JOURNAL OF THE AMERICAN WATER RESOURCES ASSOCIATION

AMERICAN WATER RESOURCES ASSOCIATION

HYDROLOGICAL VARIABILITY AND UNCERTAINTY OF LOWER MISSOURI RIVER BASIN UNDER CHANGING CLIMATE[1]

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ABSTRACT: The lower Missouri River Basin has experienced increasing streamflow and flooding events, with higher risk of extreme hydrologic impacts under changing climate. The newly available North American Regional Climate Change Assessment Program (NARCCAP) climate projections were used as atmospheric forcing for Soil and Water Assessment Tool (SWAT) model which runs with varying potential evapotranspiration (PET) methods to assess the hydrological change and uncertainty of 2040-2069 over 1968-1997. The NARCCAP temperature and precipitation predictions were refined using a bias correction method. The results show that, following the seasonal variability of precipitation, various water fluxes would increase in most seasons except the summer. Expected precipitation tends to increase in intensity with little change in frequency, triggering faster surface water concentration to form floods. The greatest streamflow increase would occur from November to February, increasing by around 10% on average. An increase of 3% occurs in the other months except for July and August in which river discharge decreases by around 2%. The climate predictions contribute more uncertainty annually, but PET algorithms gain more influence in winter or when other weather factors such as wind play a relatively more important role on evapotranspiration flux. This study predicts an even wetter environment compared to the historically very wet period, with the possibility of more flooding.

(KEY TERMS: climate change; lower Missouri River Basin; hydrological variability; NARCCAP; SWAT.)

Qiao, Lei, Zaitao Pan, Robert B. Herrmann, and Yang Hong, 2013. Hydrological Variability and Uncertainty of Lower Missouri River Basin Under Changing Climate. *Journal of the American Water Resources Association* (JAWRA) 1-15. DOI: 10.1111/jawr.12126

INTRODUCTION

Floods have been the major natural hazard in the upper Mississippi River and lower Missouri River valleys. Within the past decades, the Mississippi and Missouri floodplains have experienced several large flooding events (e.g., 1973, 1993, and 2008). Nevertheless, flood risk has been increasing either by climate change or by land cover/use change and river engineering along the large rivers (Mississippi, Missouri, and Illinois rivers) and their tributaries (Belt, 1975; Pinter *et al.*, 2000; Criss and Shock, 2001; Pinter and Heine, 2005).

According to the Intergovernmental Panel on Climate Change (IPCC) report (IPCC, 2007), the global temperature rise has increased the evaporation rate and moisture-holding capacity in the atmosphere,

[1]Paper No. JAWRA-12-0268-P of the *Journal of the American Water Resources Association* (JAWRA). Received December 27, 2012; accepted August 5, 2013. © 2013 American Water Resources Association. **Discussions are open until six months from print publication**.

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which in turn alters the hydrological cycle and changes precipitation, and thus river discharges and soil water content. However, precipitation changes are not consistent seasonally and regionally, resulting in worsening expectations of water surplus and deficit problems in many areas worldwide (Milly *et al.*, 2005). In contrast with the dryness of the western United States (U.S.), especially for the Colorado River Basin (Christensen *et al.*, 2004; Christensen and Lettenmaier, 2007; Maurer, 2007; McCabe and Wolock, 2007), relative wetness (Douglas *et al.*, 2000; McCabe and Wolock, 2002; Mauget, 2003; Groisman *et al.*, 2004) has emerged over the mid-continental U.S. With a regional atmospheric simulation model, Pan *et al.* (2004) projected a "warming hole" in the 2040s over the central U.S., and suggested 21% more precipitation would fall in the upper Mississippi River Basin compared to the 1990s, which likely results in streamflow increase (50%) for this region through integrated simulations by a regional climate model (RCM) and Soil and Water Assessment Tool (SWAT) as reported by Jha *et al.* (2004). Stone *et al.* (2003) compared simulations with a coarse-resolution general climate model (GCM) and a fine-resolution RCM which was nested in the GCM. They suggested that water yield would increase in the lower Missouri River Basin (LoMRB), though the fine-resolution climate scenarios provided an overall greater increase.

Prediction of the climate change impacts on a regional hydrological system has inherent uncertainties, depending on the specific climate scenarios, spatial and temporal downscaling methods, and hydrological model structure, parameters, and related precision of input dataset. The two general methods generating fine-resolution meteorological variables from GCMs' dynamical downscaling (Takle *et al.*, 1999; Mearns *et al.*, 2009) and statistical downscaling (Wilby and Harris, 2006; Maurer *et al.*, 2007), can introduce more uncertainty in addition to inheriting the GCMs' uncertainty (Wood *et al.*, 2004; Castro *et al.*, 2005; Fowler *et al.*, 2007; Lo *et al.*, 2008). Some studies found that climate models constituted the largest source of uncertainty in predicting hydrological responses to climate change (Arnell, 2004; Minville *et al.*, 2008; Prudhomme and Davies, 2009a, b). Others, however, argued that the uncertainty of climate change impacts could be significantly amplified when using a variety of hydrological models that have different structures, parameter sets, and potential evapotranspiration (PET) computations (Butts *et al.*, 2004; Jiang *et al.*, 2007; Clark *et al.*, 2008; Bae *et al.*, 2011).

As stated above, the assessment of climate change impact on hydrological systems must deal with two major sources of uncertainty: (1) the uncertainty of climate scenarios that are generated by climate models including GCMs and RCMs and (2) the responding hydrological models comprising of different physical structures and mathematical parameterizations. Both are very complicated to be exactly quantified. Multimodel ensembles and stochastic weather realizations are commonly used to quantify climate change uncertainty, but they are also within the range of available climate models resulting from uncertain estimates of greenhouse gas emissions and other perturbations such as aerosols, clouds, and land covers. Similarly, the hydrological models encounter the equifinality problem related to parameter compensations, the quality of input data for model calibration and validation, and the reliability and stability of model predictions with time extension. Of these problems, the parameter uncertainty is relatively feasible to be physically quantified through parameter space exploration (Abbaspour *et al.*, 2004; van Griensven *et al.*, 2006; Yang *et al.*, 2008; Zhang *et al.*, 2009).

In this study, the hydrological variations due to climate change in the LoMRB are investigated using the SWAT model, which was well benchmarked with multisite river gauges, gravity recovery and climate experiment data, and groundwater head observations from a large number of wells (Qiao *et al.*, 2013). Compared with single-gauge calibrated models which are likely to improperly partition water fluxes (e.g., evapotranspiration [ET], surface flow, and base flow) and water storages (e.g., soil storage and shallow aquifers), the multisite calibrated SWAT model in this study had high agreement with various sources of observations and the parameter uncertainty such as the equifinality problem caused by parameter interactions was greatly reduced. The climate change scenarios are based on the newly available North American Regional Climate Change Assessment Program (NARCCAP) dynamically downscaled climate variables. Specifically, the RCM/GCM combinations of International Centre for Theoretical Physics RCM version 3/Geophysical Fluid Dynamics Laboratory (RCM3/GFDL), Canadian RCM version 4/Canadian Global Climate Model version 3 (CRCM/CGCM3), and United Kingdom Hadley Centre Regional Model version 3/Hadley Centre Climate Model version 3 (HRM3/HADCM3) were used as atmospheric forcing to the SWAT model which runs, respectively, with three PET methods of Penman-Monteith (PM) (Penman, 1956; Monteith, 1965; Allen, 1986), Priestley-Taylor (PT) (Priestley and Taylor, 1972), and Hargreaves (Hargreaves and Samani, 1985) to assess the hydrological changes in 2040-2069 relative to 1968-1997. We chose three of the four NARCCAP GCMs combined with three unique RCMs for maximally incorporating climate projection uncertainty. Some researchers, i.e., Jiang *et al.* (2007) and Bae *et al.* (2011), studied uncertainties derived from hydrological modeling sources, however, the uncertainties from PET selections and other hydrologic model components were not differentiated, and more importantly, the exploration of potential causations to seasonality of uncertainties was inadequate. Therefore, this article also tries to evaluate how PET computation changes modulate hydrological uncertainty and to what extent it compares with the uncertainty arising from climate models in a finer spatial and temporal scale.

