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Freeze-Thaw cycle representation alters response of watershed hydrology to future climate change

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ABSTRACT

Hydrologic models are widely used for projecting influences of changing climate on water resources. In this study, we compared the original Soil and Water Assessment Tool (SWAT) model and an enhanced version of SWAT model with physically based Freeze-Thaw cycle representation (SWAT-FT) for simulating future annual ET, stream flow, water yield, surface runoff, and subsurface runoff in the Upper Mississippi River Basin (UMRB). SWAT-FT projected fewer frozen days than the original SWAT model due to its better representation of snow cover insulation effects. Both models derived declining trends in annual streamflow and terrestrial water yield in the late 21st century due to increased ET under warmer climate. However, these two models exhibited contrasting mechanisms underlying the streamflow decline. For original SWAT model, the decrease in surface runoff was the major driver, while for SWAT-FT, reduced subsurface runoff was the main cause. In general, the original SWAT model predicted more surface runoff and less subsurface runoff than SWAT-FT. Further geospatial inspection shows large discrepancies between these two models, particularly in the northern colder parts of the UMRB, where the maximum differences in annual surface and subsurface runoff reached 130 mm yr^{-1} and 140 mm yr^{-1}, respectively. Collectively, the results demonstrate the importance of accounting for Freeze-Thaw cycles for reliable projection of future water resources.

1. Introduction

It is estimated that 1.8 billion people will undergo water shortage by 2025 (Connor, 2015), and water resources demand for energy and crops is projected to increase sharply by the end of the 21st century (Gesualdo et al., 2019; Jewell, 2011). Water shortage has serious impacts on social and economic development and food production (Gosling and Arnell, 2016; Schewe et al., 2014; Seung-Hwan et al., 2013). Future climate change is expected to further exacerbate water resource problems in many countries and regions (Asadieh and Krakauer, 2017; Debortoli et al., 2017; Liu et al., 2017; Mandal and Simonovic, 2017). Influences of climate change on water resources has been one of the greatest environmental concerns (McCarthy et al., 2001).

Impacts of climate change on water resources and hydrological cycles are often investigated using hydrological models driven by projections of Global Climate Models (GCMs) (Blanco-Gomez et al., 2019; Schewe et al., 2014; Seung-Hwan et al., 2013). Large model prediction uncertainty exists mainly due to two reasons: (1) model deficiency in representing essential hydrological processes, and (2) projections based on a single GCM (Wilby et al., 2006). To understand and quantify GCM projection uncertainties, multi-GCMs approaches are often employed in many studies. Meanwhile, improving process representation in hydrologic models is needed to increase credibility of future water resources projection.

Freeze-thaw cycles play a significant role in regulating surface and subsurface flows (Guo et al., 2011), determining soil water distribution (Farouki, 1981), modulating water budgets and water yield (Wang et al., 2009), altering energy exchange between land and atmosphere (Yang et al., 2007), and influencing biogeochemical processes (Duan et al., 2012; Gu et al., 2005; Ma et al., 2009; Yang et al., 2014). Despite the recognition of its importance, Freeze-Thaw cycles are under-represented in most hydrological models (Bakir and Zhang, 2008; Wu et al., 2014). As Freeze-Thaw cycles are amongst the processes most sensitive to climate change, this deficiency tends to enlarge model

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prediction uncertainty under future climate change scenarios (Guo and Wang, 2013; Yang et al., 2007).

The Soil and Water Assessment Tool (SWAT) is a hydrological model for simulating long term water quantity and quality in agriculturally dominated watersheds (Arnold et al., 1998; Borah and Bera, 2003). It has been extensively used to assess impacts of climate change on watershed hydrology and water resources availability. However, its application encountered difficulties at middle and high latitudes that are affected by seasonal Freeze-Thaw cycles (Bakir and Zhang, 2008; Wu et al., 2014). Like other commonly used hydrological models, the SWAT model employs a simplified empirical soil temperature algorithm which does not simulate phase changes of soil water and does not represent well snow insulation effects. To address this problem, a physically based soil temperature module has been developed to improve SWAT depiction of soil thermal status and snow insulation effects on Freeze-Thaw cycles (Qi et al., 2016a; Qi et al., 2016b). The enhanced version of SWAT with physically based representation of Freeze-Thaw cycles (hereafter SWAT-FT) has been successfully tested to simulate soil temperature, soil thermal status, and Freeze-Thaw cycle in both small and large watersheds in North America (Qi et al., 2016a; Qi et al., 2017; Qi et al., 2019b; Qi et al., 2019c; Qi et al., 2020). Particularly, the application of SWAT-FT in the Upper Mississippi River Basin (UMRB) has demonstrated its superior performance in soil temperature and hydrology simulation as compared with the original SWAT model.

The UMRB occupies only 18% of the whole Mississippi River Basin (Moriasi et al., 2013), but disproportionally accounts for about 35–43% of total nitrogen loading to Gulf of Mexico (Alexander et al., 1997; Panagopoulos et al., 2014). This makes the UMRB a major nitrogen source driving eutrophication and hypoxia in the Gulf of Mexico (Rabalais et al., 1996). Since the transport and fate of nitrogen is closely coupled with hydrological processes, and most soils of the UMRB experience seasonal Freeze-Thaw cycles, it is imperative to understand impacts of Freeze-Thaw cycle representations on hydrologic modeling in response to future climate change.

Our literature review shows that no studies have been conducted to predict watershed hydrology as affected by Freeze-Thaw cycles under future climate change scenarios for large agricultural watersheds. Thus, the main objective of this study is to investigate the influence of freezing-thaw cycle representation on simulating stream flow, water yield, surface runoff, and subsurface flow in the UMRB. Specifically, we employed the original SWAT and SWAT-FT models to predict future watershed hydrology in the UMRB as driven by five GCM projections under the Representative Concentration Pathways 8.5 scenario (RCP8.5). Simulations from the two models were analyzed on different temporal and spatial scales to quantify the impacts of representation of Freeze-Thaw cycles on water resources assessment in the UMRB.

2. Methods and materials

2.1. Empirical vs. physical soil temperature algorithms

SWAT is a semi-distributed and processed-based hydrological model, which has been widely used to investigate the impact of climate change, land use change, and environmental management on water quantity (Bhatta et al., 2019; Li et al., 2014; Liang et al., 2019a; Mengistu et al., 2019; Osei et al., 2019; Qi et al., 2018; Zhang et al., 2017) and water quality (Engebretsen et al., 2019; Liang et al., 2019b; Naqvi et al., 2019). An empirical equation has been used in SWAT to calculate the soil temperature as a function of the previous day's soil temperature, the average annual air temperature, the current day's soil surface temperature and the depth in the profile (Neitsch et al., 2011):

$$T_{soil}(z) = \gamma \bullet T'_{soil}(z) + (1 - \gamma) \bullet [d \bullet (\bar{T}_{Air} - T_{sur}) + T_{sur}] \tag{1}$$

where, $T_{soil}(z)$ and $T'_{soil}(z)$ are soil temperature (°C) at depth z (mm) for the current and previous day, respectively; γ is the lag coefficient regulating the influence of the previous day's soil temperature on the current day's temperature; d is a depth factor reflecting changes in soil temperature as influenced by depth from soil; $\bar{T}_{Air}$ is average annual air temperature (°C); and T_{sur} is soil surface temperature (°C). Details regarding determination of these parameters can be found in Neitsch et al. (2011).

This empirical soil temperature module was found to generate large errors in cold regions by severely underestimating soil temperatures in the winter season (Qi et al., 2016b; Qi et al., 2019c). Snow has insulating and protective effects that reduce heat loss of soil surface (Zhang, 2005). The effects are not well simulated by the empirical module (Qi et al., 2016a). Most importantly, the empirical module does not account for Freeze-Thaw cycles, because it does not simulate phase change of water in the soil profile (Bélanger, 2009; Qi et al., 2019c). Therefore, hydrological cycles impacted by Freeze-Thaw cycles cannot be accurately simulated in regions with seasonal snow cover (Zhang et al., 2008). Recently, Qi et al. (2016b) have developed a physically based soil temperature module to better represent the insulating and protective effects of snow, as well as Freeze-Thaw cycles with phase change of soil water (Qi et al., 2016a; Qi et al., 2016b; Qi et al., 2019b; Qi et al., 2019c). For the physically based method, soil temperature is calculated as (Qi et al., 2016b):

$$\frac{\partial T}{\partial t} = \frac{\partial}{\partial x}\left(\frac{k}{C} * \frac{\partial T}{\partial x}\right)\frac{s}{C} \tag{2}$$

where, T is soil temperature (°C), t is time step (day), k is soil thermal conductivity (J cm^{-1} d^{-1} °C^{-1}), C is soil heat capacity (J cm^{-3} °C^{-1}), x is downward depth from soil/snow surface (cm), and s is soil latent heat in source or sink (J cm^{-3} d^{-1}). Detailed algorithms and parameter determination are provided in Qi et al. (2016b). It is worth noting that the only difference between SWAT-FT and the original SWAT model used in the present study is that SWAT-FT used the physically based soil temperature module instead of the empirical module to calculate soil temperature. All other hydrological algorithms remained the same for both models.

2.2. Study area and data collection

2.2.1. Upper Mississippi River Basin

The UMRB originates from the Lake Itasca in upper Minnesota and extends 492,000 km^2 southward into the Ohio River near Cairo, Illinois (Fig. 1). Over 52% of the UMRB is used to plant crops for food and biofuel production (Deb et al., 2015). It is one of the most productive region in the U.S. that provides about 40% corn production (Wu et al., 2012). Silty loam and loam soils are the main soil types in the UMRB and flat and rolling terrains are the main topography (Deb et al., 2015). Climate of the UMRB is sub-humid continental (Qi et al., 2019c). Average annual precipitation is around 900 mm and decreases from south to north. About 75% of annual precipitation falls in growing season between April and October (Qi et al., 2019c).

