

Article

Assessments of Impacts of Climate and Forest Change on Water Resources Using SWAT Model in a Subboreal Watershed in Northern Da Hinggan Mountains

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Abstract: Water resources from rivers are essential to humans. The discharge of rivers is demonstrated to be significantly affected by climate change in the literature, particularly in the boreal and subboreal climate zones. The Da Hinggan Mountains in subboreal northeast China form the headwaters of the Heilongjiang River and the Nenjiang River, which are important water resources for irrigation of downstream agriculture and wetlands. In this study, long-term (44 years) hydrologic, climate and forest dynamics data from the Tahe were analyzed using the soil and water assessment tool (SWAT) model to quantify the effects of climate and forest change on runoff depth. Meanwhile, downscaled precipitation and temperature predictions that arose from global climate models (GCMs) under four representative concentration pathways (RCP 2.6, RCP 4.5, RCP 6.0 and RCP 8.5) were forced using the SWAT model to investigate the climate change impacts on the Tahe River flows in the future. The results indicated that compared with the 1972–1982 period, the forest biomass in the 1984–1994 period was reduced by 17.6%, resulting in an increase of 16.6% in mean annual runoff depth. On the contrary, with reforestation from the 1995–2005 period to the 2006–2016 period, the mean forest biomass was increased by 9.8%, resulting in the mean runoff depth reduction of 11.9%. The tree species composition shift reduced mean annual runoff depth of 13.3% between the 1984–1994 period and the 2006–2016 period. Compared with base years (2006–2016), projections of GCM in the middle of the 21st century indicated that both mean annual temperature and precipitation were expected to increase by -0.50 °C and 43 mm under RCP 2.6, 0.38 °C and 23 mm under RCP 4.5, 0.67 °C and 36 mm under RCP 6.0 and 1.00 °C and 10 mm under RCP 8.5. Simulated results of the SWAT model showed that annual runoff depth would increase by 18.1% (RCP 2.6), 11.8% (RCP 4.5), 23.6% (RCP 6.0), and 11.5% (RCP 8.5), compared to the base years. Such increased runoff was mainly attributed to the increase in April, July, August, September and October, which were consistent with the precipitation prediction. We concluded that the future climate change will increase the water resources from the river, thereby offsetting the possible decline in runoff caused by the forest recovery. The findings of this study might be useful for understanding the impacts of climate and forest change on runoff and provide a reasonable strategy for managers and planners to mitigate the impact of future climate change on water resources in the subboreal forested watersheds.

Keywords: climate change; forest change; subboreal forested watershed; SWAT model; CMIP5; RCPs; water resources

1. Introduction

Water resources have always been an important topic in hydrological research. It is widely recognized that climate variability (e.g., global warming) and forest change (e.g., deforestation, reforestation and tree species composition shift) are two major drivers of river discharge in a forested watershed [1]. Most of the case studies reported in literature showed that afforestation can reduce runoff substantially, increasing shortage of water resources [1–3]. Only a few studies had different conclusions, for instance, Zhou et al. [4] found that the afforestation did not reduce water yield, and play a positive role in redistributing water from the wet season to the dry season over the past 50 years in Guangdong province, China. Meanwhile, many studies have shown that global warming may lead to increased surface aridity and more droughts in the twenty-first century [5]. For example, Wang et al. [6] found that climate change enhanced the severity and variability of drought in the Pearl River Basin in South China. Therefore, understanding the impacts of climate and forest change on water resources and the trends in the future water supplies are of great importance to water resources management. However, such study was rare in the northeast of China.

The Da Hinggan Mountains are important headwaters of the Heilongjiang River and the Nenjiang River. The downstream has the important national grain production area and the biggest wetlands in northeast China [7,8]. Song et al. [9] found that the annual precipitation showed a decreasing trend and the number of continuous drought days showed an increasing trend in the agricultural areas of downstream during the past 50 years. The water resources in the upstream are crucial to mitigate the possible water shortages of downstream in the future and are especially important for food security and wetland protection. Additionally, the Da Hinggan Mountains are an important national forest area of China, which historically have experienced deforestation and reforestation. The reforestation program began in the early 21st century after forestry authorities stopped commercial logging in the Da Hinggan Mountains. From the earlier studies in the Da Hinggan Mountains [10–12], we found that deforestation increased the annual runoff depth, while reforestation decreased it. There is no doubt that the future reforestation of Da Hinggan Mountains will decrease the water resources. On the other hand, the impact of climate change on water resources cannot be ignored. To the authors' knowledge, the impact of future climate change on river discharge in the Da Hinggan Mountains has never been explicitly explored.

In order to evaluate the effects of future climate change on the river discharge, future climate scenarios have been widely simulated. The (global climate model (GCM) for climate projection had been realized via the intergovernmental panel on climate change (IPCC), coupled model intercomparison project five (CMIP5) [13–15]. GCM can be applied to hydrological models directly by downscaling the spatial data from the global scale to a watershed scale. The representative concentration pathways (RCPs) were used as the basis for defining future climate scenarios in CMIP5 and named according to the radiative forcing (RF) target level for the end of the century [16]. According to the forcing of greenhouse gases and other forcing agents, four pathways were produced by IPCC that lead to the RF levels of 2.6 (mitigation scenario), 4.5, 6.0 (stabilization scenarios) and 8.5 (very high baseline emission scenarios) W/m^2 [16]. The future climate scenarios of the Tahe watershed were simulated via the four radiative forcing levels of RCPs. Usually, hydrological models were applied to combine climate change with hydrological processes. The soil and water assessment tool (SWAT) model can simulate hydrological processes and has the capability of incorporating the climate change effect for simulation [17], which has been widely used worldwide [18].

