Uncertainty analysis for propagation effects from statistical downscaling to hydrological modeling

Hongjing Wu, Bing Chen*

The Northern Region Persistent Organic Pollution Control (NRPOP) Laboratory, Faculty of Engineering and Applied Science, Memorial University, A1B 3X5, St. John's, Canada

**Corresponding author's e-mail:* bchen@mun.ca

Abstract

To understand the water balance and environmental effects under climate change condition, hydrological models are always used to simulate the hydrological cycle and predict future scenarios by using global climate models (GCMs) outputs. Due to the mismatch of the spatial resolution problem, different downscaling techniques are usually applied to GCMs outputs to generate the high resolution data for fitting the data requirement of hydrological models. As it is known, hydrological modeling always suffers from a number of uncertainties and leads to inaccuracy and unreliability of prediction. Uncertainties associated with climate change have 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 quantify the propagation effects of uncertainties from statistical downscaling to hydrological modeling for improving the accuracy and reliability of hydrological prediction. A real-world 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 for uncertainties evaluation during hydrological modeling when the GCM outputs are used as inputs of a distributed hydrological model.

Keywords: GCMs, SWAT, hydrological modeling, statistical downscaling, uncertainty analysis.

Introduction

The growth of population and modern industries increases greenhouse gas emissions, which is considered to be the main reason for changing climate conditions. The Intergovernmental Panel on Climate Change (IPCC) claimed that there is strong evidence can 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 (Bae *et al.*, 2011; Hassan *et al.*, 2013). Global climate models (GCMs) can provide the credible prediction and projections of climate changes into the next 100 years. However, the resolutions of GCMs are too coarse (normally 350km per grid) to be directly applied to hydrological studies. 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 resolution mismatch problems when conducting hydrological studies. Traditionally, downscaling methods can be classified into two major categories: dynamic downscaling and statistical downscaling. Due to the high computational demand and cost, dynamic downscaling methods (e.g. RCMs) are 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 is 45km) for most practical applications, such like hydrological studies. The statistical downscaling methods are developed to overcome these challenges. Compared to 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 efficient ways (Chen *et al.*, 2011). Therefore, statistical downscaling methods are the most popular methods and widely used in hydrological impact studies under climate change scenarios (Ahmed *et al.*, 2013; Khan *et al.*, 2006; Tofiq and Guven, 2014).

The terms “persistent”, “deep” and “irreducible” have been used to describe the uncertainties associated with the climate change, and these uncertainties exist at global and the regional scale (Ficklin, 2010). The major uncertainty in downscaling studies comes from the selection of different GCMs. Practically, different GCMs and scenarios will lead to considerable difference for downscaled results. However, those uncertainties come from different sources in GCMs, and it is hard to be quantified. For hydrological studies, one constant and well performed GCM is good enough for prediction in future projection for the specific study area. Moreover, the uncertainty propagation effect from statistical downscaling to hydrological modeling is the key concern in this study. Therefore, only one GCM model was selected for the study area and the evaluation of the corresponding propagation effect of uncertainties were conducted.

The purpose of this study is to quantify and evaluate the uncertainty during statistical downscaling to hydrological modeling. 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) model was used for hydrological modeling for the study area, and statistical downscaling model (SDSM) was used to address the mismatch of data requirement between the GCM outputs and hydrological models.

Methodology

SWAT

SWAT was developed by the United States Department of Agriculture (USDA) Agricultural Research Service (ARS) and designed to predict the impacts of management practices on hydrology, sediment, and water quality in large complex watersheds with various soils, land use and management conditions over long periods of time (Arnold *et al.*, 1995). As a physically based continuous distributed model, SWAT operates on a daily time step in an ungauged watershed. According to the digital elevation model (DEM), SWAT can partition watershed into many sub-basins for the modeling purposes, because the sub-areas within a watershed are dominated by different land uses or soils and are dissimilar enough in properties to impact hydrology of areas. Surface runoff volume is calculated by using the Curve Number (CN) method (USDA Soil Conservation Service, 1972). Channel routing is calculated using either the variable storage routing method or the Muskingum routing method, and Modified Universal Soil Loss Equation (MUSLE) is used to estimate the sediment yield at hydrological response units (HRUs) (Arnold *et al.*, 1998).

