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Uncertainty assessment of climate change impacts on the hydrology of small prairie wetlands

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SUMMARY

With increasing evidences of climate change in the prairie region, there is an urgent need to understand the future climate and the responses of small prairie wetlands. This study integrated two regional climate models (RCMs), two weather generators and a distributed hydrological model to examine uncertainties in hydrological responses to climate change in the Assiniboia watershed, Canada. Comparing to baseline conditions (1971–2000), annual water yield and evapotranspiration in the period of 2041–2070 were generally unchanged, while annual reservoir storage was generally reduced. However, projected hydrological regimes were less consistent at monthly level, particularly for March and July. Such uncertainties in simulated hydrological responses were derived from the implementations of different integrated downscaling methods, reflecting our imperfect knowledge of the future climate. We identified a warming temperature trend from climatic projections, but had less confidence in the future pattern of precipitation. Uncertainties in integrated downscaling were primarily derived from the choice of RCM, and were amplified through the incorporation of different weather generators. Results of any climate change study based on only one RCM and/or one weather generator should be interpreted with caution, and the ensemble framework should be advised to generate a comprehensive vision of the future climate. This study demonstrated that the incorporation of precipitation occurrence change contributed to a full translation of RCM outputs, but also introduced additional uncertainty. A balance is thus desired between the information loss and the additional uncertainty in order to effectively utilize RCM outputs.

1. Introduction

The semi-arid northern plains of North America are studded with millions of small depressions that are frequently occupied by ponds or lakes (Woo and Rowsell, 1993). These small wetlands play an important role in the prairie hydrology and are increasingly crucial to many economical and ecological services (Price et al., 2005; Su et al., 2000; Voldseth et al., 2007). Most of prairie wetlands are located in closed catchments with largely internal drainage, and natural outflows are rare under normal weather conditions (Fang and Pomeroy, 2008; Hayashi et al., 1998). With a relatively impermeable glacial till substrate, groundwater flow is generally slow and presents a minor component of the water balance (van der Kamp et al., 2003). Short-duration events such as snowmelt in spring and storm in summer are critical to the existence and functions of these wetlands. Owing to the unstable and dry prairie climate where potential evaporation greatly exceeds precipitation, small prairie wetlands are highly sensitive to changes in temperature and precipitation that affect runoff and atmospheric energy fluxes (Conly and Van der Kamp, 2001; Voldseth et al., 2009). With increasing evidences of climate change in the prairie region, there is an urgent need to comprehensively explore the future climate changes and the responses of small prairie watersheds to these changes (Huang et al., 1998, 2005; Qin et al., 2008).

General Circulation Model (GCM) is the primary tool in the assessment of climate change. However, GCM-predicted runoff is often over-simplified, and hydrological models driven directly by GCM outputs have poor performance (Fowler et al., 2007). There is a clear mismatch between the coarse resolution of GCMs and the scale of local hydrological processes. Different downscaling approaches have been applied to bridge this gap, varying from simple techniques that constantly modify the time series of meteorological variables (Ficklin et al., 2009; Somura et al., 2009) to complex statistical or dynamical methods (Franczyk and Chang, 2009; Marshall and Randhir, 2008; Stone et al., 2001; Toews and Allen, 2009). Among them, dynamical downscaling (or regional climate model, RCM) is of increasing attention because it can simulate regional climatic features through parameterized physical atmospheric

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processes. Nevertheless, the spatial resolution of RCMs still exceeds the scales of small prairie watersheds. A viable solution is to apply statistical downscaling approaches to RCM outputs (Fowler et al., 2007; Wilby et al., 2000). For example, Diez et al. (2005) used a two-step standard analogue technique to improve the performance of the Rossby Centre Climate Atmospheric model for downscaling seasonal precipitation over Spain. Hellstrom and Chen (2003) downscaled the RCM projection of precipitation in Sweden with a multiple regression model. Wood et al. (2004) applied three statistical methods to RCM outputs for producing inputs required by hydrological modeling. Such integrated downscaling methods were able to improve RCM projections through incorporating the present climate normals that were often available with high spatial resolution.

However, few investigations have been made to effectively examine the uncertainties in integrated downscaling and related impact modeling. Firstly, while the comparisons are common among RCMs or among statistical downscaling methods, few attempts have been conducted to explore differences among integrated downscaling methods. Uncertainties are derived from not only the structure of RCMs but also the formulations of statistical downscaling tools. The combined effects of these uncertainties on impact models have not been clearly understood. Secondly, precipitation amount is commonly downscaled in impact studies, but precipitation occurrence is rarely considered. Changing length of wet spell may have important effects on moisture balance and runoff generation, especially for semi-arid regions where potential evaporation often exceeds precipitation. Exclusion of precipitation occurrence change may lead to an impaired interpretation of RCM outputs, but incorporating this information may also introduce additional uncertainty. Thirdly, the impacts of the above uncertainties are seldom examined together with hydrological modeling. Different hydrological systems possess different degrees of sensitivity to climate change; within one system, the responses are also different among hydrological components. Uncertainties in climate change projections will impose complicated influences on the studied hydrological system. It is desired that these influences be explored through a hydrological model that can effectively utilize the downscaling outputs and simulate the watershed behaviour at a fine scale.

Small prairie watersheds provide favourable sites for exploring these knowledge gaps in downscaling-based impact studies. Each watershed constitutes an independent hydrological system where it is relatively simple to characterize drainage features and differentiate climate change from other driving forces on hydrological system. Therefore, this study aims to explore the uncertainties of climate change impacts on the hydrology of a small prairie watershed through: (1) developing downscaled climate scenarios by integrating different RCMs and stochastic weather generators with a specific consideration on precipitation occurrence and (2) conducting distributed hydrological modeling driven by downscaled climate scenarios to examine key hydrological processes.

