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Quantification of Uncertainty Propagation Effects during Statistical Downscaling of Precipitation and Temperature to Hydrological Modeling

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ABSTRACT. To understand the water balance and other environmental impacts under climate change condition, hydrological models are used to simulate the hydrological cycle and predict future scenarios by using general circulation models (GCMs) outputs. Due to the mismatch of the spatial resolution, different downscaling techniques are usually applied to GCMs outputs to generate higher resolution data for the use with the hydrological models. It is known that there are many uncertainties with hydrological models which lead to inaccuracy and unreliability of the predictions. The uncertainty associated with climate change has been described as irreducible and persistent, and downscaling GCM outputs using downscaling methods also lead to considerable uncertainties. The purpose of this study is to propose a method to quantify the propagation effects of uncertainties from statistical downscaling to hydrological modeling. A case study has been provided in this study to demonstrate the feasibility of the proposed method. Statistical downscaling model (SDSM) was applied to downscale H3A2a (A2 emission scenario in Hadley Centre Coupled Model 3) outputs, and the downscaled results were used as inputs to a distributed hydrological model - the soil and water assessment tool (SWAT). The surface runoff prediction has been made for 2016 ~ 2020 by using downscaled precipitation and temperature. The uncertainty associated with statistical downscaling has been quantified through the evaluation of surface runoff simulation from the application of the hydrological modeling study.

Keywords: GCMs, SWAT, hydrological modeling, statistical downscaling, propagation effect, uncertainty analysis

1. Introduction

The growth of population and modern industries are major contributors to increases in greenhouse gas emissions, which is considered to be the main reason for causing climate change. The Intergovernmental Panel on Climate Change (IPCC) claimed that there is strong evidence to support the conclusion that climate change has considerable impacts on the water basin and region (IPCC, 2007). Due to the changes in hydrological cycle, climate change can affect many aspects of water resources, including drinking water supplies, flood and drought, irrigation, and hydropower production, etc (Hassan et al., 2013). Therefore, there is a need to predict and quantify the impacts of climate change, especially the impacts on water resource management. However, climate change is a very complicated problem involving different conditions and interactions among ocean, atmosphere, and land surface. In order to use mathematical descriptions to simulate the physical process, general circulation models (GCMs) were developed and considered to be able to provide credible predictions and projections of climate changes into the next 100 years (Jiang et al., 2007; Mpelasoka and Chiew, 2009). However, the resolutions of GCMs are too coarse (normally 350 km per grid) to be directly applied to hydrological studies at basin or regional scale. The direct use of the coarse-resolution GCM outputs for regional hydrological studies has been proved to yield unrealistic hydrological results (Wood et al., 2004; Bae et al., 2011; Hassan et al., 2013). The mismatches of spatial and temporal resolutions between GCM outputs and the data requirements of hydrological models are the major obstacles for evaluating the hydrologic impacts of climate change (Chen et al., 2012).

Downscaling methods are developed to solve the spatial and temporal resolution mismatch problems when conducting hydrological studies. Traditionally, downscaling methods can be classified into two major categories: dynamic downscaling and statistical downscaling. Dynamic downscaling methods are based on dynamic formulations using the initial and time-dependent lateral boundary conditions of GCMs to establish regional climate models (RCMs) for producing finer resolution climate outputs (Caya and Laprise, 1999). However, due to the high computational demand and cost, dynamic downscaling methods are only available for limited areas and studies (Solman and Nuñez, 1999). Moreover, the outputs of RCMs are still too coarse (e.g., the grid resolution for Canadian GCM

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is 45 km) for most practical applications, such as hydrological studies. Therefore, statistical downscaling methods are developed to overcome these difficulties. Compared with dynamic downscaling methods, statistical downscaling methods are normally easier and cost efficient to implement, and can link the state of some variables representing a large spatial scale and the state of other variables representing a smaller scale by using computationally more efficient ways (Chen et al., 2012). Therefore, statistical downscaling methods are the most widely used methods in hydrological impact studies under climate change scenarios (Huang et al., 1995; Huang et al., 1996; Khan et al., 2006; Nie et al., 2006; Huang and Cao, 2011; Ahmed et al., 2013; Tan et al., 2011;Tofiq and Guven, 2014).

The terms “persistent" and “irreducible” have been used to describe the uncertainty associated with the climate change, and the uncertainty extensively exists at the global and regional scale for different complex systems (Ficklin, 2010; Huang et al., 1997; Li et al., 2013; Chen et al., 2015). Normally, the major uncertainty in climate change studies comes from the selection of different GCMs, and the outputs of different GCMs and scenarios will lead to considerable differences in the downscaled results (Cai et al., 2007; Rowell, 2006; Kay et al., 2009; Prudhomme and Davies, 2009; Ahmed et al., 2013). On the other hand, the characteristics of each downscaling method lead to different future climate scenarios even using a single GCM output, indicating that the downscaling methods will involve additional uncertainty in climate projections. Although GCMs are considered to be the largest uncertainty contributors of climate change studies, the uncertainty related to downscaling also needs to be taken into account for a better estimation and understanding of the impacts of climate change. However, the greatest interests have been given to the uncertainty that arise from GCMs, and the uncertainty during downscaling has been given much less attention (Graham et al., 2007; Li et al., 2007; Lv et al., 2010; Chen et al., 2011).

