Impacts of Climate Change on TN load and Its Control in a River Basin with Complex Pollution Sources

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Abstract

It is increasingly recognized that climate change could affect the quality of water through complex natural and anthropogenic mechanisms. Previous studies on climate change and water quality have mostly focused on assessing its impact on pollutant loads from agricultural runoff. A sub-daily SWAT model was developed to simulate the discharge, transport, and transformation of nitrogen from all known anthropogenic sources including industries, municipal sewage treatment plants, concentrated and scattered feedlot operations, rural households, and crop production in the Upper Huai River Basin. This is a highly polluted basin with total nitrogen (TN) concentrations frequently exceeding Class V of the Chinese Surface Water Quality Standard (GB3838-2002). Climate change projections produced by 16 Global Circulation Models (GCMs) under the RCP 4.5 and RCP 8.5 scenarios in the mid (2040-2060) and late (2070-2090) century were used to drive the SWAT model to evaluate the impacts of climate change on both the TN loads and the effectiveness of three water pollution control measures (reducing fertilizer use, constructing vegetative filter strips, and improving septic tank performance) in the basin. SWAT simulation results have indicated that climate change is likely to cause an increase in both monthly average and extreme TN loads in February, May, and November. The projected impact of climate change on TN loads in August is more varied between GCMs. In addition, climate change is projected to have a negative impact on the effectiveness of septic tanks in reducing TN loads, while its impacts on the other two measures are more uncertain. Despite the uncertainty, reducing fertilizer use remains the most effective measure for reducing TN loads under different climate change scenarios. Meanwhile, improving septic tank performance is relatively more effective in reducing annual TN loads, while constructing vegetative filter strips is more effective in reducing annual maximum monthly TN loads.

Key words

Climate Change, SWAT, Nitrogen, Water Pollution Control, Scenario Analysis

1. Introduction

Climate change has posed a serious challenge to the water security of many regions around the world (IPCC, 2014). Process-based models have been widely used in assessing the impacts of climate change on the various components of regional water systems. The majority of the water-related climate change impact studies have focused on assessing the potential impacts of climate change on the hydrological processes and the water balance of regional water systems (Milano *et al.*, 2015; Natkhin *et al.*, 2015; Ramos and Martinez-Casasnovas, 2015; Wang and Zhang, 2015). A dearth of studies of the potential impacts of climate change on water quality has recently been noted (Jiménez Cisneros *et al.*, 2014). However, in recent years, it is increasingly recognized that climate change could affect the quality of water through complex natural and anthropogenic mechanisms (Peterson *et al.*, 2014; Xia *et al.*, 2015). For example, changes in hydrological cycle could directly affect the transport of various water pollutants in the environment. Changes in the physical and chemical properties of water bodies may directly affect the transformation processes of various pollutants. Climate change may also have indirect impact on water quality through changes in land use and agricultural practices. Accordingly, there has been a noticeable increase in the number of studies assessing the potential impacts of climate change on the quality of water, especially on water pollutant loads and concentrations (Wilson and Weng, 2011; Wu *et al.*, 2012; Luo *et al.*, 2013; Molina-Navarro *et al.*, 2014; Glavan *et al.*, 2015; Johnson *et al.*, 2015).

China is currently faced with the serious issue of widespread water pollution. River Huai is one of the most polluted rivers in China. For example, five classes of water bodies have been specified in the Chinese Surface Water Quality Standard (GB3838-2002). Among them, Class IV water is only suitable for industrial production or recreation without direct body contact. According to the latest 2016 Annual Report of China's Environment Quality, water quality fell in Class IV or below at 46.7% of the 180 national routine monitoring sites in the Huai River basin. The tributaries of the Huai River have been even more seriously polluted than the main reach, with 54.4% of the 101 national routine monitoring sections falling in Class IV or below.

Like many regions around the world, a variety of pollution sources are contributing pollutant loads to its water environment in the Huai River basin including industries, municipal sewage treatment plants, concentrated animal feedlot operations (CAFOs), scattered small-scale animal feedlot operations (SAFOs), crop production, and rural households. Meanwhile, situated in a transition zone between the northern and southern climates in China, the Huai River basin is one of the most sensitive areas to climate change in China. Climate change has posed additional challenges and uncertainties to the water pollution mitigation efforts in the basin.

Up to date, however, the majority of the studies on climate change and water quality have focused on assessing its impact on pollutant loads from non-point sources especially those from agricultural runoff (e.g. Fan and Shibata, 2015; Culbertson *et al.*, 2016; Teshager *et al.*, 2016; Serpa *et al.*, 2017; Shrestha *et al.*, 2017; Trang *et al.*, 2017). Some studies have also further evaluated the impacts of climate change on the effectiveness of various best management practices (BMPs) in reducing pollutant loads from agricultural runoff (Woznicki and Nejadhashemi, 2012; Jayakody *et al.*, 2014; Mehdi *et al.*, 2015; Panagopoulos *et al.*, 2015). In general, few studies have been conducted to evaluate the potential impacts of climate change on the discharge, transport, and transformation of water pollutants as well as the effectiveness of water pollution control measures in river basins with complex pollution sources. Meanwhile, in assessing the impacts of climate change on water quality, most studies have only made comparison between the average amount of pollutant loads simulated under the baseline climate conditions and those simulated under predicted future climate conditions.