2. The study system

2.1. Study area

The Assiniboia watershed is located in southern-central Saskatchewan, Canada (Fig. 1). It is a typical small watershed in the prairie pothole region. It has a gross drainage area of 49.6 km^2, and elevation ranges from 677 m to 771 m with an average slope of 3%. The majority of land is developed for agriculture. Soil is dominated by Brown Chernozemic soils formed in a mixture of variable, clayey lacustrine materials and clay loam glacial till. Because Rocky Mountains block moisture-bearing winds from the Pacific, a pronounced semi-arid climate prevails, featured by long and cold winter, short and warm summer, and strong winds. Annual mean temperature is 3.9 °C, and monthly mean temperatures are −13.1 °C in January and 18.6 °C in July, respectively. Annual precipitation is 393.4 mm with 25% falling as snow, while annual potential evapotranspiration is 1135.5 mm. The period of May–July accounts for 48% of the annual rainfall, and summer storms are often severe. Snow accumulation on the ground generally starts in November, and the melt of snowpack occurs from March to April. Runoff is over 80% derived from snowmelt and shows great interannual variations.

The Assiniboia watershed is a non-contribution drainage area although it is classified as a part of the Missouri River basin. To adapt the persistent prairie droughts, two reservoirs were consecutively built based on natural wetlands. At the water level of emergency spillway, the Old Willows Reservoir has a storage capacity of 0.86 million m^3 with a surface area of 21.5 ha, and the downstream Willows Reservoir has a storage capacity of 6.75 million m^3 with a surface area of 43.2 ha. The Old Willows Reservoir receives water yield from 82% of the watershed area and releases water into the Willows Reservoir during spring runoff peak. The Willows Reservoir has rarely reached its full capacity (even in spring) and has negligible outflow to downstream area in a normal year. Therefore, the Assiniboia watershed generally behaves as an isolated hydrological region in the Canadian Prairies.

2.2. Geographic and hydro-climatic data

Soil data was digitized from 1:100,000 soil map of Rural Municipality No. 72. Data of land use was derived from the vector map of GeoBase and was updated based on survey records of local agricultural agency. National 1:50,000 digital elevation model was used to determine surface slope; it was improved through a hydrological correction method (Zhang and Huang, 2009) for establishing a reasonable drainage structure. Weather data from the Assiniboia Airport station was provided by Meteorological Service of Canada. It consisted of daily series of minimum and maximum temperatures, precipitation, humidity, and wind speed for the period of 1973–2009. Solar radiation was estimated based on the empirical equations recommended by Allen et al. (1998). Daily inflow of the Old Willows Reservoir (1976–2003) was provided by the Prairie Farm Rehabilitation Administration (PFRA) of Agriculture Canada; weekly water level of the Willows Reservoir (1978–2008) was obtained from the Town of Assiniboia.

2.3. Data of regional climate models

Two RCMs were employed in this study. PRECIS (Providing Regional Climates for Impacts Studies) is a regional climate modeling system developed by the Hadley Centre of UK (Jones et al., 2004). It allows the HadRM3P model to be run on a personal computer and has been applied in many countries (Akhtar et al., 2009; Marengo et al., 2009; Yang et al., 2010). Canadian Regional Climate Model (CRCM) is developed and operated by a consortium of Canadian institutions (Caya and Laprise, 1999). It can be set up to run on a domain covering any part of the globe, but its experiments have focused on Northern America (de Elia et al., 2008; Mailhot et al., 2007; Music and Caya, 2007). To our present knowledge, PRECIS and CRCM are the only two RCMs that have been applied to a Canadian domain. However, considerable disagreements existed between their projections for both present and future climates of Canada, which introduced large uncertainties in assessing climate change impacts; for example, see reports of two projects implemented for Ontario recently (Bourdages and Huard, 2010; CSEE, 2010).

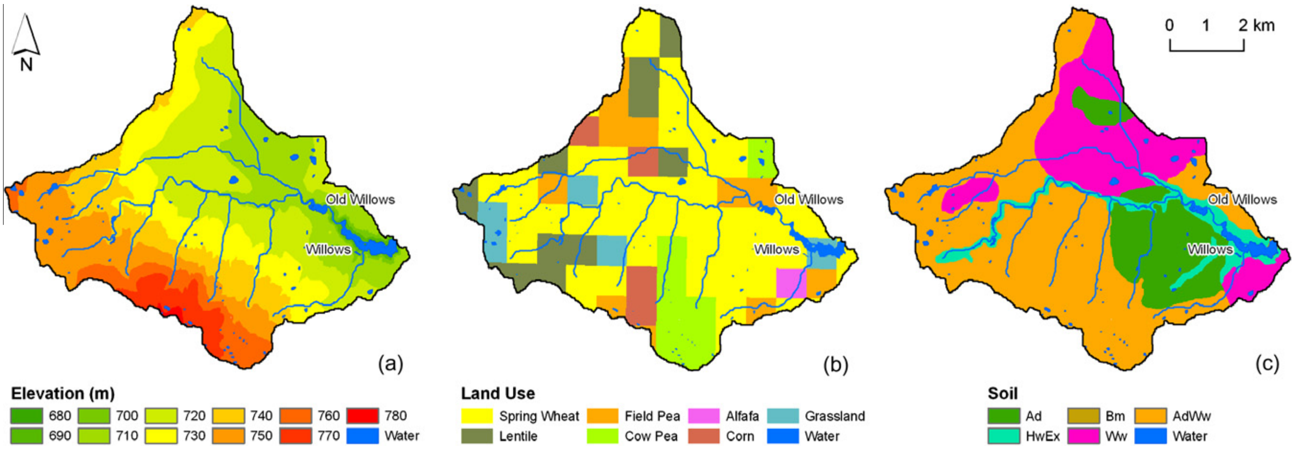


Fig. 1. The (a) topography, (b) land use and (c) soil of the Assiniboia watershed. Ad: Brown Chernozemic soils formed in clay loam glacial till; HwEx: a mixture of Regosolic and Chernozemic soils and bedrock outcrops formed in various deposits and bedrock materials; Bm: a mixture of Gleysolic and Regosolic soils formed in clayey alluvial materials; Ww: Brown Chernozemic soils formed in variable, clayey lacustrine materials; AdWw: Brown Chernozemic soils formed in a mixture of clay loam glacial till and variable, clayey lacustrine materials.

