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# Comparative analyses of hydrological responses of two adjacent watersheds to climate variability and change scenarios using SWAT model

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**Abstract**

Water quality problems in the Chesapeake Bay Watershed (CBW) are expected to exacerbate under climate variability and change. However, climate impacts on agricultural lands and resultant nutrient loads into surface water resources are largely unknown. This study evaluates the impacts of climate variability and change on two adjacent watersheds in the Coastal Plain of the CBW, using Soil and Water Assessment Tool (SWAT) model. We prepared six climate sensitive scenarios to assess the individual effects of variations in $CO_2$ concentration (590 and 850 ppm), precipitation increase (11 and 21 %) and temperature increase (2.9 and 5.0 °C), and considered the predicted climate change scenario using five general circulation models (GCMs) under the Special Report on Emissions Scenarios (SRES) A2 scenario. Using SWAT model simulations from 2001 to 2014, as a baseline scenario, the predicted water and nitrate budgets under climate variability and change scenarios were analyzed at multiple temporal scales. Compared to the baseline scenario, precipitation increase of 21% and elevated $CO_2$ concentration of 850 ppm significantly increased stream flow and nitrate loads by 50 % and 52 %, respectively, while, temperature increase of 5.0 °C reduced stream flow and nitrate loads by 12 % and 13 %, respectively. Under the climate change scenario, annual stream flow and nitrate loads showed an average increase of nearly 40 %, relative to the baseline scenario. Differences in hydrological responses observed from the two watersheds were primarily attributed to contrasting land use and soil characteristics. The watershed with larger percent croplands indicated increased nitrate yield of 0.52 kg N·ha$^{-1}$ compared to the one with less percent croplands under the climate change scenario, due to increased export of nitrate derived from fertilizer. The watershed dominated by poorly-drained soils showed a lower increase in nitrate yield than one dominated by well-drained soils, due to a high potential of nitrate loss in surface runoff and enhanced denitrification. To

mitigate increased nitrate loads potentially caused by climate change, the enhanced implementation of conservation practices would be necessary for this region in the future. These findings assist watershed managers and regulators as they seek to establish effective adaptation strategies to mitigate water quality degradation in this region.

## 1 Introduction

The Chesapeake Bay (CB) is the largest and most productive estuary in the Mid-Atlantic region of the United States (US). The Chesapeake Bay Watershed (CBW) covers an area of 166,000 km$^2$ and is home to more than 18 million people and 3,600 species of plants and animals (Chesapeake Bay Program, 2016). Despite significant restoration efforts, the health of the Bay has continued to deteriorate, primarily due to excessive nutrients and sediment loadings from agricultural lands (Rogers and McCarty, 2000). Najjar et al. (2010) suggested that the current water quality problems in the Bay are expected to worsen under climate variability and change. General Circulation Models (GCMs) have projected increases in temperature and precipitation of up to 5.0 °C and 21 %, respectively, by the end of this century in the CB region (Najjar et al., 2009), which could lead to substantial changes in the hydrology and nitrogen (N) cycle. For instance, Howarth et al. (2006) reported that greater precipitation is anticipated to increase N loads to the CB by ~ 65%. With precipitation and temperature changes, elevated $CO_2$ concentration affecting stomatal conductance has also been viewed as one of decisive factors modifying watershed hydrological processes (Chaplot, 2007; Wu et al., 2012a and 2012b).