P-factor and R-factor

The degree of all uncertainties considered is evaluated by using 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. R-factor is another measurement for quantifying the performance of uncertainty analysis, which is calculated at the average distance of uncertainty bands divided by the standard deviation of the observed data. Ideally, a P-factor of 1 and R-factor of 0 is the simulation which absolutely matches the observed data (Abbaspour, 2011). However, due to measurement errors and model uncertainties, the 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):

$$R = \frac{\overline{d_x}}{\sigma_x} \quad [1]$$

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

where, σ_x is the standard deviation of the observed variable x, $\overline{d_x}$ is the average thickness 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 derived by:

$$P = \frac{nq_{in}}{N} \cdot 100\% \quad [3]$$

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

Sequential uncertainty fitting version 2 (SUFI-2)

Based on 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 following two rules: 1) 95PPU band brackets most of the observations (larger P-factor) and 2) the average thickness of upper (at 97.5%) and 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 a desired result for an acceptable uncertainty analysis (Wu and Chen, 2014).

Statistical downscaling model (SDSM)

SDSM is an important statistical downscaling tool, and can be best described as a hybrid of the stochastic weather generator and transfer function method. During downscaling with SDSM, a multiple regression-based model can be developed between some selected large scale GCM predictor variables and local scale predictants (such as precipitation and temperature). The parameters of regression equation can be estimated by using the efficient dual simplex algorithm.

SDSM is able to construct climate change scenarios for small sites at daily time scale by using gird resolution of GCM outputs (Wilby and Dawson, 2007).

There are six major types of emissions scenarios provided on Special Report on Emissions Scenarios (SRES), including the A1FI, A1B, A1T, A2, B1, and B2 scenarios (IPCC, 2007). Because A2 scenario predicted the greatest changes in temperature and precipitation by the end of this century, 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 model (HadCM3) for A2 scenario (which is named as H3A2a) was selected in this study for downscaling purposes, and SDSM is applied to downscale the GCM outputs. The downscaled GCM outputs will apply to the SWAT model and make corresponding assessment on surface runoff for the future projection.

The case study

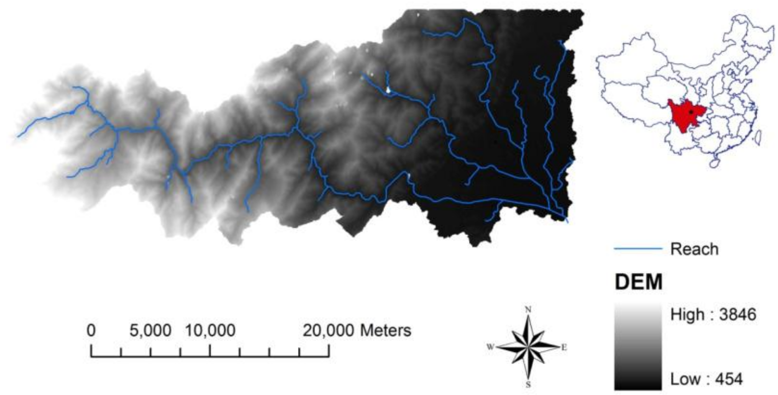

Figure 1. The DEM and location of the study area (Wu and Chen, 2014).