Limited attempts have been made to quantify and compare the uncertainty during downscaling on hydrological studies. Mpelasoka and Chiew (2009) compared the impact of three empirical downscaling methods (including constant scaling, daily scaling and daily translation) using a daily rainfall-runoff model driven with future daily rainfall series in Australia. The uncertainty associated with the choice of different empirical downscaling methods was much smaller comparing with that related to GCMs. Chen et al (2011) compared six downscaling methods to investigate the uncertainty of downscaling methods in quantifying climate change impact on the hydrology of a Canadian River basin. The results indicated the selection of downscaling methods could also lead to large uncertainty up to the level of GCMs and greenhouse gas emission scenarios (GGESs). Teutschbein et al. (2011) assessed the uncertainty by using three statistical downscaling methods (including an analog sorting method, a multi-objective fuzzy-rule-based classification and the statistical downscaling model) to model precipitation from two GCMs, and the monthly mean streamflow and flood peaks in spring and autumn for a meso-scale watershed. They concluded that the choice of the downscaled precipitation time series had a major impact on the streamflow simulation. Chen et al. (2013) evaluated the uncertainty of six empirical downscaling methods by quantifying the impact of climate change through the hydrological modeling results from two case studies in North America. The results indicated that both the empirical downscaling method and RCM simulation leads to great uncertainty on simulated str- eamflow and the uncertainty associated with the choice of the empirical downscaling method is slightly smaller than that of RCM.

These limited studies assessed the uncertainty related to the choice of downscaling methods; however, fewer studies have focused on estimating the uncertainty associated with a single downscaling method and the propagation effect on the uncertainty of hydrological responses. The purpose of this study is to quantify and evaluate the propagation uncertainty during downscaling to hydrological modeling through a single statistical downscaling framework. A case study in Sichuan province of China was conducted to demonstrate the feasibility and performance of the developed method. The soil and water assessment tool (SWAT) was used for hydrological modeling for the study area, and the statistical downscaling model (SDSM) was used to address the mismatch of data requirement between the GCM outputs and hydrological models.

2. Methodology

The framework in Figure 1 shows the major steps of the proposed approach. The first step is to decide which scenario and which GCM should be selected for the case study. Secondly, after the selection of the GCM, SDSM will be applied to downscale precipitation and temperature from GCM predicator variables. And then, the downscaled precipitation and temperature can be directly applied as the input to the calibrated hydrological model (SWAT) for surface runoff simulation. The SWAT model is calibrated and validated by using observed data, and a reasonably good simulation performance needs (NSE > 0.65) to be achieved before the application of downscaled GCM outputs to ensure the reliability of simulation and prediction (Yen et al., 2014; Liu et al., 2018; Xie et al., 2018; Guan et al., 2019). The quantitive analysis of uncertainty will be conducted after the application of downscaled data.

2.1. Selection of Climate Change Scenarios and GCMs

There are six major types of emissions scenarios provided in the Special Report on Emissions Scenarios (SRES), including the A1FI, A1B, A1T, A2, B1, and B2 scenarios (IPCC, 2007). The A2 scenario predicts the greatest changes in precipitation and temperature by the end of this century, hence this scenario can be considered to represent the worst case scenario for hydrological studies (Gudmundsson, 2012; Samadi et al., 2012). Therefore, the Hadley Centre Coupled Model 3 (HadCM3) for A2 scenario (which is named as H3A2a) was selected in this study for downscaling purposes. The National Center for Environmental Prediction (NCEP) reanalysis data was used to calibrate parameters for downscaling H3A2a in SDSM. The downscaled H3A2a outputs will be used as inputs to the SWAT model to make an assessment of the future projections of surface runoff. For hydrological studies, one

