The impacts of climate change on water resources in the Second Songhua River Basin, China

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Abstract. The Northeast China Plain is one of the main grain growing regions in China. Due to the high latitude and black soil ecological system, the crop growth in there is vulnerable to climate change, which makes it important to evaluate the influences of climate change on water resources. In this study, the influences of climate change on water resources of a typical basin in northeast China, the Second Songhua River Basin were assessed using the SWAT model. Ensemble downscaled output from sixteen GCMs for A1B emission scenario in 2050s was adopted as the regional climate scenario and was used to drive SWAT model to predict hydrological changes. The prediction shows that mean evapotranspiration of whole basin increases in most time of a year. Stream flow of Fuyu gauging station downstream this basin exhibits a decrease trend from April to June, November and December, and increases in the remaining period of the year. It is indicated that water resources may not be sufficient in spring for irrigation and the possibility of flood in summer may increases, indicating countermeasures should be made to ensure agricultural water use and prevent possible damages of flood on crop.

1. Introduction

Climate change is now a leading issue on the environmental and socioeconomic agenda worldwide [1]. The Soil and Water Conservation Society (SWCS) [2] stated that, under climate change, there is clear potential for increased risks of environmental consequences. Since the climate system interacts with the hydrological cycle, the impact of climate change on hydrology has become a growing concern [1, 3]. Xu et al. [4] indicated that the impact of climate change on water resources and the potential implications for water resource management have been the focus of a multitude of scientific investigations over the past two decades. Jiang et al. [5] argued that changes in the availability of local and regional water resources are one of the most important and immediate effects.

The report of the IPCC (Intergovernmental Panel on Climate Change) (2013) concluded that the speed of climate change is faster than the estimation in the past and the increase of the global mean atmospheric temperature will likely be more than 1.5 and 2.0 °C by the end of this century (compared with 1850-1900). This increase process will not end by 2100, and the increase of temperature only might be controlled within 2.0 °C with the most strict emission scenario. As to the precipitation, generally, the contrast in precipitation between wet and dry regions and between wet and dry seasons will increase. Changes in the global hydrological cycle in response to climate change over the 21st century will not be uniform [6], and need to carry out further research. Increased temperatures in winter and spring will affect the precipitation phase, and, as a consequence, the snow/precipitation

ratio and the volume of water stored in snow cover will be changed [7]. Therefore, the hydrology of rivers in the northern hemisphere is sensitive to climate change [7]. Meanwhile, there still remain some uncertainties regarding the responses of the hydrological cycle to climate change, such as uncertainties in future climate projections and in the response of hydrological processes [8].

Also, the impact of climate change on vegetation growth is significant, especially the influence on crop growth, water consumption and grain production [9]. The northeast of China is the main grain producing region, and as such, the influence of climate change on the hydrological cycle, water resources, and crop growth in this area deserve more attention. Crop responses to rising temperatures are nonlinear, and may be different below and above threshold points [10]. Changes in precipitation variability and air humidity affect water consumption and the degree of water stress, resulting in changes in transpiration rates at leaf level [11].

To date, there have been many studies spanning various disciplines documenting climatic predictions around the word. However, there are still some limits associated with these predictions [12]. For example, some previous studies have predicted future climate scenarios simply from analysis of historical data and their trends [13]. This method blatantly ignores the uncertainty in climate change and the increased frequency of abnormal climates event in recent decades, so historical data and their trends are unreliable, and cannot represent a realistic picture of the current and future situations [14].

Climate scenario model takes account of this climate uncertainty and has been considered as an effective means to predict future climate [15-17]. GCMs (General Circulation Models) are based on the fundamental laws of physics. These models consider the content of greenhouse effect in the atmosphere. Meanwhile, it is also recognized that different climate model provide different projection. So it is recommended to consider several GCMs to obtain the better projection when undertaking any study of impacts on the hydrological regime [18]. GCMs are also subject to several limitations, in particular the limited spatial detail of the relatively coarse grid of a GCM, and their consequent inadequacy to model small scale variability. Gratifyingly is that a variety of methods, such as dynamical downscaling and statistical downscaling, have been developed to create finer spatial resolution data sets [19]. Therefore, at present, GCMs provide us with the most reliable and robust methods for assessing the response of the climate system to changes in forcing [20], and have been widely used in many studies [3, 21, 22].

Located in the cold temperate zones, Northeast China Plain is a sensitive area of climate changes [23]. Its high latitude and black soil ecosystem also serve to exacerbate its sensitivity, and the changes in climate are obvious [24, 25]. In the context of warming, the climate in there warmed significantly [26], and the frequency of severe dryness is increased [27]. Consecutive dry days, rainstorms and floods occurred frequently in the 1990s [28]. The precipitation extremes over 1-5 days increased significantly [29]. Several studies showed that the cloud amount in northeast China had decreased strongly since 1950 [30], thus generating more events of serious drought [27]. As the major agricultural region in northeast China, studies about the impact of climate change on water resources in the Northeast China Plain are very significant and will provide information to promote protection of soil hydrology and ecology [14]. That is, because the variability in climate in the Northeast China Plain plays a vital role in the aspect of ecological and agricultural water requirements [31], it's necessary to analyse the impact of climate change on water resources in the future in there. To date, the water resources prediction researches are not so numerous in this region, and the future climate prediction method is lack of reliability in the existing researches. Coupling research of climate prediction and hydrological simulation and their uncertainty analysis are lack of in-depth study. Therefore, the coupling prediction of water resource with mechanism model in the context of warming in this basin is urgent.