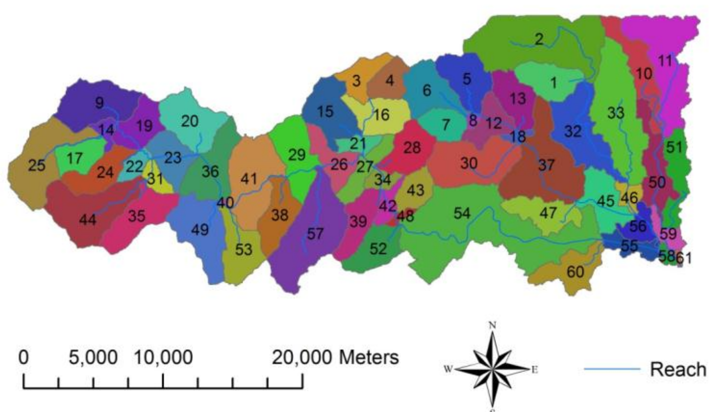

Figure 2. The subbasin of the study area.

The upper reaches of the Wenjing River watershed located at Sichuan province in western China were selected as study area. The study area is about 25 km east to Chengdu, the capital city of Sichuan province, and the drainage area is 653 km^2. Fig. 1 shows the DEM map and location of the study area. The annual mean temperature and sunshine duration are 15.9 ℃ and 1161.5 h, respectively, and the average annual precipitation is 1012.4 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 water scarcity and growing population problems become severe in China recently, as the main drinking water source for Chengdu and major water source for irrigation activities in the downstream area, the upper reaches of the Wenjing River watershed urgently require efficient water resource management. Due to this reason, this area was selected as the study area (Wu and Chen, 2014). This study can provide scientific supports for local water resource department and good reference for long term water management based on future predictions.

Results and discussion

Hydrological modeling

Based on 10 groups of land uses and 16 types of soil, the study area was delineated into 61 sub-watersheds, and the outlet is located in the southeast of the watershed. If the hydrological model performs poor simulation to match the observed data, then it may continue to perform poorly in the future climate scenarios (Hay *et al.*, 2014). Therefore, a well-performed model is basic and essential requirement for conducting downscaling studies on hydrological modeling. Calibration and uncertainty analysis were conducted by using SUFI-2 with three iterations (1000 runs each iteration) in this study. The 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 below:

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

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

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.

Based on sensivity analysis results and recommendation of the user manual, there are total 11 parameters selected for calibration. After calibration, the NSE and R^2 of the best simulation can reach to 0.77 and 0.80 for the calibration period (**Fig. 3**), and 0.74 and 0.87 for the validation period (**Fig. 4**), respectively. The P-factor and R-factor are 0.56 and 0.48, respectively, indicating most of observed data are bracketed in a small band of 95PPU. The good performance model can provide enough confidence for applying the downscaled GCM results. In order to evaluate the propagation effect of uncertainties from downscaling to hydrological modeling, the parameter set which perform the best simulation was used as the default parameter setting. Therefore, the uncertainties during hydrological modeling have been fixed and controlled. The propagation effect will only be evaluated from downscaling GCM outputs to hydrological modeling.

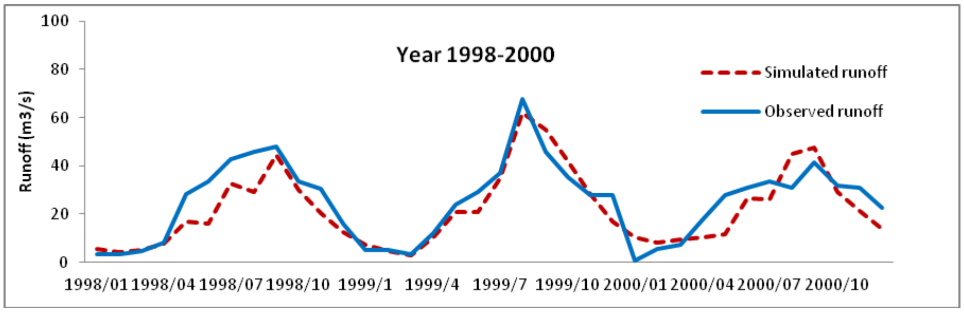

Figure 3. The average monthly simulated runoff and observed runoff in the calibration period of 1998-2000