The Soil and Water Assessment Tool (SWAT) has been extensively used to simulate the movement of water, sediments, and various pollutants in river basins worldwide (Arnold *et al.*, 2012; Gassman *et al.*, 2014; Zhang *et al.*, 2016). It has also proven to be an effective tool worldwide for evaluating the effectiveness of various best management practices (BMPs) in reducing non-point source pollution loads (Jiang *et al.*, 2014; White *et al.*, 2014). A sub-daily SWAT model has been developed and shown to simulate the discharge and transport of N from all known anthropogenic sources in the Upper Huai River basin satisfactorily (Yang *et al.*, 2016a). Built upon previous work, this study aims to use the sub-daily SWAT model to evaluate the potential impacts of climate change in the mid (2040-2060) and late (2070-2090) century on the region's N loads. In addition, three potentially feasible water pollution control measures have been identified based upon the socio-economic conditions and pollution characteristics of the region, including reducing N fertilizer use, constructing vegetative filter strips, and improving septic tank systems. SWAT simulation results before and after the implementation of each pollution control measure are used to evaluate its effectiveness in reducing N loads under the current and projected climate conditions. Assessment results of the impacts of climate change on TN loads as well as the effectiveness of various pollution control measures are expected to help guide the development of proper watershed pollution control programs in response to the imminent challenges of climate change.

In evaluating the impacts of climate change on water pollutant loads and the effectiveness of pollution control measures, this study differs from previous studies in the following aspects:

(1) We evaluated the potential impacts of climate change on N loads and their control in a river basin with complex pollution sources, where a variety of point and non-point sources discharge N into different parts of the system across the region at different frequencies and times.

(2) In view of the inherent variability of the climatic system and the uncertainties associated with climate change projections, we examined the impacts of climate change not only on the mean TN loads, but also on their distributions and extreme values.

2 Materials and Methods

2.1 Study Region

The Ru River is a second-order tributary of the Huai River. It is approximately 223 km in length, passing through nine counties and one district of the Zhumadian City, Henan Province before it joins to the Hong River, a first-order tributary of the Huai River. Our study region is the upstream contribution area to the Shakou hydrological station with a drainage area of 5803 km^2 (Fig 1). The Ru River basin has remained one of the most seriously polluted regions in the entire Huai River basin with its water quality status classified as “severely polluted”. Monthly water quality monitoring results from local Environmental Protection Agency showed that TN concentration at the outlet of the Ru River basin had fallen below Class V for 11 out of 12 times in 2015. According to the Chinese Surface Water Quality Standard (GB3838-2002), Class V water is deemed only suitable to be used in agriculture and landscape.

The Ru River basin is mostly agricultural, with farmland, wood land, and grassland accounting for 85% of its land coverage. It is located in the transition zone between the northern subtropical climate and warm temperate climate with four distinctive seasons. Its annual mean temperature is around 15 °C and annual precipitation is around 900 mm. Under the significant influence of monsoon, its precipitation usually concentrates in the summer months from June to August.

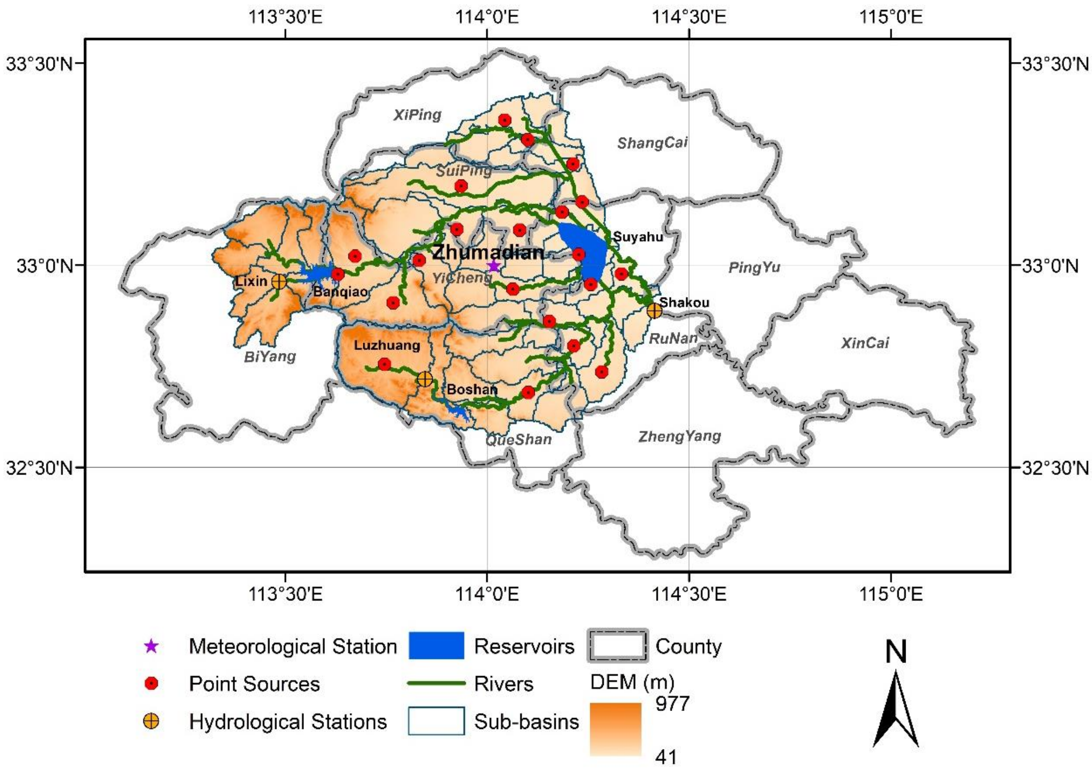

Fig 1 The location, digital elevation model (DEM), meteorological and hydrological stations, and point sources of the study region