Simulation results of PRECIS and CRCM were obtained from the North American Regional Climate Change Assessment Program (NARCCAP) (Mearns et al., 2009). The RCMs were nested within GCMs for the baseline period (1971–2000) and the future period (2041–2070). PRECIS run was driven by HADCM3, while CRCM run was driven by CGCM3. The area of integration covered the conterminous United States and most of Canada, and has a spatial resolution of 50 km. The GCMs had been forced with the SRES A2 emissions scenario for the 21st century. The A2 emission scenario was selected due to its position at the higher end of the SRES emissions scenarios which can facilitate the impacts and adaptation studies. The story line of the A2 emission is characterized by heterogeneity. Self reliance and local identities are emphasized, population increases continuously, economic development is regionally oriented, and economic and technological improvements are relatively slow compared to the other story lines (Nakicenovic et al., 2000). More details about these GCM-RCM combinations can be obtained at the website of NARCCAP (http://www.narccap.ucar.edu/about/index.html).

3. Methodology

3.1. Statistical downscaling

To ensure that the predictive elements from RCMs are realistic for a small watershed, statistical downscaling methods such as stochastic weather generator (SWG) are required to link the regional- and local-scale processes. SWG first predicts the occurrence and amount of daily precipitation. Estimations of other climatic variables are generated depending on the wet or dry status of the day. SWG is efficient in reproducing the local climate with similar climate normals to that of the long-time observation. Because SWG does not rely on a correlation between predictants and predictors, the information of climate change from RCM simulations can be incorporated in a flexible manner.

Two SWGs are employed in this study. WXGEN (Williams, 1995) uses a first-order Markov chain model to define the day as dry or wet. The daily precipitation amount is estimated based on a skewed or exponential distribution. Daily maximum and minimum temperatures are then generated based on the weakly stationary generating process. LARS-WG (Semenov and Barrow, 1997) is based on the series approach, aiming to overcome the limitations of the Markov chain model of simulating the maximum dry spell. The precipitation occurrence is modelled as alternate wet and dry series. Length of each series and precipitation amount are chosen randomly from monthly semi-empirical distributions. Daily minimum and maximum temperatures are generated through stochastic processes with daily means and standard deviations (SD) conditioned on the precipitation status of that day.

Future climate is projected through SWG by adjusting the baseline normals with monthly shift terms, which are absolute or relative changes between two simulated climate states. Shift terms of temperature include means and standard deviations of daily maximum and minimum temperatures for each month. For shift terms of precipitation amount, both SWGs use the monthly total precipitation, while LARS-WG also uses standard deviation and skew coefficient of daily precipitation for each month. For shift terms of precipitation occurrence, WXGEN incorporates the probabilities of a wet day following a dry day ($P_{w/d}$) or a wet day ($P_{w/w}$), and the average number of days of precipitation; while LARS-WG uses the relatively changes in the lengths of wet and dry spells.

In this study, uncertainties in the downscaling process are mainly derived from three sources: (1) the differences between RCMs, (2) the differences between SWGs, and (3) the differences for whether precipitation occurrence changes are incorporated. Eight scenarios of future climate are designed, e.g., the combinations among two RCMs, two weather generators, and two types of shift terms (Table 1). The shifts terms are calculated from the RCMs outputs for the periods of 1971–2000 and 2041–2070. The precipitation threshold of a wet day is defined as 0.01 mm that is consistent with the data quality of station observation. In each scenario, the weather generator is driven by different random seeds to generate 20 synthetic weather series; each weather series consists of 30-year daily series of minimum temperature, maximum

Table 1
Scenarios of future climate (2041–2070) for downscaling studies.

Scenario	RCM	SWG	Precipitation occurrence
1	CRCM	LARS-WG	
2	CRCM	LARS-WG	√
3	CRCM	WXGEN	
4	CRCM	WXGEN	√
5	PRECIS	LARS-WG	
6	PRECIS	LARS-WG	√
7	PRECIS	WXGEN	
8	PRECIS	WXGEN	√

temperature and precipitation, and is feed into the hydrological model independently.

3.2. Hydrological modeling

The SWAT model (Arnold et al., 1998) is used in this study to examine hydrological processes driven by synthetic weather. It is a continuous, spatially-distributed simulator of hydrological system at the watershed scale. The watershed is divided hydrological response units (HRU) defined by unique combinations of soil, land use and slope. Surface runoff is generated using a modified curve number (CN) method. HRU outflows are summed within subwatershed and then routed through channel network to the watershed outlet. A reservoir is considered as an impoundment located at the main channel. Reservoir water balance takes into consideration the inflow, outflow, precipitation and evaporation at the surface area, and bottom seepage. For an uncontrolled reservoir, water is released whenever the reservoir volume is greater than the principal spillway volume.

The calibration of SWAT is achieved through a two-step composite scheme. Before the calibration, sensitivity analysis is conducted to reduce the number of parameters involved in calibration. In the first step, parameters related to snowmelt process are calibrated based on observations of early spring only. In the second step, other parameters are added into the pool to fit rainfall-runoff process in the whole hydrological year. In both steps, manual calibration is firstly undertaken to obtain initial ranges of parameter values, followed by automatic calibration for locating the best solution.

Three goodness-of-fit measures are used for evaluating the simulation performance of SWAT. The Nash–Sutcliffe efficiency (*NS*) is a normalized statistic that determines the relative magnitude of the residual variance compared to the measured data variance (Nash and Sutcliffe, 1970):

$$NS = 1 - \frac{\sum (Q - \widehat{Q})^2}{\sum (Q - \overline{Q})^2} \tag{1}$$

where $\widehat{Q}$ is the simulated flow, and $\overline{Q}$ is the average of observed flow *Q*. *NSE* takes values between $-\infty$ and 1, with $NS = 1$ indicating a perfect fit. *NS* has been widely used which facilitates the comparison among studies. For the same reason, the Pearson's correlation coefficient (R^2) is also calculated. R^2 ranges between 0 and 1, with 1 indicates a perfect agreement. The Percent Bias (PBIAS) is used to measure the average tendency of the simulated data to be larger or smaller than their observed counterparts:

$$PBIAS = \frac{\sum (Q - \widehat{Q}) * 100}{\sum Q} \tag{2}$$

The optimal value of *PBIAS* is zero, with positive (negative) values indicating model underestimation (overestimation) bias.