The focus of this study was to understand the impacts of climate and forest change on river discharge and provide a forest management strategy for managers and planners to mitigate the impact of future climate change on water resources. Thus, the Tahe forested large watershed (6581 km^2) was selected as a case study in the Da Hinggan Mountains that had reasonable-term (44 years) data of hydrometeorology and forest resource inventory. The specific key objectives were: (1) to establish the SWAT hydrological model, (2) to quantify the relative contributions of climate and forest change on water resources in the past 44 years, and (3) to predict the water resources response to climate change in the 2050s under CMIP5 RCP scenarios.

2. Study Watershed and Data Collection

2.1. Study Watershed

The Tahe River, with a length of 148 km, originates in the northern slope of the Da Hinggan Mountains in northeastern China (Figure 1), flowing northeast into the Huma River. Eventually, it in turn feeds the Heilongjiang, the world's tenth longest river, and forms the border between Russia and China. The climate of the region is subboreal continental monsoon. The Tahe hydrometric station (124°42'56" N, 52°17'42" E) is located on the lower Tahe watershed, with a control basin area of 6581 km². It is dominated by gentle hills and a broad valley [10]. The elevation ranges from 340 to 1309 m above sea level, with an elevation range of 573–834 m and a mean slope of 11.7°, which accounts for 75% of the total watershed area. Records of meteorological stations in the Tahe watershed (1972–2016) show annual mean values of: temperature of −2.2 °C, precipitation of 505 mm, and potential evapotranspiration of 562 mm. Precipitation is mainly concentrated in summer and autumn, accounting for 75% of the total. The vegetation period begins at the end of April and ends in mid-October. The synchronization of high temperature and ample precipitation is conducive to the growth of vegetation. The tree species are dominated by larch (*Larix gmelinii*), Mongolian pines (*Pinus sylvestris* var. *mongolica*) and picea (*Picea koraiensis*), and broadleaf species, such as birch (*Betula platyphylla*), and poplar (*Populus davidiana*). Main land use types are forestland, accounting for over 90% of total watershed [12].

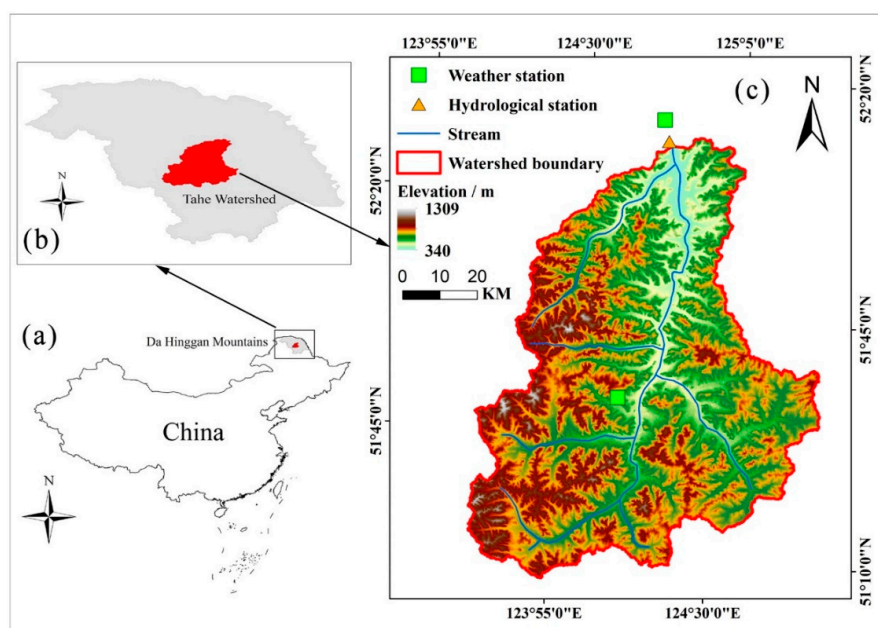


Figure 1. (a,b) Location of the study watershed in the Da Hinggan Mountains, China, (c) location of two meteorological stations and hydrological stations in the digital elevation model (DEM) of the Tahe watershed.