2.2 SWAT Model and Climate Projections

Like many regions around the world, the Ru River Basin is affected by complex water pollution sources such as agriculture, livestock, industry, and households. SWAT has previously been calibrated for simulating daily streamflow and monthly TN loads from multiple point and non-point pollution sources (industries, municipal sewage treatment plants, concentrated and scattered animal feedlot operations, crop production, and rural domestic wastewater) in the Ru River basin. In the studies, two

SWAT models were developed driven by daily and hourly rainfall inputs, respectively. Comparisons of the model performances have indicated that the SWAT model driven by hourly rainfall simulated both the region's water balance and N pollution processes better than the one driven by daily rainfall. Full details of data sources, parameters, and performances of the SWAT models could be found in Yang *et al.* (2016a) and Yang *et al.* (2016b). Since it could provide satisfactory simulation results for both streamflow and TN loads, the sub-daily SWAT model was used for evaluating the impacts of climate change and water pollution control measures on the TN loads in the Ru River Basin in this study.

Climate scenarios used in this project are based on two of the Representative Concentration Pathways (RCPs) (Moss *et al.*, 2010), a set of four radioactive forcing time-series developed for the climate modeling community as the basis for long-term and near-term modeling experiments. The scenarios are named according to the radioactive forcing reached at the end of the century, such as 4.5 or 8.5 W/m^2. The global temperature rise relative to pre-industrial levels in the RCP4.5 scenario used here is 2.0±0.3°C by mid century and 2.4± 0.5°C by the 2080s; whereas for RCP8.5 the corresponding figures are 2.6±0.4°C by the 2050s and 4.3±0.7°C by the 2080s (Collins *et al.*, 2013). The RCP4.5 and RCP 8.5 scenarios represent the intermediate and high emission pathways, respectively.

Projected changes in monthly precipitation and temperature by 16 GCMs (ST1) at the four closest 0.5x0.5 degree grid cells surrounding the Zhumadian meteorological station under the RCP4.5 and RCP8.5 emission scenarios in the mid (2040-2060) and late (2070-2090) century were extracted from the Community Integrated Assessment System (CIAS) (Warren *et al.*, 2008). CIAS uses greenhouse gas emissions time series corresponding to the four RCP emission scenarios to drive the global climate change model MAGICC 6 (Meinshausen *et al.*, 2011).The resulting projections of global temperature change are consistent with GCM simulations and then are used to drive a pattern scaling module ClimGen to produce climate change patterns at 0.5 x 0.5 degree resolution (Deryng *et al.*, 2014; Osborn *et al.*, 2016). The pattern scaling process involves combining patterns of change obtained directly from certain GCM simulations with observational climate data (Osborn *et al.*, 2016).

LARS-WG is a “serial” stochastic weather generator that uses a semi-empirical distribution for the lengths of dry and wet day series, daily precipitation, and daily solar radiation. With a flexible specified set of intervals, the distribution is able to approximate precipitation occurrence and amount with respect to certain climatic characteristics. Up to date, LARS-WG has been used in a number of climate change studies worldwide (Hashmi *et al.*, 2011; Chen *et al.*, 2013; Lehmann and Finger, 2013; Hassan *et al.*, 2014; Sarkar and Chicholikar, 2015; Ma *et al.*, 2016).

In this study, LARS-WG was used to generate 100 years of synthetic daily weather time series based on the averages of the projected monthly changes in temperature and precipitation at the four grid cells for each of the 64 combinations of future scenarios, combining16 GCMs, 2 emission scenarios (RCP 4.5 and RCP 8.5), and 2 time periods (mid and late century). By assuming no change in monthly precipitation and temperature, it was also used to generate 100 years of daily weather time series to represent baseline weather conditions. This addressed the bias issue that could be caused by comparing the SWAT model outputs driven by the long-term downscaled GCM projections for a future period with those driven by shorter historical meteorological observations.

The synthetic daily rainfall data series generated by LARS-WG was further disaggregated into the hourly scale with an analog method similar to what was proposed by Mendoza-Resendiz *et al*. (2013). The basic idea of the method is to use the hourly distribution of the randomly selected historical rainfall events to disaggregate future daily rainfall of similar magnitude. The main steps to disaggregate daily rainfall into hourly data are explained as follows:

(1) Calculate the quartiles of the historical daily rainfall, and assign each historical daily rainfall event to one of the four quartile rainfall groups based on its total daily rainfall.

(2) Within each of the four rainfall groups, assign each historical daily rainfall event with a serial number.

(3) Assign each synthetic daily rainfall event to one of the four quartile rainfall groups as in step (1).