4. Results

4.1. Calibration and validation of hydrological model

Table 2 shows the SWAT parameters selected for calibration. During the first calibration step, TIMP was identified as the most influential parameter. The calibrated TIMP value was close to the low end of calibration range, revealing that the snowpack temperature was relatively stable against the influence of the current day temperature. SWAT performance was also sensitive to two snowmelt parameters, SMFMX and SMFMN. Their diverse calibrated values suggested strong seasonal variations. Particularly, the large value of SMFMX was expected because snowmelt in the Canadian Prairies could occur in as late as April. Calibrated SMTMP was slightly above 0 °C, favoring a late start of the melting process. During the second calibration step, sensitive parameters included CN2, SOL_AWC, SOL_K and SURLAG. Comparing with their initial values for major land uses, CN generally decreased, while SOL_AWC and SOL_K generally increased, facilitating reduced surface runoff and enhanced soil storage. Calibrated SURLAG was close to the upper bound, indicating a very low capacity of surface storage.

Fig. 2 compares observed and simulated mean monthly inflows of the Old Willows Reservoir. The calibration period (1978–1992) and validation period (1997–2003) were designed to cover a wide spectrum of prairie hydrological conditions including two multi-year droughts (e.g., 1980–1989 and 1999–2002). In the calibration period, SWAT showed good performance in snowmelt season, but yielded underestimations in dry season, with $NS = 0.73$, $R^2 = 0.76$ and $PBIAS = 10.2$. In the validation period, SWAT demonstrated accepted predictability, with $NS = 0.60$, $R^2 = 0.72$ and $PBIAS = 16.8$. According to the general ratings recommended by Moriasi et al. (2007) for hydrological simulations, the performance of SWAT at the Assiniboia watershed was good or satisfactory.

4.2. Projections of climate change

The simulation results of CRCM and PRECIS are presented in Fig. 3. Both RCMs were able to reproduce seasonal variations of temperature for the baseline period. However, CRCM tended to underestimate temperatures with the maximum deviation for February (4.2 °C), while PRECIS yielded overestimation bias particularly for in winter (6.9 °C) and late-summer (3.7 °C). In terms of precipitation, CRCM reproduced seasonal patterns with moderate overestimation bias for summer rainfall (0.38 mm/day higher). In the PREIS projection, the temporal pattern of precipitation was one month earlier than observation, and the annual precipitation was overestimated by 14%. For the future period, both RCMs predicted a warmer world, with high increments in winter and late-summer and intensified monthly variation in spring and summer. As comparison, precipitation projections showed significant discrepancies. CRCM estimated a wetter climate, with increased

Table 2
Calibrated SWAT parameters.

Parameter	Definition	Initial value	Calibration range	Calibrated value
TIMP	Snowpack temperature lag factor	1	0.01–1	0.39
SMFMX	Melt factor for snow on June 21 (mm H_2O/°C-day)	4.5	5.5–7.5	7.09
SMFMN	Melt factor for snow on December 21 (mm H_2O/°C-day)	4.5	0.5–3.5	1.74
SFTMP	Snowfall temperature (°C)	1	−1.5 to 1.5	−0.28
SMTMP	Snow melt base temperature (°C)	0.5	−0.5 to 1.5	1.03
CN2	Initial SCS CN II value	81–85	±20%	−18.9% to 5.2%
ALPHA_BF	Baseflow alpha factor (days)	0.048	0 to1	0.005
SOL_AWC	Available water capacity (mm H_2O/mm soil)	0.14–0.18	±25%	−0.6% to 18.2%
SOL_K	Saturated hydraulic conductivity (mm/hr)	6.8–32.9	±25%	10.4% to 23.9%
GW_REVP	Groundwater "revap" coefficient	0.02	±50%	−38.8%
SURLAG	Surface runoff lag time (days)	4	0–10	8.3
ESCO	Soil evaporation compensation factor	0.9	0.8–1.0	0.80–0.81

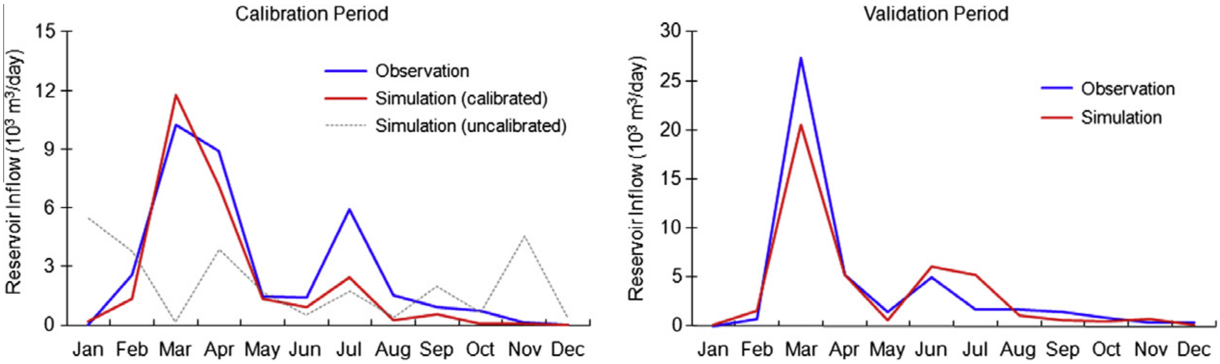


Fig. 2. Comparison of simulated and observed monthly inflows of the Old Willows Reservoir (1978–2003).

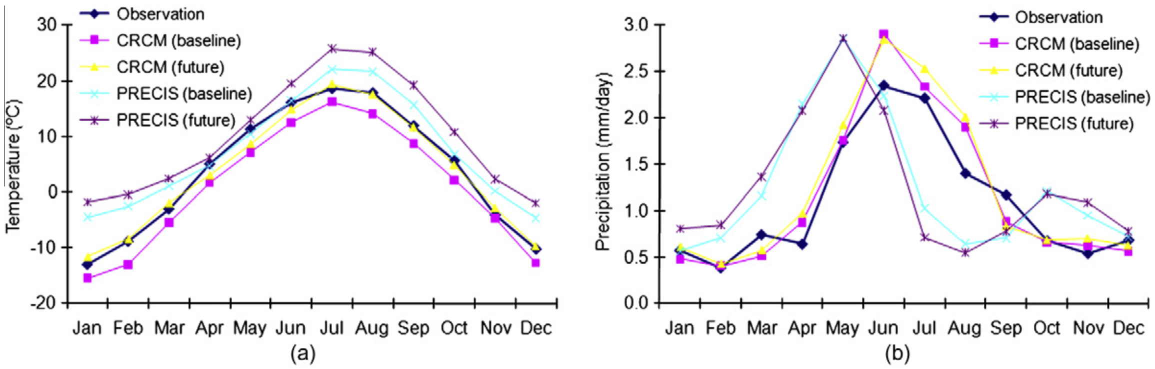


Fig. 3. Comparison of simulated and observed climate normals for the baseline period (1961–1990).

precipitation by 26% in winter and by 10% in summer. PRECIS predicted increased winter precipitation and largely reduced summer rainfall (by 30%), while annual precipitation was close to the baseline condition. In terms of precipitation occurrence, both RCMs predicted longer wet spell for winter and less frequent rainfall in late-summer, but showed disagreement for the period of April through June. Based on the performance of RCM for the baseline period, however, it was doubtful whether their projections on the future period can be directly utilized in regional impact studies, especially for hydrological issues at small scale.