The section Study Area Hydrology History of this article describes the historic hydrological regime of the study area. The section NARCCAP Simulations and Bias Correction provides description of the NARCCAP climate projections and explores their pros/cons by comparison with historical observations and applies a bias correction procedure to improve their accuracy for hydrological simulations. The Results and Discussion section analyzes the results of climate change and its impact on the hydrological system in the LoMRB and discusses the potential influence on water issues and the manner of interaction between the sources of uncertainty. The Summary section presents conclusions from the results and discussions of this study.

STUDY AREA HYDROLOGY HISTORY

The Missouri River Basin has a drainage area of 1,370,000 km^2 with elevation range from 120 m to 4,399 m, within which the Missouri River flows from northwest to southeast over a distance more than 4,000 km and finally flows into the Mississippi River just upstream of St. Louis. The LoMRB that covers most of Missouri and marginal parts of Kansas and Iowa, accounts for 10% of the area of the whole basin, but provides more than 50% of river streamflow at the outlet (gauge Hermann) due to the very high precipitation in the lower basin. In this study, the LoMRB is divided into three subbasins measured by three river gauges: Boonville at Missouri River, Hermann at Missouri River, and St. Thomas at Osage River (Figure 1).

Historical observations based on National Oceanic and Atmospheric Administration (NOAA) Climate Prediction Center Precipitation records and the U.S. Geological Survey water information website (http://waterdata.usgs.gov/nwis) show that the Missouri

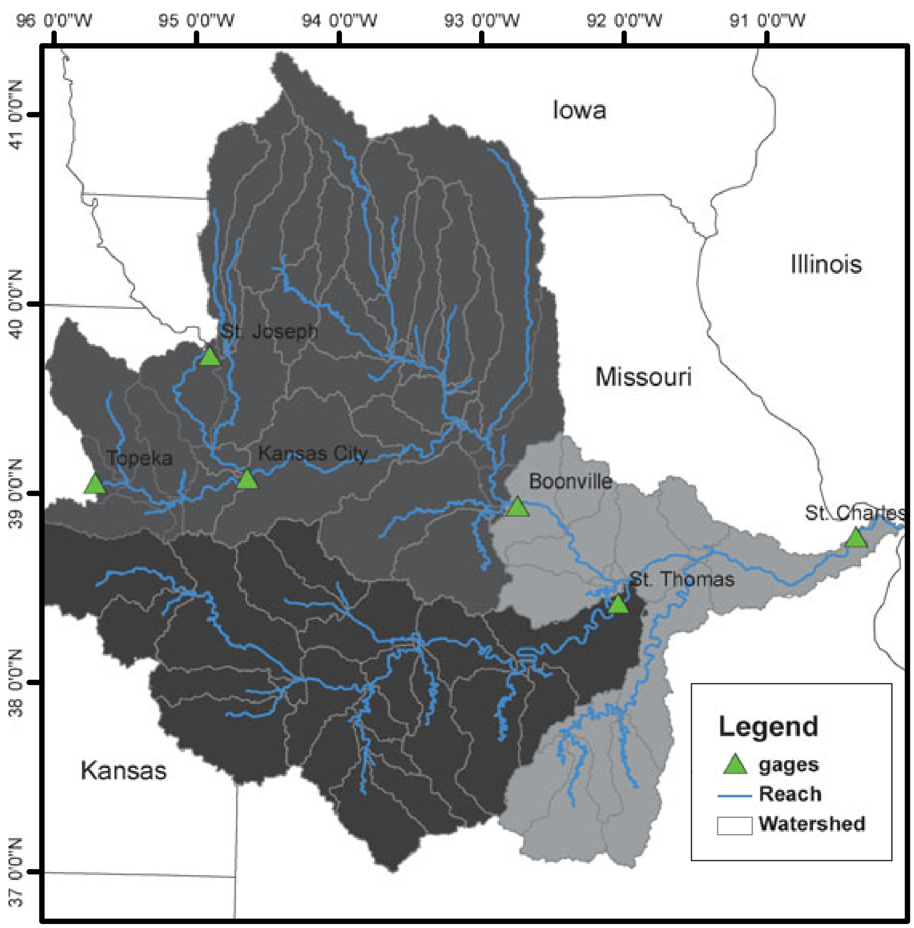

FIGURE 1. The Study Area, Lower Missouri River Basin, with River and Watershed Features. The gauges at Boonville, Osage River below St. Thomas, and St. Charles were the outlets for the three subwatersheds.

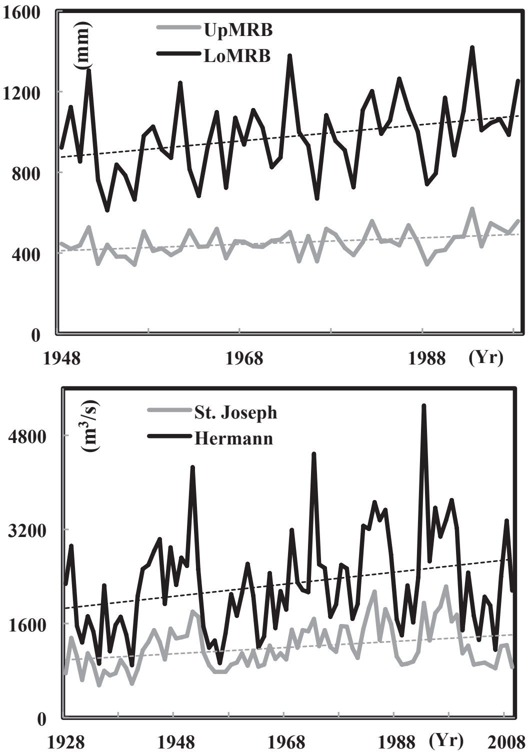

FIGURE 2. The Annual Precipitation (a) in the Upper and Lower Missouri River Basin and the River Discharges (b) of the Missouri River at the Gauges of St. Joseph and Hermann, Missouri.

River Basin has experienced increasing precipitation and streamflow during the 20th Century and that the lower basin, as a gaining system, produces larger flow rate and interannual varying breadth than the upper basin (Figure 2). The higher interannual variability indicates that the lower basin is more subject to extreme event impacts like droughts and floods.

NARCCAP SIMULATIONS AND BIAS CORRECTION

The NARCCAP is the most comprehensive regional climate modeling project for the North America (Mearns *et al.*, 2009, 2012). Four GCMs were chosen in the project to provide boundary conditions to six RCMs for running fine-resolution (50 km) regional climate simulations for the historic period 1971-2000 and the future period 2041-2070. The A2 scenario that the global average CO_2 reaches 850 ppm by 2100 is the only emission scenario in NARCCAP. This represents a very high but not the greatest climate change in the IPCC Special Report on Emission Scenarios (IPCC, 2000). For pure RCM evaluation, the project also includes the reanalysis data produced by the National Centers for Environmental Prediction (NCEP) and the U.S. Department of Energy to drive the RCMs in the time period 1979-2004. Gutowski *et al.* (2010) examined the NARCCAP's RCM simulations and found the models replicated very well the interannual variability in occurrences of extreme events. Here, we chose three different RCM/GCM simulation products from the NARCCAP archive. There is no model overlapping among these three RCM/GCM combinations to capture a wide range of climate variations from climate models. For example, if we choose different RCMs with the same GCM, the uncertainty would be underestimated because it removes the uncertainty caused by the GCM. The meteorological variables input for SWAT generally include precipitation, temperature, humidity, wind, and solar radiation, which are provided by NARCCAP in 3-h time scale except the daily temperatures.