(4) Generate a random number for each combination of month (1 to 12), year (1 to 100), and quartile rainfall group (1 to 4). The hourly rainfall distribution of the historical daily rainfall event whose serial number matched the random number was used to disaggregate the synthetic daily rainfall of a particular month, year, and rainfall group into hourly data for all GCMs.

2.3 Scenario Analysis

To assess the potential impacts of climate change on the TN loads in the Ru River basin, the 100 years of synthetic weather data series representing both the baseline and projected weather conditions under the RCP 4.5 and RCP 8.5 emission scenarios in the mid and late century were used to drive the sub-daily SWAT model to simulate the discharge, transport, and transformation of N in the study region. A total of 65 SWAT modeling runs were performed under the baseline and 64 projected future climate conditions. The distributions of the 100 simulated monthly TN loads in February, May, August, and November from each modeling run were compared among the 64 combinations of GCMs, emission scenarios, and time periods.

In addition, three water pollution control measures were simulated with SWAT under both the baseline and future climate conditions to evaluate the impacts of climate change on their effectiveness in reducing TN loads, which include reducing N fertilizer use, constructing vegetative filter strips around agricultural land, and improving septic tank performance. A total of 65 SWAT modeling runs were performed to simulate the implementation of each water pollution control measure under the baseline and different future climate conditions. TN loads simulated with and without its implementation were used to calculate both the percentages of annual TN load reduction and the percentages of annual maximum monthly TN load reduction by each pollution control measure. The percentages of TN load reduction by each pollution control measure were compared among different GCMs, emission scenarios, and time periods to evaluate the impacts of climate change on its effectiveness.

3 Results

3.1 Projected Changes in Precipitation

Projected changes in monthly precipitation by the 16 GCMs vary greatly (Fig 2). For both emission scenarios and time periods, in every single month the direction of projected change in precipitation is inconsistent between various GCMs. In addition, the differences in precipitation projections among GCMs vary monthly, with the least variation in January and the largest in September. In mid-century, for example, GCMs variously project that January precipitation may rise by 7.9 mm or fall by 3.2 mm (a range of 11.1 mm) , whereas September precipitation may rise by 33.5 mm or fall by 19.2 mm (a range of 52.7 mm) under RCP 4.5. Under RCP 8.5, projected changes in January precipitation range from -3.9 mm to 9.3 mm, compared to -22.7 mm to 42.8

mm in September.

