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Assessment of climate change impact on hydrological processes based on statistical approaches

Y. Lu
School of Civil & Environmental Engineering, Nanyang Technological University, 50 Nanyang Ave., 679798 SINGAPORE

X. S. Qin*
School of Civil & Environmental Engineering, Nanyang Technological University, 50 Nanyang Ave., 679798 SINGAPORE
(*Correspondence author; Tel: 65-67905288; Fax: 65-67921650; e-mail: xsqin@ntu.edu.sg).

Abstract: The changed climate could cause more frequent extreme meteorological events, and lead to exacerbated hydrological disasters such as floods or droughts. The impact assessment of climate change on hydrological processes is thus imperative before any adaptation plans are to be made. This study aimed to assess the river discharge response under climate change using the multiple statistical approaches in the Bow River Basin, Alberta, Canada. There are two major components in this study, including climate downscaling and hydrological simulation. Firstly, the large-scale predictors from Hadley Centre Coupled Model, version 3 (HadCM3) A2 scenarios were downscaled using support vector machine (SVM) to generate the local meteorological information including precipitation, minimum and maximum temperature. An integrated-multiple-steps SVM model was applied to address spatial correlations. Secondly, the downscaled weather variables were applied into a trained Bayesian neural network (BNN) model to simulate the monthly runoff. The BNN model in this step was trained by the observed local weather dataset. Based on the HadCM3 A2 emission scenario, the future variation of the river discharge was projected. The dry-/wet-spells and extreme events are examined and compared with the current condition. This study relies only on statistical methods, which are advantageous in less data demand and flexible way of usage. The main limitation is that the statistical method has to assume stationary relationships for current and future periods.

Keywords: Climate change, Statistical downscaling, SVM, BNN

I. INTRODUCTION

Global climate would change to warmer in this century, and could increase the frequency of storms in many regions around the world [1] [2]. To investigate the climate change impact on hydrological processes is an important task for water resources management. The Global Circulation Model (GCM) is a powerful tool for the climate study. However, the resolution of GCM grid is generally about 300 km, which is too coarse to be applied directly into hydrological models [3]. Two downscaling approaches, dynamical and statistical downscaling could help bridge the gap between GCM and local weather information [4]. Comparing to the dynamical downscaling method, the statistical one can offer station/point-scale weather data, and is computationally more efficient [4] [5]. The regression models are one of the major types of statistical downscaling. Over the past decades, the Statistical DownScaling Model (SDSM) [6] and Automated Statistical Donwcaling (ASD) [7] tools are two famous methods and have been successful applied to many regions. Hseeami et al. (2008) compared the performances of ASD and SDSM

in Canada. The results showed that ASD performs as well as SDSM [7]. Tripathi et al. (2006) applied the Support Vector Machine (SVM) method to downscale monthly precipitation at India, and also compared it with a multi-layer back-propagation artificial neural network (ANN) model [8]. The results demonstrated that SVM outperformed ANN.

Combining climate model and hydrological model is a common way to investigate the climate change impacts on hydrological processes. The conventional physical-based hydrological model, such as SWAT (Soil and Water Assessment Tool), HBV and SLURP (Semi-distributed Land Use-based Runoff Processes) generally require a large number of input variables, including weather data, land use, soil property, and etc. In comparison, the statistical models are less data-demanding and easier to use. Gao et al. (2010) employed an ANN model to simulate monthly streamflow in the Huaihe River Basin, China. The study plugged the output of ECHAM5 into the ANN model to predict the future variations of streamflow under climate change [9]. Zarghami et al. (2011) also coupled an ANN model with LARS-WG to examine climate change impact on runoffs in East Azerbaijan, Iran [10].

In this study, two statistical methods, SVM and Bayesian Neural Network (BNN) [11], are applied to investigate the runoff variations under climate change in the Bow River Basin, Canada. The method is novel in the sense of using a data-driven framework with combined BNN and SVM techniques. It does not involve complex physical processes and is readily applicable in different regions. The weather data is downscaled by SVM, including monthly precipitation, maximum temperature, and minimum temperature. The hydrological process is modelled by BNN with 5 neurons. The future climate scenario is based on the HadCM3 A2 emission scenario.

II. STUDY AREA AND DATA

The study area is the Bow River Basin, located in Alberta, Canada. The basin has a catchment area of 26, 200 km^2, and is one of sub-watersheds of South Saskatchewan River Basin. The hottest month and coolest month are July and January, respectively. The annual total precipitation over the basin is about 418 mm, including both rainfall and snow. The rainiest month is June, and month with most snowfall is March [12]. In this study, the maximum and minimum temperature are collected from one station (CALGARY, STN-1), the total precipitation is collected from two stations, including CALGARY and GLEICHEN (STN-2) which are located at different regions. The available range of the data is from 1972 to 2000. The hydrological data is collected from the station BOW RIVER AT CALGARY from 1972 to 2000. For the large-scale predictors, the NCEP (National Centers for Environmental Prediction) reanalysis data and HadCM3 A2 scenario are used for statistical downscaling.