Although the NARCCAP simulations provide effective high-resolution weather variables, they are still biased when compared with observed data. In this study, bias means a difference between observed and predicted variables. Bias corrections to the GCM output and downscaled products have been widely used to improve climate impacts assessment in regional scale (Wood *et al.*, 2002; Ines and Hansen, 2006). The University of Washington's (UW's) gridded precipitation and temperature (Maurer *et al.*, 2002) were used as observation reference in our study. The dataset is in one-eighth degree grid size, which is interpolated with elevation effects correction by the Parameter-Elevation Regressions on Independent Slopes Model (Daly *et al.*, 1994).

Our bias correction is applied to daily NARCCAP variables of precipitation and maximum and minimum daily temperatures for each grid in the study basin. Specifically, the correction steps include the following:

1. Resize and transform the UW data into NARCCAP's georeference system to make spatial agreement between the two types of dataset.
2. Sort the variables, and select the observed precipitation values that are greater than 0.1 mm (rainy days) and select the simulated precipitation to determine the total number of rainy days equal to the selected observations. Sometimes, the rainy days cannot be kept equal if simulations have fewer rainy days than observations.
3. Build up cumulative density function (CDF) for observations and NARCCAP simulations grid point by grid point and month by month. A gamma fitting curve is applied to the precipitation

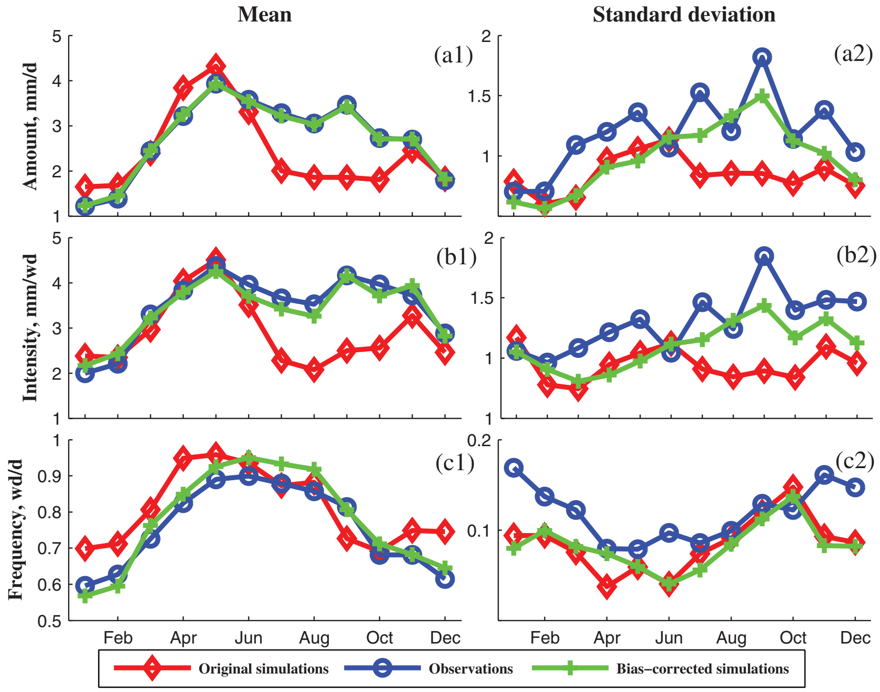

FIGURE 3. Comparison of Observation and Original and Bias-Corrected CRCM/CGCM3 Simulations in Precipitation Amount (a1, a2), Intensity (b1, b2), and Frequency (c1, c2). Left column (a1, b1, c1) is interannual mean, and the right column (a2, b2, c2) is standard deviation for the historical period (1968-1997).

data, whereas temperature is modeled with empirical CDFs.

4. Equalize the CDF between historical simulations and observations by multiplication for precipitation and by addition for temperature, and record the alternations for each percentile and apply them to the future climate predictions.

This procedure can correct the intensity and frequency of precipitation at most grids/locations in the study area. However, it underestimates frequency when the simulations have more nonrainy days than observed, because the zero values have to be excluded when doing gamma fitting. Figure 3 shows the comparison of UW data and original and bias-corrected CRCM/CGCM3 simulations in precipitation, which are averaged from all the grids in the study area. The left column (a1, b1, c1) is interannual mean, and the right column (a2, b2, c2) is standard deviation in the historical period. After bias correction, the mean values in cumulative amount, intensity, and frequency are much closer to observations, whereas the standard deviations are still lower in spite of being improved. The lower interannual variability in the precipitation simulations suggests that the climate models tend to distribute water more evenly in temporal dimension, although the total amount is corrected. Figure 4 shows the result for maximum daily temperature correction. Compared with precipitation, the temperature can be corrected in both mean values and standard deviations, especially for the mean values that agree very well with the observations. Bias correction to minimum daily temperatures (data not shown) also performs well for the maximum temperature.

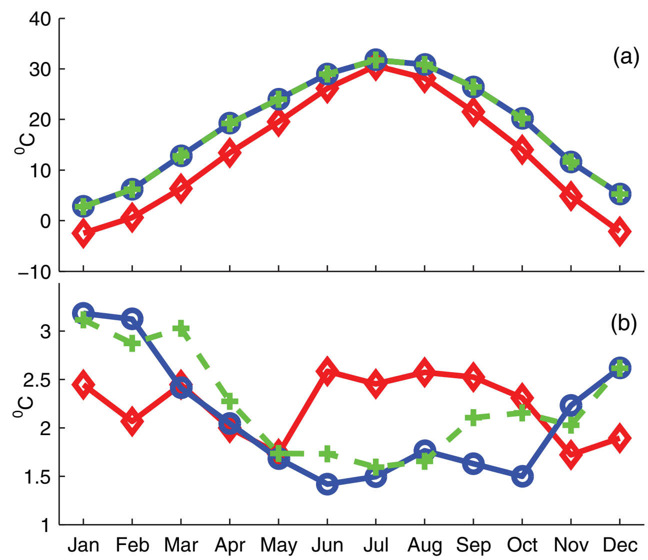

FIGURE 4. Similar to Figure 3, but It Is for (a) Mean and (b) Standard Deviation of Maximum Temperatures.

RESULTS AND DISCUSSION

Historical Hydrologic Evaluations with SWAT

We calibrated and validated the SWAT model with the PM method over the period 1998-2009, for which the model can maintain water balance well with excellent simulations of streamflow and the total water and groundwater storages, suggesting that the ET flux was also partitioned at a correct level (Qiao *et al.*, 2013). However, the same model overpredicts streamflow and underpredicts ET with the PM and PT methods over the period 1968-1997. The causes of this problem could be the input forcing which is from different sources for the two time periods (more discussions in following text about Figure 6). Figure 5 shows the interannual means of streamflow simulation for the three gauges of Hermann (a1-a3), Boonville (b1-b3), and St. Thomas (c1-c3) over the historical period from 1968 to 1997. Different atmospheric forcing sources of the UW's data and original and bias-corrected NARCCAP are used with different PET methods in SWAT simulation. For comparison, the streamflow observations are also displayed in this figure. As can be seen, the bias-corrected atmospheric inputs can provide much better streamflow simulations than the original ones for all the river gauges, whose performance is even better than the UW's data. The sensitivity of simulations with the UW's data and bias-corrected NARCCAP is much larger than that with original NARCCAP dataset. Generally speaking, the bias-corrected NARCCAP inputs can be used to replicate well the monthly variation in streamflow, including the dual peak of annual river flow as depicted by observations, whereas the application of original NARCCAP inputs overpredict the streamflow with a single peak throughout the year.