In this study, we set up a semi-distributed hydrological model, and analysed the future climate in the Second Songhua River Basin in the Northeast China Plain from 2040 to 2069 from sixteen GCMs. The influence of climate change on hydrological cycle and water resources in this basin has been evaluated by using the semi-distributed hydrological model with this future climate. Then, some countermeasures for agriculture addressing climate change in this basin have been proposed. This

analysis would allow us to evaluate and draw conclusion about the influence of climate change on water resources.

2. Study area

The Second Songhua River Basin, located between 124.62°-128.8°E，41.75°-45.4°N in the Northeast China Plain. This river originates from Tianchi Lake in the Changbai Mountain and travels 958km from southeast to northwest draining a total area of 73400 km^2, and flows through 26 counties in Jilin Province (Figure 1). The 90- m resolution digital elevation map shows that the basin elevation ranges from 121 m to 2729 m and decreases from the southeast to the northwest. The Second Songhua River Basin is mainly covered by black soil in northeast China, and has become one of the most important regions for cereal grain production. In this basin, the main types in the southeast mountains are the dark brown earth and albic bleached soil, and the main types in the northwest plain are chernozem, meadow soil and black soil. To date, many valleys and tablelands between the Changbai Mountains have been reclaimed for cultivation so far. The main land use types in this basin are forest and agricultural land, and rice is the main crop (Figure 2, Table 1). Forest mostly situates in the southeast mountains, which is the headstream of Songhua River, and paddy land mostly situates in the northwest plain.

The region has a mid-latitude monsoon climate, and the amount of precipitation decreases from southeast to northwest. Precipitation mainly occurs in summer, and is accompanied by high temperatures [14]. According to the long-term history data, the average annual precipitation ranges from 400 mm to 600 mm, 70% of which occurs in the period from June to September. Daily average temperatures are below freezing from late November to early March of the following year. According to the statistics data of gauging station in the river downstream outlet, the observed average monthly stream flow from July to September is greater than 500 cubic meters per second.

According to the statistical analysis of meteorological disasters on crops during recent four decades in Jilin Province, the rice is sensitive to the impact of flood and the maize is more sensitive to the drought than to the flood [32]. Through the quantitative evaluation of the meteorological disaster from 1971-2008, the influence of drought on agricultural production has become more serious over time. Thus the massive crop in this basin makes it sensitive to climate change. In their study of climate change and extreme climate events in northeast China, Zhao [33] indicated that there was a significant increasing trend in the annual mean temperature in northeast China, which, over the last 40 years, was higher than both the global and national rate. In the Jilin Province, the impact of drought on the agriculture is larger than the sum of flood, wind and hailstone and cold impact, and the drought impact increased seriously [34]. In the analysis of characteristic of drought and flood evolution from 1950-2010, Yang et al. [35] indicated that the drought has happened 30 times and the flood 25 times in Jilin Province. The drought increased obviously especially from the 1970s, and the flood frequency has the highest in1980s and then has a small decrease. Jilin province undergoes the characteristic of drought and flood coexists currently. As the major agricultural region with black soil ecosystem and high latitude in northeast China, studies about the impact of climate change on water resources in this area are very significant and will provide information to promote protection of soil hydrology and ecology [13].
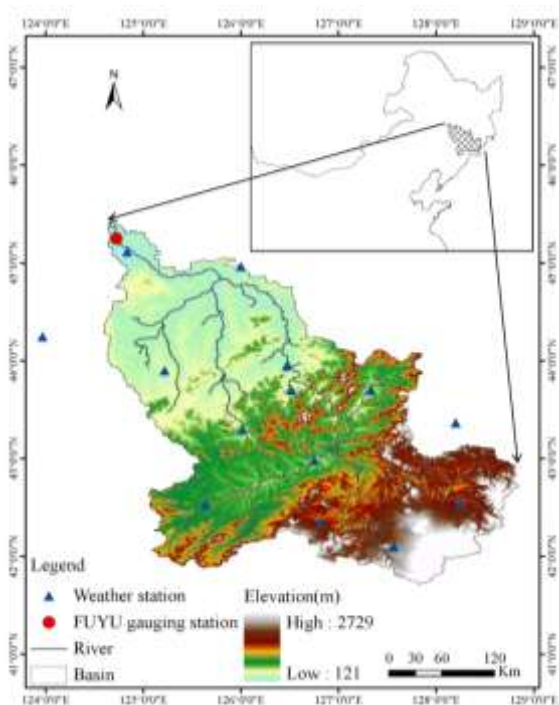
Figure 1. Geographic information of the Second Songhua River Basin and its stream flow gauging station and weather stations.
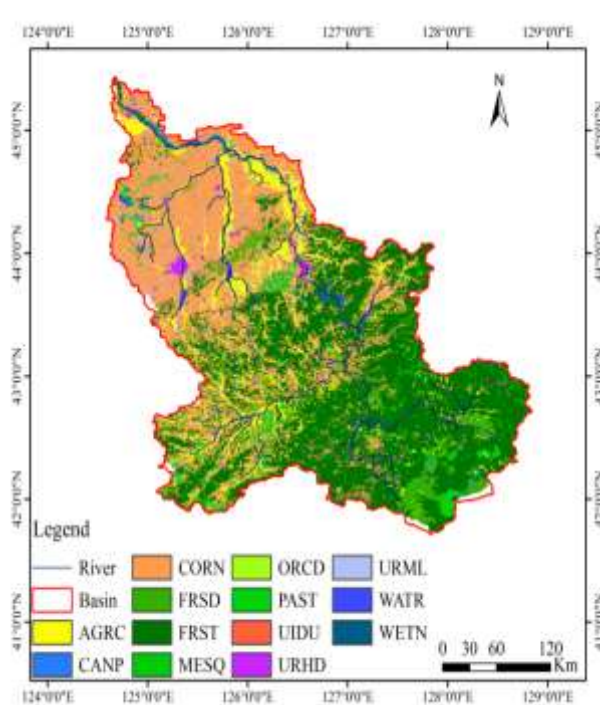