Numerous studies have been conducted to demonstrate the impacts of changes in $CO_2$ concentration, precipitation and temperature on stream flow and N loads. Elevated $CO_2$ concentration is predicted to increase stream flow by reduction of evapotranspiration (ET) that results from a decrease in plant stomatal conductance (Field et al., 1995; Jha et al., 2006; Wu et al., 2012a and 2012b). Jha et al. (2006), for example, showed that a doubling of $CO_2$ concentration increased water loads by ~ 36 % in the upper Mississippi river basin. Precipitation increase/decrease was found to directly cause the rise/fall of stream flow levels (Jha et al., 2006; Ficklin et al. 2009; Wu et al., 2012a; Praskievicz, 2014; Uniyal et al., 2015). Similarly, the study by Ficklin et al. (2009) found that precipitation change of + 20 and – 20 % led to changes in water loads by nearly + 17and – 14 %, respectively, in the San Joaquin River watershed, California. Temperature increase was reported to reduce stream flow during summer seasons due to the intensified ET values, but increase stream flow during winter seasons due to an upsurge of snow melting (Jha et al., 2006; Ficklin et al. 2009; Wu et al., 2012a; Ficklin et al., 2013; Praskievicz, 2014). Interestingly, in most studies, the responses of N loads to climate variability were found to be similar to stream flow (Ficklin et al. 2009; Wu et al., 2012a; Praskievicz, 2014; Gombault et al., 2015). According to the projected climatic conditions (e.g., elevated $CO_2$ concentration, precipitation and temperature increases) illustrated in Najjar et al. (2009), substantial variations in stream flow and N loads are anticipated in the CBW. Therefore, it is important to investigate potential climate change impacts on watershed hydrological processes to efficiently mitigate water quality degradation.

However, climate change impacts on hydrological processes have not been fully investigated in the CB region. Howarth et al. (2006) attempted to quantify N loads under modified climate conditions, but their projections relied on the statistical relationships between river discharge/precipitation and N loads. Lee et al. (2015) predicted changes in stream flow and nitrate loads at the outlet of the watershed in response to climate variability (e.g., elevated $CO_2$ concentration, precipitation and temperature increase). However, their results did not demonstrate climate change impacts on hydrology and nutrient cycles within a watershed system (Lee et al., 2015). To cope with climate change-driven modifications, it is imperative to have an understanding of a wide range of changes in hydrological processes (Najjar et al., 2010). A simple projection of the future trend of sediment and nutrient loadings would not be sufficient to prepare strategies to curb climate change impacts. N reduction using conservation practices is most effective when based on comprehensive insight into watershed hydrologic processes (McCarty et al., 2014). Moreover, responses of watershed hydrological processes to climate variability and change can vary by watershed characteristics (e.g., land use and soil drainage conditions). For example, cropland area was found to be positively correlated with in-stream nitrate concentration in this region (Jordan et al., 1997; Hively et al., 2011; McCarty et al., 2014; Lee et al., 2016). Furthermore, field studies showed that watersheds with a greater area of cropland released a higher amount of nitrate than areas with less cropland, mainly due to agricultural N inputs (Jordan et al., 1997; Hively et al., 2011; McCarty et al., 2014). Thus, climate change can lead to greater nitrate export from watersheds with a larger percent cropland area, due to increased export of N from fertilizer application. Additionally, different soil characteristics also can lead to different responses in watershed-scale water and N cycles under climate change. The study by Chiang (1971) showed that well-drained soils with a high infiltration rate promote water percolation, increasing groundwater contribution to stream flow. Nitrate leaching was also found to frequently occur in well-drained soils (Lee et al., 2016). In contrast, poorly-drained soils with a low infiltration rate provide anaerobic conditions conducive to denitrification, resulting in nitrate removal in soils and groundwater (Denver et al., 2010; Lee et al., 2016; Sharifi et al., 2016). For example, prior converted croplands, which are also known as "currently farmed historical wetlands", often associated with areas of poorly-drained soil were also shown to have prominent impacts on reducing agrochemical loadings in this region during winter seasons, when ET is low which results in a higher groundwater table (Tiner and Burke, 1995; Denver et al., 2014; McCarty et al., 2014; Sharifi et al., 2016). Artificial drainage systems in agricultural lands are also widely developed on poorly-drained soils in this region, resulting in an increase of water and nutrient transport from lands to nearby streams through surface runoff

(McCarty et al., 2008; Fisher et al., 2010). Therefore, water and nitrate fluxes in the watersheds with different soil characteristic would show different responses to climate variability and change.

Nitrate export from Coastal Plain watersheds was found to be substantially greater than export from other regions of the CBW, due to the relatively high abundance of croplands (Ator and Denver, 2012). Recent observations from two adjacent watersheds with contrasting land use (cropland-dominant vs. forest-dominant) and soil characteristics (well-drained vs. poorly-drained) on the Coastal Plain were shown to have distinctive characteristics of fate and transport, both for streamflow and nitrate loads (McCarty et al., 2008; Lee et al., 2016; Sharifi et al., 2016).