The PM method is the most complicated, combining both energy and atmospheric controls that consider all aspects of weather impacts, including wind, solar radiation, and relative humidity, along with the temperature which is a requirement of all PET methods. The PT method estimates the PET with the energy controls but does not include wind effect. The Hargreaves method only accounts for temperature effect in PET computation. Table 1 provides the required weather inputs for PET calculation with the three methods. The major reason, causing the ET to be underpredicted by the PM and PT methods, probably arises from the errors in weather datasets which are from different sources for the two time periods. In the SWAT calibration period (1999-2009), we used the data from 36 precipitation and 33 temperature

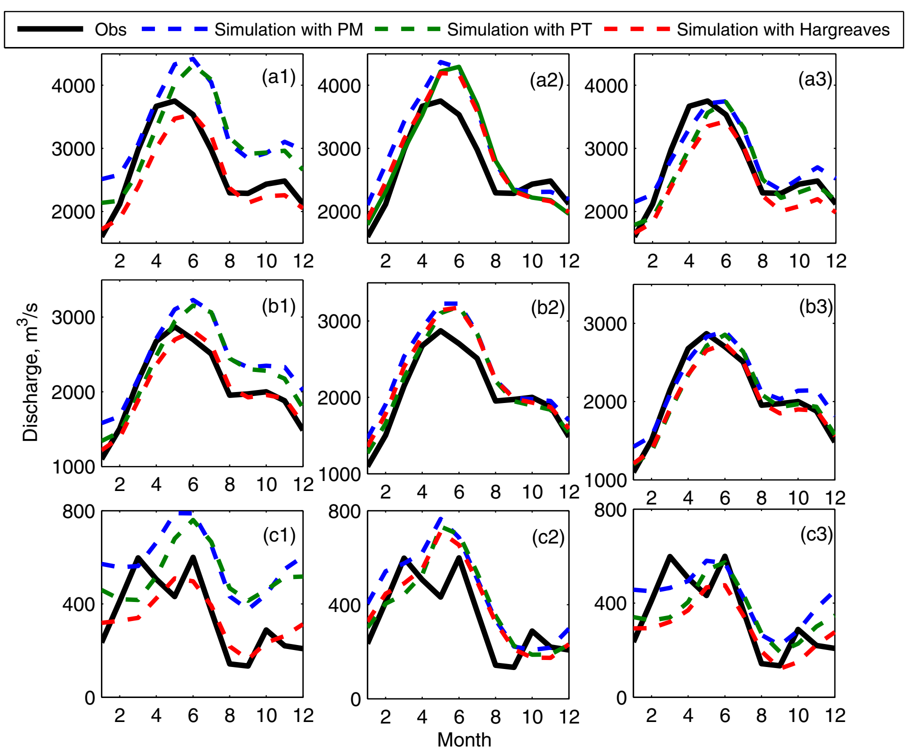

FIGURE 5. Monthly Streamflow Means at the Three Gauges of Hermann (a1-a3), Boonville (b1-b3), and St. Thomas (c1-c3) for the Historical Period between 1968 and 1997. The columns from left to right are, respectively, the simulations with University of Washington data and original and bias-corrected North American Regional Climate Change Assessment Program weather variables.

TABLE 1. Potential Evapotranspiration (PET) Methods and Required Weather Inputs in Soil and Water Assessment Tool.

PET Method	Data Inputs
Penman-Monteith (PM)	Temperature, solar radiation, wind speed, and air humidity
Priestley-Taylor (PT)	Temperature, solar radiation, and air humidity
Hargreaves (Har.)	Temperature

gauges evenly sampled from the National Climate Data Center. Solar radiation, wind speed, and relative humidity were retrieved from the National Centers for Environmental Prediction/North American Regional Reanalysis (NCEP/NARR) dataset. Unlike the minor difference in extensively measured temperatures, other variables such as solar radiation depend heavily on estimation methods. The solar radiation from the NCEP-NARR turned out to be highly overestimated (Figure 6). Therefore, the model could underpredict the ET when using relatively underestimated solar radiation that was generated by the default weather generator (WXGEN) (Sharpley and Williams, 1990) in SWAT for the period 1968-1997. Of course, the errors from other weather variables such as precipitation, wind, and relative humidity and from the parameter uncertainties and model structures could also make hydrologic simulations unstable for the two different time periods. Overall, the wide spread in simulations using the different PET methods cover the observations reasonably well (Figures 5a3, 5b3, and 5c3), which indicates it would be more acceptable to take advantage of all the PET methods in understanding the basin's hydrologic responses to climate change.

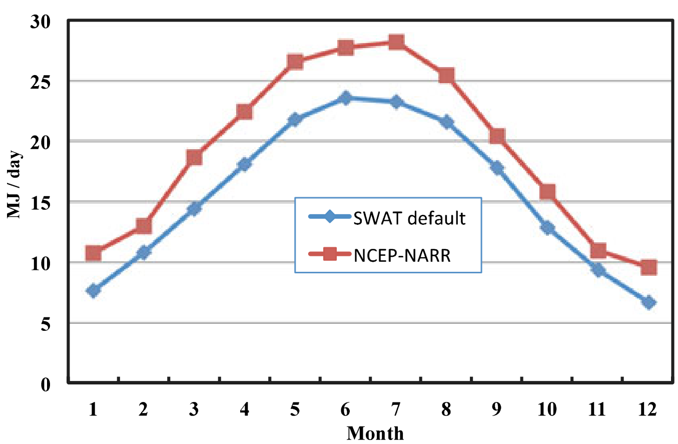

FIGURE 6. Short Wave Solar Radiation Comparison in the Lower Missouri River Basin from National Centers for Environmental Prediction-North American Regional Reanalysis (NCEP-NARR) and Soil and Water Assessment Tool (SWAT) Default Database.

In addition to the interannual mean, Figure 7 shows standard deviations of streamflow for the gauge Hermann from observation and the SWAT simulations with the different weather variables. The streamflow simulations are averaged from the results of the three PET methods, and for NARCCAP the three RCM/GCMs are also averaged. The UW data drive overprediction of streamflow, but provide a better agreement in interannual variability. Bias-adjusted NARCCAP data can provide better mean streamflow than their originals, but the interannual variability is still underpredicted as in the original model, suggesting that climate models intrinsically tend to distribute precipitation more evenly in temporal dimension and barely trigger extreme streamflows as those in reality. Although the bias correction procedure has produced good matches for precipitation amount, intensity, and even frequency, it is unable to change the timings of precipitation. As a result, the same amount of rainfall distributed in different consecutive wet days could definitely yield different streamflows.

Climate Changes from the NARCCAP RCM/GCMs

Changes of temperature and precipitation, the two major concerns in climate change impact studies, are quite uncertain seasonally and spatially given the wide ranges of climate model projections. Globally, GCMs project an increase in mean surface air temperature between 1.8 and 5.4°C in the current century, with much more disagreement on the precipitation changes. We chose three of the four GCMs utilized by NARCCAP, which are combined with three unique RCMs for maximally incorporating climate projection uncertainty. In our study area, the averaged temperature from the three RCM/GCMs increases by around 3°C between the historical period, 1968-1997 and the future period, 2040-2069. The increase is consistent over each month throughout the year (Figure 8). However, for each specific RCM/GCM, the increase varies differently in seasons, with maximum increases of 5.5°C in winter by the HRM3/HADCM3 and 4.9 and 3.8°C in summer by the CRCM/CGCM3 and RCM3/GFDL, respectively.