Figure 2. Types of land use in the Second Songhua River Basin.

Table 1. The definition of land use type ID and the area proportion.

ID	Ratio (%)	Area (km²)	Definition
FRST	41.3	30328.9	Forest-Mixed
CORN	32.6	23928.4	Agricultural Land-dry land
AGRC	8.8	6429.8	Agricultural Land-paddy field
FRSD	4.4	3251.6	Forest-Deciduous
URML	3.8	2759.8	Residential-Med/Low Density
MESQ	2.5	1842.3	Shrub
PAST	2.0	1475.3	Pasture
WATR	1.7	1247.8	Water
ORCD	0.9	638.6	Orchard
URHD	0.8	565.2	Residential-High Density
WETN	0.6	469.8	Wetlands-Non-Forested
CANP	0.6	433.1	Bare land
UIDU	0.1	36.7	Industrial

3. Hydrological model

3.1. Model description

Hydrological model is a useful tool in analysing the hydrological processes in large basin. Physical model represents the underlying hydrological and land surface processes in greater detail than

conceptual or statistical models [36]. SWAT model is a physically-based model to evaluate watershed hydrology and water developed by the United States Department of Agriculture (USDA) [37]. Studies have demonstrated that it performs especially well when simulating hydrological, environmental, and biological processes and it has been applied in many parts of the world for a range of climate conditions and resolutions [38-40].

Daily weather data have to be input into the model. Climate change scenarios for precipitation and temperature can be easily manipulated as the weather input files. After calibration and validation of its parameters, the SWAT model was used in this study to evaluate and understand the impacts of climate change on hydrologic cycle and water resources. The Nash-Sutcliffe (E_{NS}) coefficient of efficiency [41] and the Deterministic Coefficient (R^2) were used as the objective functions for optimizing the model performance. They are defined as:

$$E_{NS} = 1 - \frac{\sum\limits_{i=1}^{n}(Q_{m,i} - Q_{s,i})^2}{\sum\limits_{i=1}^{n}(Q_{m,i} - Q_{ma})^2} \tag{1}$$

$$R^2 = \frac{\left[\sum\limits_{i=1}^{n}(Q_{m,i} - Q_{ma})(Q_{s,i} - Q_{sa})\right]^2}{\sum\limits_{i=1}^{n}(Q_{m,i} - Q_{ma})^2 \sum\limits_{i=1}^{n}(Q_{s,i} - Q_{sa})^2} \tag{2}$$

Where $Q_{m,i}$ (m^{3}s^{-1}) and $Q_{s,i}$ (m^{3}s^{-1}) are the observed and simulated stream flows for a time step i, Q_{ma} (m^{3}s^{-1}) is the average observed stream flow, and Q_{sa} (m^{3}s^{-1}) is the average observed stream flow for the whole simulation period.

Calibration and validation are performed in SWAT Calibration and Uncertainty Programs (SWAT-CUP), which is a computer program for calibration of SWAT model. In this study, the sensitivity analysis and uncertainty analysis of parameters, calibration and validation are performed in SWAT-CUP. In order to do these, the results of SWAT model and observed data are required input into the SWAT-CUP.