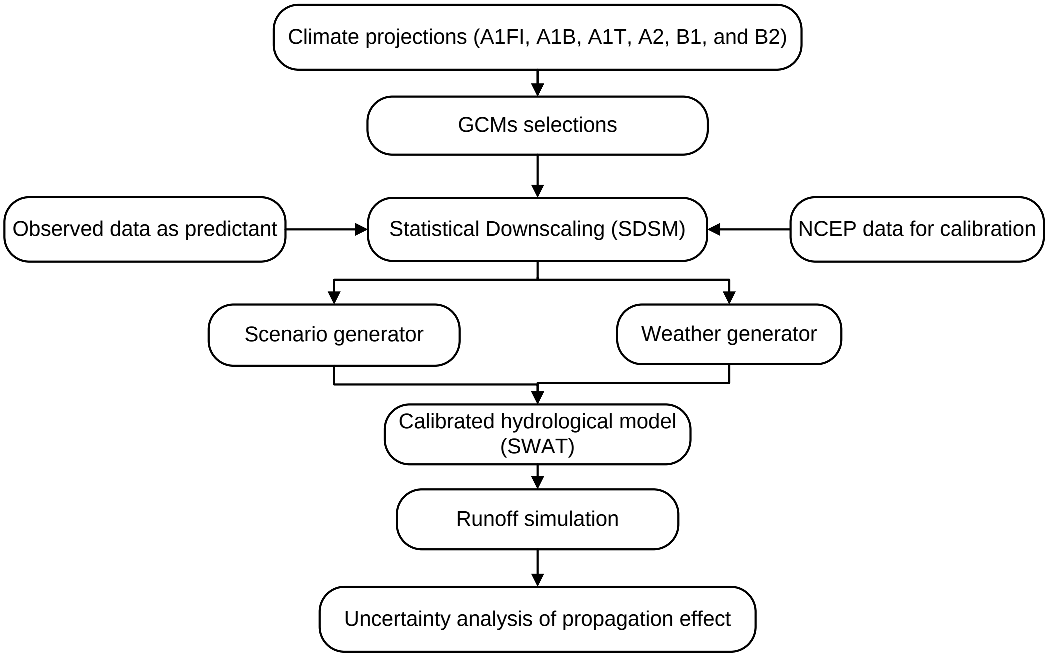

Figure 1. The framework of the proposed study.

constant and well performing GCM and a well calibrated hydrological model will be able to produce reasonably good prediction for the specific study area. Moreover, the uncertainty pro- pagation effect from statistical downscaling to hydrological modeling is the key concern in this study. Therefore, only one GCM model was selected for this study, and the corresponding propagation effect of the uncertainty during statistical do- wnscaling were quantified through the evaluation of the surface runoff simulation from the application of a hydrological modeling study.

2.2. Statistical Downscaling Model (SDSM)

The gridded GCM dataset has a resolution of 2.5 ° latitude by 3.75 ° longitude. Therefore, downscaling is necessary before the data can be used in the hydrology model. As a popular statistical downscaling method, SDSM was applied to downscale the H3A2a outputs in this study. SDSM, developed by Rob Wilby and Christian Dawson in the UK, is one of the most popular statistical downscaling tools, and can be best described as a hybrid of the stochastic weather generator and transfer function method (Wilby et al., 2002; Hassan et al., 2013; Yu et al., 2019). SDSM is able to construct climate change scenarios for small sites at daily time scale by using gird resolution of GCM outputs. Downscaling with SDSM involves a multiple regression-based model between selected large scale GCM predictor variables and local scale predictants (such as precipitation and temperature). The NCEP reanalysis data were applied to screen the sensitive predictor variables and compute the parameters of regression equations. The parameters of the regression equations can be estimated by using the efficient dual simplex algorithm (Wilby and Dawson, 2007) or some other algorithms. Some bias may occur when using daily time-scale results with SDSM. However, the downscaled climate variables should be more reasonable for monthly time-scale water resource planning studies. Some studies suggested multiple downscaling methods could be applied for prediction purposes; however, a well-calibrated downscaling model should still be able to reflect the future situation to guide the long term strategy for water resource management.

2.3. SWAT Hydrological Model

SWAT is a physically based continuous distributed model developed by the United States Department of Agriculture (USDA) Agricultural Research Service (ARS). SWAT operates on a daily time step for an ungauged watershed, and is designed to predict the impacts of management practices on hydrology, sediment, and water quality in large complex watersheds over long periods of time (Arnold et al., 1995). By using the local digital elevation model (DEM), SWAT can partition a watershed into many sub-basins for modeling purposes. Using local geographic information system (GIS) information (such as land uses and soil types), the sub-basins can be classified into different hydrological response units (HRUs). Each HRU is dominated by different land uses or soils and dissimilar enough in properties to impact the hydrology of the areas. In SWAT, surface runoff volume is calculated by using the Curve Number (CN) method, and channel routing is calculated using either the variable storage routing method or the Muskingum routing method (USDA Soil Conservation Service, 1972). The Modified Universal Soil Loss Equation (MUSLE) is used to estimate the sediment yield at HRUs (Arnold et al., 1998; Xue et al., 2014; Xin et al., 2018). Previously, SWAT has been shown to be a successful model of runoff and water quality simulation for different areas, demonstrating its feasibility and flexibility for various regions and environmental conditions (Yang et al., 2008). From the data available and ungaged properties of the study area, SWAT is considered to be able to perform reasonably well for surface runoff in the study area. Therefore, SWAT was selected for this study.

2.4. P-factor and R-factor

The degree of all uncertainties considered is evaluated by using the P-factor, which is the percentage of observed data bracketed by the 95% prediction uncertainty (calculated at 2.5% and 97.5% levels of the cumulative distribution of output variables), or called 95PPU. The R-factor is another measure for quantifying the performance of uncertainty analysis, which is calculated by the average distance of uncertainty bands divided by the standard deviation of the observed data. Ideally, if the P-factor is 1 and the R-factor is 0, then the simulation results absolutely match the observed data (Abbaspour, 2011). However, due to measurement errors and model uncertainties, a perfect simulation will generally not be achieved. The P-factor and R-factor is calculated using following equations (Abbaspour et al., 2007; Wu and Chen, 2014; Xue et al., 2014):

$$R = \frac{\overline{d_x}}{\sigma_x} \tag{1}$$

$$\overline{d_x} = \frac{1}{k}\sum_{l=1}^{k}\left(x_U - x_L\right)_l \tag{2}$$

where, σ_x is the standard deviation of the observed variable x, $\overline{d_x}$ is the average distance of the uncertainty band, l is a counter, k is the number of observed data points for variable x.