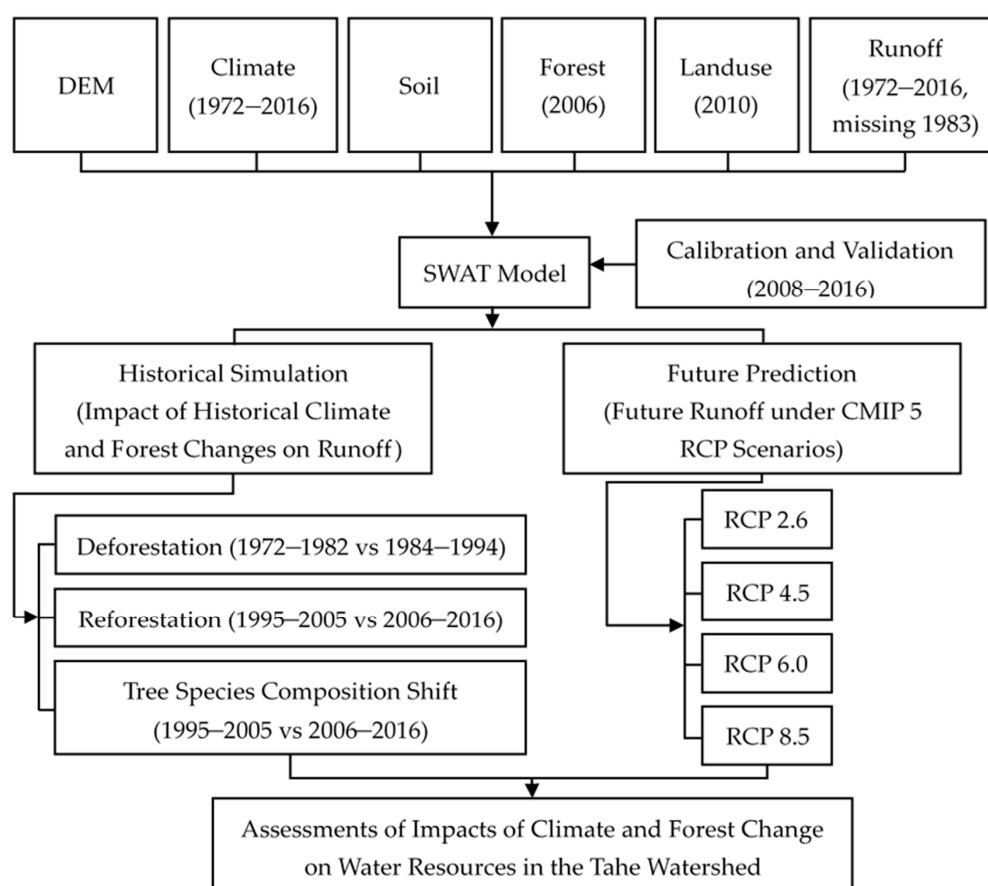
2.2. Datasets Used in the Study

The SWAT model is a physically-based, semi-distributed and continuous time-step hydrological model [19]. Therefore, it has strict standards for model input data. The daily hydrometeorological datasets were compiled for SWAT model construction from the Xinlin meteorological station (ID: 50349), the Tahe meteorological station (ID: 50246) and the Tahe hydrometric station in the study area over the period of 1972–2016 (missing runoff data in 1983). Daily meteorological data were collected from the China Meteorological Administration (CMA, Beijing, China), which include daily mean (Tmean), maximum (Tmax), minimum (Tmin) temperatures, and precipitation (P). Daily runoff data was provided by the Hydrographic and Water Resources Bureau of Heilongjiang province (Harbin, China).

Geographical information used in this study includes digital elevation data (DEM), land use data and soil data. The DEM data with 30 m spatial resolution used in this study were obtained from the ASTER GDEM V2 database (Geospatial Data Cloud, www.gscloud.cn, Beijing, China). Six scenes of the original DEM images were obtained, and they were spliced and transformed into a unified projection coordinate system, and then used to extract the study area. Land use data in 2010 with a scale of 1:100,000 were obtained from Data Center for Resources and Environmental Sciences, Chinese Academy of Sciences (<http://www.resdc.cn>, Beijing, China) and a forest spatial distribution vector dataset in 2006 were collected from Xinlin Forestry Bureau of the Da Hinggan Mountains region. The land cover database used in the SWAT was the combination of the above two databases. Ten land cover types were related to the SWAT database. Harmonized world soil database (HWSD) was used in the SWAT model with a scale of 1:1,000,000. The dataset is provided by Cold and Arid Regions Science Data Center (<http://westdc.westgis.ac.cn>, Lanzhou, China).

3. Methodologies

This study was mainly conducted by the following three parts (Figure 2): (1) Based on the datasets described in Section 2.2, the SWAT model for the Tahe watershed was built and used to reconstruct the runoff in the entire periods for the following application. (2) The calibrated SWAT model was used to quantify the contribution of climate and forest change impacts on runoff. (3) Impacts of climate change under CMIP5 RCP scenarios on the river discharge were simulated by the SWAT model.



(SWAT = the soil and water assessment tool, CMIP 5 = coupled model intercomparison project five, RCP = representative concentration pathways).

Figure 2. Technical route.

3.1. Division of Forest Change Periods

Referring to the previous study [12], the study period was also subdivided into four periods based on the forest biomass and species composition: Period 1 (1972–1982), Period 2 (1984–1994), Period 3 (1995–2005), and Period 4 (2006–2016). The forest biomass and proportional species composition at different forest change periods are shown in Table 1. The mean biomass of the forest in Period 1 is about 45.6 t/ha before widespread deforestation in the 1980s. Then, the high-intensity deforestation in Period 2 reduced mean forest biomass by 17.6%, and birch secondary growth started to appear in the logging area. Due to the starting of the Natural Forest Protection Project in 2007, the forest biomass in Period 4 increased by 9.8% compared to Period 3. Additionally, the species composition gradually changed from an almost 100% larch-dominated forest in the 1970s [10] to a composite forest of 50% larch and 50% birch in the 2010s.

Table 1. Forest biomass per hectare and proportional species composition of the two forest types in the four periods.

Period	Mid-Year	Needleleaf Forest (Larch-Dominated)		Broadleaf Deciduous Forest (Birch-Dominated)		Total (t/ha)
		Biomass (t/ha)	Area Ratio	Biomass (t/ha)	Area Ratio	
1	1978	45.6	100%	0.0	0%	45.6
2	1990	28.7	70%	8.9	30%	37.6
3	2001	19.0	60%	13.9	40%	33.0
4	2012	18.3	50%	17.9	50%	36.2

3.2. Hydrological Model: SWAT

The SWAT model is widely used to quantify the impact of climate change and human activities on hydrological processes, and to predict water river discharge responses from future climate change and land management practices [20–22]. Except for the subboreal climate zone, the SWAT model has been successfully applied in various temperature zones in China, for example, tropical [23], subtropical [24,25], warm-temperate [20,26], temperate [27,28], and Qinghai-Tibet Plateau temperate zone [29]. The detailed description of the SWAT model can be found in the literature [30,31].