3.2. Uncertainty analysis
In the application of hydrological model with GCMs coupling model, the uncertainties in predicting water resources include climate modelling uncertainty and the uncertainty associated with the hydrological model. There are many existing studies that report climatic projections and uncertainty for different emission scenarios [7, 42] and downscaling methodologies [43, 44]. Parallel research activities, such as those discussed by Semmler et al. [43] have focused on generating an ensemble of climate simulations based on different GCMs and multiple future climate scenarios. In that study, combination of different GCMs was used to evaluate the projected changes in stream flow in Ireland. To date the use of an ensemble median (or mean) is an effective means to improve the outcome of climate simulations that is often better than any individual future climate projection [45]. In order to reduce the uncertainty, this study used the ensemble average projected temperature and precipitation from 16 GCMs for A1B emission scenario (medium CO_2 emission, and leveling-off of emission in the mid-21st century) downscaled to a resolution of 0.5 °C for the period from 2040 to 2069. These GCMs result are created by using fine resolution observed data and statistical downscaling method to generate the climate scenario at fine spatial scale. This ensemble GCMs for A1B emission scenario with downscaling method can reduce the uncertainty associated with the climate change modelling.

Parameter is the other main source of uncertainty in hydrological model. The questions of how to identify the sensitive parameters and how to quantify the uncertainty of these parameters have been widely investigated [46].

Three soil parameters chosen for this study are the available water content (*AWC*), bulk density (*BD*), and soil saturated hydraulic conductivity (*Ks*). They can all be obtained by calibrating the

hydrological model based on the optimization algorithm [47]. However, if these significant soil parameters take part in the calibration may increase the "Equifinality" effect (same simulations with different parameter values), which can increase the uncertainty of hydrological model [48]. And the values obtained by calibration ignored the physical significance of parameters. Through comparative analysis of different computation methods, this study calculated these parameters using the following soil transfer functions, which have been widely used [49, 50].

$$AWC = \theta_{33} - \theta_{1500} \tag{3}$$

$$BD = (1 - \theta_S) \times 2.65 \tag{4}$$

$$Ks = 1930 \times (\theta_S - \theta_{33})(3 - \lambda)$$

$$\lambda = 1/B$$

$$B = \frac{[\ln(1500) - \ln(33)]}{[\ln(\theta_{33}) - \ln(\theta_{1500})]} \tag{5}$$

Where θ_{33} and θ_{1500} are the water contents at capillary pressures of 33 and 1500 kPa, θ_s is the saturated soil moisture.

This study adopted the General Likelihood Uncertainty Estimation (GLUE) method to analyse the parameter uncertainty of SWAT model, and chose the E_{NS} as the likelihood objective function. The parameter uncertainty was assessed by E_{NS}, R^2, the posterior distribution of the parameter cumulative probability, P_factor and R-factor. In Figure 3, x-axis is the value range of parameter, and y-axis is the cumulative probability. In the simulation that used the calculated parameters, the posterior distributions of the other parameters were closer to the prior distribution, which indicated that calculated soil parameters reduced the impacts of other parameters on the posterior distribution. In Table 2, the P_factor and R-factor were raised by Abbaspour et al. [51] as the indexes of model uncertainty by analysing the cumulative probability distribution output variables in the 2.5 % and 97.5 % quintiles. The P_factor indicates the probability that the measured values are located within the confidence interval (95 PPU), while the R-factor indicates the width of the confidence interval. When the P_factor is close to 1 and the R-factor is close to 0, the uncertainty is less. In this study, the confidence interval (95 PPU) contained more measured values with calculated soil parameters, and the R^2 and E_{NS} results were generally higher than those simulated with calibrated soil parameters. Thus, the simulation obtained from calculation is closer to the actual hydrological regime of the river. As a result, the high sensitive soil parameters (AWC, BD, Ks) obtained from this calculation method instead of calibration can obviously reduce the uncertainty of hydrological model.
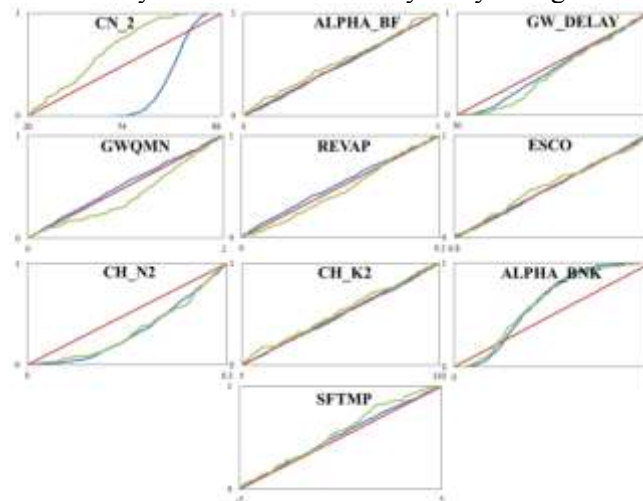

Figure 3. Posterior cumulative probability distributions of the other ten parameters in two conditions (—priori cumulative probability distribution;—simulation with calculated soil parameters;— simulation with validated soil parameters).