The percentage P of observed data bracketed by 95PPU band is defined by:

$$P = \frac{nq_{in}}{N} \times 100\% \tag{3}$$

where, N is the total number of observed values, nq_{in} is the number of the observed data bracketed by 95PPU.

2.5. Sequential Uncertainty Fitting Version 2 (SUFI-2)

Based on a Bayesian framework, SUFI-2 determines uncertainties through the sequential and fitting process, and it requires several iterations to achieve the final estimates. SUFI-2 starts by assuming a large parameter uncertainty to account for different possible sources (including model input, structure and parameter and measured data), so that the measured data will initially falls within 95PPU. And then, the uncertainty can be decreased by considering the following two rules: 1) 95PPU band brackets most of the observations (larger P-factor) and 2) the average distance of the upper (at 97.5%) and the lower level (at 2.5%) of 95PPU is small (smaller R-factor) (Abbaspour et al., 2007). Therefore, a balanced P-factor and R-factor is the desired result for an acceptable uncertainty analysis (Wu and Chen, 2014). In this study, three iterations were applied, and the ranges of each parameter were reduced after each iteration for seeking the optimal parameter set which can achieve the best simulation.

3. The Case Study

The upper reaches of the Wenjing River watershed located in Sichuan province in western China are selected as the study area. The study area is about 25 km east to Chengdu, the capital city of Sichuan province, and the drainage area is about 653 km^2. Figure 2 shows the location and 61 sub-basins of the study area. The annual mean temperature and sunshine duration are 15.9 ℃ and 1,161.5 h, respectively, and the average annual precipitation is 1,012.4 mm. The annual amount of precipitation is high in summer (588.0 mm) and can be as low as 29.9 mm in winter (IWHR, 2005). Since the main drinking water source for Chengdu and major water sources for irrigation activities in the downstream area are from the upper reaches of the Wenjing River, this watershed urgently requires efficient water resource management. For to this reason, this watershed was selected for the case study (Wu and Chen, 2014). It is hoped that this study will provide scientific supports for the local water resources department and provide a good reference for long term water management based on future predictions.

4. Results and discussion

4.1. Hydrological Modeling

By using 30 m resolution DEM, the study watershed was delineated into 61 sub-basins, and the outlet is located at subbasin No. 61 in the southeast of the watershed (see Figure 2). The digital river channels were used for calibrating the water channel created by using DEM. Based on 10 groups of land uses, 16 types of soil and slope information, the study area was the watershed was divided into 270 HRUs for hydrological modeling. All observed meteorological data, including temperature, precipitation, wind speed, solar radiation, relative humidity data, were used as the input for the SWAT model.

If a hydrological model performs poorly, then it may continue to perform poorly in dealing with future climate scenarios (Hay et al., 2014). Therefore, a model that performs well is a basic and essential requirement for conducting downscaling studies for hydrological modeling. Calibration and uncertainty analysis were conducted using SUFI-2 with three iterations (1000 runs each iteration) in this study. A three-year surface runoff data from 1998 to 2000 were used for calibration, and the remaining two years (2001 ~ 2002) data were used for validation. The Nash-Sutcliffe coefficient (NSE) and coefficient of determination (R^2) were selected to evaluate the performance of simulation, and NSE was also selected as the objective function of SUFI-2. The definitions of NSE and R^2 are shown in equations 4 and 5 (Wu and Chen, 2014):

$$NSE = 1 - \frac{\sum_{i=1}^{n}\left(Q_{s,i} - Q_{o,i}\right)^2}{\sum_{i=1}^{n}\left(Q_{o,i} - \overline{Q_o}\right)^2} \tag{4}$$

$$R^2 = \frac{\left[\sum_{i=1}^{n}(Q_{o,i} - \overline{Q}_o)\left(Q_{s,i} - \overline{Q}_s\right)\right]^2}{\sum_{i=1}^{n}(Q_{o,i} - \overline{Q}_o)^2 \sum_{i=1}^{n}(Q_{s,i} - \overline{Q}_s)^2} \tag{5}$$

where n is the total number of values within the period of analysis; Q_o and Q_s represent the observed and simulated surface runoff (m^3/s); $Q_{o,i}$ and $Q_{s,i}$ are the observed and simulated values on day i; and $\overline{Q_o}$ and $\overline{Q_i}$ are the average values of the observed and simulated surface runoff (m^3/s), respectively.

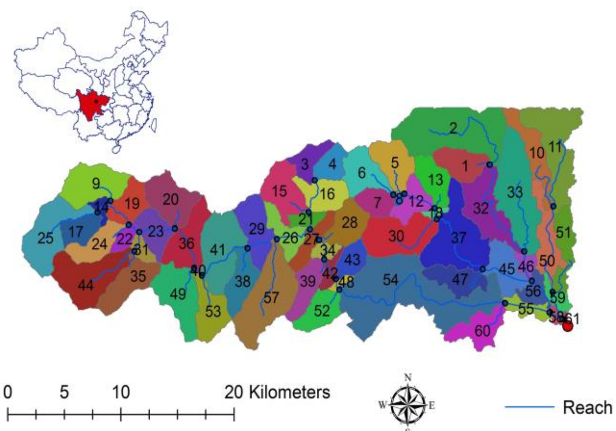

Figure 2. The location and 61 sub-basins of the study area.