The bias of RCM projections can be largely avoided through using monthly shifts based on the differences between two simulated climate states. The applied monthly shifts are presented in Tables 3 and 4, and temperature and precipitation downscaled by SWGs are shown in Fig. 4. Both SWGs had similar results in temperature downscaling, but LARS-WG generated more precipitation than WXGEN did (except for May). These difference was amplified when precipitation occurrence changes were incorporated. Changes in $P_{w/d}$ and $P_{w/w}$ had only slight effects on WXGEN results, but LARS-WG was sensitively to altered spell length of wet and dry spells. This was particularly evident for the largely reduced July precipitation (by 30%) in PRECIS projection. WXGEN reproduced this change exactly when only precipitation amount shifts were used, and slightly overestimated it (32%) when precipitation occurrence shifts were included. As comparison, LARS-WG generated a 22% decrease using amount shifts only, and 16% when occurrence shifts were incorporated. A similar disagreement was also identified for March. July and March are crucial periods of prairie hydrology, because July has over 23% of annual precipitation and March is the major snowmelt period. Such diverse translations of RCM-derived climate change information introduce considerable uncertainties into impacts studies on water resources planning and management.

4.3. Hydrological responses to climate change

4.3.1. Water yield

Water yield is the total amount of water that reaches the channel system of the watershed, consisting of surface runoff and lateral flow. It significantly relates to the availability of surface water. Increased or intensified precipitation facilitates the increasing of water yield. Warm temperature in winter and spring months also speeds the snowmelt process that strongly contributes to the water yield. Overall, the Assiniboia watershed experienced slightly decreased annual water yield in 2050s. The absolute changes of monthly water yield in different scenarios are presented in Fig. 5. In CRCM scenarios, water yield increased up to 5 mm in February, but largely decreased in March due to diminished snowmelt runoff. LARS-WG favoured higher water yield and was more sensitive to the changed precipitation occurrence that could further enhance the water yield. In July, for example, LARS-WG resulted in increased water yield when precipitation occurrence shifts were used. In PRECIS scenarios, large uncertainty lay in March. While WXGEN resulted in reduced water yield, LARS-WG yielded an opposite situation. This disagreement was mainly due to the fact that LARS-WG generated 17% more precipitation in March than WXGEN did (Fig. 4b). Another reason could be that LARS-WG favoured the snow accumulation before March. Although both weather generators estimated a warmer and wetter winter comparing to the baseline, the maximum daily temperature generated by LARS-WG had less variations, suggesting less rainfall and snowmelt in the mid-winter; as a result, there was enhanced snowpack available for snowmelt in March.

4.3.2. Evapotranspiration

The mean annual evapotranspiration (ET) was projected to be slightly increased in 2050s. The absolute changes of monthly ET

Table 3
Monthly shifts based on CRCM projections for the periods of 1961–1990 and 2041–2070.

Month	Maximum temperature (°C)		Minimum temperature (°C)		Monthly precipitation (mm)		Daily precipitation (mm)		Number of rain days	$P_{(W/W)}$	$P_{(W/D)}$	Length of wet spell*	Length of dry spell*
	Mean	SD*	Mean	SD*	Mean	SD*	SD*	Skewness*					
January	3.52	−0.03	4.12	−0.05	0.26	0.30	0.21	0.08	1.90	0.06	0.01	0.06	−0.07
February	3.98	0.00	5.09	0.06	0.05	0.92	0.34	1.26	0.23	0.03	−0.02	0.22	0.08
March	2.62	−0.13	4.36	−0.22	0.13	0.29	0.41	0.88	0.10	0.01	−0.01	0.05	0.00
April	1.44	−0.06	1.27	−0.26	0.11	0.34	0.21	0.16	1.10	0.06	−0.02	0.10	0.01
May	1.18	0.05	1.78	0.05	0.10	0.36	0.04	−0.20	1.27	0.08	−0.03	0.22	0.04
June	2.35	0.09	2.26	−0.02	−0.02	−0.20	−0.11	−0.38	0.43	0.02	−0.01	0.24	−0.07
July	3.13	0.08	3.25	0.04	0.09	0.24	−0.01	−0.42	−0.37	−0.02	0.01	−0.17	0.04
August	3.63	0.05	3.15	−0.01	0.06	0.52	0.15	−0.09	−1.53	−0.08	0.03	−0.18	0.09
September	3.07	0.05	2.87	0.14	−0.05	−0.22	0.09	0.28	−0.53	−0.01	−0.01	−0.02	0.09
October	3.28	0.08	2.12	0.08	0.03	0.80	0.09	0.06	−0.83	−0.05	0.02	−0.06	0.01
November	1.36	−0.06	2.32	−0.12	0.12	0.47	0.07	−0.08	1.43	0.08	−0.03	0.17	−0.02
December	2.45	0.07	3.65	0.07	0.11	0.07	0.08	−0.12	0.83	0.02	0.00	0.01	0.05

* Relatively variation.

Table 4
Monthly shifts based on PRECIS projections for the periods of 1961–1990 and 2041–2070.