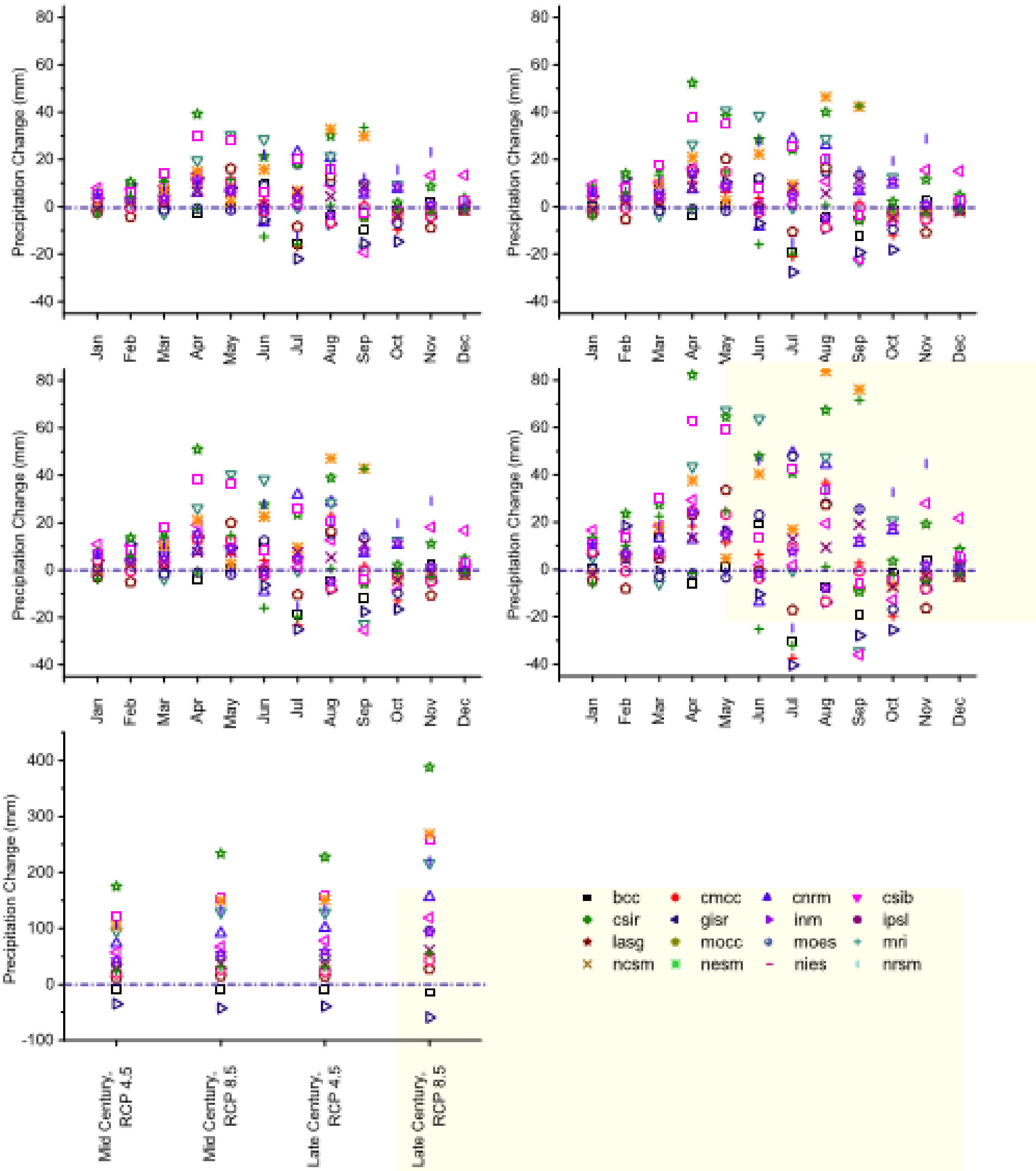

Fig 2 Projected changes in precipitation by 16 GCMs for four combinations of emission scenarios and time periods: (a) monthly precipitation under RCP 4.5 in mid century; (b) monthly precipitation under RCP 8.5 in mid century; (c) monthly precipitation under RCP 4.5 in late century; (d) monthly precipitation under RCP 8.5

in late century; (e) annual precipitation under RCP 4.5 and RCP 8.5 in mid and late century

Despite the large variability, there are some common patterns of change in projected precipitation. First, all GCMs predict an increase in annual precipitation under both RCP 4.5 and RCP 8.5 scenarios in the mid and late century except two (bcc and gisr). Secondly, most GCMs predict increasing monthly precipitation in winter (December to February) and spring (March to May) under both emission scenarios in both time periods. Projected changes in summer (June to August) and fall (September to November) are more variable. Slightly more GCMs predict an increase in monthly precipitation for the three summer months, whereas a decrease for October and November. For September, an equal number of GCMs project an increase or decrease in its monthly precipitation. Thirdly, precipitation predictions under RCP 8.5 are generally more variable than those under RCP 4.5. In the mid century, for example, predicted changes in July precipitation range from -27.6 to 28.8 mm under RCP 8.5, compared to -22.0 to 23.0 mm under RCP 4.5. In the late century, predicted changes in July precipitation range from -40.5 to 49.3 mm under RCP 8.5, compared to -25.1 to 31.8 mm under RCP 4.5.

3.2 Potential Impacts of Climate Change on TN Loads

To study the potential impacts of climate change on TN loads, the sub-daily SWAT model was used to simulate the discharge, transport, and transformation of N in the Ru River basin with weather data inputs reflecting both the baseline weather conditions and the predicted changes in future climate conditions. In total, 64 SWAT model runs were independently conducted to estimate TN loads under the climate conditions predicted by 16 GCMs under two emission scenarios (RCP 4.5 and RCP

8.5) for two time periods (mid and late century). In addition, one SWAT model run was conducted to estimate TN loads under the baseline weather conditions.

With 100 years of synthetic weather data as inputs, each SWAT model run produced 100 TN load estimates for each month. Due to the distinct seasonal difference in the discharge and transport of N in the Ru River basin(Yang *et al.*, 2016a), distributions of simulated monthly TN loads in February, May, August, and November under different climate conditions were separately examined and compared to account for the potential seasonal difference in the impacts of climate change.

3.2.1 Impacts of Climate Change on TN Loads in February, May, and November

In general, projected changes of TN loads exhibit similar patterns in February, May, and November. First, under the baseline weather conditions, average TN loads in February, May, and November were estimated to be 166, 242, and 293 tons, respectively. They are mostly projected to increase under all four climate change scenarios (Table 1). Under both RCP 4.5 and RCP 8.5, average February and May TN loads were predicted to increase in response to 13 or more GCMs in the mid century and 14 or more GCMs in the late century (SF1-SF2). The increasing trend in TN loads is less definite in November. In both time periods, average November TN loads in response to 9 and 12 GCMs exceeded baseline levels under RCP 4.5 and RCP 8.5, respectively (SF 3).

Table 1 Average simulated TN loads in response to the baseline climate and 16 GCM projections

	Annual	Feb	May	Aug	Nov
Baseline	4793	166	242	985	293
RCP 4.5, Mid Century	3974-6086	162-212	233-386	647-1136	253-357
RCP 8.5, Mid Century	3883-6398	165-214	232-407	597-1131	229-388
RCP 4.5, Late Century	3980-5961	167-217	238-378	678-1035	243-366
RCP 8.5, Late Century	4282-8353	169-407	235-656	707-1230	242-462

Second, there is a tendency of increase in the extreme values at the high end in the distribution of monthly TN loads under all four climate change scenarios. In the mid century, the 90th percentiles of February TN loads in response to 13 and 15 GCMs, the 90th percentiles of May TN loads in response to 11 and 14 GCMs, and the 90th percentiles of November TN loads in response to 15 and 14 GCMs were predicted to increase under RCP 4.5 and RCP 8.5, respectively. In the late century, the 90th percentiles of February TN loads in response to all 16 GCMs, the 90th percentiles of May TN loads in response to 12 and 15 GCMs, and the 90th percentiles of November TN loads in response to 14 and 15 GCMs were predicted to increase under RCP 4.5 and RCP 8.5, respectively (Table 2, SF1-SF3).