2.2.2. Model setup and input data collection

The SWAT model requires detailed information about land use, soil, and topography of the UMRB to simulate water quantity and quality. We adopted the input data from Srinivasan et al. (2010) that divided the UMRB into 131 subbasins in line with the eight-digit United States Geological Survey (USGS) hydrologic unit codes (HUCs). Watershed configuration and topographic parameter estimation were derived from National hydrography Dataset (NHD) stream dataset and a 90 m digital elevation model (DEM) (Srinivasan et al., 2010). Two sources of land use information, i.e., the Cropland Data Layer (CDL) and 2001 National Land Cover Data were used to represent crop rotation and non-agricultural land use, respectively. Soil properties were derived from the State Soil Geographic (STATSGO) 1:250,000 scale soil map. Management practices such as tile drainage, tillage, crop rotation, and fertilizer application were included in the project (Srinivasan et al., 2010).

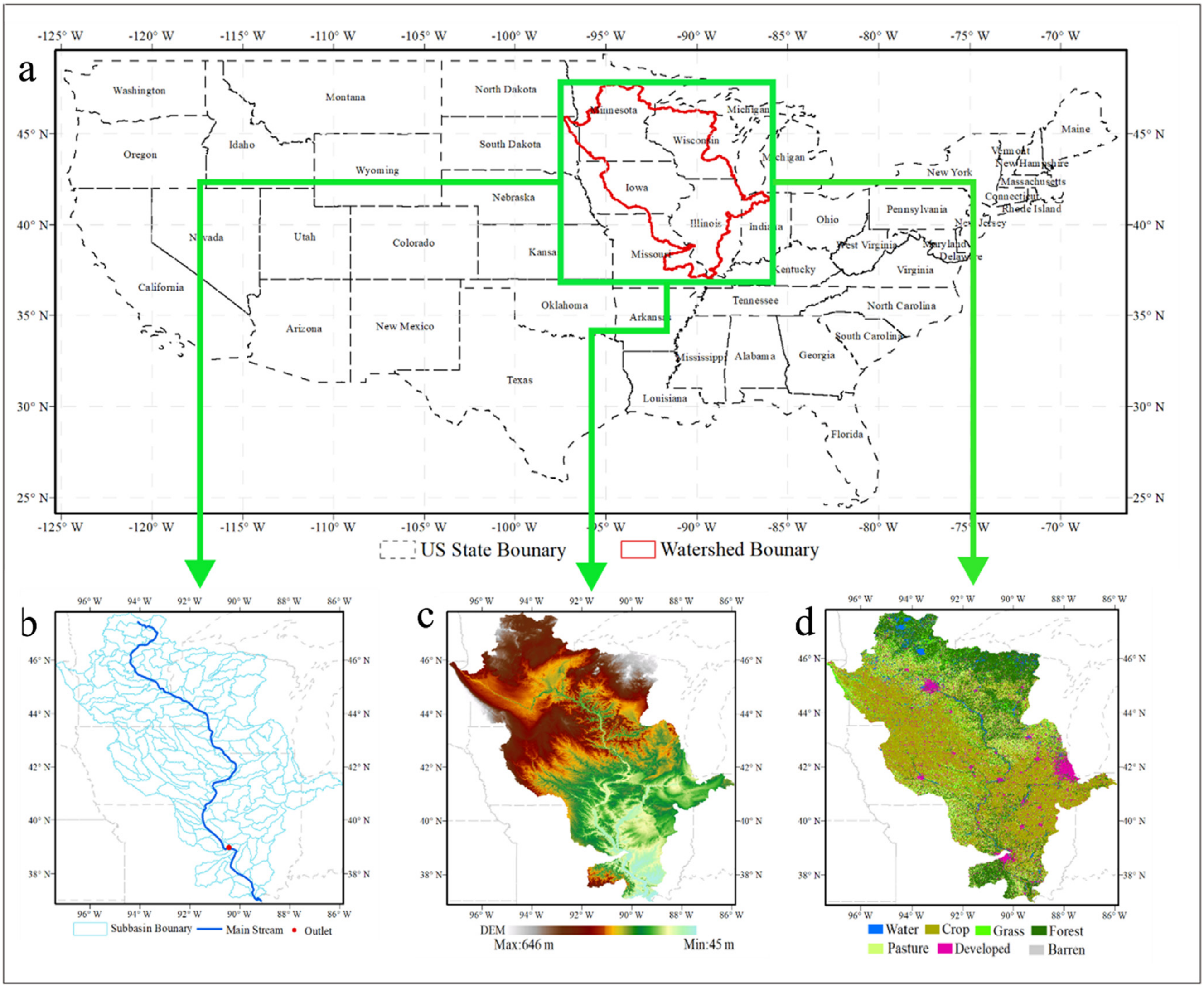

Fig. 1. Location of the Upper Mississippi River Basin (a) and its mainstream and subbasins based on eight-digit hydrologic unit catalogue (b), elevation (c), and major land use types (d).

Historical climate input data (1979 to 2018) were obtained from the NASA North-American Land Data Assimilation System phase 2 (NLDAS2; ldas.gsfc.nasa.gov/nldas/) (Qi et al., 2019a; Qi et al., 2019c; Xia et al., 2012). Monthly observed stream flow data were obtained at the U.S. Geological Survey (USGS) gauge station # 05,587,450 (Grafton, Illinois) during 1980–2015.

2.2.3. Climate change data

To derive future climate change scenarios, we compiled daily precipitation, solar radiation, relative humidity, maximum/minimum air temperature, and wind speed data from five Coupled Model Intercomparison Project (CMIP5) GCMs from 1960 to 2099. The five GCMs are GFDL-ESM2M (Geophysical Fluid Dynamics Laboratory-Earth System Model version.2; hereafter referred to as GFDL), HadGEM-ES (Hadley Centre Global Environmental Model, version 2, Earth System; hereafter referred to as HadGEM2), IPSL-CM5A-LR (Institute Pierre-Simon Laplace version 5a, low-resolution configuration; hereafter referred to as IPSL), MIROC-ESM-CHEM (Model for Interdisciplinary Research on Climate, Earth System Model, Chemistry Coupled; hereafter referred to as MIROC), and NorESM1-M (Norwegian Earth System Model 1-Medium resolution; hereafter referred to as NorESM1). Those future climate change projections were bias-corrected against observed climate data using the bias-correction and spatial-downscaling approach (Wood et al., 2004; Yang et al., 2019). We chose the RCP 8.5 for our study to assess water resources in the UMRB reflecting the business-as-usual emissions scenario.

2.3. Model performance evaluation

The monthly observed stream flow data from 1980 to 2015 at the USGS gauge station # 05,587,450 were used to evaluate the performance and reliability of the two SWAT models under historical conditions. Model performance was evaluated with three widely used metrics, i.e., Nash-Sutcliffe efficiency (*NS*) (Nash and Sutcliffe, 1970), coefficient of determination (R^2) (Parajuli et al., 2009), and percentage bias (*PBIAS*) (Moriasi et al., 2007), defined in the following.

$$NS = 1 - \frac{\sum_{i=1}^{n}(O_i - P_i)^2}{\sum_{i=1}^{n}(O_i - \bar{O})^2} \tag{3}$$

$$R^2 = \left(\frac{\sum_{i=1}^{n}(O_i - \bar{O}) * (P_i - \bar{P})^2}{\sqrt{\sum_{i=1}^{n}(O_i - \bar{O})^2 * \sum_{i=1}^{n}(P_i - \bar{P})^2}}\right)^2 \tag{4}$$

$$PBIAS = \frac{(\bar{P} - \bar{O})}{\bar{O}} * 100 \tag{5}$$

where, O_i and P_i are observed and simulated values, respectively; and $\bar{O}$

and $\bar{P}$ are the average of the observed and simulated values, respectively.

2.4. Statistical analysis

The two SWAT models were implemented with the projected climate change data from the five GCMs for 1960–2099. We calculated annual precipitation and average daily air temperature across the UMRB for each decade from 1960 to 2099. We also used the non-parametric Mann–Kendall (MK) test to detect monotonic trends, and computed slope and intercept of the trendline for each GCM using the Sen's method (Kendall, 1975; Mann, 1945; Sen, 1968). These statistical methods are commonly used in analyses of environmental, climate, and hydrological data. For the MK test, the global trend for the entire series is significant when P-value < 0.05.

The MK test and Sen's method were also used for detecting trends in hydrological variables (including ET, streamflow, water yield, surface runoff, and subsurface runoff) and soil thermal state (frozen days). In addition, the non-parametric Wilcoxon test was used to detect significant difference between simulations by SWAT and SWAT-FT for the baseline period (1960–1999) and each decade of the 21st century (Raje, 2014). We used the Wilcoxon test rather than the *t*-test because simulated hydrologic variables do not follow normal distribution (Raje, 2014). A P-value < 0.05 indicates a significant difference between the two model predictions.

3. Results

3.1. Future climate change in the UMRB

Trend analysis results for annual precipitation and average daily air temperature over the UMRB are shown in Fig. 2a and 2b, respectively. In general, most GCMs projected a significant increase in annual precipitation, except for IPSL. The Sen's slope ranged from -2.97 to 10.53 mm decade^{-1} for annual precipitation time series projected by the five GCMs (Fig. 2a). For air temperature, significant increases were found for all five GCMs, ranging from 0.32 to 0.7 °C decade^{-1} (Fig. 2b). Compared with baseline period (1960–1999), annual precipitation increases by 90 to 129 mm (except for a 32 mm decrease for IPSL), while annual temperature increases by 4.19 to 8.88 °C by the end of the 21st century.

3.2. Model performance evaluation

Fig. 3 shows monthly streamflow simulated by the two SWAT models against observations at the UMRB outlet. According to the model performance criteria suggested by Moriasi et al. (2007) and Wallace et al. (2018), both models performed satisfactorily (i.e., *NS*/$R^2 > 0.5$ and $-25\% < PBIAS < +25\%$). The results also indicate that SWAT-FT performed better than SWAT with larger *NS* and R^2 values and smaller *PBIAS* due to model improvement (Qi et al., 2020).