Month	Maximum temperature (°C)		Minimum temperature (°C)		Monthly precipitation (mm)		Daily precipitation (mm)		Number of rain days	$P_{(W/W)}$	$P_{(W/D)}$	Length of wet spell*	Length of dry spell*
	Mean	SD*	Mean	SD*	Mean	SD*	SD*	Skewness*					
January	2.47	−0.09	2.96	−0.12	0.43	0.70	0.40	0.29	1.70	0.06	0.00	0.12	−0.10
February	2.13	−0.09	1.94	−0.12	0.20	0.72	0.30	0.37	0.77	0.03	−0.01	0.00	0.08
March	1.14	0.08	1.52	0.13	0.18	0.28	0.26	0.05	0.17	0.03	−0.03	0.16	0.15
April	1.28	0.07	1.47	0.08	−0.03	−0.08	−0.13	−0.22	0.03	−0.01	0.02	−0.14	−0.03
May	2.52	0.03	2.43	0.01	0.00	−0.20	−0.14	−0.44	−0.27	−0.03	0.02	−0.03	−0.06
June	3.32	−0.05	3.00	−0.05	−0.07	0.48	0.08	0.47	−1.27	−0.05	0.01	−0.12	0.06
July	4.03	0.07	3.38	0.03	−0.30	−0.25	−0.30	−0.24	−2.40	−0.07	−0.01	−0.15	0.21
August	3.51	−0.07	3.56	−0.01	−0.15	−0.08	0.01	0.05	−0.73	−0.03	0.01	−0.12	−0.03
September	3.14	−0.01	3.86	0.03	0.10	−0.03	0.08	0.10	0.83	0.01	0.02	−0.02	−0.09
October	4.05	−0.05	3.88	−0.04	−0.02	−0.13	0.01	0.40	−0.50	−0.03	0.01	−0.07	−0.02
November	2.13	0.06	2.15	0.02	0.15	0.13	0.20	0.06	0.03	−0.01	0.01	0.02	0.04
December	2.60	−0.02	2.63	−0.03	0.08	0.57	0.20	0.34	−0.43	−0.02	0.01	−0.08	−0.05

* Relatively variation.

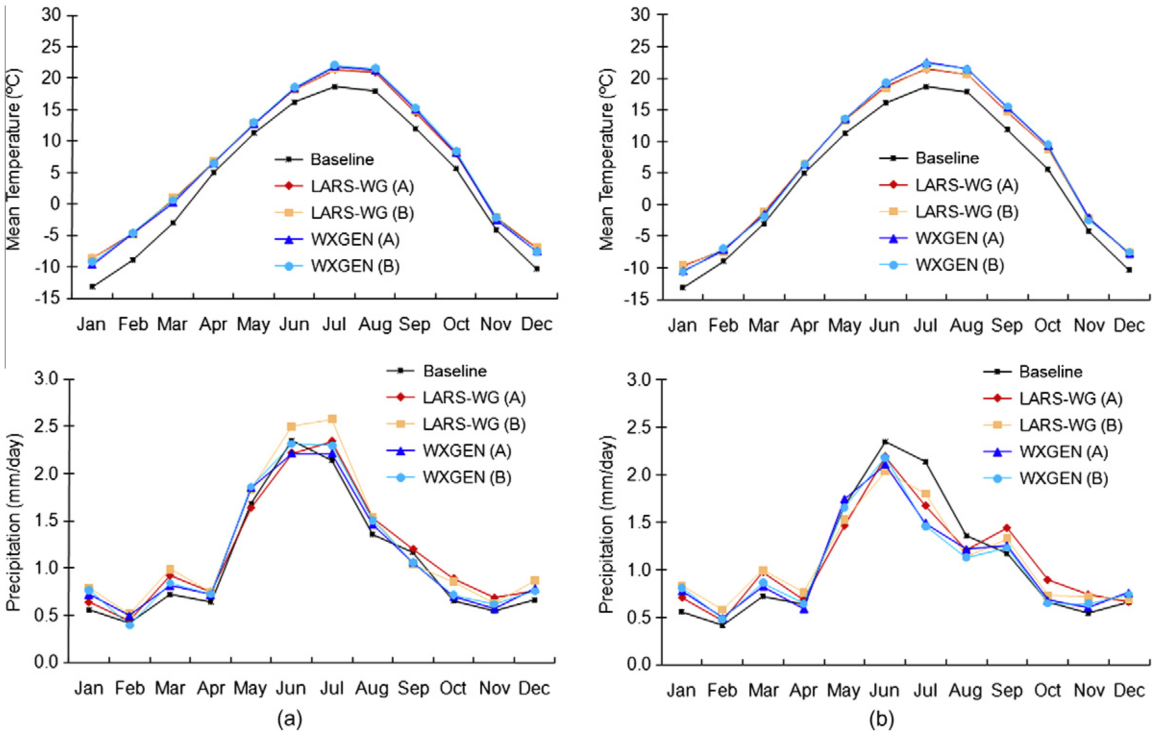


Fig. 4. Downscaled temperature and precipitation based on the outputs of: (a) CRCM and (b) PRECIS. (Note: the exclusion and inclusion of precipitation occurrence shifts are denoted by A and B, respectively.)

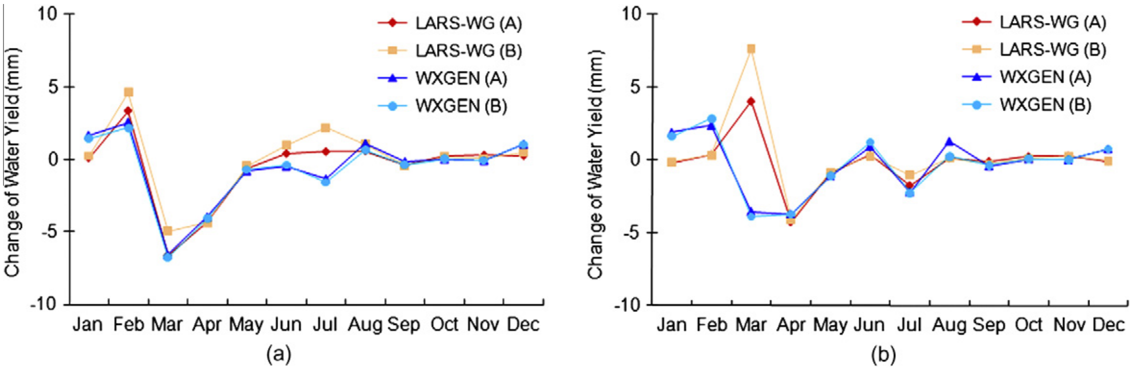


Fig. 5. Absolute changes of mean monthly water yields under the downscaled projections of: (a) CRCM and (b) PRECIS. (Note: the exclusion and inclusion of precipitation occurrence shifts are denoted by A and B, respectively.)

are presented in Fig. 6. Comparing with the baseline condition, Assiniboia experienced decreased ET during April through July, and the same or slightly increased ET for other months. This temporal pattern of ET changes was consistent with that of precipitation changes (Fig. 4). LARS-WG generally resulted in larger ET changes than WXGEN did, except for December and January. When precipitation occurrence shifts were incorporated, ET further increased through LARS-WG, but remained the same magnitude through WXGEN. For example, in CRCM scenarios, the intensified rainfall caused the monthly ET to increase 4.3 mm, 8.0 mm and 8.1 mm for May, June and July, respectively though LARS-WG. Figs. 4–6 also suggest that the sensitivity of LARS-WG to precipitation occurrence changes had consistent effects on simulated runoff and soil moisture at the watershed level.