In this study, the SWAT model was used to quantify the impacts of climate variability and forest change on river discharge and to predict the changes in the water resources of the Tahe watershed in the 2050s. The ArcSWAT 2012 version (Washington DC, WA, USA) was used to do the specific analysis work. In ArcSWAT, the Tahe watershed was divided into 43 sub-basins, which were further sub-divided into 1094 hydrologic response units (HRUs) using the threshold values of 10% for land use, 10% for soil, and 20% for the dominant land use. Furthermore, the sequential uncertainty fitting (SUFI-2) algorithm of the SWAT-CUP 2019 version (SWAT calibration and uncertainty programs) was applied for model calibration. Since the forest spatial distribution dataset (2006) was only collected in Period 4 (2006–2016), this period was selected as the baseline period and was used to build the SWAT model. The data from 2006 to 2012 was calibrated for the whole basin on a monthly and yearly scale, respectively. The model was then further validated over the period 2013–2016. Model performance can be judged based on the general performance threshold. The Nash-Sutcliffe efficiency coefficient (NSE), the correlation coefficient (R^2) and the percent bias (PBIAS) are widely used to assess the predictive power of model [32] as shown in Equations (1–3):

$$NSE = 1 - \frac{\sum_{i=1}^n (Q_{obs}^i - Q_{sim}^i)^2}{\sum_{i=1}^n (Q_{obs}^i - \overline{Q_{obs}})^2}, \quad (1)$$

$$R^2 = \frac{[\sum_{i=1}^n (Q_{obs}^i - \overline{Q_{obs}})(Q_{sim}^i - \overline{Q_{sim}})]^2}{\sum_{i=1}^n (Q_{obs}^i - \overline{Q_{obs}})^2 \sum_{i=1}^n (Q_{sim}^i - \overline{Q_{sim}})^2}, \quad (2)$$

$$\text{PBIAS} = 100 \times \frac{\sum_{i=1}^n (Q_{obs}^i - Q_{sim}^i)}{\sum_{i=1}^n Q_{obs}^i}, \quad (3)$$

where Q_{obs}^i and Q_{sim}^i are the observed runoff and the simulated runoff in the year i , respectively; $\overline{Q_{obs}}$ and $\overline{Q_{sim}}$ are the average observed runoff and the simulated runoff, respectively. The model performance can be judged as satisfactory if $R^2 > 0.60$, $\text{NSE} > 0.50$, and $\text{PBIAS} \leq \pm 25\%$ [33,34].

Based on the forest spatial distribution dataset of the baseline period, the annual runoff during the entire study period was reconstructed. Under the same climate data, the difference between the observed runoff and the reconstructed runoff was assumed to result from forest change. Moreover, the sole effect of climate variability on runoff can be calculated from the reconstructed runoff during a contrast period minus the observed runoff during the baseline period, because the two periods were based on the same forest spatial data. The following formulas are widely used in the SWAT model to separate and quantify the impacts of climate variability and forest change on annual runoff depth [35]:

$$\Delta Q^F = Q_{OC} - Q_{RC}, \quad (4)$$

$$\Delta Q^C = Q_{RC} - Q_{OB}, \quad (5)$$

where Q_{OC} and Q_{OB} are observed mean runoff depth during the contrast period and the baseline period, respectively; Q_{RC} is the mean reconstructed runoff depth during the contrast period.

3.3. Impacts of Climate Change under CMIP5 RCP Scenarios on the Runoff

The CMIP5 in the World Climate Research Programme (WCRP, Geneva, Switzerland) defined a set of thirty-five climate model experiments from scientific institutions around the world; the experiments were based on RCPs for future simulation, which were important data support in the IPCC 5 report. In this study, the “BCC-CMS1-1” model proposed by the National Climate Center of China in CMIP5 under the RCP 2.6, RCP 4.5, RCP 6.0, and RCP 8.5 emission scenarios were used, and GCMs were used to determine the future climate change scenarios of the Tahe watershed. The GCMs used in this study were obtained from the US Department of Energy’s Lawrence Livermore National Laboratory (<https://esgf-node.llnl.gov>, Livermore, USA). The spatial resolution was 30 seconds, and the time resolution was monthly. The boundary vector data of the Tahe watershed was used for mask cutting to obtain prediction data of temperature and precipitation in the 2050s under the four emission scenarios. In order to better understand the future climate change, the year was divided into four seasons: spring (April to May), summer (June to August), fall (September to October), and winter (November to March).

4. Results

4.1. Calibration and Validation for the SWAT model

Firstly, the data during 2006–2012 was used to calibrate the parameters of the SWAT model. The parameters, which were related to runoff simulation, were selected from previous literature for initial sensitivity analysis (Supplementary Materials Table S1). The sensitive parameters were identified by using the global sensitivity analysis and one-at-a-time sensitivity analysis in SWAT-CUP [36]. Details of the key sensitive parameters for the monthly and annual runoff simulations are listed in Supplementary Materials (Tables S2 and S3). Secondly, the optimized ranges of those sensitive parameters can be calibrated by the SUFI-2 algorithm in SWAT-CUP, automatically. Here, the monthly and annual calibrations were performed separately (Tables S2 and S3). Finally, the values of calibrated parameters were kept unchanged and used to simulate the runoff during 2013–2016.