Precipitation changes in monthly average are also different among the three NARCCAP selections. Figure 9 shows the averaged shift of intensity and frequency of precipitation relative to the historical observations from the UW data. Intensity change in extreme high precipitations is also shown to indicate potential flood in the future. Floods are more correlated with the extreme weather and the total precipitation increase does not necessarily imply increased flood expectation if the intensity of high precipitation decreases while the intensity of low precipitation

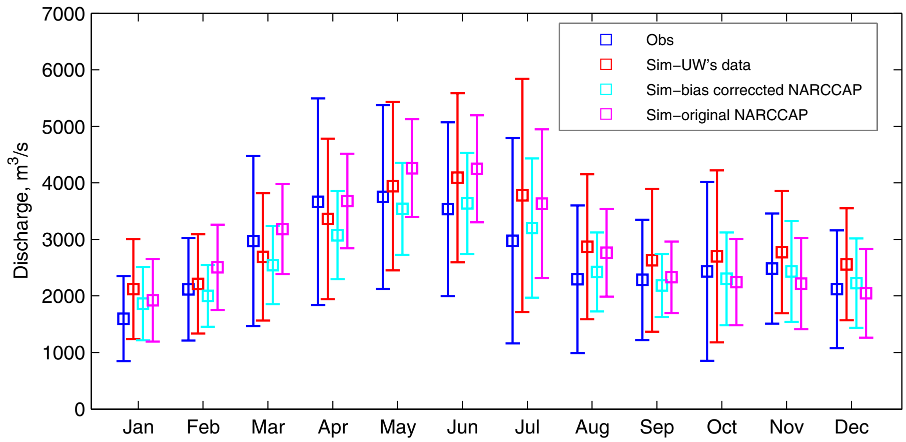

FIGURE 7. Monthly Means and Standard Deviations of Streamflow at Gauge Hermann at the Missouri River. The observation and the Soil and Water Assessment Tool simulations with University of Washington (UW) data and bias-corrected and original North American Regional Climate Change Assessment Program (NARCCAP) climate forcing are arranged from left to right for each month.

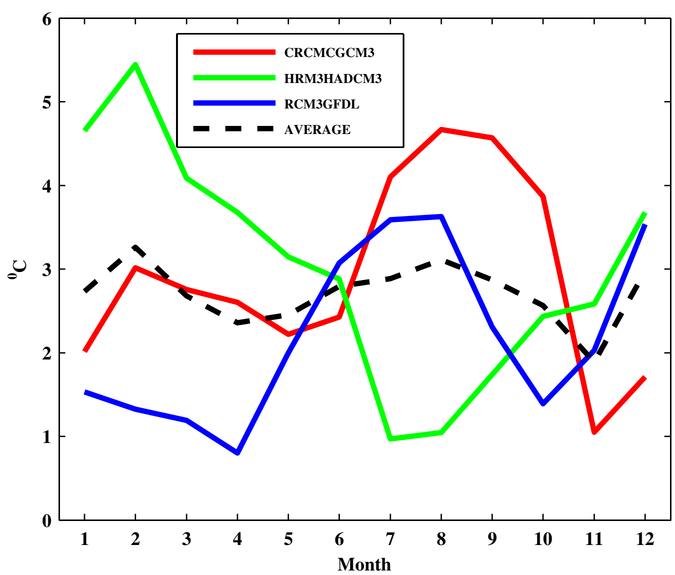

FIGURE 8. Temperature Changes between 1968-1997 and 2040-2069 from the Selected Three North American Regional Climate Change Assessment Program Regional Climate Model/General Climate Models (RCM/GCMs).

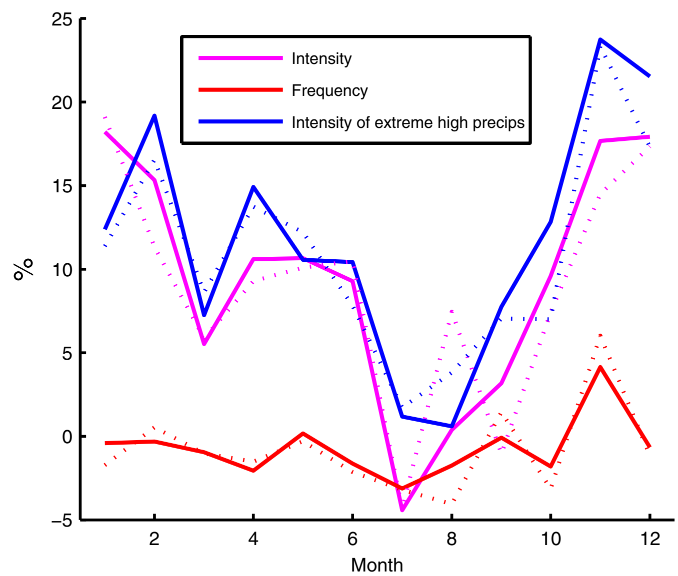

FIGURE 9. Averaged Shifts of Intensity and Frequency of Precipitation in 2040-2069 Relative to the Historical Observations from the University of Washington Data. Monthly change in intensity of extreme high precipitations is also shown to reflect potential flood in the future. The solid lines and dashed lines represent bias-corrected and original regional climate model/general climate models, respectively.

increases. Figure 9 suggests that intensities in both total and extreme high precipitations increase at an almost equal percentage level (slightly more increases in high precipitations) over each month, which have highest increase (20%) in winter, second highest increase (13%) in spring and autumn, and the least increase (even decrease in July) of less than 5% in summer. The frequency of precipitation is fairly constant and has no significant variation, suggesting that precipitation mainly increases through magnifying intensity, thereby the flood situations would become worse in the future relative to the historical period. The difference in relative changes between the two datasets of bias-corrected and original RCM/GCMs is minimal because the same relative base, the UW data, is selected.

Subbasin Streamflow Changes and Uncertainty

Figure 10 shows an ensemble of streamflow changes for the gauge Hermann. For consistent comparison,

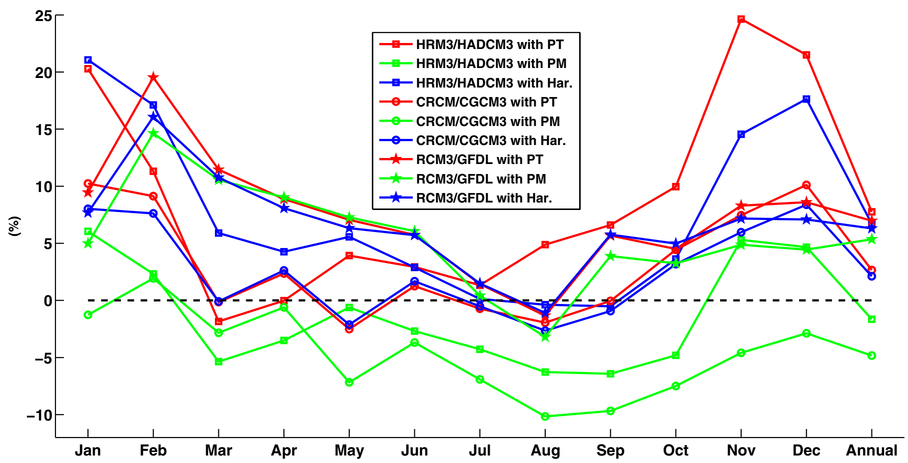

FIGURE 10. Ensemble of River Discharge Changes for the Gauge Hermann between the Two Periods of 2040-2069 and 1968-1997 from Different Combinations of Potential Evapotranspiration Methods and Regional Climate Model/General Climate Model (RCM/GCM) Inputs.