This study aimed at evaluating the impacts of potential climate variability and change on water and nitrate budgets in the two adjacent watersheds on the Coastal Plain of the CBW, using the Soil and Water Assessment Tool (SWAT) model. This process-based water quality model has been widely used to predict climate change impacts on numerous watersheds (Gassman et al., 2007; Luo et al., 2013; Uniyal et al., 2015). We prepared six climate sensitivity scenarios to assess the individual effects of changes in $CO_2$ concentration (590 and 850 ppm), precipitation (11 and 21 %) and temperature (2.9 and 5.0 °C), and the GCM-based climate change scenario to evaluate the long-term watershed hydrological processes under projected future climate conditions. We first analyzed climate change impacts on water and nitrate budgets considering modified hydrology, N cycle, and crop growth. Then, comparative analyses between two watersheds were conducted to identify critical landscape characteristics that profoundly affect nitrate loads under climate variability and change, and finally suggestions were provided for conservation practices to improve the resilience of coastal watersheds to the future climate change in this region.

## 2 Materials and Methods

### 2.1 Study area

This study was undertaken on two adjacent watersheds, Tuckahoe Creek Watershed (TCW, ~220.7 km$^2$) and Greensboro Watershed (GW, ~290.1 km$^2$). They are sub-watersheds of the Choptank River Watershed located in the Coastal Plain of the CBW (Figure 1). The Choptank River Watershed is one of the Conservation Effects Assessment Project (CEAP) Benchmark watersheds of the United States Department of Agriculture (USDA), Agricultural Research Services (ARS). The US Environmental Protection Agency (USEPA) has listed this watershed, as "impaired" under Section 303(d) of the 1972 Clean Water Act, primarily due to the excessive nutrients and sediment loadings (McCarty et al. 2008). The two adjacent sub-watersheds have distinctive characteristics considering the distribution of land use and soil drainage conditions (Figure 2 and Table 1). The TCW is dominated by agricultural lands (54 %) and forest (32.8 %) with well-drained soils, classified as hydrologic soil groups (HSG) – either A or B. These soils account for 56% of the total watershed and 69.5 % of the agricultural lands (Figure 2). Thus, water and nitrate fluxes tend to be easily percolated/leached into soils and groundwater, and thus groundwater flow is considered as a major water pathway for nutrient fluxes to streams in TCW (Lee et al., 2016). In comparison, forest (48.3 %) is the major land use type in GW, followed by agricultural (36.1 %). Soils that are poorly-drained ((HSG) – C or D) occupy 75 % of the total area and 67.2 % of agricultural lands, which results in a low infiltration and high denitrification.

[Insert Figure 1. The location of Tuckahoe Creek Watershed (left) and Greensboro Watershed (right)]

[Insert Figure 2. The physical characteristics of Tuckahoe Creek Watershed (left) and Greensboro Watershed (right); (a) land use, (b) hydrologic soil groups, and (c) elevation]

[Insert Table 1. Soil properties and land use distribution of Tuckahoe Creek Watershed (TCW) and Greensboro Watershed (GW)]

## 2.2 Soil and Water Assessment Tool (SWAT)

SWAT is a process-based watershed model, developed to assess the impact of human activities and land use on water and nutrient cycles within agricultural watersheds (Netisch et al., 2011). SWAT divides a watershed into sub-watersheds using a Digital Elevation Model (DEM), and each sub-watershed is further divided into hydrological response units (HRUs) based on a unique combination of land use, soil type, and slope. Model simulation is performed at the HRU level, and the simulated outputs aggregated at the sub-watershed and then further at the watershed level through routing processes. The amount of surface runoff and infiltration are calculated based on Soil Conservation Service (SCS) Curve Number (CN) method, and the CN values are updated daily based on soil permeability, land use type, and antecedent soil water conditions. Water infiltrated into soils is either delivered to streams through lateral flow or to groundwater. The groundwater portion is then either transported to streams, or percolated into the deep groundwater aquifer. Both inorganic and organic forms of N are simulated with the SWAT model. The amount of nitrate in soils increases by nitrification, mineralization, and fertilization, but decreases through denitrification and plant uptake. Nitrate fluxes can move via surface runoff, lateral flow, groundwater flow, and leaching.