The model was well calibrated to the observed monthly and annual runoff depth, and the calibrated model performed well for the validation data (Figure 3). As is shown in Table 2, the Nash-Sutcliffe coefficient of efficiency values (NSE) are all greater than 0.75, the coefficients of determination (R^2) are all

greater than 0.75, and the percent bias (PBIAS) are all smaller than 25%. Although model performance for the monthly runoff was not as good as annual runoff, results indicate that its performance was still satisfactory [33,34], implying that the SWAT model was applicable to the Tahe watershed.

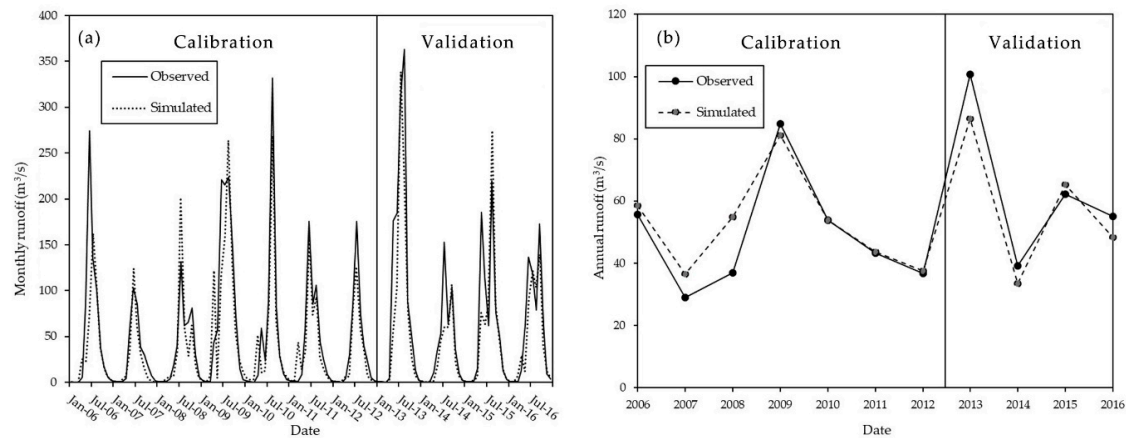


Figure 3. (a) Observed and simulated monthly runoff of the Tahe watershed during 2006–2016, (b) observed and simulated annual runoff of the Tahe watershed during 2006–2016.

Table 2. Practicability evaluation of the SWAT model.

Evaluation Index	Monthly		Annual	
	Calibration Period	Validation Period	Calibration Period	Validation Period
R ²	0.76	0.79	0.82	0.93
NSE	0.75	0.75	0.79	0.85
PBIAS	16.0%	21.8%	−6.0%	9.2%

4.2. Contribution Evaluation of Climate Variability and Forest Change on River Discharge

The calibrated SWAT model was firstly used to reconstruct the runoff in the entire periods. Then, based on Equations (4)–(5) the impacts of climate and forest change on the river discharge were evaluated in the four periods from 1972 to 2016.

As shown in Table 3: (1) Due to deforestation, the mean forest biomass in Period 2 is reduced by 17.6% compared to Period 1, resulting in an increase in mean annual runoff depth by about 36 mm. (2) With reforestation from Period 3 to Period 4, the mean forest biomass increased by 9.8%, resulting in the mean runoff depth reduction of 29 mm. (3) The tree species composition shift reduced mean annual runoff depth by 36 mm between Period 2 and Period 4, when the proportion of birch increased by 20% with a similar total forest volume in the later period.

Table 3. The contribution evaluation of climate variability and forest change on runoff depth.

Forest Change	Comparison Period	Runoff Depth (mm)		$\overline{\Delta Q_{tot}}$ (mm)	SWAT Model	
		Observed	Simulated		$\overline{\Delta Q_c}$ (mm)	$\overline{\Delta Q_f}$ (mm)
Deforestation	Period 1	216	216	+53	+17	+36
	Period 2	269	234			
Reforestation	Period 3	242	213	+17	+46	−29
	Period 4	259	260			
Species composition shift	Period 2	269	234	−10	+26	−36
	Period 4	259	260			

4.3. Assessment of Future River Discharge under CMIP5 RCP Scenarios by the SWAT Model

4.3.1. Future Climate Change

The mean annual temperature from 2006 to 2016 was $-2.20\text{ }^{\circ}\text{C}$ in the Tahe watershed. By the middle of the 21st century, the mean annual temperature was expected to fall by $0.50\text{ }^{\circ}\text{C}$ under the RCP 2.6 emission scenario, while the mean annual temperatures were expected to increase by 0.38 , 0.67 and $1.00\text{ }^{\circ}\text{C}$ under the RCP 4.5, RCP6.0, and RCP 8.5 emission scenarios, respectively. Figure 4 shows mean monthly temperature changes for the 2050s under RCP 2.6, RCP 4.5, RCP 6.0 and RCP 8.5 compared with the base years (2006–2016). The spring temperature was expected to fall in all emission scenarios with the decreases of $-1.75\text{ }^{\circ}\text{C}$ (RCP 2.6), $-0.80\text{ }^{\circ}\text{C}$ (RCP 4.5), $-1.20\text{ }^{\circ}\text{C}$ (RCP 6.0) and $-0.50\text{ }^{\circ}\text{C}$ (RCP 8.5). The mean temperature changes of the four emission scenarios in summer were $-0.22\text{ }^{\circ}\text{C}$ (RCP 2.6), $0.47\text{ }^{\circ}\text{C}$ (RCP 4.5), $0.40\text{ }^{\circ}\text{C}$ (RCP 6.0) and $1.13\text{ }^{\circ}\text{C}$ (RCP 8.5). Summer warming was expected to mainly occur in July and August. The mean autumn temperature was expected to increase with greenhouse gas emissions from $0.55\text{ }^{\circ}\text{C}$ in RCP 2.6 to $2.33\text{ }^{\circ}\text{C}$ in RCP 8.5. Except in the RCP 2.6 scenario ($-0.6\text{ }^{\circ}\text{C}$), the mean winter temperature in the other scenarios increased by $0.32\text{ }^{\circ}\text{C}$ (RCP 4.5), $1.07\text{ }^{\circ}\text{C}$ (RCP 6.0) and $1.16\text{ }^{\circ}\text{C}$ (RCP 8.5).