the base case is the average of simulations for the historical period using the UW data and the three PET methods. A wide range of streamflow change is shown because of varying combinations of climate models and PET computations in SWAT modeling. Consistent to the precipitation change (Figure 9), river flows predicted in most combinations have higher percent increases in winter and smaller or no changes in summer. However, the simulations with PM method predict the river discharges decrease in most months. Compared with the PM method, the streamflow changes are narrower if the PT and Hargreaves methods are selected. The PM and Hargreaves methods provide maximum and minimum breadths of streamflow change, respectively, because the former intakes all weather variables whereas the latter only considers temperatures. Here, we define the uncertainty as the breadth of projected variations of streamflow and other water components due to varying combinations of climate models and PET methods in SWAT modeling. The star-marked lines are close together rather than widely spread as the square and circle marked lines, suggesting that RCM3/GFDL predicts less variation in climate variables of wind, relative humidity, and solar radiation so that the effects of PET choice become negligible. The huge difference between predictions with PM and PT methods from the CRCM/CGCM and HRM3/HADCM3 outputs, respectively, indicates that wind changes could impose significant impacts on hydrology. More specifically, the tendency to predict streamflow reduction by using the PM method suggests that wind would increase, drive more water to be evaporated, and leave river flow decreased. The minor difference between PT and Hargreaves simulations suggests that changes in solar radiation and relative humidity do not have a significant influence on hydrology. Overall, the choices of PET computations affect the hydrologic change not only by magnitudes but also by uncertainty ranges.

Amplified uncertainties (e.g., Hermann discharge change spanning −4.8 to +7.8% in Table 2 compared with precipitation change spanning 10.5 to 2.2% in Table 3) have propagated into the hydrological variations due to complexities of climate and hydrological simulations and nonlinear effects of interaction between them. The monthly and annual streamflow change uncertainties specific to climate models and PET methods are shown in Figure 11. The uncertainty-specific analysis produced uncertainties from varying climate models under a specific PET method and uncertainties from varying PET methods under a specific RCM/GCM. The lines in the bars from top to bottom represent maximum, intermediate, and minimum uncertainties, respectively. Although the climate models as expected contribute more uncertainty annually and dominate in some months (March-June), in winter or when other weather factors like wind play a relatively more important role on ET flux, PET methods significantly perturb hydrologic simulations and increase uncertainties. The wide maximum-to-minimum variability of PET-driven uncertainties indicates that the PET computations respond to climate models very differently. As suggested in Figure 10, streamflow changes related to RCM3/GFDL are barely altered by PET methods, but those related to CRCM/CGCM and RCM3/GFDL behave oppositely. The climate models drive constantly high uncertainties regardless the PET choice, although the maximum uncertainties are all from PM method simulations, which indicate that climate changes only in precipitation and temperature could

TABLE 2. Average, Maximum, and Minimum River Flow Changes from the Three RCM/GCMs, Which Were Simulated with Three PET Methods by SWAT.

	Hermann at Missouri River			Boonville at Missouri River			Osage River below St. Thomas		
	Mean (%)	Max (%)	Min (%)	Mean (%)	Max (%)	Min (%)	Mean (%)	Max (%)	Min (%)
January	9.6	21.1	−1.3	7.8	13.9	2.1	13.5	34.0	−3.1
February	11.1	19.5	1.9	7.0	13.6	0.4	20.2	33.0	5.0
March	3.2	11.4	−5.4	0.8	6.9	−5.5	8.9	23.6	−6.5
April	3.5	9.0	−3.5	1.0	5.0	−3.2	11.2	20.5	−6.1
May	2.0	7.3	−7.2	0.6	4.6	−4.6	5.6	14.0	−11.6
June	2.2	6.1	−3.7	1.5	5.1	−2.7	5.2	11.3	−9.3
July	−0.8	1.5	−6.9	−0.4	2.3	−5.4	−2.0	8.0	−12.9
August	−2.5	4.9	−10.2	−1.2	5.6	−7.6	−7.7	5.3	−22.7
September	0.5	6.6	−9.7	1.9	9.0	−5.7	−2.8	10.3	−27.2
October	2.4	10.0	−7.5	3.3	10.9	−3.4	0.1	22.3	−21.5
November	8.2	24.6	−4.6	4.7	13.1	−2.0	20.5	54.2	−3.3
December	8.8	21.5	−2.9	5.9	13.1	−0.3	17.4	39.4	−3.9
Annual	3.5	7.8	−4.8	2.2	5.4	−2.8	7.7	13.8	−6.7

Note: RCM/GCMs, Regional Climate Model/General Climate Models; PET, potential evapotranspiration; SWAT, Soil and Water Assessment Tool.

TABLE 3. Average, Maximum, and Minimum Water Flow Changes from the Three RCM/GCMs Which Were Simulated with Three PET Methods by SWAT.

	% Precipitation			% Snowmelt			% PET			% AET		
	Mean	Max	Min	Mean	Max	Min	Mean	Max	Min	Mean	Max	Min
January	15.7	22.0	6.8	−7.7	6.9	−19.2	28.4	118.9	−17.9	28.3	82.7	−3.1
February	13.9	35.8	0.6	−18.5	9.5	−42.2	28.3	100.8	0.1	23.3	61.1	5.6
March	4.6	11.4	0.6	−105.8	−61.5	−155.3	19.8	58.6	6.3	15.7	31.9	5.7
April	8.6	12.2	6.6	−170.9	−20.4	−380.0	12.8	32.9	0.4	12.0	25.4	4.3
May	10.8	20.1	2.7	N/A	N/A	N/A	10.3	26.8	3.9	19.6	36.1	11.8
June	9.9	26.3	−3.6	N/A	N/A	N/A	10.8	20.7	0.9	23.4	30.2	12.0
July	−8.8	10.6	−25.5	N/A	N/A	N/A	13.4	29.2	−1.8	0.1	11.2	−7.9
August	−1.8	13.3	−23.4	N/A	N/A	N/A	14.3	42.5	−2.5	−19.2	−12.5	−33.7
September	6.4	19.5	−4.7	N/A	N/A	N/A	12.8	46.5	−0.1	2.4	9.6	−3.3
October	5.5	16.3	−11.0	N/A	N/A	N/A	11.7	38.2	−0.9	8.6	23.2	0.7
November	26.1	37.1	16.9	−71.6	−13.4	−135.5	9.3	40.0	−1.1	12.9	44.0	2.1
December	19.0	20.4	16.9	−35.4	12.6	−73.5	25.6	99.4	−7.8	28.3	87.3	6.6
Annual	7.7	10.5	3.2	−39.4	−29.9	−53.9	13.8	28.5	6.5	7.7	19.2	1.1