3.3. Climate change impacts on future soil thermal status

Average annual frozen days (when surface soil temperature < 0°C) across the UMRB for the baseline period and each decade of the 21st century were shown in Supplementary Fig. S1. Fig. 4 shows aggregated results based on the five GCM projections. In general, both models predicted decreases in annual frozen days (P-value < 0.05; Fig. 4a). Simulated average annual frozen days were significantly different between the two models (P-value < 0.05), though the difference tended to narrow with time (Fig. 4a). Fig. 4b compares the percentage change in annual frozen days in each decade of the 21st century relative to the baseline period. The percentage decreases simulated by SWAT-FT were greater than those by the original SWAT model, and the percentage difference between the two models increases over time (Fig. 4b).

3.4. Future streamflow in the UMRB

Average annual streamflow simulated by both models with five GCM projections for different periods are shown in Fig. 5a. Overall, both models predicted decreases in streamflow at the outlet of the UMRB (P-value < 0.05). There is no significant difference in average annual streamflow between the two SWAT models for each decade in the 21st century (P-value > 0.05; Fig. 5a). Fig. 5b further compares the percentage change in average annual streamflow relative to the baseline period between the two models. Overall, SWAT predicted higher percentage decreases than SWAT-FT in each decade of the 21st century, and the difference between the two models increases with time (Fig. 5b).

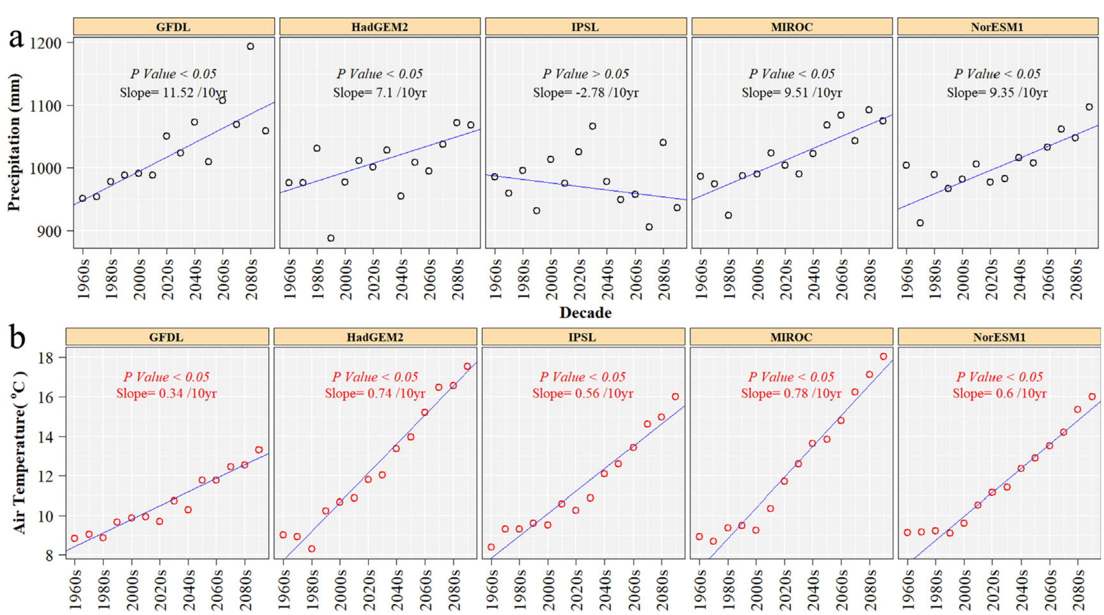

Fig. 2. Trends of decadal changes in annual precipitation (a) and daily air temperature (b) from1960s to 2090 s as projected by five GCMs under RCP8.5 in the UMRB.

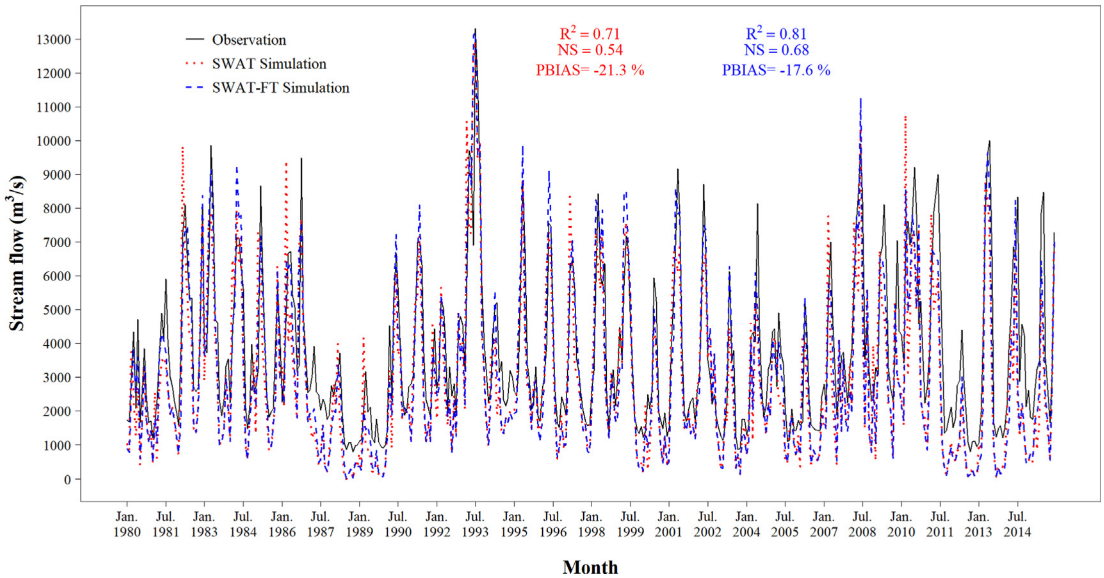

Fig. 3. Simulated vs. observed of monthly stream flow at the outlet of the UMRB from 1980 to 2015. Statistics for original SWAT and SWAT-FT are shown in red and blue fonts, respectively. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Since SWAT and SWAT-FT predicted significantly different winter soil thermal status, we further compared streamflow generated during the nongrowing season (from Nov. to Apr.) as shown in Fig. 6a. Like the results for annual total streamflow (Fig. 5a), there was no significant difference between the two models for nongrowing season (P-value > 0.05). Compared with the baseline period, both models predicted increased non-growing season streamflow with maximum increases of 21.7% and 13.1% in the 2080s for SWAT-FT and the original SWAT model, respectively (Fig. 6b).

3.5. Future water cycle in the UMRB

Fig. 7 shows average annual water yield and surface and subsurface runoff for the baseline period and each decade of the 21st century as aggregated over the five GCMs. Supplementary Figs. S2 and S3 show more detailed surface and subsurface runoff simulations for each GCM. There was a decreasing trend for average annual water yield for both models (P-value < 0.05), but the difference between the two models was not significant (P-value > 0.05; Fig. 7a). The largest percentage decrease in annual water yield occurred in 2070 s and were 9.9 and 11.2%, respectively, for SWAT-FT and the original SWAT model (Fig. 7d).

Further statistical analyses indicate significant differences in both annual surface and subsurface runoff between the two models (P-value < 0.05). The differences tended to diminish over time in the 21st century (Fig. 7b and 7c). Compared with the baseline period, the original SWAT model predicted a decline in both surface (P-value < 0.05) and subsurface runoff (P-value > 0.05). In contrast, SWAT-FT predicted an increase in surface runoff (P-value > 0.05) but a decrease in subsurface runoff (P-value < 0.05). The percentage decrease in subsurface runoff predicted by SWAT-FT was greater than the original SWAT model in the 21st century (Fig. 7e and 7f). For example, at the end of this century, SWAT-FT predicted a −17.1% decrease in subsurface flow while the original SWAT model predicted a −7.6% decrease.

Average annual ET across the UMRB is shown in Fig. 8a. Clearly, both models predicted increasing annual ET and there was no significant difference between them (P-value < 0.05). At the end of the 21st century, both models predicted as much as 37% increase in ET (Fig. 8b). The difference in ET between the two models was too small to detect. This is mainly because the two models used the same ET algorithm of SWAT which currently was not affected by the soil temperature.

3.6. Spatial distribution of future water resources in the UMRB

We selected the baseline period (1960–1999) and three future 30-year periods (i.e., 2010–2039, 2040–2069, and 2070–2099) to illustrate the differences between SWAT and SWAT-FT in simulating annual surface and subsurface runoff (Fig. 9). Those three 30-year periods represent near term, mid-term, and long-term future conditions, thereby allowing us to analyze changes in spatial differences between the original SWAT model and SWAT-FT over time (Fig. 9). The difference in surface runoff was greatest in the northern parts of the UMRB (with maximum difference of about 130 mm) and least in the southern UMRB. Note that surface runoff simulated by the original SWAT model was greater than that of SWAT-FT across most subbasins (the difference is positive), except for small areas with negative values in the south during 2070–2099 (Fig. 9a). The difference between simulations of SWAT-FT and the original SWAT model tended to narrow over time which is consistent with the results from temporal analyses in Fig. 7. Similar spatial patterns were found for subsurface runoff, for which the differences between the two models are greatest in the northern UMRB (with maximum difference of about 140 mm) and gradually reduced towards south. In addition, the difference in subsurface runoff between the two models also tended to diminish over time. In contrast with surface runoff, the subsurface runoff simulated by the original SWAT was less than that by SWAT-FT for most subbasins (Fig. 9).