Table 2. Simulation results of two methods to obtain soil parameters.

Situation	P_factor	R-factor	R^2	E_{NS}
soil parameters obtained from calculation	0.7	0.9	0.69	0.67
soil parameters obtained from validation	0.61	0.87	0.64	0.58

3.3. Model setup and calibration

To set up the SWAT model, the observed stream flow data are needed to calibrate the SWAT model parameters. Due to limitations in the observed data, this study only used the observed stream flow data from one hydrological gauging station, the Fuyu station (45.17N, 124.8E, the mouth of the river basin). The data at the Fuyu station can be used to represent the complete hydrological process of the whole basin, so it is appropriate to use data from this station for the calibration. Daily observed data for the period from 1980-1986 and 2006-2011 were used. After the uncertainty analysis about these three soil parameters, calculating by soil transfer functions can reduce the uncertainty of hydrological model. Then, there are seven other parameters need to be calibrated, as listed in Table 3. These parameters of each watershed were obtained through SWAT-CUP based on the observed stream flow at the Fuyu gauging station.

Table 3. Model parameter description.

Parameter	Description	Unit	Range		Value
v__CN2.mgt	The runoff curve number	-	20	90	80.555
v__ALPHA_BF.gw	Base flow alpha factor	days	0	1	0.79664
v__GW_DELAY.gw	Groundwater delay time	days	30	450	253.33
v__GWQMN.gw	Threshold depth of water in the shallow aquifer required	mm H_2O	0	2	1.48305
v__GW_REVAP.gw	Groundwater "revap" coefficient	-	0	0.2	0.19834
v__ESCO.hru	Soil evaporation compensation factor.	-	0.01	1	0.9850
v__CH_N2.rte	Manning's "n" value for the main channel	-	0	0.3	0.15494
v__CH_K2.rte	Effective hydraulic conductivity in main channel alluvium	mm/hr	5	130	97.822
v__ALPHA_BNK.rte	Base flow alpha factor for bank storage	days	0	1	0.20515
v__SFTMP.bsn	Snowfall temperature	℃	-5	5	-2.1091

Meteorological data drive the hydrological model, and should include at least daily precipitation and daily max/min temperature data. For this study, we used daily meteorological data from 14 weather stations (Table 4), obtained from the Chinese Meteorological Data Sharing Service System. The observation period is from 1980 to 2011, and the data format is daily. Other input data for the SWAT model included a 90 m resolution Digital Elevation Map, a 90 m resolution land cover map, a 1:10 00000 resolution soil map, and soil texture information. All the input data were fully quality controlled and their properties and sources are tabulated in Table 5. The SWAT model can fully use the spatial variation of these 14 weather stations to simulate the hydrological process of each sub basin. Based on the observed stream flow data from the Fuyu station, the calibration and validation periods were from 1980-1986 and from 2006-2011, respectively.

Table 4. The information of weather station used in this paper.

Station name	Latitude	Longitude	Elevation
Qianguoerluosi	45.12	124.83	134.70
Changling	44.25	123.97	189.30

Sanchahe	44.97	126.00	196.60
Changchun	43.90	125.22	236.80
Yantongshan	43.30	126.02	271.60
Yongji	43.70	126.52	229.50
Jinlin	43.95	126.47	183.40
Jiaohe	43.70	127.33	295.00
Dunhua	43.37	128.20	523.70
Meihekou	42.53	125.63	339.90
Huadian	42.98	126.75	263.30
Jinyu	42.35	126.82	549.20
Donggang	42.10	127.57	774.20
Songjiang	42.53	128.25	591.40

Table 5. Data used in SWAT modelling in the Second Songhua River Basin.

Description	Remark
Digital Elevation Map (DEM)	From GLOBE data ,90 arc second resolution, Available at: http://www.ngdc.noaa.gov/mgg/topo/globe.html
Land cover map	Interpreted by remote sensing data,90 arc second resolution
Soil map	From China Soil Scientific Database,1:10 00000 resolution, Available at http://www.soil.csdb.cn/
Soil texture	From China Soil Scientific Database, Available at http://www.soil.csdb.cn/
Daily precipitation	From China Meteorological Date Sharing Service System, Available http://cdc.cma.gov.cn/home.do
Daily max/min temperature	From China Meteorological Data Sharing Service System, Available at: http://cdc.cma.gov.cn/home.do
Monthly precipitation, max/min temperature, wind speed, solar radiation, relative humidity	From China Meteorological Data Sharing Service System, Available at: http://cdc.cma.gov.cn/home.do
Daily observed stream flow	From China hydrological yearbook

After calibration and validation, these seven parameters were then used in SWAT model to simulate the hydrological processes across the whole basin in reference period and future scenario.