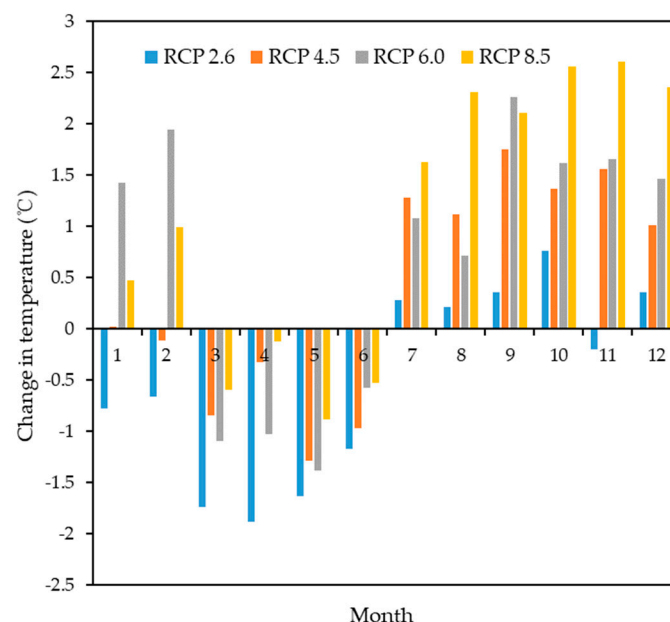


Figure 4. Monthly temperature changes for the 2050s under RCP 2.6, RCP 4.5, RCP 6.0 and RCP 8.5 emission scenarios compared with the base years (2006–2016).

Compared with the mean annual precipitation of 545 mm from 2006 to 2016, the annual precipitation was expected to increase under all four emission scenarios (43 mm in RCP 2.6, 23 mm in RCP 4.5, 36 mm in RCP 6.0 and 10 mm in RCP 8.5) in the 2050s. Figure 5 illustrates the projected change in the monthly precipitation under the four scenarios (RCP 2.6, RCP 4.5, RCP 6.0 and RCP 8.5) compared with the base years (2006–2016). The total spring precipitation was expected to decrease, but increased in April. Except for the RCP 8.5 scenario, the total summer precipitation under the RCP 2.6, RCP 4.5, and RCP 6.0 scenarios will expect to increase by 17.2, 1.6, and 1.7 mm, respectively. The increase in precipitation was expected to mainly occur in autumn. The maximum increase was expected to appear in the RCP 6.0 scenario with 35.0 mm, while the minimum increase was expected to be 18.4mm in the RCP 2.6 scenario. The winter precipitation was expected to mainly occur in the form of snowfall and increase by 12.5 mm (RCP 2.6), 8.6 mm (RCP 4.5), 8.8 mm (RCP 6.0) and 11.6 mm (RCP 8.5).

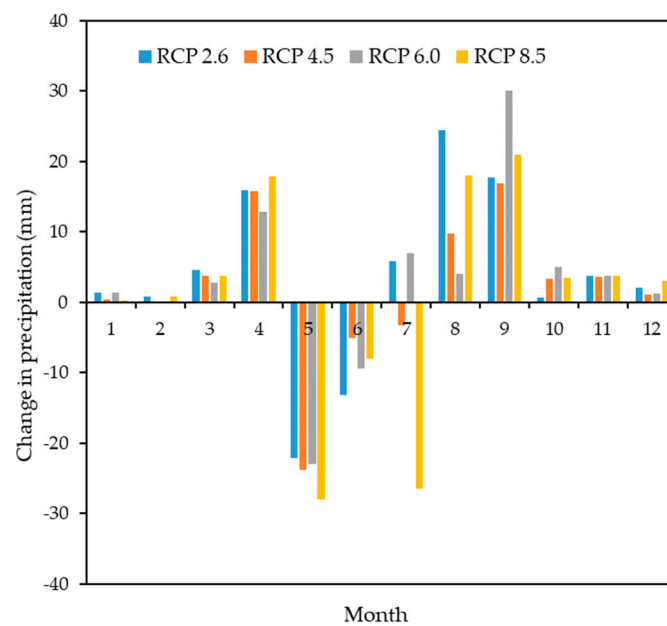


Figure 5. Monthly precipitation changes for the 2050s under RCP 2.6, RCP 4.5, RCP 6.0 and RCP 8.5 emission scenarios compared with the base years (2006–2016).

4.3.2. Response of Future Annual and Seasonal River Discharge to Climate Change

The SWAT model was used to simulate the river discharge of the Tahe watershed in the 2050s under the four CMIP5 RCP scenarios. As shown in Figure 6, compared with the base years (2006–2016), the mean annual runoff depth in the four emission scenarios increased in the 2050s. Under the RCP 6.0 scenario, the mean annual runoff depth was predicted to be 315 mm, which was an increase of 23.6% over the base years. Although the greenhouse gas emissions were different between the two scenarios of RCP 4.5 and RCP 8.5, the predicted mean annual runoff depth in the 2050s was the same (285 mm), an increase of 11.7% over the base years. The RCP 2.6 scenario was the most ideal emission scenario recommended by the IPCC for human development in the future. If countries around the world can control carbon emissions in accordance with the recommendations of the IPCC, the SWAT model predicted that annual runoff depth would increase by 18.1% over the base years.