4.3.3. Reservoir storage

The relative changes of monthly reservoir storage are plotted in Fig. 7. Overall, storage decreased in both reservoirs through the year, especially in spring and summer. The Old Willows Reservoir was more sensitive to climate change impact. Its storage variation generally matched the fluctuation of water yield (Fig. 5), suggesting a negligible transmission loss through channel system. Storage changes of the Willows Reservoir were less significant due to the regulation of its upstream counterpart. Different downscaling approaches resulted in diverse projections, particularly for the Old Willows Reservoir. In terms of RCM, the magnitude of storage changes was continually decreasing from spring (18%) to fall (4%) in CRCM scenarios, but such a seasonal pattern was not clear in PRECIS scenarios. In terms of SWG, LARS-WG generally led to more reservoir storage than WXGEN did. Resulted uncertainties particularly lay in two sensitive periods. For July–August in CRCM scenarios, LARS-WG generated positive changes (high as 8%), while WXGEN had negative estimations (low as −7%). For March in PRECIS scenarios, the storage increased up to 10% through LARS-WG and decreased up to 11% through WXGEN. When precipitation occurrence shifts were included, intensified precipitation caused enhanced reservoir storage through LARS-WG, but had insignificant effects through WXGEN.

The two reservoirs are at the core of water resource management in the Assiniboia watershed. The impacts of climate change on reservoir performance are important to community economy and health issues. The simulated reservoir storage changes have significant implications on community water supply. For example, estimated storage change for July ranged from −9% to 8%, indicating a possible water level change over 1 m. As reservoir storage reaches its lowest in summer, such uncertain predications can cause difficulties in making decisions such as whether the inlet of water treatment plant should be relocated.

5. Discussion

In climate change impact studies, it was common to change the mean and variance of precipitation amount based on the monthly shifts predicted by GCMs/RCMs, but the structure of precipitation occurrence was unchanged. An important reason for the exclusion of precipitation occurrence was that daily-scale GCMs/RCMs data was not available or not reliable enough (Toews and Allen, 2009). Such exclusion was assumed to be acceptable for cold regions where the most important hydrological features were linked to snow accumulation and snowmelt (Minville et al., 2008). However, the results of this study demonstrated that the effects of changed precipitation occurrence were complicated and important to climate downscaling and hydrological modeling in the Canadian Prairies. We found that using precipitation occurrence shifts in SWGs

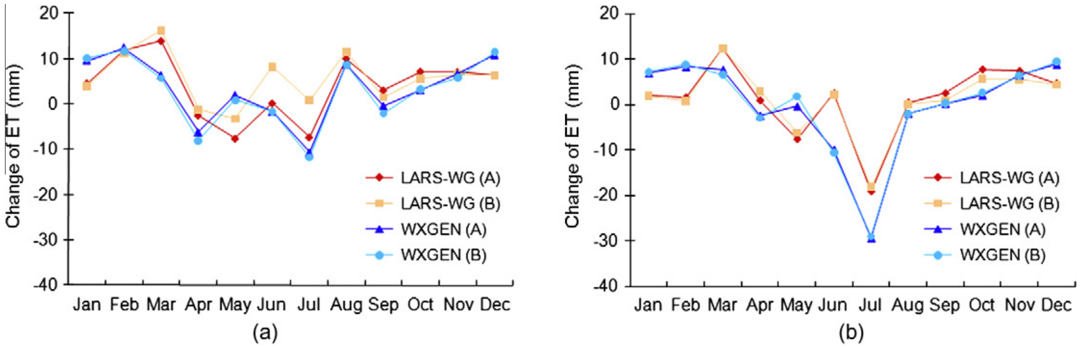
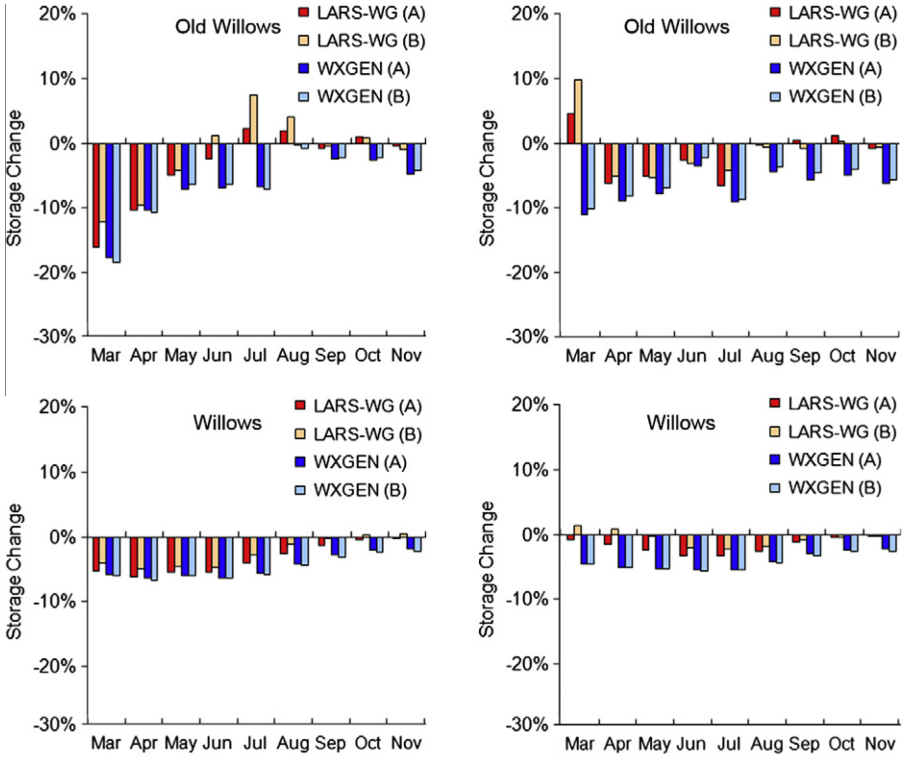


Fig. 6. Absolute changes of mean monthly evapotranspiration under the downscaled projections of: (a) CRCM and (b) PRECIS. (Note: the exclusion and inclusion of precipitation occurrence shifts are denoted by A and B, respectively.)