Hydrol. Earth Syst. Sci. Discuss., doi:10.5194/hess-2017-178, 2017
Manuscript under review for journal Hydrol. Earth Syst. Sci.
Discussion started: 19 April 2017



SWAT also has the capability of simulating the impacts of $CO_2$ concentration on ET, plant stomatal conductance, and biomass accumulations. We used the Penman-Monteith method to consider $CO_2$ effects on ET. It calculates potential ET regarding plant canopy resistance that is adjusted by $CO_2$ concentration as shown in Eq. (1).

$$r_c = r_l \times \left[(0.5 \cdot LAI) \cdot (1.4 - 0.4 \times (CO_2 / 330))\right]^{-1} \quad (1)$$

where $r_c$ is plant canopy resistance, $r_l$ is the minimum effective stomatal resistance of a single leaf, and $LAI$ is the leaf area index of the canopy. According to Eq. (1) elevated $CO_2$ concentration decreases plant canopy resistance, subsequently reducing ET regarding the relationship with plant canopy resistance. Refer to Neitsch et al. (2011) for details on the Penman-Monteith method. The impacts of $CO_2$ concentration on plant stomatal conductance is simulated using a function of $CO_2$ as shown in Eq. (2). The equation simulates the linear reduction of conductance with increasing $CO_2$ and estimates 40 % reduction in leaf conductance for all plants when $CO_2$ concentration is doubled (Neitsch et al., 2012).

$$g_{l,co_2} = g_l \times \left[1.4 - 0.4 \times (CO_2 / 330))\right]^{-1} \quad (2)$$

where $g_{l,co_2}$ is the leaf conductance modified to reflect $CO_2$ effects, and $g_l$ is the leaf conductance without the effect of $CO_2$.

The simulation of the crop growth in SWAT is based on potential heat unit theory. SWAT considers the impacts of $CO_2$ concentration on crop biomass growth by modifying radiation-use efficiency (RUE) of the plant as follows:

$$RUE = \frac{100 \cdot CO_2}{CO_2 + \exp(r_1 - r_2 \cdot CO2)} \quad (3)$$

where $RUE$ is radiation-use efficiency of a plant, and $r_1$ and $r_2$ are coefficients.

$$\Delta bio = RUE \cdot H_{phosyn} \tag{4}$$

where $\Delta bio$ is a potential increase in plant biomass on a given day and $H_{phosyn}$ is the amount of intercepted photosynthetically active radiation on a given day.

### 2.3 Baseline SWAT input data

Climate and geospatial data needed for SWAT simulation are summarized in Table 2. Daily precipitation and temperature were obtained from three meteorological stations operated by the National Oceanic and Atmospheric Administration (NOAA) National Climate Data Center (NCDC) at Chestertown, Royal Oak, and Greensboro (USC00181750, USC00187806, and US1MDCL0009, respectively). Due to data unavailability, humidity, wind speed, and solar radiation were generated using the SWAT built-in weather generator (Neitsch et al., 2011). Monthly stream flow data were downloaded from US Geological Survey (USGS) gauge stations on the Tuckahoe Creek near Ruthsburg (USGS#01491500) and the Choptank River near Greensboro (USGS#01491000) (Figure. 1). The USGS LOAD ESTimator (LOADEST, Runkel et al. (2004)) was used to generate continuous monthly nitrate loads from nitrate grab sample data that were obtained from the Chesapeake Bay Program (CBP, TUK#0181) for TCW and USGS gauge station (USGS#01491000) for GW. The land use and soil maps, and DEM were prepared as shown in Table 2.

[Insert Table 2. List of SWAT model input data]

We identified representative agricultural practices for this region using multiple geospatial data (Lee et al., 2016). Major crop rotations and their year to year placement was derived through analysis of the USDA-National Agricultural Statistics Service (NASS) Cropland Data Layer (CDL) for the period of 2008 – 2012. We assumed that crop rotation and land use did not change over the simulation period so that agricultural N input did not vary for the baseline and climate change scenarios. Detailed agricultural management information (e.g., the amount, type, and application timing of fertilizer, and planting and harvesting timings of individual crops) was developed through literature review and communications with local experts (Table A1). Detailed information about the development of crop rotation and land management is available in Lee et al. (2016).