III. METHODOLOGY

There are three components in the methodology adopted. The first one is to select a hydrological model. In this study, four different models, SVM, BNN with 10 neurons, BNN with 5 neurons and BNN with 3 neurons would be used and compared. All of these models are trained by the observed weather data, including precipitation at two stations and maximum and minimum temperature at one site. In this study, the historical record (1972-2000) is divided into two periods, including calibration (1972-1990) and verification (1991-2000). The input of weather variables are chosen based on the Spearman correlation coefficients. Table 1 illustrates the correlation coefficients between variables and hydrological data. The gray grids mean the selected variables, which has a threshold defined at 0.35. The second component is to downscale the weather variables. SVM method is used for downscaling multiple variables, including the monthly precipitation at two stations and regional maximum/minimum temperatures at one station. The NCEP reanalysis data and observed weather data would be used for training the SVM model. Then, the trained SVM model is employed to downscale the current and future conditions based on HadCM3 A2 scenario. The spatial correlation of precipitation at the two stations is also considered. The last component is to project future runoff. The downscaled weather variables from last step would be coupled with the trained BNN hydrological model to simulate the runoff for current and future periods under HadCM3 A2 scenario. Fig. 1 shows the overall roadmap of

this study. Technical details of BNN and SVM could refer to the studies of Khan and Coulibaly (2006) and Tripathi et al. (2006) [8] [11].

Table 1. Correlations between weather variables and hydrology data

Correlation	Tmin	Tmax	STN-1 (PCP)	STN-2 (PCP)
Lag-0	0.676	0.648	0.637	0.554
Lag-1	0.644	0.636	0.432	0.370
Lag-2	0.440	0.454	0.169	0.148

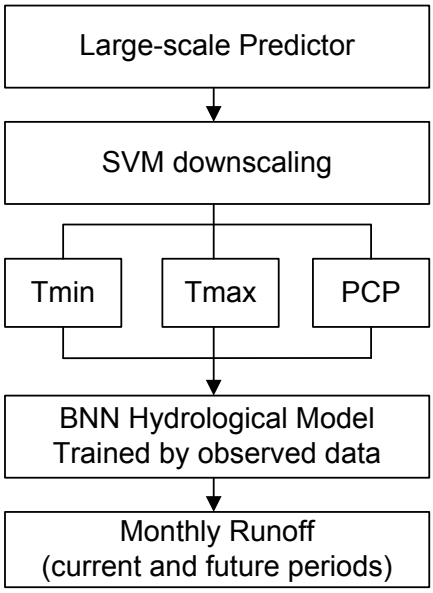

Fig. 1. The roadmap of this study.

IV. RESULT ANALYSIS

A. Selection of hydrological model

Four models, SVM, BNN with 10 neurons (BNN_10), BNN with 5 neurons (BNN_5) and BNN with 3 neurons (BNN_3) are used for hydrological forecasting. The observed weather data are divided into two periods, including calibration (1972-1990) and verification (1991-2000). Fig. 2 shows the comparison of SVM and BNN models in runoff simulations. The results show that all of the four models could well capture the seasonal fluctuations. Except for BNN_10, the rest three models present similar RMSE (Root – Mean – Square - Error) values. Since BNN_5 has the lowest RMSE value (i.e. 24.25), it is chosen as the hydrological model for further studies.

B. Weather variables downscaling

In this section, SVM would be applied for downscaling multiple weather variables (including precipitation and temperature). Firstly, the Spearman correlation coefficient is used for screening the large-scale predictors. Table 2 illustrates the selected predictors for the weather variables. The NCEP reanalysis data and observed historical record is used for calibration (1972-1990) and verification (1991-2000) (i.e. the results are not shown in this study). Once the model is validated and the result is acceptable, all of reanalysis data and observed record (period 1972-2000) are used for training SVM model. The large-scale predictors of HadCM3 A2 would be used as input for the trained SVM model to project both current and future conditions. Fig. 3 shows downscaled minimum and maximum temperatures using SVM from HadCM3 A2. The results show that there is a slight underestimation in several months for two variables. The RMSE values of Tmin and Tmax are 3.45 and 4.07, respectively. Fig. 4 shows the downscaled monthly precipitations at two stations. It is indicated that the precipitation of STN-1 is significantly higher than that of STN-2. In terms of the average monthly rainfall, the simulated values of two stations (i.e. 37.04 mm and 29.8 mm, respectively) are both close to the observed data (i.e. 34.15 mm and 28.26 mm, respectively). For the spatial correlation of precipitation, the simulated data (i.e. 0.94) shows a slight overestimation compared with the observed data (i.e. 0.86). Overall, the SVM model presents a good capability in downscaling the weather variables.