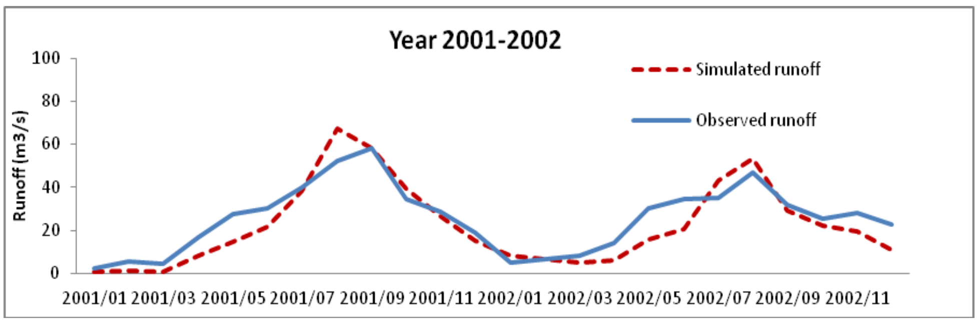

Figure 4. The average monthly simulated runoff and observed runoff in the validation period of 2001-2002

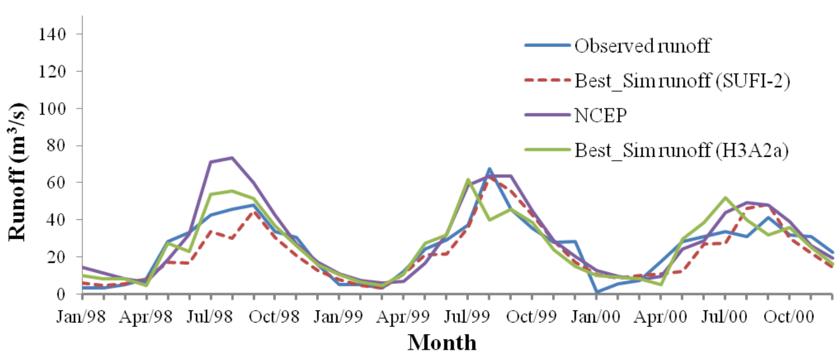

Figure 5. The hydrograph of observed, simulated runoff from SUFI-2, downscaled NCEP and H3A2a results for 1998-2000.

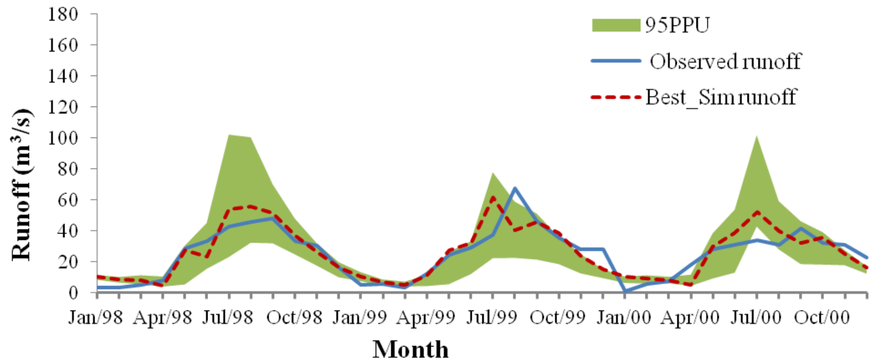

Figure 6. The hydrograph of the observed and best simulated runoff with 95PPU from downscaled H3A2a results for 1998-2000.

Precipitation is key component of hydrological cycle and more important and sensitivity to the surface runoff for hydrological studies (Tofiq and Guven, 2014). Because of the climate condition of the study area (no extremely cold days in winter), for this preliminary study, only precipitation data is downscaled using the statistical downscaling method. Normally, downscaling precipitation data is inevitably more problematic 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).