4. Discussion

4.1. Impacts of warming temperature on streamflow/water yield

Annual precipitation and daily air temperature projected by the five GCMs show upward trends from 1960 to 2099 in the UMRB, which agree with previous studies in the same area (Qian et al., 2007; Tao et al., 2014). Warming air led to increases in annual ET (which offsets the gently increased annual precipitation) and resulted in reduced streamflow/water yield simulated by both SWAT models (Figs. 8, 5 and 7a). In general, average annual streamflow was predicted to decrease starting in the 2030 s (Fig. 5). Both the original SWAT model and SWAT-FT predicted a maximum decrease of 11 and 9.1%, respectively,

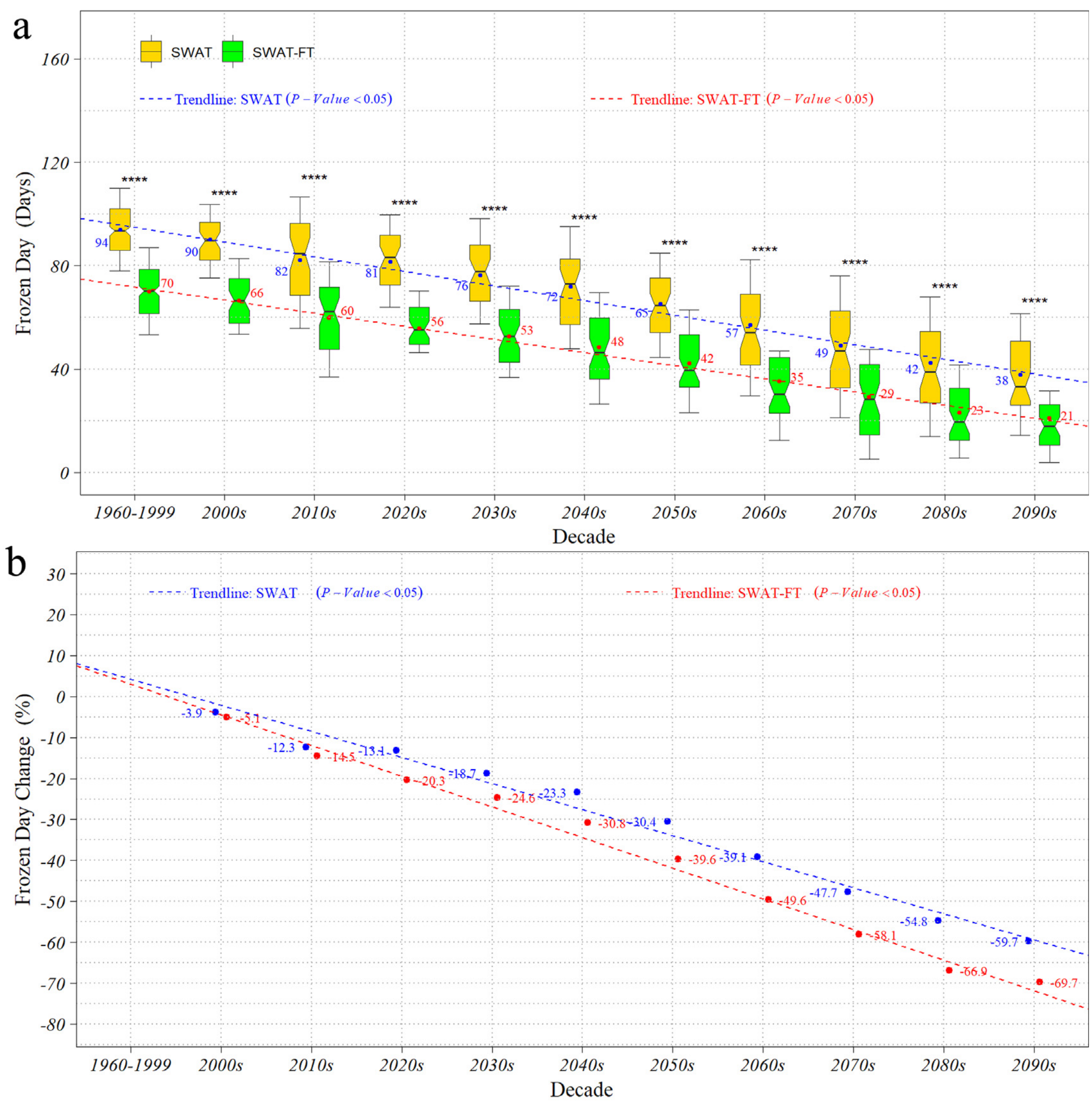

Fig. 4. Average annual frozen days across the UMRB simulated by the two SWAT models (a) and percentage change (%) with respect to the baseline period (1960–1999) for each decade of the 21st century (b). "****" indicates the significant difference between two model simulations with the P-value < 0.0001.

in annual streamflow during 2070 s (Fig. 5). The fact that 2070 s and 2090 s had greater percentage changes in stream flow than those of 2060 s and 2080 s indicates a long-lasting unstable climatic period after 2050 s in the UMRB (Fig. 5). Similar results were found for water yield (Fig. 5a and 5b vs. Fig. 7a and 7d). Different from streamflow (which can be monitored at the outlet of a basin), water yield is the summation of surface runoff and subsurface runoff (=lateral flow + tile flow + base flow) from uplands of the basin (which is difficult to measure at a watershed scale). The difference between streamflow and water yield includes a relatively small amount of transmission losses (ET from waterways and losses to riverbeds). Water yield and its components are directly associated with water cycles at the field scale, and the quantity and quality of these waters have important implications for agricultural water resources management.

Although annual total stream flow was predicted to decrease by both models, annual streamflow of the non-growing season tended to increase (Fig. 6a), which implies a shifted precipitation pattern and warmer winter (causing more snow melt) in the 21st century. Similar conclusions were drawn in northern Eurasia and North America under future climate change scenarios (Smith et al., 2007; Walvoord and Striegl, 2007). SWAT-FT predicted greater percentage increase in streamflow during the nongrowing season (with a maximum increase rate of 21% in the 2080 s) relative to the baseline period (Fig. 6b), which indicate higher risks of sediment erosion during non-growing season when less biomass is left on ground to protect soils.

4.2. Impacts of warming temperature on soil thermal status

Driven by temperature increases, annual frozen days averaged over the UMRB reduced over time, with SWAT-FT predicting less annual frozen days in any periods than the original SWAT model (Fig. 4a). This is because the physically based soil temperature module better addressed snow insulation effects than the empirical algorithm. The difference in annual frozen days between the two models tended to minimize when snow cover extent and depth decreased due to warming air temperature in the late 21st century (Fig. 4a). SWAT-FT simulated greater percentage decrease in annual frozen days indicating high sensitivity of the physically based soil temperature module to future climate change (Fig. 4b). Studies from snow removal experiments at the site scale have shown more frozen days and deeper frozen depth implying that global warming could lead to "cooler" soils (Freppaz et al., 2008; Sulkava and Huhta, 2003). Our numerical simulation results demonstrate otherwise. This is understandable that those field experiments were conducted under current winter temperature, while future

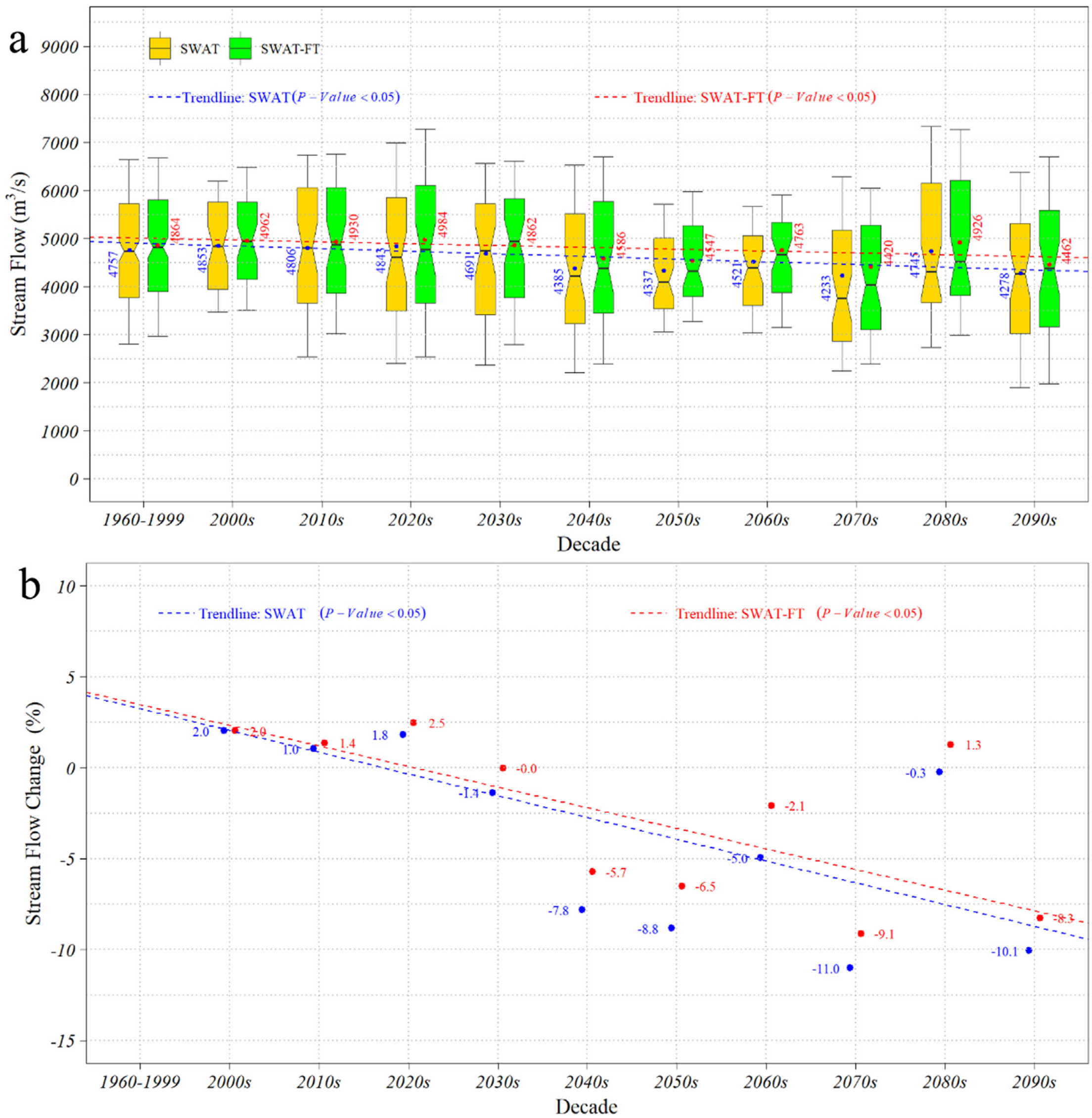

Fig. 5. Average annual streamflow (m^3 s^{-1}) simulated by the two SWAT models (a) and percentage change (%) in streamflow with respect to the baseline period (1960–1999) for each decade of the 21st century (b).

winter temperature increases will lead to "warmer" soils, even though snow cover shrinks. Changes in frozen days in general reflect the sensitivity of the physically based soil temperature module to snow cover change (which is expected to reduce) and demonstrate the importance of including physically based soil temperature for better future prediction of soil thermal status.