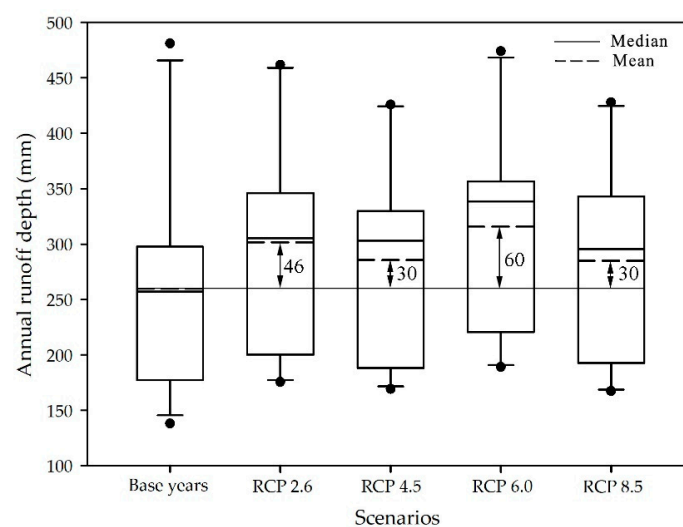


Figure 6. Annual runoff depth changes for the 2050s under RCP 2.6, RCP 4.5, RCP 6.0 and RCP 8.5 emission scenarios compared with the base years (2006–2016).

Figure 7 shows the changes in the mean monthly runoff depth under the four emission scenarios compared with the base years (2006–2016). The predicted monthly runoff depth had a similar trend with the monthly precipitation since the Tahe watershed was a rainfall-dominated watershed. The spring runoff depth was expected to increase by about 25% under the four scenarios, which occurred during the early spring period. The increase in runoff depth was expected to occur in April, and the increases in runoff depth in RCP 2.6, RCP 4.5, RCP 6.0 and RCP 8.5 scenarios were 100.1%, 70.6%, 73.7% and 92.1%, respectively. The runoff depth was expected to decrease in May, and the reduction of runoff depth was 20% under the RCP 6.0 scenario, and the other three scenarios were expected to decrease by about 30%. The summer runoff depth was expected to increase by 13.6% under RCP 2.6, 7.3% under RCP 4.5, 18.0% under RCP 6.0 and 1.4% under RCP 8.5. The runoff depth decreased in June and increased in other months under the four scenarios, except for the RCP 8.5 scenario in July. The autumn runoff depth was also expected to increase, with increases of 62.6% (RCP 2.6), 59.4% (RCP 4.5), 106.9% (RCP 6.0), and 84.5% (RCP 8.5). The runoff depth under the RCP 6.0 scenario was expected to increase mostly among the four scenarios, including an increase of 99.1% in September and 122.8% in October. The winter runoff depth was expected to increase under the four scenarios from 3.1 to 6.2 mm, which is positively related to emissions.

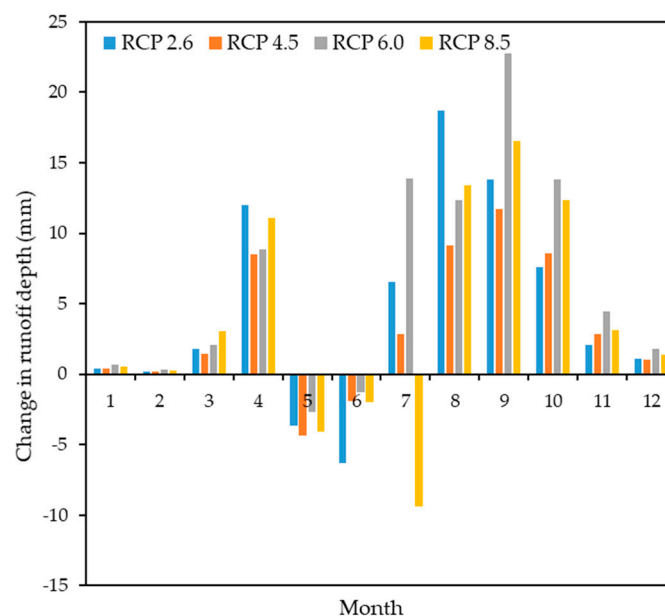


Figure 7. Monthly runoff depth changes for the 2050s under RCP 2.6, RCP 4.5, RCP 6.0 and RCP 8.5 emission scenarios compared with the base years (2006–2016).

5. Discussion

5.1. Discussion

At present, statistical approaches and hydrological models are two common methods for quantifying the relative contributions of climate and forest change on hydrology in large watersheds [37]. In this study, the SWAT hydrological model was used to quantitatively estimate the impact of forest change on river discharge in the Tahe watershed. Our results indicated that deforestation increased annual runoff depth while tree species composition shift and reforestation decreased annual runoff depth in the Tahe watershed, which were similar to the results by statistical approaches in the previous study [12]. The results were also consistent with previous studies on the impacts of deforestation and reforestation on water resources around the world [3]. For example, Zhang et al. [1] examined about 312 watersheds across multiple spatial scales and indicated that the increase in annual runoff associated with deforestation was statistically significant at multiple spatial scales whereas the effect

of reforestation was statistically inconsistent. Li et al. [2] conducted a synthetic analysis on the basis of the studies from 162 large watersheds and confirmed that deforestation increases annual water resources and reforestation decreases it. The mechanism that was provided in previous studies suggested that deforestation mainly decreased evapotranspiration due to the reduction of forest cover and soil infiltration capacity, and reforestation reversed these changes [38,39]. In addition, tree species composition shift reduced mean annual runoff; this may explain the changes in forest evapotranspiration. Previous studies indicated that due to the different tree crown characteristics, the canopy interception of the secondary birch forest was lower than that of natural larch forest (about 8% of the total rainfall and 7.8% of total snowfall) [40–42]. In contrast, the fast-growing pioneer birch species used more water for transpiration than larch [43,44]. Overall, with the increase in the proportion of birch, the increase of forest transpiration exceeded the increase of throughfall, resulting in a decrease in runoff.