As the first step, the National Centers for Environmental Prediction (NECP) reanalysis data were applied first for calibrating the model. 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 screened NCEP predictor variables were used to downscale the H3A2a outputs. The downscaled precipitation results were treated as input of the hydrological model, and the simulated surface runoff was compared to the observed runoff data. To be noticed, the mean precipitation of 40 NCEP ensembles (scenarios) generated by SDSM were used as the input of the hydrological model, because only the uncertainties from H3A2a to the hydrological model are the key concerns of this study; and all 40 H3A2a ensembles were reserved and used to conduct uncertainty analysis.

As it is shown in **Fig. 5**, the hydrograph contains four surface runoff simulation series, which are observed runoff, simulated runoff by using observed precipitation, using mean downscaled NCEP data, and using downscaled H3A2a outputs with the best performance. The surface runoff simulation produced by observed precipitation can reach 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) performs better than the simulations using the mean precipitation of NCEP ensembles (with NSE and R^2 values of 0.6 and 0.69, respectively). There are some underestimations during April to July each year when conducting simulation using observed data, but simulations from two downscaled GCM data perform better in these three months. However, the simulations from two downscaled GCMs perform relatively poor for capturing the peak flow. Therefore, the corresponding uncertainties cannot be neglectable, and the 95PPU was calculated to improve the reliability of predictions.

The 95PPU of the simulation from downscaled H3A2a are calculated at 2.5% and 97.5% levels of the cumulative distribution of downscaled precipitation for each month. Total of 40 ensembles were generated from SDSM and used for uncertainty analysis. The lower bound and upper bound of downscaled precipitation results were applied to the calibrated hydrological model, and the corresponding surface runoff simulations were provided above. In **Fig. 6**, the 95PPU can cover most of observed runoff data indicating a good coverage for extreme events. The details of statistic summary are provided in Table 1. Although the width of uncertainty range is relatively large (R-factor of 1.34), by considering the large coverage (P-factor = 0.67) the uncertainties have been controlled well for a downscaling study. The results have demonstrated that the downscaled H3A2a model results are well performed for prediction purposes, and can provide a reliable scientific reference for local water resource management.

Table 1. The statistic summary of the results of three uncertainty analysis methods.

Variable	P-factor	R-factor	R^2	NSE
Third iteration SUFI-2	0.56	0.48	0.8	0.77
Downscaled NCEP (mean)	N/A	N/A	0. 69	0.6
Downscaled H3A2a	0.67	1.34	0.73	0.67

Conclusions

In this study, the hydrological modeling for the up reaches of the Wenjing River watershed was successfully conducted. SDSM was used to downscale the H3A2a model and generate future scenarios. The propagation effect of uncertainties from statistical downscaling to hydrological modeling was evaluated. The NSE and R^2 of the best simulation by using downscaled H3A2a data are 0.67 and 0.73, respectively, indicating a good simulation performance. The P-factor and R-factor for uncertainty from downscaling are 0.67 and 1.34, respectively, also demonstrating an acceptable uncertainty analysis result for a downscaled study. Therefore, the downscaled H3A2a model is capable for future prediction with high confidence, and can provide a reliable scientific reference for long term evaluation and estimation of future water resource situation in the study area.

References

Abbaspour, K.C. (2011). SWAT-CUP4: SWAT Calibration and Uncertainty Programs - A User Manual., Swiss Federal Institute of Aquatic Science and Technology, Switzerland.

Abbaspour, K.C., Yang, J., Maximov, I., Siber, R., Bogner, K., Mieleitner, J., Zobrist, J., & Srinivasan, R. (2007). Modelling hydrology and water quality in the pre-alpine/alpine Thur watershed using SWAT. *Journal of Hydrology, 333*(2-4), 413-430. doi: 10.1016/j.jhydrol.2006.09.014

Ahmed, K.F., Wang, G., Silander, J., Wilson, A.M., Allen, J.M., Horton, R., & Anyah, R. (2013). Statistical downscaling and bias correction of climate model outputs for climate change impact assessment in the U.S. northeast. *Global and Planetary Change, 100*, 320-332. doi: 10.1016/j.gloplacha.2012.11.003

Arnold, J.G., Srinivasan, R., Muttiah, R.S., & Williams, J.R. (1998). Large area hydrologic modeling and assessment Part I: Model development. *Journal of the American Water Resources Association, 34*(1), 17.