Based on the sensivity analysis results and recommendation in the user's manual, there is a total of 11 parameters selected for calibration. The parameter ranges are updated after each iteration. After calibration, the NSE and R^2 of the best simulation were 0.77 and 0.80 for the calibration period (Figure 3), and 0.74 and 0.87 for the validation period (Figure 4), respectively. The good simulation performance indicates that the model can be applied to downscaling studies with some confidence. To evaluate the propagation effect of uncertainties from statistical downscaling to hydrological modeling, the parameter set which performs the best simulation was used as the default setting. Therefore, the uncertainties involved in hydrological modeling have been manually fixed and controlled, and the propagation effect of uncertainties reflected and evaluated using the simulated surface runoff is mainly from the application of statistical downscaling methods as well as the GCM outputs.

4.2. Statistical Downscaling and Uncertainty Analysis

SWAT model requires a large number of meteorological data input (such as participation, temperature, solar radiation, relative humidity, wind speed). As it is known, precipitation is a key component of the hydrological cycle and is more important and sensitive to the surface runoff (Tofiq and Guven, 2014). Therefore, in this study, the assumption has been made that the biggest impacts to surface runoff are from precipitation. Due to the climate condition of the study area (no extremely cold days in winter), for this preliminary study, only the uncertainty related to precipitation is considered during statistical downscaling. Usually, precipitation data is inevitably more problematic during downscaling comparing to temperature. The reason is that the daily precipitation amounts at sites are normally poorly related to regional scale predictor variables, and precipitation is also a conditional process-- both the occurrence and amount processes must be specified when conducting downscaling (Wilby and Dawson, 2007). The downscaled temperature data were used as the input of the SWAT model as well, but the uncertainty of temperature was not considered in this study.

As the first step, the National Centers for Environmental Prediction (NECP) reanalysis data were applied first for calibrating the downscaling model. SDSM can screen the sensitive predictor variables to establish the empirical relationship between NCEP predictor variables and observed predictands. The calibration procedure can compute the parameters of multiple regression equations for NCEP predictor variables and observed predictands through optimization algorithms. And then, the parameters can be used for downscaling the H3A2a data. The 30 years (1981 ~ 2010) observed precipitation data were used as predictants for calibration. According to the coordinates of the study area, four H3A2a grid spots around study area (including 28X, 22Y; 28X, 23Y; 29X, 22Y and 29X, 23Y) were selected for screening the best NCEP predictor variables. After calibration, the 10 out of 26 screened NCEP predictor variables were applied to downscale the H3A2a outputs, including p_thas (wind direction at 1000 hPa height), p_zhas (divergence at 1000 hPa height), p5_fas (wind speed at 500 hPa height), p5_zas (vorticity at 500 hPa height), p5zhas (divergence at 500 hPa height), p8_fas (wind speed at 800 hPa height), p8_uas (zonal velocity component at 800 hPa height), p500as (geopotential at 500 hPa height), p850as (geopotential at 850 hPa height), and shumas (specific humidity at 1000 hPa height). The downscaling parameters were calculated by using above 10 sensitive predictor variables. Totally 20, 30, 40, 50 and 60 downscaled precipitation ensembles were generated using SDSM for calculating 95 PPU. When the number of ensembles is greater than 40, the 95PPU barely changed. Therefore, in order to improve the simulation efficiency, 40 downscaled precipitation ensembles have been used for calculating 95PPU. The temperature has been downscaled in the similar way. However, comparing to precipitation, the temperature has less contribution to surface runoff. Therefore, only precipitation data have been downscaled to 40 ensembles to quantifying the propagation uncertainty effects.

Both the precipitation and temperature data were downscaled and used as input of SWAT for surface runoff simulation. Because the NSE was selected as the objective function for calibration using SUFI-2, the assumption has been made that the best simulation is the simulation which achieves the greatest NSE value. The mean precipitation of 40 NCEP ensembles (scenarios) generated by SDSM was used in the hydrological model for comparison purposes, because only the uncertainties from the GCM (H3A2a) to the hydrological model are the key concerns of this study. Therefore, all 40 H3A2a

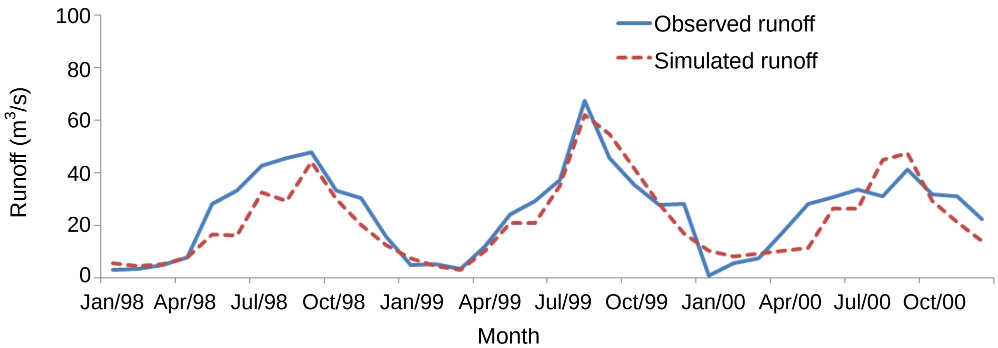

Figure 3. The average monthly simulated runoff and observed runoff in the calibration period of 1998 ~ 2000.