	% Percolation			% Overland Flow			% Base Flow			% Water Yield		
	Mean	Max	Min	Mean	Max	Min	Mean	Max	Min	Mean	Max	Min
January	28.5	41.4	4.7	9.5	52.5	−21.7	18.1	34.7	−2.9	16.8	36.8	−3.1
February	24.0	42.9	5.3	6.6	48.6	−26.5	24.6	40.4	8.9	20.4	36.5	3.6
March	−5.4	4.2	−13.7	−36.1	16.4	−84.3	18.2	30.0	−0.2	7.7	26.4	−11.2
April	−1.4	11.1	−19.9	22.4	42.2	−6.6	3.9	14.4	−8.5	7.9	20.4	−6.6
May	0.8	12.0	−19.0	23.8	43.9	−7.8	−1.1	8.9	−17.3	4.5	16.6	−15.2
June	1.6	9.9	−8.9	25.1	61.6	1.1	0.8	11.1	−16.3	4.5	10.6	−5.4
July	−10.7	6.8	−23.0	−7.0	15.0	−30.2	−0.9	3.5	−12.0	−1.6	3.5	−14.2
August	−4.4	75.0	−48.0	−8.8	113.8	−105.4	−5.2	7.3	−18.0	−5.3	13.0	−22.6
September	14.0	45.4	−31.0	20.6	48.9	−14.8	−2.5	31.1	−31.8	4.5	18.6	−21.0
October	−3.3	11.2	−23.8	14.6	80.2	−33.8	4.5	24.5	−30.2	6.8	26.1	−14.8
November	13.5	40.5	−4.5	70.1	166.6	25.5	4.5	25.0	−21.5	19.8	57.9	−10.4
December	24.3	43.3	8.2	41.9	65.5	19.9	11.0	33.4	−8.9	16.2	38.1	−4.0
Annual	5.4	14.4	−11.7	18.9	25.0	4.4	5.3	14.8	−12.6	7.8	16.7	−9.4

Note: RCM/GCMs, Regional Climate Model/General Climate Models; PET, potential evapotranspiration; SWAT, Soil and Water Assessment Tool; AET, actual evapotranspiration.

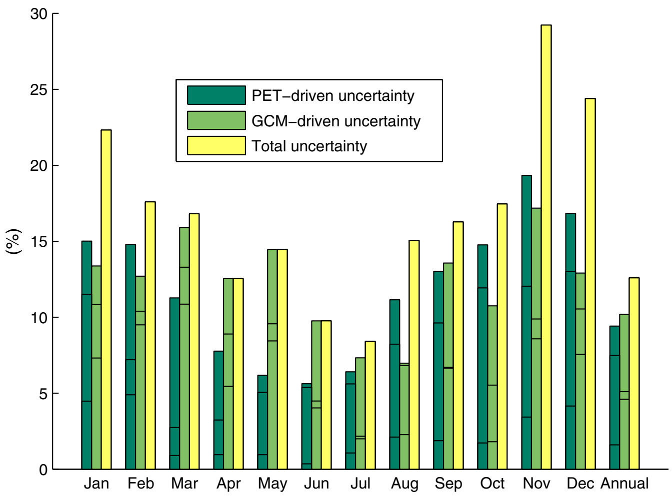

FIGURE 11. Uncertainties of River Discharge Changes at Gauge Hermann Derived Specifically from Potential Evapotranspiration Computations (PET), Regional Climate Model/General Climate Models (GCMs), and Both of Them.

be enough to significantly impact the hydrology in the basin. It is interesting to note that from March to July, the season with highest precipitation, most flooding days, and highest river discharge (Figure 5), the total uncertainties can be entirely attributed to the uncertainties derived from the climate models. During this season, the rainfall amount is large and the difference among climate model outputs overwhelm the relatively minor differences in ET flux due to PET computations. Thereby, more attention should be paid to climate models for wet seasons, whereas the selection of PET methods would be more important for dry seasons. The total uncertainty is not a simple addition of the maximums of the two specific uncertainty sources. It is impossible to completely separate one contributor from another because there is dependency relationship in that PET computation needs data from climate models; therefore, PET-driven uncertainty is partly attributed to RCM/GCMs.

We assume the upper basin contribution is constant, as it is less important to the whole LoMRB water budget as discussed in the section Study Area Hydrology History. In addition, the highly regulated dams in the upper basin could make the hydrological process unnatural and hard to be predicted. Here, we treat every alternative in the ensemble equally, as there is no solid evidence to exclude or prefer any one of them. Figure 12 shows ensemble means of streamflow changes for the three gauges in the study area. In addition to the average changes, maximum and minimum changes are shown in Table 2. Streamflow spatial variations generally are consistent in the LoMRB, with prominent increase in winter and intermediate increase in spring and autumn and a small decrease in summer. The higher decrease in streamflow and lower decrease in rainfall in August compared to July suggest the time lags between precipitation and runoff. The annual streamflow at Boonville increases by 2.22%, but the increase at St. Thomas is greater (with 7.73%), indicating that the proportion of water contribution from the Osage River would increase in the future time period.

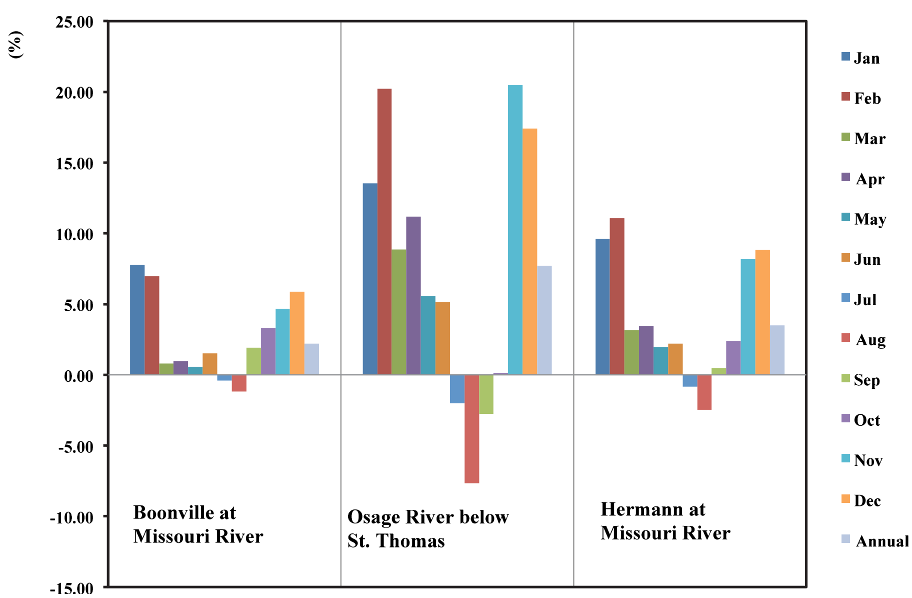

FIGURE 12. Ensemble Means of Streamflow Changes for the Three Gauges. Streamflow at Hermann is controlled by the streamflows from both Boonville and St. Thomas. Although the streamflow from Boonville still dominates in the lower Missouri River Basin, contribution from the Osage River would increase in the future.

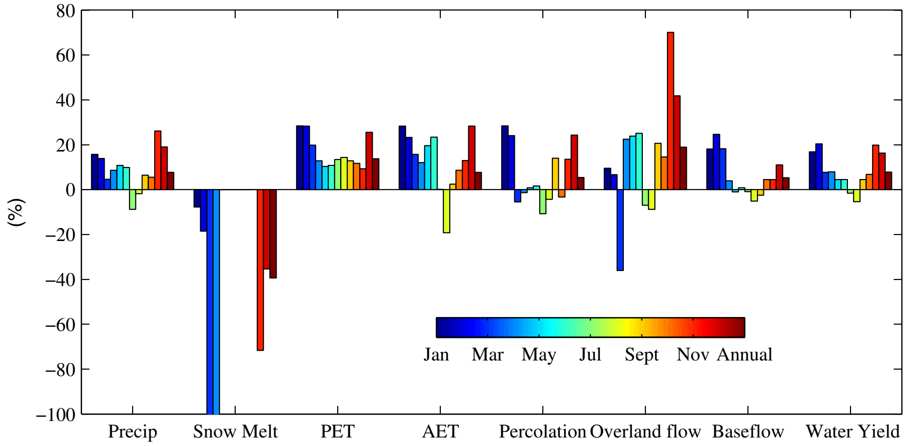

FIGURE 13. The Grouped Bars of Monthly and Annual Changes of Various Water Fluxes Over the Lower Missouri River Basin. PET, potential evapotranspiration; AET, actual evapotranspiration.