4. Future scenario of climate change

The future regional mean precipitation and maximum and minimum temperatures projected by the ensemble of 16 GCMs under an A1B emission scenario were derived for the Second Songhua River Basin for 2050s (2040-2069) from the Climate Wizard dataset (available at: http://www.climatewizard.org/index.html) . The data at finer spatial scale in this dataset are created by downscaling techniques and are revised by past observed data [52]. In this dataset, the relative change in monthly precipitation and the absolute change in the mean temperature were downscaled to a resolution of 50 km using the two-step bias correction spatial downscaling method. This method is simple and inexpensive, and can be repeatedly rerun to generate large ensemble of daily precipitation series at the point or catchment scale, which has been applied extensively at regional, continental, and global scales [42, 52, 53]. The future climate prediction of the 16 GCMs is provided as the monthly relative change and absolute change. The percentage changes in the monthly mean precipitation between the future scenario (2050s) and the reference period were used to scale the daily precipitation

data for the 2050s. The absolute change in the monthly mean temperature and the reference period data were directly used as input data for the 2050s. The reference period data were the observed daily data of 14 weather stations from 1980 to 2011, which represented the current climate situation across the whole basin. The future scenario data obtained from the relative and absolute changes of 16 GCMs in the 2050s reflected the future climate situation across the whole basin. The hydrological regime differences between these simulations of reference period and future scenario are considered as the impact of climate change on hydrological processes.

The average relative changes in the monthly mean precipitation and the absolute change in the monthly mean temperature of the whole basin between the reference period and the future climate scenario in the 2050s, respectively, are shown in Figure 4. With the exception of October, the precipitation will increase throughout the year. For the period from December to February, precipitation is predicted to increase significantly (30 %-33.7 %). Similarly, the temperature increase is greater in winter than in summer. The monthly mean temperature is predicted to increase in all of the twelve months, with an average increase of 2.93 °C. These changes were in general agreement with the IPCC report (2014). The increased temperatures in the winter and spring seasons will accelerate the speed of snow melting and will result in increased heat availability. The changes in precipitation and temperature will have significant effects on plant growth and ecosystem health in the Second Songhua River Basin.
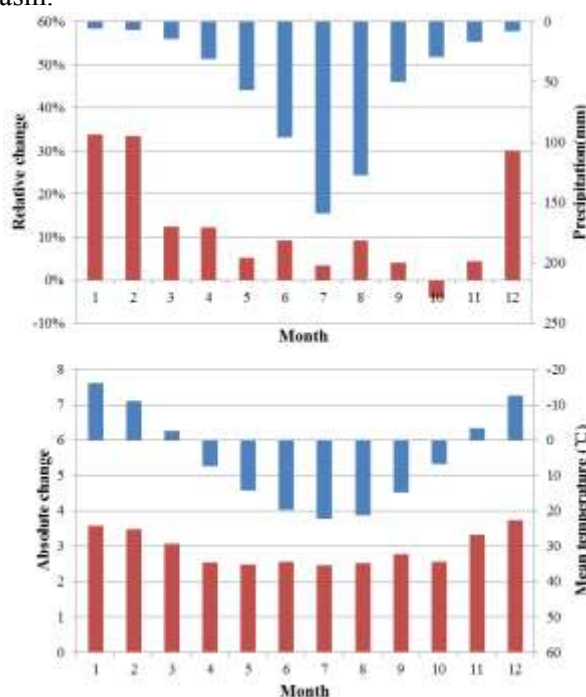

Figure 4. Basin averaged changes (red columns) of monthly mean precipitation and temperature between baseline (blue columns) and future climate scenario in 2050s.

5. Result and discussion

5.1. The performance of SWAT model

Stream flow data collected at the Fuyu gauging station downstream of this basin reflects the river discharge of the whole basin and was used to calibrate and validate the model. The daily observed and simulated stream flow for the Fuyu gauging station is shown in Figure 5. The simulation of calibration period shows better agreement with the observed data than the simulation of validation. As the impacts of climate change will be explored at the monthly scale at Fuyu, the monthly simulated stream flow was examined and is demonstrated in Figure 6. The monthly simulation both in calibration and

validation is better than the daily one. According to the analysis, the average relative error of yearly total volume between observed stream flow and simulated stream flow is 0.298, and the average relative error of peak value is 0.215. The daily and monthly model performance for the calibration and validation period is tabulated in Table 6, which indicates that the simulation of stream flow by SWAT model is reasonable. The good performance at both the daily and monthly scale demonstrates that the SWAT model is an appropriate choice for the impact assessment being planned.
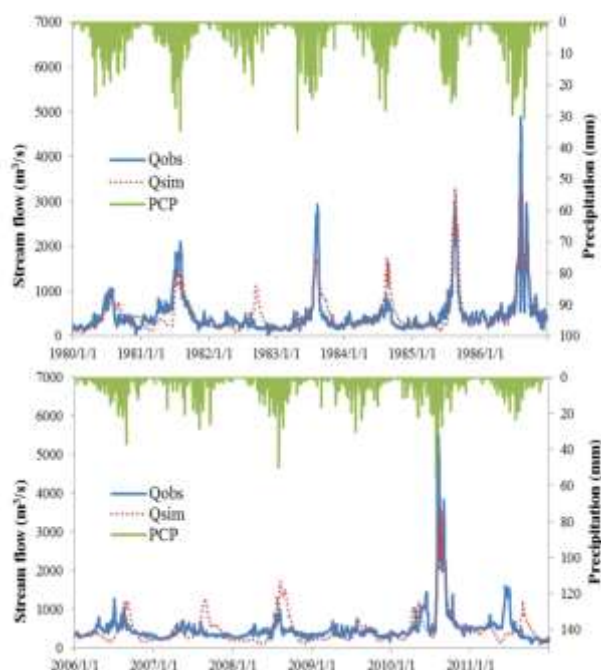