Table 2 The 90th percentiles of the projected TN loads in response to the baseline climate and 16 GCM projections

	Annual	Feb	May	Aug	Nov
Baseline	8093	197	351	2416	400
RCP 4.5, Mid Century	6062-9395	187-313	322-573	1371-2820	371-588
RCP 8.5, Mid Century	5353-9824	193-329	324-569	1201-2984	331-627
RCP 4.5, Late Century	6013-9135	198-347	337-551	1448-2283	360-617
RCP 8.5, Late Century	6922-11937	200-632	315-988	1354-2816	347-702

Finally, TN loads in response to some GCMs under RCP 8.5 in the late century were much larger and more variable than those under the other three scenarios. Under RCP 8.5 in the late century, average February TN loads were predicted to increase by more than 100%, 80%, and 40% in response to one, two, and three GCMs, respectively. In contrast, the largest predicted increase in average February TN loads was all around 30% under the other three scenarios (SF1). Similarly, average May TN loads in response to two GCMs were predicted to increase by more than 100% under RCP 8.5 in the late century, while the largest predicted increase was less than 70% under the other three scenarios (SF2). In addition, under RCP 8.5 in the late century, the 90th percentiles of February TN loads in response to 5 GCMs were predicted to increase by more than 100%; the 90th percentiles of May TN loads in response to 2 GCMs were respectively predicted to increase by more than 150% and 70%; the 90th percentiles of November TN loads in response to 4 GCMs were predicted to increase by more than 50% (SF1- SF3).

3.2.2 Impacts of Climate Change on TN Loads in August

Under the baseline weather condition, the estimated average August TN load of 985 tons was much higher than the other three months. With CVs ranging from 0.85 to 1.46, simulated TN loads in August were also much more variable than those in the other three months. Under projected climate change conditions, simulated TN loads in August did not exhibit an increasing trend as the other three months. Under the four climate change scenarios, for example, average August TN loads and the 90th percentiles of August TN loads were predicted to increase in response to at most 5 and 4 GCMs, respectively (Table 1-2, SF 4).

3.3 Impacts of Climate Change on the Effectiveness of Water Pollution Control Measures

On the basis of the local socio-economic conditions and pollution characteristics, three potentially feasible water pollution control measures were selected to evaluate their effectiveness in reducing TN loads under the current and future climate conditions, including reducing N fertilizer use, constructing vegetative filter strips, and improving septic tank systems.

Application of N fertilizers is an importance source of TN load in the Ru River basin. Agricultural runoff was estimated to account for 29.4% of TN loads in spring, 45.3% in summer, 53.8% in fall, and 41.9% in winter (Yang *et al.*, 2016a). Field interview results have indicated that most of the crop fields in the study region were under the wheat-corn rotation with fairly homogeneous crop management practices. Farmers generally apply 750 kg/ha of compound fertilizers and 337.5 kg/ha of urea for growing corn, and 750 kg/ha of compound fertilizers and 187.5 kg/ha of urea for growing wheat, respectively (Yang *et al.*, 2016a). In evaluating the effectiveness of reducing N fertilizer use, we assumed that the current urea application rates for growing corn and wheat were both cut by 50%.

Vegetative filter strips are vegetated areas that are situated between surface water bodies and land. They could slowdown surface runoff, entrap larger soil and organic particles, and facilitate the absorption of nutrients (Waidler *et al.*, 2009). Currently, vegetative filter strips have not been widely implemented in the Ru River basin. To assess the effectiveness of constructing vegetative filter strips in reducing N loads, we simulated the establishment of vegetative filter strips in all hydrological response units (HRUs) with agricultural land in SWAT by setting VFSCON (the fraction of total runoff from the entire field entering the most concentrated 10% of the vegetative filter strips) to be 0.5 and VFSRATIO (field area to vegetative filter strip area) to be 40 (Waidler *et al.*, 2009).

There is a large rural population in the Ru River basin, whose domestic wastewater has not been collected for central treatment. Municipal wastewater treatment technologies that have been used for the centralized treatment of urban sewage are not feasible in rural China due to the high construction costs, the need for regular maintenance, and the difficulty of wastewater collection from diffusive sources. At the time being, septic tanks are the main facilities for rural domestic sewage treatment in China. To evaluate the impacts of improving septic tank performance on N load reduction, we assumed that TN concentration in the effluent of septic tanks was reduced from the current level of 90 mg/l to 45 mg/l.

The sub-daily SWAT model was used to simulate the implementation of the above three water pollution control measures under the baseline and various future weather conditions. Simulated TN loads before and after the implementation of each pollution control measure under different climate change scenarios were compared to evaluate the impacts of climate change on its effectiveness in reducing annual TN loads and annual maximum monthly TN loads.

3.3.1 Impacts on Reducing Annual TN Loads

The percentages of annual TN load reduction due to cutting urea usage, constructing vegetative filter strips, and improving septic tank systems under the baseline and various future weather conditions were calculated and their distributions were compared in Supplementary Fig 5 to Fig 7, respectively. Under the baseline weather conditions, cutting urea usage is the most effective in reducing annual TN load followed by improving septic performance and constructing filter strips (Table 3).