Basin-Wide Water Flux Changes and Uncertainty

Figure 13 shows monthly and annual changes of various water fluxes including precipitation, snowmelt, PET, actual ET (AET), percolation, overland flow, base flow, and water yield, which are averaged from simulations driven by the three RCM/GCMs and three PET methods within SWAT. The percent changes are relative to the base simulation (1968-1997) with the UW atmospheric forcing of precipitation and temperatures. In general, precipitation increase drives increases in most water fluxes in the basin, except the snowmelt which is decreased because increase in temperature results in more precipitation in the form of rainfall rather than snowfall in cold seasons. The averaged shifts of 7-8% are generally comparable among those water fluxes of precipitation, AET, water yield, and base flow, meaning that an overall uniform shift of water components follows the precipitation changes. PET increases constantly over the whole year following the increasing pattern of temperature, but AET flux varies more with precipitation compared with PET, which again suggests that the climate models, which produce significant differences in precipitation predictions, would serve as the major source of the hydrologic uncertainty. Water yield consisting of base flow and overland flow apparently has a similar variability to the streamflow at gauge Hermann shown in Figure 12. Although water yield is still mainly contributed by the base flow, the greater increase in overland flow suggests that the quick flow component becomes more important in flood and total streamflow generations in the future period. The maximum and minimum changes shown in Table 3 show negative changes could be the case for water yield but it is exceptional for overland flow that would increase strictly due to the increase in precipitation intensity. Figure 14 shows the uncertainties of changes for different water fluxes in terms of annual average. The climate models contribute more uncertainty than the PET-varied SWAT model in most water flux components except PET and AET that are more affected by the PET methods. Uncertainties, for precipitation which is 7.3% and totally dominated by climate models, could be amplified in other water fluxes such as percolation (25%), overland flow (20.5%), base flow (27.4%), and water yield (26.1%) because of additional uncertainty introduced by other climate variables and hydrological simulations. The wide range of uncertainties from maximum to minimum due to different computation structure indicates that varying PET could significantly increase hydrological uncertainty. However, the induced uncertainty is partly caused by incorpo-

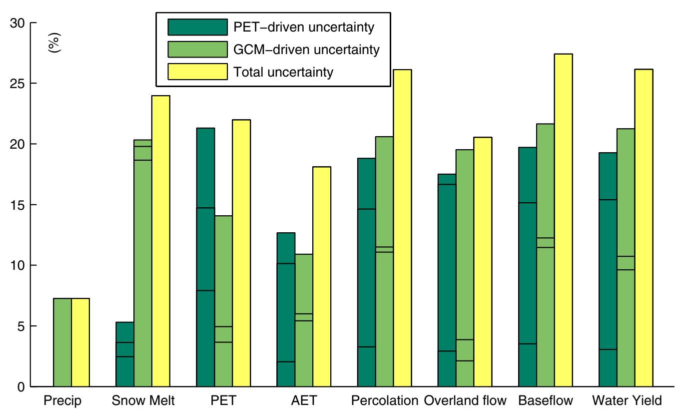

FIGURE 14. Uncertainties of Annual Changes in Various Water Fluxes Derived from Potential Evapotranspiration (PET) Methods, Climate Models, and Both of Them. The lines within the bars from top to bottom represent maximum, intermediate, and minimum uncertainties, respectively. GCM, general climate model.

rating more climate variables. The uncertainties caused by RCM/GCMs in other water components (Figure 14) are constantly higher than the precipitation uncertainty regardless of the PET choices and suggest that the amplification of hydrological variability could be only induced by climate models without the introduction of the PET computation-related uncertainties.

SUMMARY

The LoMRB accounts for only 10% of the whole basin, but generates more than 50% of streamflow at the gauge Hermann due to the relatively much higher precipitation in the lower basin. By differentiating the local water contribution from the upper basin, we found only 34% of flooding water at Hermann coming from the upper basin, which indicates the lower basin itself is the main source for flood generation. The lower basin has experienced increasing precipitation and streamflow during the 20th Century, worsening the extreme event impacts such as droughts and floods due to its higher weather and hydrology interannual variability.

Hydrological variations due to climate change and river engineering of channelization are usually blamed for flood exaggeration in the study region. Based on the newly available NARCCAP dynamically downscaled climate forcing and a comprehensively calibrated hydrological model — SWAT, this study investigated the climate change impacts on hydrologic processes in the LoMRB and analyzes the effects of the climate variation on flood potential in the future period of 2040-2069 relative to the historical period of 1968-1997. Three bias-corrected NARCCAP RCM/GCM projections and three PET methods coupled in SWAT were selected to compare the uncertainty derived from the two respective sources. The results about climate change impact on the hydrologic system in the LoMRB are summarized as follows:

1. The averaged shifting amplitudes are generally comparable among those water fluxes of AET (7.7%), base flow (5.3%), and surface runoff (7.8%), meaning an overall increasing shift of hydrologic regime as a result of the precipitation changes. The annual precipitation increases by 7.7% with highest increase (20%) in winter, second highest increase (13%) in spring and autumn, and the lowest increase (even decrease in July by 8.8%) of less than 5% in summer.
2. The increase in temperature by around 3°C drives a dramatic increase in PET and decrease in the snow precipitation over the whole year. AET flux varies more with precipitation compared with PET, indicating that the climate models that produce significant differences in precipitation predictions would serve as the major source of the hydrologic uncertainty.
3. It is suggested that precipitation tends to increase in intensity (especially for the extreme precipitations) with little variation in frequency, which triggers prominent increase in surface flow (+18.9%) and enables water accumulating easier and faster to likely increase flood severity in the future term.
4. Assuming the upper basin contribution unchanged, the greatest increase in streamflow in the LoMRB would occur from November to February, on average, increasing by around 10%. Slight increases by 3% emerge in the other months except July and August in which river discharge decreases by around 2%. Annually, total streamflow would increase by 3.5%, which is a result from increases of 7.7 and 2.2% from Boonville at the Missouri River and St. Thomas at the Osage River, respectively. Although the streamflow from Boonville still dominates in the LoMRB, the proportion of the Osage River water contribution would increase.
5. Amplified uncertainty propagates into the hydrological variations due to complexities of climate and hydrological simulations and nonlinear effects of interaction between them. The total uncertainty is not a simple addition of the maximums of the two sources of uncertainty. The uncertainty-specific analysis (e.g., uncertainty among varying climate models under a specific PET method, or vice versa) in this study suggests that the climate models contribute more uncertainty annually. From March to July, the season with highest precipitation, most flooding days and highest river discharge, the total uncertainties can be entirely attributed to the uncertainties (mainly in precipitation) derived from climate models. However, in winter or when temperature imposes less influence whereas other weather factors such as wind play a relatively more important role on ET flux, the different PET methods significantly increase the uncertainty in hydrologic simulations.
6. The study area was historically very wet and experienced two great floods (1973 and 1993) during the time period from 1968 to 1997 as shown in the historical time series of precipitation and streamflow (Figure 2). This study suggested that an even wetter environment would be present in the future time period from 2040 to 2069, which likely results in more severe floods especially in

magnitude due to the projected increase in precipitation intensity, whereas the frequency of floods would have no significant increase due to the minimal change in the frequency of precipitation events.

ACKNOWLEDGMENTS

We thank the North American Regional Climate Change Assessment Program (NARCCAP) for providing the data used in this article. This study is partly supported by the NOAA project NA11OAR4310094.

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