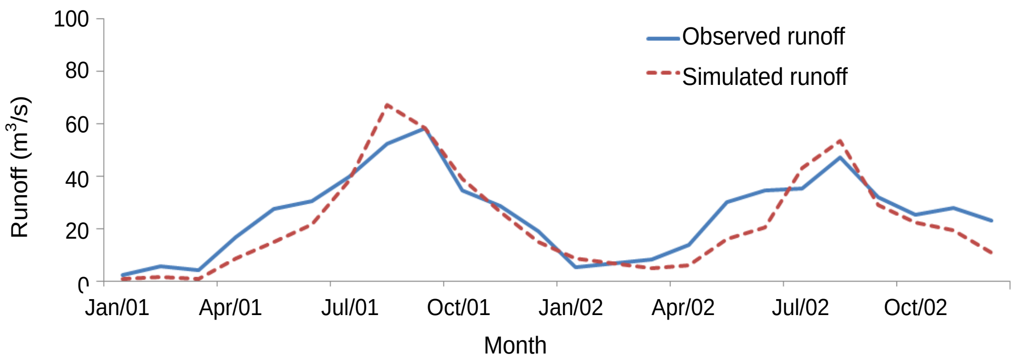

Figure 4. The average monthly simulated runoff and observed runoff in the validation period of 2001 ~ 2002.

ensembles were reserved and used for uncertainty analysis.

Figure 5 shows the hydrographs of observed runoff and three series of surface runoff simulations, which are simulated runoff by using observed precipitation, mean downscaled NCEP precipitation outputs, and downscaled precipitation outputs from H3A2a with the best simulation. The overall simulation performance from the three different sources of precipitation input provided acceptable results. The surface runoff simulation produced by observed precipitation gave the highest NSE and R^2 values, which are 0.77 and 0.8 respectively. The surface runoff generated by using downscaled H3A2a precipitation (with NSE and R^2 values of 0.67 and 0.73, respectively) performed better than the simulations using the mean value of NCEP precipitation outputs (with NSE and R^2 values of 0.55 and 0.79, respectively). There are some underestimations during April to July each year when conducting simulation using observed precipitation data, but simulations generated by using precipitation data from two downscaled GCM models perform better in these three months. However, the simulations from two downscaled GCMs perform relatively poorly for capturing the time and magnitude of the peak flow. Therefore, the corresponding uncertainties cannot be ignored, and the 95PPU was calculated to improve the reliability of future predictions.

The 95PPU of the surface runoff simulation using downscaled H3A2a outputs is calculated at 2.5% and 97.5% levels of the cumulative distribution of surface flow simulated by using downscaled precipitation for each month. A total of 40 ensembles were generated from the SDSM and used for uncertainty analysis. The lower and upper bounds of surface runoff corresponding to 2.5 and 97.5% levels of cumulative runoff simulations were obtained by applying the 40 ensembles of downscaled precipitation results to the calibrated hydrological model. Because the uncertainty of surface runoff was caused by using different combinations of parameter sets, the uncertainty stemmed from hydrological modeling was mainly reflected by using parameter uncertainty in this study. After calibration using SUFI-2, the best simulation (with the greatest NSE) was achieved, and the parameter set which leads the best simulation (NSE = 0.77 and R^2 = 0.8) was recorded as the optimum parameter set. When using the optimum parameter set for simulation, there are no other stochastic pa- rameters in the SWAT model. Therefore, there is no extra uncertainty from the hydrological modeling. Different downscaled ensembles as the input of the SWAT model were propagating the uncertainty from statistical downscaling to hydrological modeling. When using the optimum parameter set for simulation of downscaling studies, the uncertainty of surface runoff only arose from the application of different ensembles from the statistical downscaling. Therefore, the uncertainties evaluated using 95PPU are mainly from the application of the statistical downscaling method.

The 95PPU of surface runoff by using downscaled H3A2a results are shown in Figure 6. In Figure 6, the 95PPU can co-

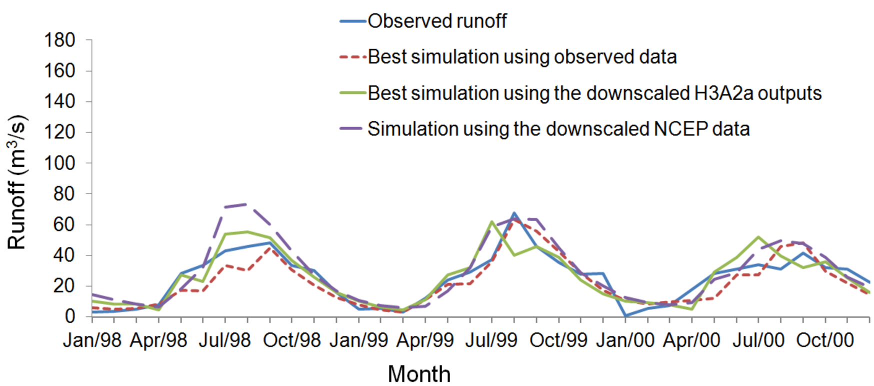

Figure 5. The hydrograph of observed, simulated runoff from SUFI-2, downscaled NCEP and H3A2a results for 1998 ~ 2000.