(a) (b)

Fig. 7. Relative changes of monthly reservoir storage under the downscaled projections of: (a) CRCM and (b) PRECIS. The values for January, February and December are excluded because the hydrological model can hardly analyze the water balance when the reservoir is persistently frozen. (Note: the exclusion and inclusion of precipitation occurrence shifts are denoted by A and B, respectively.)

not only changed spell length and transition probability, but also led to additional changes in monthly mean precipitation and mean temperature; this was consistent with the findings by Katz (1996). These effects were then translated into great variations in hydrological processes (e.g., further augmented ET in summer as shown in Fig. 6b). The profound influences of precipitation occurrence on climatic and hydrological variables were mainly due to its unique role in the stochastic weather generation process. Monthly precipitation amount was associated with precipitation occurrence through the number of wet days. In LARS-WG, daily temperatures were considered as stochastic processes with their means and standard deviations conditioned on the wet or dry status of the day through separated Fourier series; in WXGEN, daily maximum temperature were conditioned to the precipitation status by separated cosine functions (Semenov et al., 1998). The change in precipitation occurrence thus brought unanticipated disturbance into the downscaling that was additional to the pre-defined monthly shifts, and resulted in more uncertainties in hydrological modeling driven by downscaled climate. On the other hand, the information of precipitation occurrence was indeed a valuable component of RCM outputs, because it could improve our understanding on the effects of regional-scale forcings (such as orography and land cover) on precipitation formation and distribution. Therefore, A balance is desired between the information loss and the additional uncertainty for effectively utilizing the changes of precipitation projected by RCMs.

There were several limitation of the integrated downscaling approaches presented in this study. Firstly, there was a loss of trend information that was possibly contained in the raw RCM outputs. Because RCM simulations were continuous processes, climatic variability of one year was not only driven by the boundary conditions given by the GCM on that year, but also conditioned to variations of previous time steps. The tendency hidden in the interannual variability of climatic variables, if there was any, could not be fully reflected through monthly shifts that were only the averaged differences between simulation results of two 30-year time slices. Furthermore, SWG treated each year as an independent period. All of the years were equally plausible "realisations" of the same climate normal, but their sequences did not form a reasonable time series. However, this limitation was of minor importance to the present study, because that the performance of current RCMs on time series simulation was not effectively validated yet and that the estimation of multi-year averages would be more meaningful than the forecast of a single year for most impact studies. Another limitation of this study was the use of only one emission scenario. The A2 emission scenario used in this study was one of the scenarios recommended by IPCC for inter-comparison studies. IPCC provided 40 scenarios under four large families, but RCM outputs were only available for a few of them through several continent-scale inter-comparison projects such as the ENSEMNBLES Project and the PRUDENCE Project in Europe and the NARCCAP Project in Northern America (Christensen et al., 2008; Fischer and Schar, 2010; Fowler et al., 2007). This was mainly due to the lack of boundary data from GCMs and the extensive computation cost of RCM runs. In terms of methodology, the present integrated downscaling approach should have no difficulties in incorporating more emission scenarios in the future studies.

6. Conclusions

This study used multiple integrated downscaling methods coupled with distributed hydrological modeling to examine the hydrological responses of small prairie wetlands to climate change.

Comparing to baseline conditions, annual water yield and ET in 2050s were largely unchanged, while annual reservoir storage was generally reduced. However, projected hydrological regimes were less consistent at monthly level, particularly for March and July. These uncertainties in simulated hydrological responses were derived from the implementations of different integrated downscaling methods, reflecting our imperfect knowledge of the future climate. Overall, we was able to identify a warming temperature trend from climatic projections, but had less confidence in the future pattern of precipitation at both monthly and daily scales. Uncertainties in integrated downscaling were primarily derived from the choice of RCM, and were then amplified through the incorporation of different weather generators. Each combination of RCM and weather generator constituted a plausible solution of projecting future climate at regional scale, but none of them was superior to others. Therefore, results of any impact study based on only one RCM and one weather generator should be interpreted with caution, and the multi-model framework should be advised for generating a comprehensive vision of the future climate. Furthermore, this study demonstrated that the incorporation of precipitation occurrence change contributed to a full translation of RCM outputs, but introduced additional uncertainty at the same time. A balance is thus desired between the information loss and the additional uncertainty in order to effectively utilize RCM outputs for regional impact studies.

This study provided insights into the challenges that climate change could impose on the water resources management in terms of extreme hydro-climatic events. On one hand, the findings of this study can benefit the assessment of long-term events such as drought. Most existing drought indexes use monthly precipitation and temperature as basic inputs, and some indexes may employ a simple accounting of hydrological balance. The projected variations in climatic and hydrological variables from this study are directly useful for exploring the characteristics of prairie hydrological and meteorological droughts in 2050s. On the other hand, this study can also facilitate the assessment of short-term events such as storm and flood. Most existing impact studies tend to focus on the change of precipitation amounts only; for example, see Toews and Allen (2009). We found that projections on future precipitation occurrence were uncertain and had considerable impacts on hydrological modeling. Information of precipitation time series allows strong links between the climatic models and the hydrological models that often operate at daily or finer steps, which is important to characterize storm and flood in prairie summers. Although this study was implemented in a small prairie watershed in southern Saskatchewan, the conclusions are generally applicable to other prairie regions because the methodology of integrated downscaling are not area-specific. To extrapolate this study to a broader geographic context, considerations on spatial patterns of climatic elements (e.g., precipitation gradient) and human interventions (e.g., water diversion for irrigation) will be needed to better explain the uncertainties in hydrological signals.

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