4.3. Influence of Freeze-Thaw cycle representation on temporal changes in hydrological processes

The influence of freeze and thaw cycles on hydrological processes was clearly demonstrated by the difference between the original SWAT model and SWAT-FT in predicting surface and subsurface runoff in the UMRB. Surface and subsurface water flows from uplands are important components of watershed hydrology. SWAT-FT predicted less surface runoff and more subsurface runoff than the original SWAT model for the baseline and every decade of the 21st century. The differences tended to diminish over time in the 21st century (Fig. 7b and 7c), which echoes the narrowed difference in predicted frozen days between the two models (Fig. 4a). The results reflect the impacts of Freeze-Thaw cycle on the partition between surface runoff and subsurface flow, and further suggest that Freeze-Thaw cycle representation is critical for accurate assessment of future water resources in the UMRB. In addition, different from the original SWAT model, SWAT-FT tended to predict increases in annual surface runoff despite reduced total water yield in the 21st century (Fig. 7b and 7e).

It is worth noting that the increasing trend of surface runoff for SWAT-FT and the decreasing trend of subsurface flow for the original SWAT were not significant (Fig. 7). This indicates that the reduction in total water yield was caused by the decrease in surface runoff for the original SWAT model, while for SWAT-FT, it was mainly caused by the decrease in subsurface runoff. The results reflect the impacts of different soil thermal statuses on hydrological cycles and highlight the importance of accounting for Freeze-Thaw cycles in hydrological models.

4.4. Influence of Freeze-Thaw cycle representation on spatial changes in hydrological processes

Spatial variabilities of surface and subsurface runoff provide important information for water resources management and implementation of adaptation strategies. In the northern UMRB, the large differences in simulated surface/subsurface runoff between the two models reflect the influence of freeze and thaw cycles on the partition of

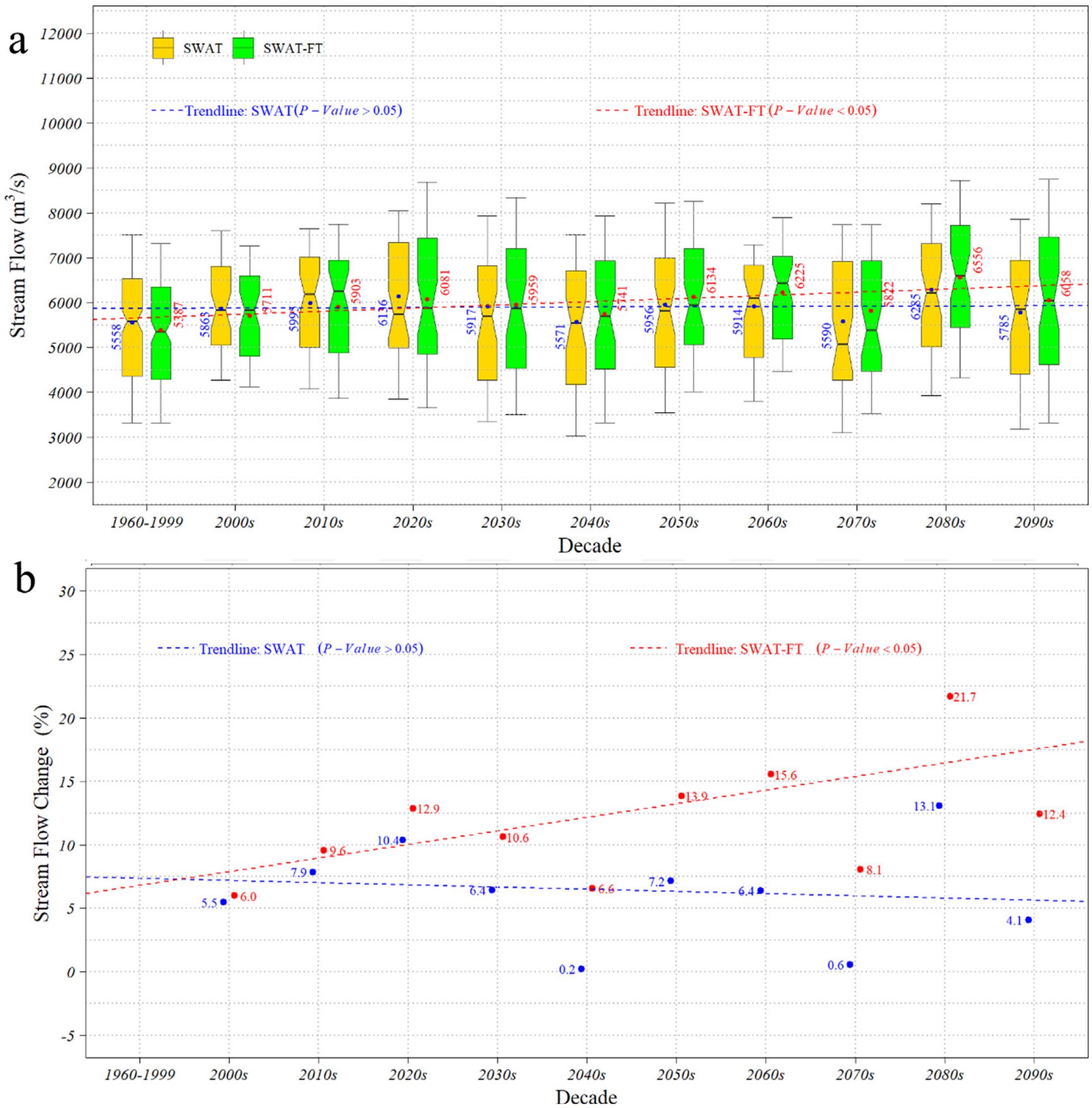

Fig. 6. Average annual streamflow ($m^3\ s^{-1}$) for the nongrowing season (Nov.-Apr.) (a) and percentage change (%) with respect to the baseline period (1960–1999) for each decade of the 21st century (b).

surface and subsurface water (Fig. 9). More attention is deserved for the northern agricultural areas of the UMRB, because SWAT-FT predicted increasing subsurface runoff over time implying potentially more nitrate leaching through baseflow. For the southern part of the basin, the differences in simulations of surface and subsurface runoff between the two models were not as dramatic as in the northern parts, and they tended to diminish over time (Fig. 9). Reliable assessment of management practices and land use change under future climate scenarios requires accurate simulations of hydrological processes and the nutrient transport and fate. This study demonstrates that hydrological modeling should not ignore the impacts of freeze and thaw cycles, particularly in regions affected by cold climate. Collectively, water resources assessment under future climate change scenarios based on the original SWAT model likely yields biased results because of its incapability of depicting Freeze-Thaw cycles.

Notably, the difference between SWAT and SWAT-FT varies between different GCM projections (Fig. 9). In general, GFDL projections translated to less differences in simulated surface and subsurface runoff between SWAT and SWAT-FT, while NorESM1 projections led to large differences, particularly towards the end of the 21st century. This results clearly demonstrate the differences between GCM projections, therefore using multiple GCM is critical to understand and quantify the uncertainties.

4.5. Impacts, limitations, and future work

Apart from anticipated changes in climate (e.g. more frequent and severe storms) (Pryor et al., 2014), land use change to meet food security, energy independence, and environmental sustainability goals (EISA, 2007; NRC, 2012; USDA-NRCS, 2009) are expected to influence both hydrologic processes and water quality in the UMRB. For example, UMRB contributes > 30% of nutrients to the Gulf of Mexico (Dale et al., 2007), where hypoxia and harmful algal bloom are causing significant damage to environmental integrity and commercial fishing (Scientists, 2020). Numerous conservation practices, such as efficient fertilizer application, reduced tillage, and cover crops, are being incentivized to reduce nitrogen pollution from the UMRB (USDA-NRCS, 2012). In addition, cropland expansion is occurring in the URMB in response to bioenergy and food demand (Lark et al., 2015). Currently, the SWAT model is being used to understand and quantify impacts of these complex natural and human drivers in the UMRB. Accurate simulation of hydrologic processes (such as surface runoff and baseflow) is the prerequire for reliable assessment of water quality. Surface runoff is the major pathway for particulate nutrient transport (such as particulate