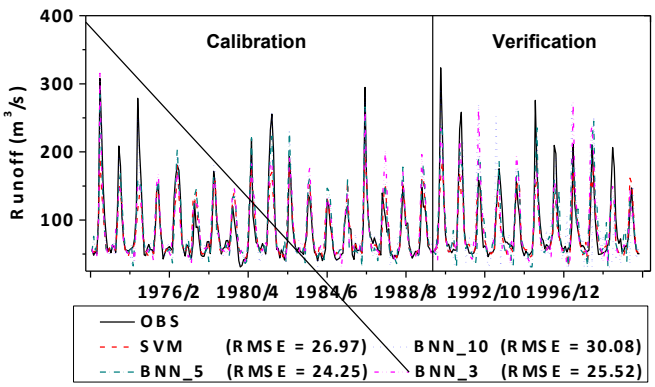

Fig. 2. Comparison of SVM and BNN model in hydrological forecasting.

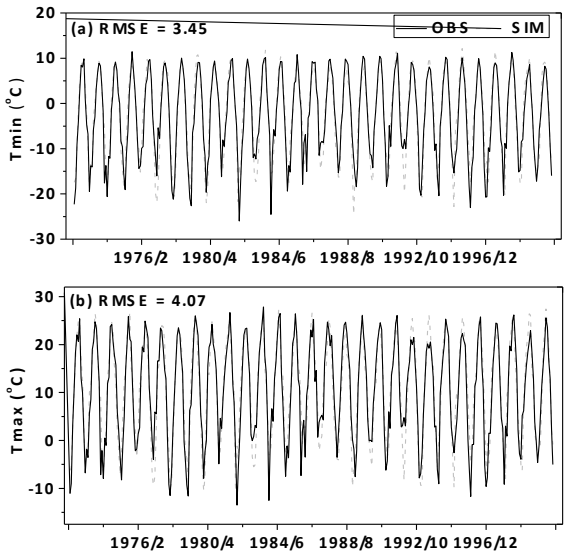

Fig. 3. Comparison of observed and downscaled (a) minimum temperature, and (b) maximum temperature using SVM from HadCM3 A2 scenario.

Table 2. Selected large-scale predictors for different weather variables.

Variables	Large-scale Predictor					
Tmin	p5_v	p5zh	p500	p850	shum	temp
Tmax	p_u	p500	p850	shum	temp	
PCP	p5_v	p5zh	p8_z	r500	shum	temp

Through comparison between the observed and simulated data during current period, SVM is used for predicting future climate scenarios. Fig. 5 shows the downscaled annual Tmin, Tmax at one station and PCP at two stations for future periods (2001-2099). From the figure, the temperature variables (Tmin and Tmax) indicate a notable increasing trend. At the end of this century (2080-2099), the Tmin and Tmax would reach up to 1.46 °C and 15.65 °C, respectively. Regarding the precipitation, the increase rates of two stations for the period of 2080-2099 are 21% and 24%, respectively. The maximum annual amounts both occur at the year of 2079, with the values being higher than 500 mm. Comparing to the baseline data of current condition, this is a notable change on the local weather.

C. *Runoff simulation based on downscaled data*

Based on previous two procedures, the downscaled weather variables could be input into the trained BNN model for hydrological predictions. Fig. 6 shows the simulated annual runoff during the current period. The result shows that the coupled approach by downscaling and hydrological models could reproduce the monthly runoff well. The simulated average monthly runoff (i.e. 93.62 m^3/s) is slightly overestimated, and the error is about 8% (i.e. based on the observed value at 86.52 m^3/s). For future period, the runoff also presents a notable increasing tendency (Fig. 7), which is similar to that with the weather variables. At the end of this century, the increase rate of annual runoff is about 32.85% compared with the value of the simulated baseline data (i.e. 93.62m^3/s). The results demonstrate that the precipitation is the dominate factor which would lead to the flooding problem. Although the temperature also increases, the evaporation loss may not affect the runoff amount significantly. Moreover, the increased temperature also would lead to more snow melt which could be another factor of runoff increasing. Therefore, the risk of flooding would increase due to the climate change, and proper adaptation efforts are necessary.