Arnold, J.G., Williams, J.R., & Maidment, D.R. (1995). Continuous-Time Water and Sediment-Routing Model for Large Basins. *Journal of Hydraulic Engineering, 121*(2), 171-183. doi: 10.1061/(ASCE)0733-9429(1995)121:2(171)

Bae, D.-H., Jung, I.-W., & Lettenmaier, D.P. (2011). Hydrologic uncertainties in climate change from IPCC AR4 GCM simulations of the Chungju Basin, Korea. *Journal of Hydrology, 401*(1-2), 90-105. doi: 10.1016/j.jhydrol.2011.02.012

Chen, J., Brissette, F.P., & Leconte, R. (2011). Uncertainty of downscaling method in quantifying the impact of climate change on hydrology. *Journal of Hydrology, 401*(3), 190-202. doi: 10.1016/j.jhydrol.2011.02.020

Chen, J., Brissette, F.P., & Leconte, R. (2012). Coupling statistical and dynamical methods for spatial downscaling of precipitation. *Climatic Change, 114*(3-4), 509-526. doi: 10.1007/s10584-012-0452-2

Ficklin, D.L. (2010). *Modeling the Impacts of Climate Change on Hydrology and Agricultural Pollutant Runoff in California's Central Valley.* (Dissertation/Thesis), University of California, the United States.

Gudmundsson, L. (2012). Assessing the suitability of weather generators based on Generalised Linear Models for downscaling climate projections. Norwegian Meteorological Institute, Norway.

Hassan, Z., Shamsudin, S., & Harun, S. (2013). Application of SDSM and LARS-WG for simulating and downscaling of rainfall and temperature. *Theoretical and Applied Climatology, 116*(1-2), 243-257. doi: 10.1007/s00704-013-0951-8

Hay, L.E., LaFontaine, J., & Markstrom, S.L. (2014). Evaluation of Statistically Downscaled GCM Output as Input for Hydrological and Stream Temperature Simulation in the Apalachicola–Chattahoochee–Flint River Basin (1961–99). *Earth Interactions, 18*(9), 1-32. doi: 10.1175/2013ei000554.1

Khan, M.S., Coulibaly, P., & Dibike, Y. (2006). Uncertainty analysis of statistical downscaling methods using Canadian Global Climate Model predictors. *Hydrological Processes, 20*(14), 3085-3104.

Samadi, S., Carbone, G.J., Mahdavi, M., Sharifi, F., & Bihamta, M.R. (2012). Statistical downscaling of climate data to estimate streamflow in a semi-arid catchment. *Hydrology and Earth System Sciences Discussions, 9*(4), 4869-4918. doi: 10.5194/hessd-9-4869-2012

Solman, S.A., & Nuñez, M.N. (1999). Local estimates of global climate change: a statistical downscaling approach. *International Journal of Climatology, 19*(8), 835-861.

Tofiq, F.A., & Guven, A. (2014). Prediction of design flood discharge by statistical downscaling and General Circulation Models. *Journal of Hydrology, 517*, 1145-1153. doi: 10.1016/j.jhydrol.2014.06.028

Wilby, R.L., & Dawson, C.W. (2007). SDSM 4.2 -- A decision support tool for the assessment of regional climate change impacts. Loughborough Unuiversity, UK.

Wu, H., & Chen, B. (2014). Evaluating uncertainty estimates in distributed hydrological modeling for the Wenjing River watershed in China by GLUE, SUFI-2, and ParaSol methods. *Ecological Engineering*. doi: 10.1016/j.ecoleng.2014.05.014

Xue, C., Chen, B., & Wu, H. (2014). Parameter Uncertainty Analysis of Surface Flow and Sediment Yield in the Huolin Basin, China. *Journal of Hydrologic Engineering, 19*, 1124-1236. doi: 10.1061/(asce)he.1943-5584