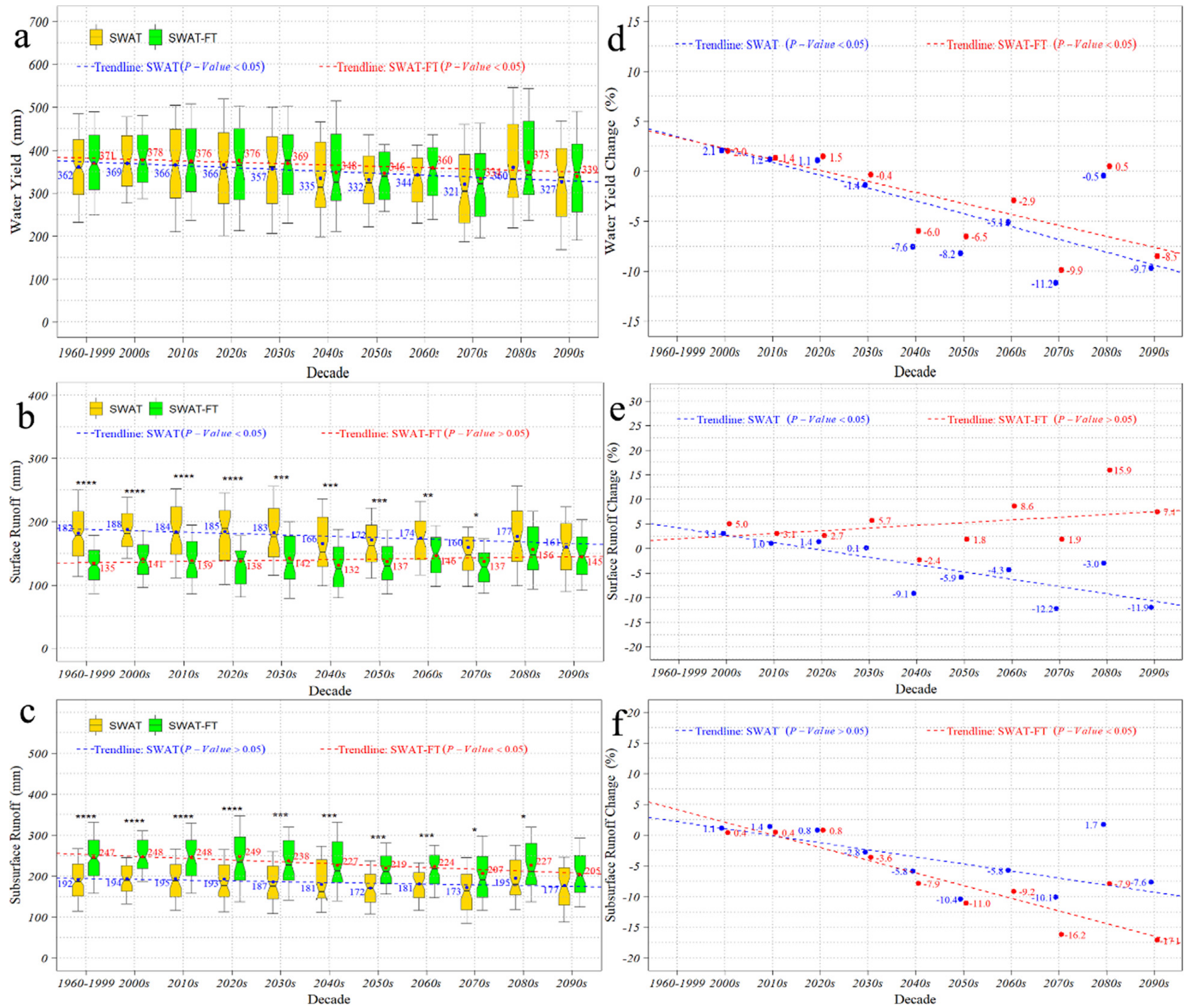

Fig. 7. Average annual water yield (a), surface runoff (b), and subsurface runoff (c) simulated by the two SWAT models with five GCM projections; and percentage change (%) relative to the baseline period (1960–1999) for each decade of the 21st century (d, e, and f for water yield, surface runoff, and subsurface runoff, respectively). "****" denotes P-value $<$ 0.0001, "***" denotes P-value $<$ 0.001, "**" denotes P-value $<$ 0.01, and "*" denotes P-value $<$ 0.05.

organic nitrogen and sediment loss) from land to downstream waterbodies, while baseflow is the major contributor to dissolved organic and inorganic pollutants (such as nitrate). The improvement with SWAT-FT not only helps better predict future water resources availability but also serves as the foundation for reliable assessment of water quality impacts of agricultural conservation and land use change in the UMRB. Additionally, as the SWAT model are being widely used for hydrologic and water quality modeling (Gassman et al., 2007) (https://www.card.iastate.edu/swat_articles/), we anticipate the SWAT-FT with better performance for Freeze-Thaw cycle and hydrologic modeling will contribute to other applications such as nutrient cycles and sediment loading (Anthony et al., 2009; Collins et al., 2017; Collins et al., 2010) across the globe.

Even though our previous studies demonstrated satisfactory performance of SWAT-FT for simulating soil thermal status in areas that are subject to seasonal snow cover and Freeze-Thaw cycles, we did not test the applicability of the model in regions that are permafrost or covered with glacier. Particularly for glacial regions, more detailed depiction of ice formation and melting is likely needed to achieve satisfactory performance. Therefore, application and evaluation of SWAT-FT in polar regions deserves further research.

Given the close coupling between hydrological and biogeochemical cycles, SWAT-FT applications to understand water quality and carbon cycle impacts of agricultural management and climate change await future work. Although SWAT-FT possesses physically based soil water temperature algorithms, the riverine water temperature is still calculated using empirical regression based on air temperature. Riverine temperature is a critical factor influencing numerous aquatic biogeochemical processes, such as organic matter decomposition, plankton growth and die-off, and nitrification and denitrification. Future efforts are needed to further refine physically based methods for simulating riverine water temperature, thereby allowing SWAT-FT to fully represent water temperature across both terrestrial and aquatic ecosystems.

5. Conclusion

The influence of future climate change on water resources has become a great concern in the UMRB and many other basins across the globe. By employing the original SWAT model and SWAT-FT, we demonstrated the importance of accounting for soil Freeze-Thaw cycles in hydrological models for climate change impact assessment. Specifically, projected annual ET, stream flow, water yield, surface runoff, and subsurface flow using climate scenarios simulated by five GCMs under the RCP8.5 scenarios were analyzed in this study.

Compared with the baseline period (1960–1999), annual

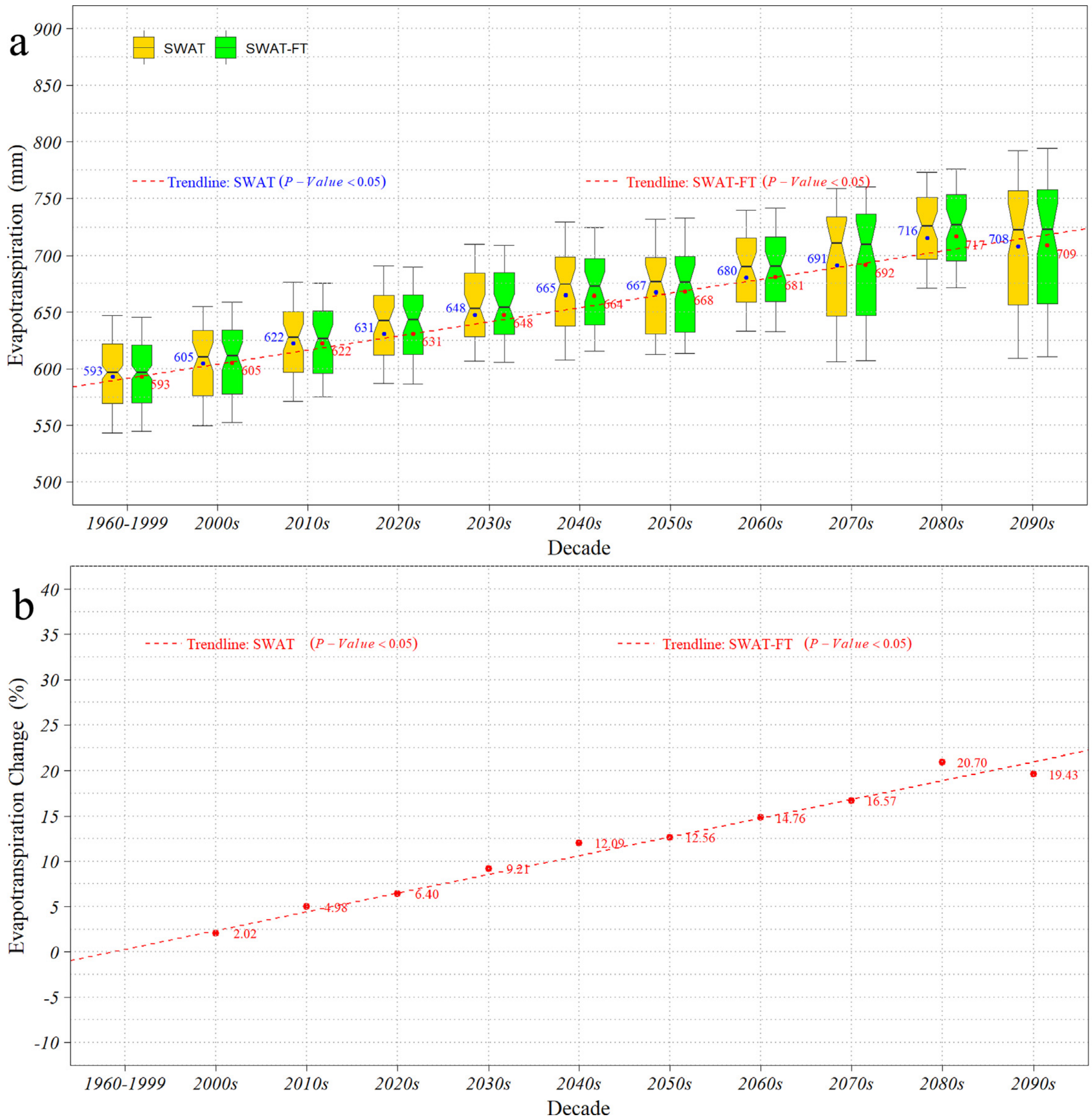

Fig. 8. Average annual ET (mm) simulated by the two SWAT models with five GCM projections (a) and percentage change (%) with relative to the baseline period (1960–1999) for each decade of the 21st century (b).

precipitation and average daily air temperature were predicted to increase ranging from 90 to 129 mm and from 4.19 to 8.88 °C in the UMRB, respectively, by the end of the 21st century. In response to the warmer climate, SWAT-FT predicted less frozen days than the original SWAT model mainly because the physically based soil temperature module better simulated snow insulation effects. Both models predicted decreases in streamflow/water yield mainly due to increased ET caused by warmer temperature. Further analyses indicate different mechanisms underlying the projected decreases in streamflow/water yield. For the original SWAT model, the reduction in total water yield was mainly caused by the decrease in surface runoff. In contrast, decreases in subsurface runoff is the major reason explaining the SWAT-FT projected decreases in water yield.

Spatial analyses show that the original SWAT model predicted more surface runoff than SWAT-FT and the difference between them was large in the northern UMRB (with maximum difference of about 130 mm with) and small in the southern parts of the UMRB. Meanwhile, the original SWAT model predicted less subsurface water flow than SWAT-FT. The large difference between the two models also occurred in the northern parts of the UMRB (with maximum difference of about 140 mm) and gradually reduced towards south.