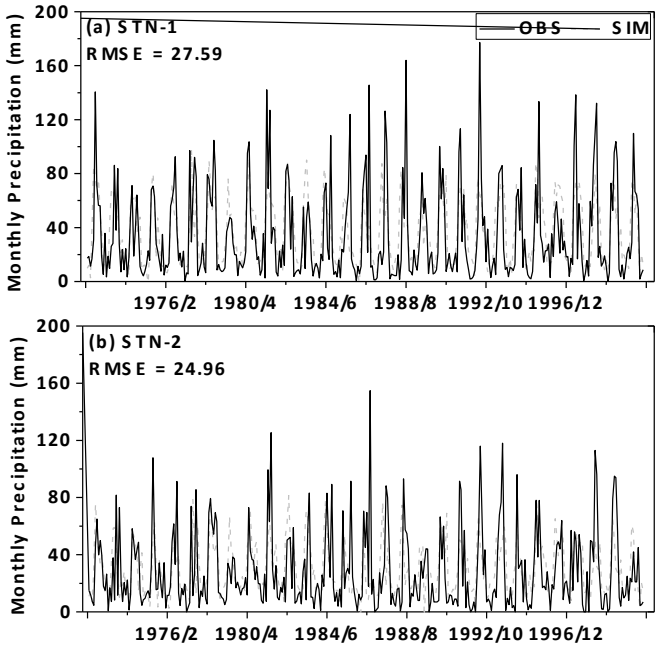

Fig. 4. Comparison of observed and downscaled monthly precipitation at two stations using SVM from HadCM3 A2 scenario.

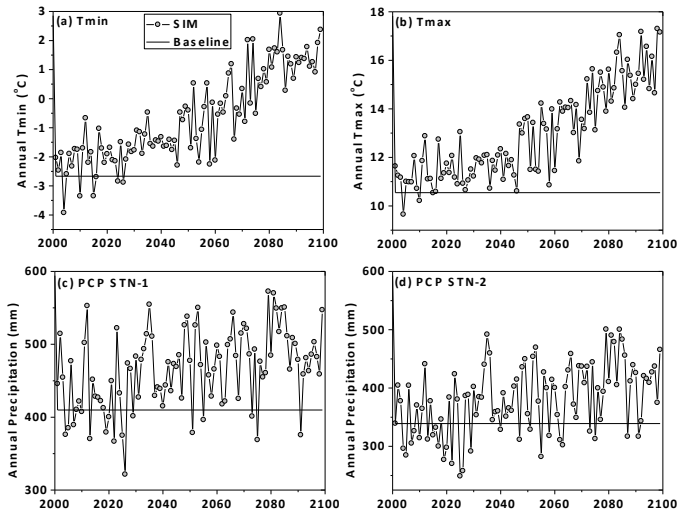

Fig. 5. The projected annual Tmin (a), Tmax (b), Precipitation (PCP) at Station-1 (c) and Station-2 (d) from HadCM3 A2 scenario.

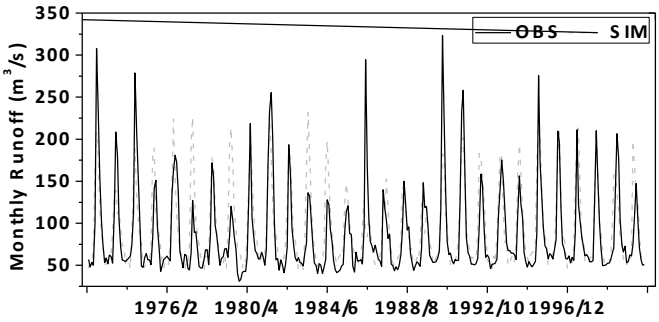

Fig. 6. Comparison of observed and simulated monthly runoff by BNN using downscaled weather variables.

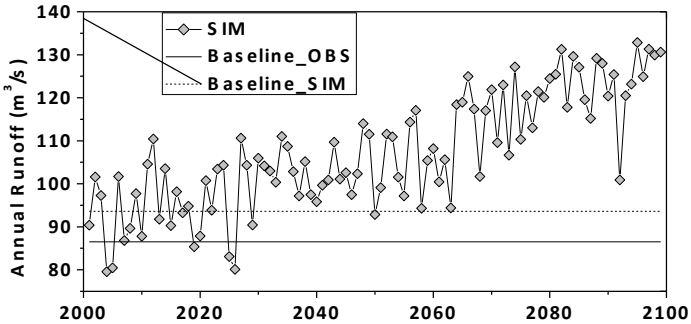

Fig. 7. The projected annual runoff using downscaled weather variables from HadCM3 A2 scenario.

V. CONCLUSION

This study applied two non-linear regression models, SVM and BNN, to investigate the climate change impact on hydrological processes in Canada. The SVM model is used for the statistical downscaling of local weather variables, and the BNN model is used for simulating the monthly runoff. The results showed that the two models could reproduce the weather variables and runoff information well for the current period. For the future condition, the local temperature and precipitation both would increase significantly. The runoff amount showed a 32.85% increase rate at the end of this century due to combined effect of snow melt and heavy rainfall. The major limitation of this study is that the projection for future conditions is based on the assumption of statistical stationarity.

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