Figure 5. Daily stream flow simulations at Fuyu station (Qobs: observed stream flow; Qsim: simulated stream flow; PCP: precipitation).
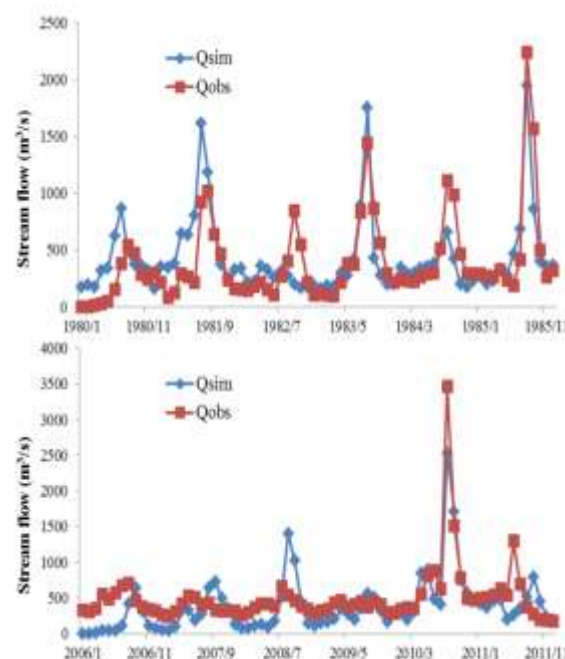
Figure 6. Comparison between monthly averaged simulated and observed stream flow at Fuyu station (Qobs: observed stream flow; Qsim: simulated stream flow).

Table 6. The model performances for calibration and validation periods.

Discharge Type	Process	Simulation Period	R^2	E_{NS}
Daily	calibration	1980-1986	0.7	0.69
	validation	2006-2011	0.5	0.46
Monthly	calibration	1980-1986	0.72	0.67
	validation	2006-2011	0.56	0.48

5.2. Hydrological response to climate change
The daily meteorological data for the 2050s A1B scenario as the input data for the SWAT model to simulate hydrological processes in the future. The impact of climate change on the hydrological regime in the Second Songhua River Basin is illustrated by comparing the ET of the whole basin and the stream flow data at the Fuyu gauging station between the reference period and 2050s. The monthly relative changes in ET and stream flow are shown in Figure 7. As regards the relative change, in most months, the ET is predicted to increase in the 2050s, with particularly obvious increases from December to February. The absolute change differs from the relative change; the largest absolute change is predicted to occur in May (19 mm), while in the other months the changes are all less than 10 mm. Because the mean temperatures across the whole year are higher in the 2050s, more energy is

available for driving evaporation or transpiration of soil water and intercepted water, which may cause the increases in ET in most months. Meanwhile, the reduced ET predicted for September and October, and the dramatic increase in ET from December to February for the 2050s are in general agreement with changes in precipitation for the 2050s, which indicates that precipitation has an impact on the availability of water for evapotranspiration.
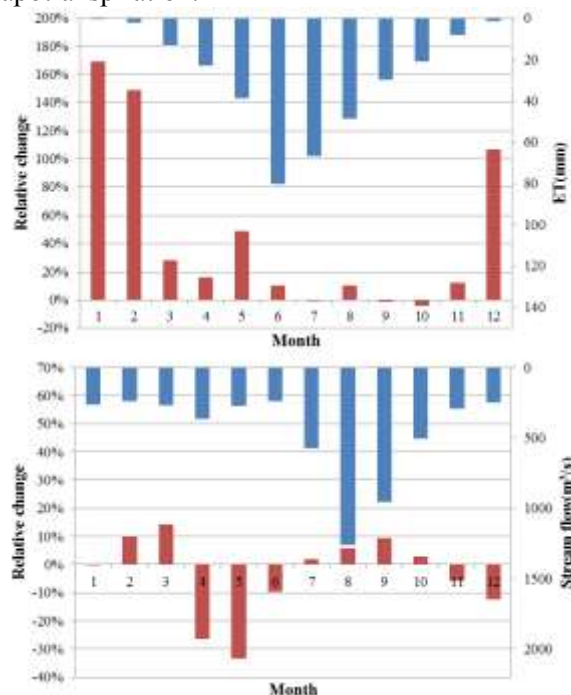

Figure 7. Averaged changes (red columns) of monthly mean ET of whole basin and stream flow at Fuyu station between baseline (blue columns) and future climate scenario in 2050s.