Our results for the first time demonstrate the significant influence of Freeze-Thaw cycles on hydrological modeling in the UMRB under future climate change conditions. Freeze-thaw cycle representation is crucial for accurate assessment of future water resources and hydrological models should consider the impacts of freeze and thaw cycles in regions affected by cold climate in order to provide reliable information to support agricultural and water management.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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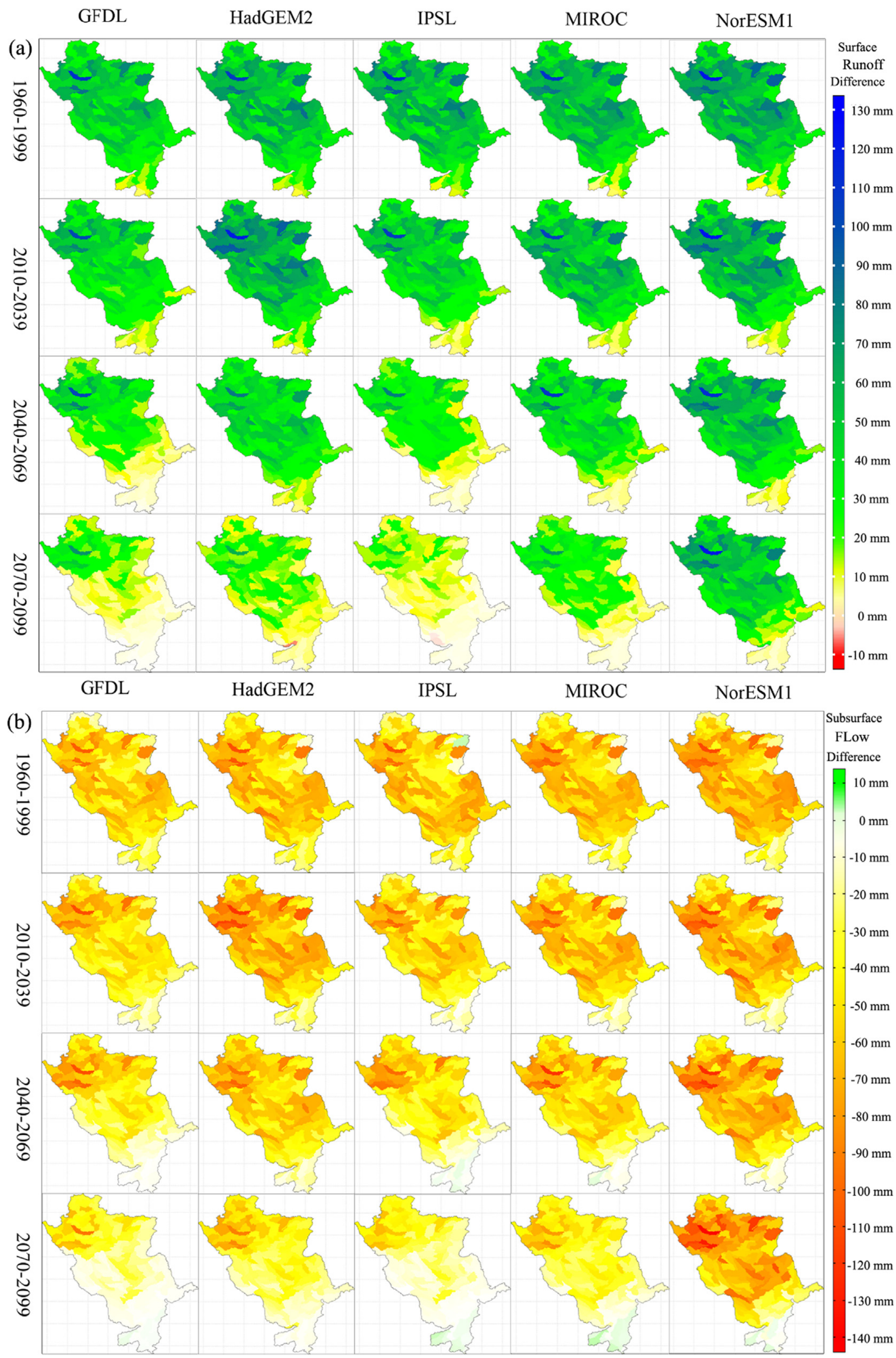

Fig. 9. Spatial distribution of the difference (simulations by the original SWAT model minus simulations by SWAT-FT) in simulated average annual surface (a) and subsurface runoff (b) during the baseline period (1960–1999), 2010–2039, 2040–2069, and 2070–2099.

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Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.catena.2020.104767.