Projected impacts of climate change on the effectiveness of the three pollution control measures in reducing annual TN load are varied. Under all four climate change scenarios, reducing fertilizer use remains the most effective measure in reducing annual TN loads. An increase in the average percentage of annual TN load reduction was predicted in response to half of the GCMs under the two emission scenarios in the mid century, and slightly more than half in the late century. On the whole, the projected changes in the measure's effectiveness in reducing annual TN loads due to climate change are modest, mostly falling between -1% and 2% (Table 3).

Table 3 Comparison of the Average Percentage of Annual TN Load Reduction by Three Pollution Control Measures

Pollution Control Measures	Baseline	Mid Century		Late Century	
		RCP 4.5	RCP 8.5	RCP 4.5	RCP 8.5
Urea reduction	8.8	7.9-10.3	7.7-11.1	7.9-10.6	8.1-12.3

Constructing filter strips	4.9	4.7-5.4	4.3-5.5	4.7-5.5	3.5-5.7
Improving septic tanks	5.9	4.7-6.2	4.6-6.2	4.8-6.1	3.3-5.6

As to constructing filters strips, projected impacts of climate change on its effectiveness tend to differ with emission scenarios. Under RCP 4.5, the average percentage of annual TN load reduction was predicted to increase in response to at least 12 GCMs in the two time periods. Under RCP 8.5, however, the average percentage of annual TN load reduction was predicted to increase in response to only 8 and 5 GCMs in the mid and late century, respectively.

Unlike the other two measures, the effectiveness of improving septic tank performance is likely to be negatively affected by climate change. Under all four climate change scenarios, the average percentage of annual TN load reduction due to improving septic tanks was predicted to decrease in response to at least 15 GCMs. However, the majority of the predicted decrease is less than 2%.

3.3.2 Impacts on Reducing Maximum Monthly TN Loads

The percentages of maximum monthly TN load reduction due to reducing N fertilizer use, constructing vegetative filter strips, and improving septic tank systems under the baseline and various future weather conditions were calculated and their distributions were compared in Supplementary Fig 8 to Fig 10, respectively.

Under the baseline weather conditions, cutting urea usage is the most effective measure for reducing maximum monthly TN loads closely followed by constructing vegetative filter strips. Improving the performance of septic tanks, on the other hand, is much less effective than the other two measures in reducing maximum monthly TN loads (Table 4).

Table 4 Comparison of the Average Percentage of Annual Maximum Monthly TN

Load Reduction by Three Pollution Control Measures

Pollution Control Measures	Baseline	Mid Century		Late Century	
		RCP 4.5	RCP 8.5	RCP 4.5	RCP 8.5
Urea reduction	10.7	10.0-11.2	10.0-12.1	10.1-11.6	8.6-11.5
Constructing filter strips	9.3	9.1-11.0	9.0-10.8	8.8-10.1	6.7-10.6
Improving septic tanks	3.7	3.1-3.9	3.0-4.0	3.0-3.8	2.4-3.6

Under all four future climate change scenarios, improving septic tank performance remains the least effective measure for reducing maximum monthly TN loads. Furthermore, climate change tends to have negative impacts on its effectiveness. Under each climate change scenario, the average percentage of maximum monthly TN load reduction due to improving septic tanks was predicted to decrease in response to at least 15 out of 16 GCMs.

Regarding constructing vegetative filter strips, climate change in the mid century tends to have a positive impact on its effectiveness in reducing maximum monthly TN loads. In the mid century, the average percentage of maximum monthly TN load reduction due to the measure was predicted to increase in response to 15 and 11 GCMs under RCP 4.5 and RCP 8.5, respectively. In the late-century, however, the percentage was predicted to increase only in response to 10 and 7 GCMs under the two emission scenarios.

The impacts of climate change on cutting urea usage are relatively uncertain. Under all four climate change scenarios, the average percentage of maximum monthly TN load reduction due to the measure was predicted to increase or decrease both in response to about half of the 16 GCMs.

4 Discussions

4.1 Implications of Climate Change’s Impacts on TN Loads

In general, SWAT simulation results under different climate change scenarios indicate that climate change tends to have considerable negative impacts on TN loads in the Ru River basin. Average monthly TN loads in February, May, and November are much likely to increase under both emission scenarios in the mid and late century (Table 1). Moreover, there is a high possibility that climate change may lead to an increase in the extreme TN loads at the high end in these three months (Table 2). Unlike the other three months, the distribution of TN loads is much more variable in August under both the baseline and future weather conditions. It does not exhibit an obvious pattern of change under all four future climate scenarios.

Despite fewer than summer loads, TN loads in spring, fall, and winter are by no means less important to the water quality of the Ru River Basin. Fig. 3 compared the monitored monthly TN concentrations at the outlet of the Ru River basin between 2006 and 2011 with the Class III and V of China’s Surface Water Quality Standard. As can be seen from the figure, 86.7% of monthly TN observations in spring failed to meet the Class V standard, compared to 58.3% in summer, 60.0% in fall, and 84.6% in winter. Hence, the predicted increases in both average and extreme TN loads in February, May, and November will surely pose additional challenges on the improvement of water quality in the study region.