Stream flow is predicted to increase from July to October and from February to March in the 2050s. This is a consequence of increased rainfall in the same period. Due to the cumulative effects of increased rainfall in previous months and lower ET, an increase in stream flow was predicted for October (relative change of 3 %). The absolute increase in stream flow in these six months ranges from 11.4 mm to 89 mm (September). Although an obvious increase in precipitation (absolute increase from 0.7 mm-8.9 mm) was predicted for the five months from November to January and from April to June, the increase in ET was greater (absolute 0.9 mm-19 mm), with the result that absolute decreases in stream flow in these six months ranging from 17 mm to 96 mm (April) were predicted. Therefore, both precipitation and evapotranspiration have a significant impact on stream flow.

From the viewpoint of water resource availability, these results demonstrate that, especially in spring (particularly April and May), there will be a decrease in the available water resources under the 2050s A1B scenario, which may lead to a lack of irrigation water. As a consequence, agricultural drought may occur under the higher temperatures. Meanwhile, the increased stream flow will enhance the risk of floods in summer (especially August and September). The AR5 (Fifth Assessment Report) of IPCC Working Group II also pointed that flood hazards will increase over about half of the globe with variability at the catchment scale (medium agreement, limited evidence) [5]. The prediction in the Second Songhua River Basin is in accord with the result of Hirabayashi et al. [54] that Northeast China will face increased risk of flood hazard. Drought and flood due to climate change may challenge existing water management systems. In the Northeast China Plain, the staple food crops (e.g., wheat, maize, rice, and soybean) need water resources from April to October. This 2050s scenario of decreased stream flow in spring and increased stream flow in summer will have a great impact on the harvest.

5.3. Countermeasure for agriculture addressing climate change in this basin
As to the water resource management, IPCC-AR5 recommends that water management should be moved from the traditional "predict and provide" approach towards adaptive water management and the adoption of resilient approaches. Adaptive approaches to water management can successfully address the uncertainty due to climate change. There are two kind of framework about adaptive water management: the three-step framework which explicitly incorporates climate change and its uncertainty and threshold-scenario framework based on risk assessment. Adaptive techniques involve learning from experience and the development of flexible solutions that are resilient to uncertainty [6]. Therefore the integrated water resource management as a promising instrument for exploring adaptation to climate change should be carried out in this basin.

The changed temperature, ET, water and other agricultural climate resources change, sequentially lead to the changes of the crop yield, quality and planting area. In order to reduce these impacts and disasters caused by climate change, this paper put forward some adaptive measures. Making full use of the advantage of the increased accumulated temperature, improved variety with high photosynthesis ability and wide adaptability would be selected to promote in this basin. According to future climate resource redistribution and the new pattern of agricultural meteorological disasters, crop varieties layout should be improved. The rational use of water resources deserved more attention and needs to be strengthened. Irrigation and water conservancy construction, water-saving agriculture system and farmland shelterbelt are beneficial to the improvement of the agricultural ability to adapt to climate change. Agricultural disaster forecast and early warning research should be invested more. Strengthening the weather forecast system can timely avoid agriculture suffering huge losses.

6. Conclusion
Research about the availability of water resources under future climate change scenarios plays an important role for the future of agricultural production. To evaluate the influence of climate change on water resources in the Second Songhua River Basin and to predict the hydrological processes in this basin, we applied GCMs and the SWAT models. After demonstrating the reasonable of model in the basin, the GCMs meteorological variables were input to the SWAT model to predict hydrological processes in the 2050s.

As the main grain base, the staple food crops need large amount of water resource from April to October. However, the prediction of hydrological process in the 2050s showed that this basin may face water deficits in spring season, and that there would be enhanced risk of summer flood. In spring, the water resources may not meet the crop irrigation demands, which would impact on crop growth. Water resources must be regulated and saved to improve crop security. In summer, the more serious flood damage would result in soil erosion and would cause huge social and economic losses. Therefore, flood forecasting and warning, and agricultural water supply and drainage facilities deserve great attention to implement the integrated water resource management in this basin. The results of this study may be beneficial for developing practical water resource management policies in the Second Songhua River Basin.

As to the water resource management, this paper recommends that traditional water management should be moved towards adaptive water management. As to the comprehensive response of agriculture to the climate change, artificial weather control ability and emergency response capacity should be strengthened in this region in the future. To make the policy and decision making in a more targeted manner, an analysis about the amount of water needed is necessary. In order to actively confront the impact of climate change on agricultural production in the future, the future water resources prediction research needs aroused widespread attention. The country also should participate into the response of climate change, including the adjustment of agricultural construction of water conservancy facilities and the establishment of agricultural catastrophe risk fund, etc.

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