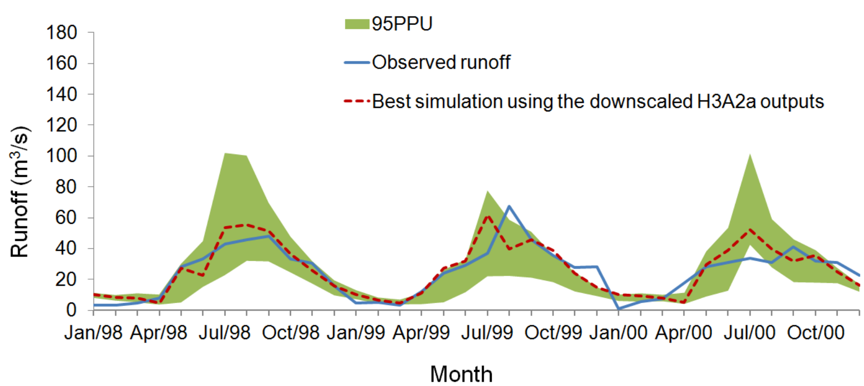

Figure 6. The hydrograph of the observed and best simulated runoff with 95PPU from downscaled H3A2a results for 1998 ~ 2000.

Table 1. Summary Statistics of the Best Simulation and Uncertainty Analysis Results for Observed, Downscaled NCEP and Downscaled H3A2a Data

Data sources of the simulation	P-factor	R-factor	R2	NSE
Observed data	0.56	0.48	0.8	0.77
Downscaled NCEP (mean)	N/A	N/A	0. 79	0.55
Downscaled H3A2a	0.67	1.34	0.73	0.67

ver most of the observed runoff data and peak flows indicating a good coverage for extreme events. The statistical summaries are shown in Table 1. For a traditional uncertainty analysis using SUFI-2, the P-factor and R-factor results of the third iteration of SUFI-2 (using observed precipitation and temperature) are 0.56 and 0.48, respectively, indicating most of observed data are bracketed in a small band of 95PPU. For this downscaling study, although the width of the uncertainty band is relatively larger (R-factor of 1.34) comparing the R-factor for the third iteration results from SUFI-2, by considering the larger coverage (P-factor = 0.67), the uncertainties have been controlled well. The results have demonstrated that the downscaled H3A2a model results performed reasonably well for prediction purposes, and can provide a reliable scientific reference for local water resource management.

Because the downscaled GCM model for SWAT simulation achieved reasonably good results, all the settings and calibrated parameter set were not changed for future prediction based on the assumption that the relationship between the local predictants and GCM predictor variables will remain the same in the future. The surface runoff prediction for the future five-year (2016 ~ 2020) period was conducted using the downscaled H3A2a data in this study. The precipitation and temperature from the H3A2a outputs for 2016 ~ 2020 were downscaled and used as the input for the SWAT model. The best surface runoff prediction was generated by applying the calibrated SWAT model and downscaled precipitation and temperature from the ensemble which achieved the best simulation for the year 1998 ~ 2000 (NSE = 0.67 and R^2 = 0.73).

The 95PPU for surface runoff simulation is calculated in a similar manner to the previous steps for uncertainty analysis. Because the uncertainty from hydrological modeling was fixed and controlled using the optimal parameter set, the 95PPU can be considered to be generated from the application of different ensembles of downscaled outputs only. The uncertainty from the statistical downscaling was propagated to the simulated

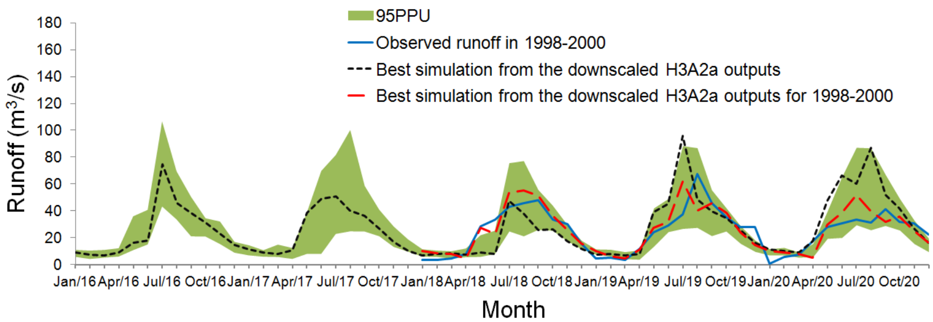

Figure 7. The best predicted surface runoff with 95PPU for 2016 ~ 2020.

