or concerning the delimitation of its frontiers or boundaries. This map has been provided by the authors.

Figure 19

Spatial distribution of the drought severity of extreme drought in the 2020s, 2050s and 2080s under RCP 2.6, 4.5 and 8.5, respectively. Note: The designations employed and the presentation of the material on this map do not imply the expression of any opinion whatsoever on the part of Research Square concerning the legal status of any country, territory, city or area or of its authorities, or concerning the delimitation of its frontiers or boundaries. This map has been provided by the authors.

Figure 20

Spatial distribution of the drought frequency of extreme drought in the 2020s, 2050s and 2080s under RCP 2.6, 4.5 and 8.5, respectively. Note: The designations employed and the presentation of the material on this map do not imply the expression of any opinion whatsoever on the part of Research Square concerning the legal status of any country, territory, city or area or of its authorities, or concerning the delimitation of its frontiers or boundaries. This map has been provided by the authors.

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