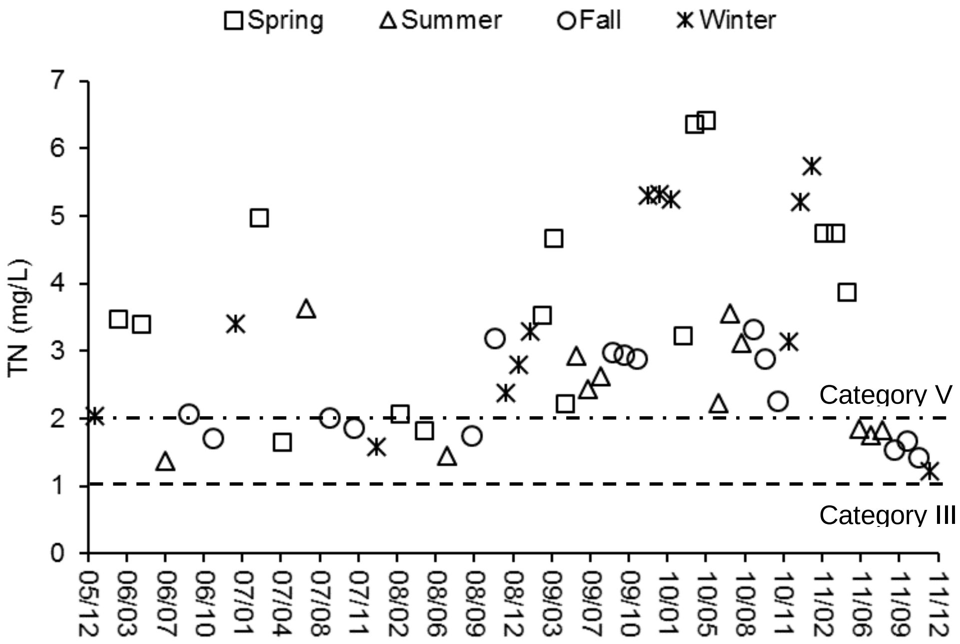

Fig. 3 Observed TN concentrations at the outlet of the Ru River Basin

In addition, in the late century, the distributions of February and May TN loads in response to some GCMs under RCP 8.5 are much different from those under the other three scenarios with large increases in both the average and extreme TN loads. This indicates that the river basin's response to climate change may begin to approach a critical threshold under the RCP 8.5 scenario in the late century.

4.2 Implications of Climate Change's Impacts on Pollution Control Measures

The effectiveness of pollution control measures have been examined in terms of both reducing annual TN loads and annual maximum monthly TN loads. In the absence of climate change, cutting urea usage reduces annual TN loads by about 9%, whereas the reductions by constructing filter strips and improving septic tanks are both less than 6%. Projected impacts of climate change on the effectiveness of the three water pollution control measures in reducing annual TN loads are varied. The effectiveness of improving septic tanks tends to be reduced under a changed climate, while the changes in the effectiveness of the other two measures are more uncertain. Nevertheless, climate change's overall impact on the effectiveness of the three measures could be categorized as modest, with the projected changes in the average percentage of TN load reduction mostly falling between ±2%.

Under both current and future climate conditions, improving septic tank performance is much less effective in reducing maximum monthly TN loads than the other two measures. This is probably because the measure mainly targets the subsurface TN loads. Maximum monthly TN loads, however, usually occur in the summer months when heavy rainfall causes large quantity of surface runoff carrying considerable TN loads. Similar to annual TN loads, climate change is projected to have a negative impact on the effectiveness of improving septic tanks in reducing maximum monthly TN loads. Meanwhile, the projected impacts of climate change on the effectiveness of the other two measures are mixed.

5 Conclusion

Around the world, river basins are receiving the pollutant loads from a variety of point and nonpoint pollution sources. Nevertheless, climate change impact studies related to water quality have so far mainly focused on assessing the impact of climate change on pollutant loads from non-point sources. In view of the gap, we made use of projected changes in future climate by 16 GCMs under RCP 4.5 and RCP 8.5 in the mid and late century to drive a sub-daily SWAT model to evaluate the potential impacts of climate change on TN loads and the effectiveness of their control measures in the Ru River basin while incorporating a variety of TN pollution sources (industries, municipal sewage treatment plants, concentrated animal feedlot operations, scattered small-scale animal feedlot operations, crop production, and rural households). Our scenario analysis results have shown that climate change under both emission scenarios is much likely to increase both the average and extreme TN loads at the high end in February, May, and November, while its impacts on August TN loads are more variable. The regional water system's response to climate change is likely to approach a threshold under the RCP 8.5 scenario in the late century.

In addition, there is much difference in their effectiveness of reducing TN loads under the baseline and predicted future weather conditions among the three considered water pollution control measures. Projected climate changes tend to have a negative impact on the effectiveness of improving septic tanks, while their impacts on cutting urea usage and constructing vegetative filter strips are more mixed. Nevertheless, cutting urea usage remains the most effective measure in reducing both TN loads under both average and extreme climate conditions. The climate change's impacts on its effectiveness in reducing annual TN loads and annual maximum monthly TN loads are mostly modest. In view of the huge investment required in facility improvement and engineering construction by the two measures of constructing vegetative filter strips and improving septic performance, as well as the measure's own effectiveness and reliability in reducing TN loads, it is suggested that improving fertilizer application practice should be put in priority for reducing N loads from non-point pollution sources and improving water quality in the study region.

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