References

Alexander, R.B., Schwarz, G.E., Smith, R.A., 1997. Regional Transport of Point and Nonpoint-source Nitrogen to the Gulf of Mexico. Gulf of Mexico Program Office.
Anthony, S.G., Silgram, M., Collins, A.L., Fawcett, L.E., 2009. Modelling nitrate river water quality for policy support. Int. J. River Basin Manage. 7, 259–275.
Arnold, J.G., Srinivasan, R., Muttiah, R.S., Williams, J.R., 1998. Large area hydrologic modeling and assessment part I: Model development. JAWRA J. Am. Water Resour. Assoc. 34, 73–89.
Asadieh, B., Krakauer, N.Y., 2017. Global change in streamflow extremes under climate change over the 21st century. Hydrol. Earth Syst. Sci. 21, 5863–5874.
Bakir, M., Zhang, X., 2008. GIS-based hydrological modelling: a comparative study of HEC-HMS and the Xinanjiang model. IAHS Publications-Series of Proceedings and Reports 319, 124–133.
Bélanger, J.A., 2009. Modelling soil temperature on the boreal plain with an emphasis on the rapid cooling period.
Bhatta, B., Shrestha, S., Shrestha, P.K., Talchabhadel, R., 2019. Evaluation and application of a SWAT model to assess the climate change impact on the hydrology of the Himalayan River Basin. Catena 181.
Blanco-Gomez, P., Jimeno-Saez, P., Senent-Aparicio, J., Perez-Sanchez, J., 2019. Impact of Climate Change on Water Balance Components and Droughts in the Guajoyo River Basin (El Salvador). Water, 11.
Borah, D., Bera, M., 2003. Watershed-scale hydrologic and nonpoint-source pollution models: Review of mathematical bases. Trans. ASAE 46, 1553.
Collins, A., et al., 2017. Sediment source fingerprinting as an aid to catchment management: a review of the current state of knowledge and a methodological decision-tree for end-users. J. Environ. Manage. 194, 86–108.
Collins, A., Zhang, Y., Walling, D., Grenfell, S., Smith, P., 2010. Tracing sediment loss from eroding farm tracks using a geochemical fingerprinting procedure combining local and genetic algorithm optimisation. Sci. Total Environ. 408, 5461–5471.
Connor, R., 2015. The United Nations world water development report 2015: water for a sustainable world. UNESCO publishing.
Dale, V., et al., 2007. Hypoxia in the northern Gulf of Mexico: An update by the EPA Science Advisory Board. EPA-SAB-08e003). EPA Science Advisory Board, Washington, DC from. https://yosemite. epa. gov/sab/SABPRODUCT. NSF/C3D2F27094E03F90852573B800601D93/$ File/EPA-SAB-08-003complete. unsigned. pdf.(Accessed 24 March 2017).
Deb, D., Tuppad, P., Daggupati, P., Srinivasan, R., Varma, D., 2015. Spatio-temporal impacts of biofuel production and climate variability on water quantity and quality in upper Mississippi river basin. Water 7, 3283–3305.
Debortoli, N.S., Camarinha, P.I.M., Marengo, J.A., Rodrigues, R.R., 2017. An index of Brazil's vulnerability to expected increases in natural flash flooding and landslide disasters in the context of climate change. Nat. Hazards 86, 557–582.
Duan, A., Wu, G., Liu, Y., Ma, Y., Zhao, P., 2012. Weather and climate effects of the Tibetan Plateau. Adv. Atmos. Sci. 29, 978–992.
EISA, 2007. One Hundred Tenth Congress of the United States of America.
Engebretsen, A., Vogt, R.D., Bechmann, M., 2019. SWAT model uncertainties and cumulative probability for decreased phosphorus loading by agricultural Best Management Practices. Catena 175, 154–166.
Farouki, O.T., 1981. The thermal properties of soils in cold regions. Cold Reg. Sci. Technol. 5, 67–75.
Freppaz, M., Celi, L., Marchelli, M., Zanini, E., 2008. Snow removal and its influence on temperature and N dynamics in alpine soils (Vallee d'Aoste, northwest Italy). J. Plant Nutr. Soil Sci. 171, 672–680.
Gassman, P.W., Reyes, M.R., Green, C.H., Arnold, J.G., 2007. The soil and water assessment tool: historical development, applications, and future research directions. Trans. ASABE 50, 1211–1250.
Gesualdo, G.C., Oliveira, P.T., Rodrigues, D.B.B., Gupta, H.V., 2019. Assessing water security in the Sao Paulo metropolitan region under projected climate change. Hydrol. Earth Syst. Sci. 23, 4955–4968.
Gosling, S.N., Arnell, N.W., 2016. A global assessment of the impact of climate change on water scarcity. Clim. Change 134, 371–385.
Gu, S., et al., 2005. Energy exchange between the atmosphere and a meadow ecosystem on the Qinghai-Tibetan Plateau. Agric. For. Meteorol. 129, 175–185.
Guo, D., Wang, H., 2013. Simulation of permafrost and seasonally frozen ground conditions on the Tibetan Plateau, 1981–2010. J. Geophys. Res.: Atmos. 118, 5216–5230.
Guo, D.L., Yang, M.X., Wang, H.J., 2011. Characteristics of land surface heat and water exchange under different soil freeze/thaw conditions over the central Tibetan Plateau. Hydrol. Process. 25, 2531–2541.
Jewell, J., 2011. The IEA model of short-term energy security (MOSES).
Kendall, M., 1975. Rank correlation measures. Charles Griffin, London 202, 15.
Lark, T.J., Salmon, J.M., Gibbs, H.K., 2015. Cropland expansion outpaces agricultural and biofuel policies in the United States. Environ. Res. Lett. 10 044003.
Li, Q., et al., 2014. An approach for assessing impact of land use and biophysical conditions across landscape on recharge rate and nitrogen loading of groundwater. Agric. Ecosyst. Environ. 196, 114–124.
Liang, J., et al., 2019. Impacts of large-scale rare earth mining on surface runoff, groundwater, and evapotranspiration: A case study using SWAT for the Taojiang River Basin in Southern China. Mine Water Environ. 38, 268–280.
Liang, K., et al., 2019. Estimated potential impacts of soil and water conservation terraces on potato yields under different climate conditions. J. Soil Water Conserv. 74, 225–234.
Liu, J., et al., 2017. Water scarcity assessments in the past, present, and future. Earth's Future 5, 545–559.
Ma, Y., et al., 2009. Recent advances on the study of atmosphere-land interaction observations on the Tibetan Plateau. Hydrol. Earth Syst. Sci. 13, 1103–1111.
Mandal, S., Simonovic, S.P., 2017. Quantification of uncertainty in the assessment of future streamflow under changing climate conditions. Hydrol. Process. 31, 2076–2094.
Mann, H., 1945. Non-Parametric Tests against Trend. Econometrica, 13, 245–259. Mantua, NJ, SR Hare, Y. Zhang, JM Wallace, and RC Francis (1997), A Pacific decadal.
McCarthy, J.J., Canziani, O.F., Leary, N.A., Dokken, D.J., White, K.S., 2001. Climate change 2001: impacts, adaptation, and vulnerability: contribution of Working Group II to the third assessment report of the Intergovernmental Panel on Climate Change. Cambridge University Press.
Mengistu, A.G., van Rensburg, L.D., Woyessa, Y.E., 2019. Techniques for calibration and validation of SWAT model in data scarce arid and semi-arid catchments in South Africa. J. Hydrology-Regional Stud. 25.
Moriasi, D.N., et al., 2007. Model evaluation guidelines for systematic quantification of accuracy in watershed simulations. Trans. ASABE 50, 885–900.
Moriasi, D.N., et al., 2013. Modeling the impact of nitrogen fertilizer application and tile drain configuration on nitrate leaching using SWAT. Agric. Water Manag. 130, 36–43.
Naqvi, H.R., Athick, A.M.A., Siddiqui, L., Siddiqui, M.A., 2019. Multiple modeling to estimate sediment loss and transport capacity employing hourly rainfall and In-Situ data: A prioritization of highland watershed in Awash River basin, Ethiopia. Catena 182 104173.
Nash, J.E., Sutcliffe, J.V., 1970. River flow forecasting through conceptual models part I—A discussion of principles. J. Hydrol. 10, 282–290.
Neitsch, S.L., Arnold, J.G., Kiniry, J.R., Williams, J.R., 2011. Soil and water assessment tool theoretical documentation version 2009. Texas Water Resources Institute.
NRC, 2012. Renewable fuel standard: Potential economic and environmental effects of US biofuel policy. National Academies Press.
Osei, M.A., et al., 2019. The impact of climate and land-use changes on the hydrological processes of Owabi catchment from SWAT analysis. J. Hydrology-Regional Stud. 25.
Panagopoulos, Y., et al., 2014. Surface water quality and cropping systems sustainability under a changing climate in the Upper Mississippi River Basin. J. Soil Water Conserv. 69, 483–494.
Parajuli, P.B., Nelson, N.O., Frees, L.D., Mankin, K.R., 2009. Comparison of AnnAGNPS and SWAT model simulation results in USDA-CEAP agricultural watersheds in south-central Kansas. Hydrological Processes: An Int. J. 23, 748–763.
Pryor, S.C., et al., 2014. Ch. 18: Midwest., https://nca2014.globalchange.gov/report/regions/midwest.
Qi, J., Li, S., Bourque, C.P., Xing, Z., Fan-Rui, M., 2018. Developing a decision support tool for assessing land use change and BMPs in ungauged watersheds based on decision rules provided by SWAT simulation. Hydrol. Earth Syst. Sci. 22, 3789–3806.
Qi, J., et al., 2016a. Assessing an enhanced version of SWAT on water quantity and quality simulation in regions with seasonal snow cover. Water Resour. Manage. 30, 5021–5037.
Qi, J., et al., 2016b. A new soil-temperature module for SWAT application in regions with seasonal snow cover. J. Hydrol. 538, 863–877.
Qi, J., Li, S., Yang, Q., Xing, Z., Meng, F.-R., 2017. SWAT setup with long-term detailed landuse and management records and modification for a micro-watershed influenced by freeze-thaw cycles. Water Resour. Manage. 31, 3953–3974.
Qi, J., Wang, Q., Zhang, X., 2019a. On the use of NLDAS2 weather data for hydrologic modeling in the Upper Mississippi River Basin. Water 11, 960.
Qi, J., Zhang, X., Cosh, M.H., 2019b. Modeling soil temperature in a temperate region: A comparison between empirical and physically based methods in SWAT. Ecol. Eng. 129, 134–143.
Qi, J., Zhang, X., Wang, Q., 2019c. Improving hydrological simulation in the Upper Mississippi River Basin through enhanced freeze-thaw cycle representation. J. Hydrol. 571, 605–618.
Qi, J., et al., 2020. SWAT ungauged: water quality modeling in the Upper Mississippi River Basin. J. Hydrol. 124601.
Qian, T., Dai, A., Trenberth, K.E., 2007. Hydroclimatic trends in the Mississippi River basin from 1948 to 2004. J. Clim. 20, 4599–4614.
Rabalais, N.N., et al., 1996. Nutrient changes in the Mississippi River and system responses on the adjacent continental shelf. Estuaries 19, 386–407.
Raje, D., 2014. Changepoint detection in hydrologic series of the Mahanadi River basin using a Fuzzy Bayesian approach. J. Hydrol. Eng. 19, 687–698.
Schewe, J., et al., 2014. Multimodel assessment of water scarcity under climate change. Proc. Natl. Acad. Sci. U. S. A. 111, 3245–3250.
Scientists, U.o.C., 2020. Reviving the Dead Zone: Solutions to Benefit Both Gulf Coast Fishers and Midwest Farmers.
Sen, P.K., 1968. Estimates of the regression coefficient based on Kendall's tau. J. Am. Stat. Assoc. 63, 1379–1389.
Seung-Hwan, Y., Jin-Yong, C., Sang-Hyun, L., Yun-Gyeong, O., Koun, Y.D., 2013. Climate change impacts on water storage requirements of an agricultural reservoir considering changes in land use and rice growing season in Korea. Agric. Water Manag. 117, 43–54.
Smith, L.C., Pavelsky, T.M., MacDonald, G.M., Shiklomanov, A.I., Lammers, R.B., 2007. Rising minimum daily flows in northern Eurasian rivers: A growing influence of groundwater in the high-latitude hydrologic cycle. J. Geophys. Res: Biogeosci. 112.
Srinivasan, R., Zhang, X., Arnold, J., 2010. SWAT ungauged: hydrological budget and crop yield predictions in the Upper Mississippi River Basi. Trans. ASABE 53, 1533–1546.
Sulkava, P., Huhta, V., 2003. Effects of hard frost and freeze-thaw cycles on decomposer communities and N mineralisation in boreal forest soil. Appl. Soil Ecol. 22, 225–239.
Tao, B., et al., 2014. Increasing Mississippi river discharge throughout the 21st century influenced by changes in climate, land use, and atmospheric CO2. Geophys. Res. Lett. 41, 4978–4986.

USDA-NRCS, 2009. Mississippi River Basin Healthy Watersheds Initiative.
USDA-NRCS, 2012. Assessment of the Effects of Conservation Conservation Effects Assessment Project Practices on Cultivated Cropland in the Upper Mississippi River Basin. 1-11.
Wallace, C.W., Flanagan, D.C., Engel, B.A., 2018. Evaluating the Effects of Watershed Size on SWAT Calibration. Water, 10.
Walvoord, M.A., Striegl, R.G., 2007. Increased groundwater to stream discharge from permafrost thawing in the Yukon River basin: Potential impacts on lateral export of carbon and nitrogen. Geophys. Res. Lett. 34.
Wang, G.X., Hu, H.C., Li, T.B., 2009. The influence of freeze-thaw cycles of active soil layer on surface runoff in a permafrost watershed. J. Hydrol. 375, 438–449.
Wilby, R., et al., 2006. Integrated modelling of climate change impacts on water resources and quality in a lowland catchment: River Kennet, UK. J. Hydrol. 330, 204–220.
Wood, A.W., Leung, L.R., Sridhar, V., Lettenmaier, D., 2004. Hydrologic implications of dynamical and statistical approaches to downscaling climate model outputs. Clim. Change 62, 189–216.
Wu, H., et al., 2014. Real-time global flood estimation using satellite-based precipitation and a coupled land surface and routing model. Water Resour. Res. 50, 2693–2717.
Wu, M., Demissie, Y., Yan, E., 2012. Simulated impact of future biofuel production on water quality and water cycle dynamics in the Upper Mississippi river basin. Biomass Bioenergy 41, 44–56.
Xia, Y., et al., 2012. Continental-scale water and energy flux analysis and validation for the North American Land Data Assimilation System project phase 2 (NLDAS-2): 1. Intercomparison and application of model products. J. Geophys. Res.: Atmos 117.
Yang, K., et al., 2014. Recent climate changes over the Tibetan Plateau and their impacts on energy and water cycle: A review. Global Planet. Change 112, 79–91.
Yang, M., et al., 2007. Diurnal freeze/thaw cycles of the ground surface on the Tibetan Plateau. Chin. Sci. Bull. 52, 136–139.
Yang, Q., et al., 2019. Climate change will pose challenges to water quality management in the st. Croix River basin. Environ. Pollution 251, 302–311.
Zhang, C., Li, S., Qi, J., Xing, Z., Meng, F., 2017. Assessing impacts of riparian buffer zones on sediment and nutrient loadings into streams at watershed scale using an integrated REMM-SWAT model. Hydrol. Process. 31, 916–924.
Zhang, T., 2005. Influence of the seasonal snow cover on the ground thermal regime: An overview. Rev. Geophys. 43.
Zhang, X., Srinivasan, R., Debele, B., Hao, F., 2008. Runoff simulation of the headwaters of the yellow river using The SWAT model with three snowmelt algorithms 1. JAWRA J. Am. Water Resour. Assoc. 44, 48–61.