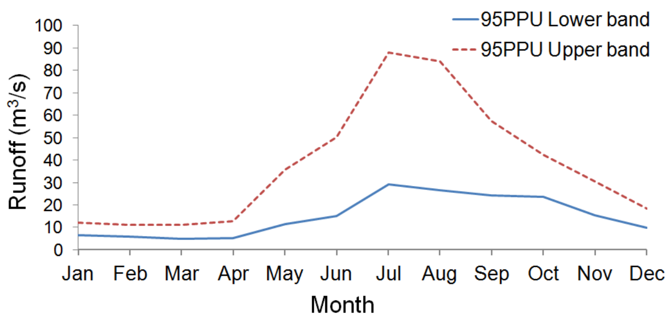

Figure 8. The annual 95PPU for surface runoff in the year 2016 ~ 2020.

surface runoff of hydrological modeling, and was revealed by using the 95PPU. As shown in Figure 7, the 95PPU contains most data of the best prediction (93.3%) with a reasonably small uncertainty band for the year 2016 ~ 2020.

The observed surface runoff and the best simulated runoff by using downscaled H3A2a outputs for 1998 ~ 2000 are also shown in Figure 7 for the comparison of the runoff 20 years later (2018 ~ 2020). It generally shows an increasing trend for the surface runoff volume after 20 years. The simulated peak flow volume in 2019 could reach 95.68 m^3/s, which is more than 1.5 times of the simulated peak flow (61.68 m^3/s) in 1999, and also more than 1.4 times of the observed peak flow (67.56 m^3/s); the simulated peak flow in 2020 is 86.65 m^3/s, and it is more than 1.6 times of the simulated peak flow (52.51 m^3/s) and also more than 2 times of the observed peak flow (41.28 m^3/s) in 2000. The results indicate that the peak flow has a considerable increase in the summer time, especially for the year 2019 ~ 2020 under the A2 climate change scenario.

Figure 8 shows the annual 95PPU of surface runoff in 2016 ~ 2020. The surface runoff uncertainty starts to increase from April to August and then begin to decrease till December. The variations of surface runoff are bigger in Spring and Summer and relatively smaller in fall and winter. The peak flow in Summer could reach as high as 87.8 m^3/s in July, and the lowest flow could be as low as 5.05 m^3/s in March. Because the application of the calibrated parameter sets, the uncertainty evaluated in this study is mainly propagated from the application of statistical downscaling methods by using different ensembles of the downscaled H3A2a outputs.

This study innovatively made use of 95PPU, P-factor and R-factor to evaluate the uncertainty propagated from statistical downscaling to hydrological modeling. After screening sensitive predictor variables, calibration and downscaling using SDSM, the downscaled precipitation and temperature outputs were used for surface runoff simulation. By fixing the uncertainty from hydrological modeling using the optimum parameter set, the uncertainty quantified using 95PPU is the uncertainty propagated from the statistical downscaling. The 95PPU is quite important for decision makers in the local water resource management department, because it provides the scientific reference for future surface runoff predictions in the watershed with reliable confidence intervals. The worst case scenario (A2 scenario) can also be evaluated and determined the precaution taken according to the future predictions to help local people reduce the risk of any property loss in the future.

5. Conclusions

In this study, hydrological modeling for the upper reaches of the Wenjing River watershed was successfully conducted. The NSE and R^2 of the calibrated SWAT model using the observed precipitation and temperature are 0.77 and 0.8, respectively, indicating reasonable performance of the calibrated model. Statistical downscaling model (SDSM) was used to downscale the precipitation and temperature data from the H3A2a model to generate future climate data based on A2 scenarios. The NSE and R^2 of the best simulation using the downscaled H3A2a results are 0.67 and 0.73 in the year 1998 ~ 2000, respectively, demonstrating that the downscaled precipitation and temperature results can achieve a reasonably good match to the observed data.

The proposed method can effectively evaluate the propagation effect of uncertainties from statistical downscaling to hydrological modeling using 95PPU, and a successful attempt has been made through the case study in this study. The different ensembles generated by statistical downscaling increased the input uncertainty of hydrological modeling. When using optimized parameter sets for simulation, the increased uncertainty of surface runoff is mainly caused by statistical downscaling using SDSM. The P-factor and R-factor of uncertainty from downscaling are 0.67 and 1.34, respectively, also indicating an acceptable uncertainty analysis result for a downscaling study. Therefore, the downscaled H3A2a model is capable for future prediction with reasonable confidence. The 95PPU and R-factor also shows the uncertainty propagated from the statistical downscaling to hydrological modeling.

The continuous five-year future runoff prediction (from 2016 to 2020) along with the uncertainty estimation through 95PPU was conducted in this study. The simulation results in 2018 to 2020 indicate an increasing trend for the surface runoff volume comparing the simulated runoff and observed runoff data in 1998 to 2000. The prediction results and 95PPU can provide a scientific reference for long term evaluation and estimation of future water resource situation in the study area. The annual 95PPU can easily indicate that the uncertainty of surface runoff is greater in spring and summer (from April to October) and smaller in the rest of year.

The developed method for quantifying the propagation uncertainty can be applied to other hydrological models as well showing its generality. Future efforts are recommended on testing and validating different hydrological models through more observation data to improve the reliability of simulation and confidence of prediction, and downscaling and applying multiple GCMs and their up-to-date results for model calibration and comparison. These improvements would provide local decision makers with more information based on different scenarios to improve the efficiency of water resource management.

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