Economic and social development and rapid increases in the available water resources have caused widespread concern among human society. Guo et al. [45] showed that although the precipitation and runoff will slightly increase under future climate, irrigation water demand will significantly increase; that will further exacerbate the future water scarcity in northwestern China. Xia et al. [46] indicated that climate change will increase the frequency of future extreme floods and droughts under IPCC-AR5 scenarios, which will be a risk to the eight major river basins in the Eastern Monsoon Region of China. Ruan et al. [47] showed that the future annual rainfall and radiation will have a small increase in southern China. However, few studies have analyzed the impact of future climate change on water resources in subboreal northeast China. The forests in the Da Hinggan Mountains will experience continuous restoration due to the Natural Forest Protection Project. Undoubtedly, with the continued recovery of forest biomass, it will reduce the water resources. However, the SWAT model predicted that annual runoff depth would increase by 30–60 mm, compared to the base years (2006–2016). By comparing the 1995–2005 period with the 2006–2016 period, the 9.8% increase of forest biomass reduced the mean runoff depth of 29 mm. Therefore, in the next 40 years, the increase in water consumption by forest recovery may offset or exceed the increase in water resources caused by future climate change, which will likely cause stress of water resources.

The implications in forest conservation and management were also proposed in this study. Our results indicated that the similar total forest biomass (20% of larch shifted to birch) reduced the water resources by 13.3% in the SWAT model. This meant that larch forests could assimilate more carbon than birch forests while providing the same water resources. Larch was the dominant tree species in the Da Hinggan Mountains, which was almost 100% distributed before disturbance by human activity. Birch was growing rapidly on the clear-cut land as the secondary tree species, and it will eventually be replaced by larch due to the natural succession. The succession can be artificially accelerated in forest management, thereby improving the forest capacity of carbon fixation and the function of hydrological ecological services. Hence, the restoration of top forest communities should be noted in the process of reforestation.

5.2. Limitations and Future Work

The assessment of the impact of climate and forest change on river discharge and the prediction of water resources in future climate scenarios had some limitations. These can be divided into two categories: (1) uncertainty of the hydrological models, and (2) uncertainty of the forecast of future climate.

Although the calibration and validation of the SWAT model showed that the model accuracy was satisfactory, there still were many uncertainties. As the usual uncertainties in the distributed hydrological models, major sources of uncertainty in the simulation from the SWAT model came from the model structure, input data and model parameters [35]. The SWAT model focused on simulating changes in land use and had limitations in simulating forest dynamic changes, such as the consumption of water resources by forest growth and forest succession. In addition, the SWAT model did not focus

on the melting of permafrost in the water cycle simulation. Duan et al. [10] and Chang et al. [48] showed that climate change and deforestation caused the melting of permafrost in the Tahe watershed, which was an important part of the hydrological process. Future studies should combine the SWAT model with forest succession models (such as JABOWA models), forest growth water consumption models and permafrost melt models. Various hydrological models will be involved in future works to explore a better hydrological model for the subboreal forest watershed.

Undoubtedly, there were always many uncertainties in forecasting the future climate, even in the GCMs commonly used around the world. One was the uncertainty in different GCMs. Global scientific institutions had proposed nearly thirty RCPs-based GCMs in the CMIP5, which projected different future climate scenarios [49,50]. The other was the uncertainty of emission concentration pathways. This uncertainty came not only from socio-economic development and population growth, but also from uncertain natural disasters (such as Amazon rainforest wildfires and bushfires in Australia). Only four emission scenarios (RCP2.6, RCP4.5, RCP6.0 and RCP8.5) were utilized and may not consider the full range of potential scenarios [49]. In order to minimize uncertainties in GCMs structure and RCP emission scenarios, multiple GCMs will be used to better quantify future climate changes [51].

6. Conclusions

Our study showed that the SWAT model was well calibrated and can be used to simulate runoff from different periods of historical forest change and predict river discharge under future climate change in the Tahe subboreal forested watershed in northeastern China. The results from the quantitative assessments on historical data indicated that deforestation increased annual runoff depth while reforestation and tree species composition shift decreased annual runoff depth. The results of projections of GCM in the middle of the 21st century indicated that both mean annual temperature and precipitation will increase. The positive effect of precipitation on river discharge outweighs the negative effect of temperature, which then results in the increase in annual runoff depth. On the monthly scale, the increased annual runoff depth is mainly attributed to the increased runoff in April, July, August, September and October. These findings indicated that future climate change may offset the negative effects of the continuous reforestation on water resources in the northern Da Hinggan Mountains, which is of great importance for both water resource and forest management in forested watersheds in the northern Da Hinggan Mountains and other subboreal forested watersheds.

Supplementary Materials: The following are available online at <http://www.mdpi.com/2073-4441/12/6/1565/s1>, Table S1: Parameters used in the sensitivity analysis, Table S2: Key SWAT model parameters, with their final value range and fitted values for monthly simulations, Table S3: Key SWAT model parameters, with their final value range and fitted values for annual simulations.

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