## 2.4 Baseline SWAT calibration and validation

SWAT model runs were performed at a monthly time step for 16 years; these include a 2-year warm-up (1999 – 2000), 8-year calibration (2001 – 2008), and 6-year validation period (2009 – 2014). Critical parameters used for model calibration were selected based on previous studies conducted in this region (Sexton et al., 2010; Yeo et al., 2014; Lee et al., 2016) and allowable ranges of these parameters were derived from literature presented in the caption of Table 3. Stream flow parameters were first manually calibrated and then nitrate parameters were adjusted following the model calibration guideline (Arnold et al., 2012). A set of parameters, that produced the best model performances and fulfilled model performance criteria suggested by Moriasi et al. (2007), were chosen for model validation. Model performance was evaluated using the following statistics: Nash-Sutcliffe Efficiency coefficient ( $NSE$ ), Root Mean Square Error ( $RMSE$ )-Standard deviation Ratio ( $RSR$ ), and Percent bias ( $P-bias$ ).

Hydrol. Earth Syst. Sci. Discuss., doi:10.5194/hess-2017-178, 2017
Manuscript under review for journal Hydrol. Earth Syst. Sci.
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$$NSE = 1 - \left[ \frac{\sum_{i=1}^{n} (O_i - S_i)^2}{\sum_{i=1}^{n} (O_i - \overline{O})^2} \right] \quad (5)$$

$$RSR = \frac{RMSE}{STDEV_{obs}} = \left[ \frac{\sqrt{\sum_{i=1}^{n} (O_i - S_i)^2}}{\sqrt{\sum_{i=1}^{n} (O_i - \overline{O})^2}} \right] \quad (6)$$

$$P - bias = \left[ \frac{\sum_{i=1}^{n} (O_i - S_i) \times 100}{\sum_{i=1}^{n} O_i} \right] \quad (7)$$

where $O_i$ is the observed data at time step i, and $S_i$ is the simulated output at time step i, $\overline{O}$ is the mean of observed data over all time steps, and $n$ is the total number of observed data. In addition, the 95 percent prediction uncertainty (95 PPU) band was computed to evaluate model uncertainty (Singh et al., 2014). The 95 PPU is computed as the range of values between top and bottom 2.5 % of the cumulative distribution of simulation outputs obtained during the calibration process.

[Insert Table 3. List of calibrated parameters]

## 2.5 Climate sensitivity and change scenarios

To evaluate the impacts of climate variability and change on watershed hydrological processes, climate sensitivity and change scenarios were prepared as illustrated below (see 2.5.1

and 2.5.2). The calibrated SWAT model was simulated using climate sensitivity and change scenarios for comparison with baseline water and nitrate budgets.

### 2.5.1 Climate sensitivity scenarios

A climate sensitivity analysis aids in identifying the degree or threshold of responses of hydrologic variables to climate-induced modifications and a sensitivity scenario generally assumes constant changes throughout the year (Mearns, 2001). Following the approach in Mearns (2001), six climate sensitivity scenarios were prepared by modifying the baseline data (1999 – 2014) to assess individual effects of elevated $CO_2$ concentration, precipitation and temperature on watershed hydrological processes (Table 4). Sensitivity scenarios were designed to change one variable while holding other variables constant throughout the simulations. Baseline precipitation and temperature were modified by percent and absolute changes using anomaly and absolute data, respectively, as illustrated in Najjar et al. (2009). They reported mean temperature and precipitation changes over the CB for three future periods (2010 – 2039, 2040 – 2069, and 2070 – 2099) relative to the baseline period (1971 – 2000) based on GCM outputs (Najjar et al., 2009). Baseline $CO_2$ concentration was set as the default value (330 ppm) for SWAT simulations. For the first and second scenarios, baseline $CO_2$ concentration was replaced with 590 and 850 ppm, respectively. The upper value of 850 ppm was used because GCMs used for temperature and precipitation sensitivity scenarios were forced under the Intergovernmnental Panel on Climate Change (IPCC) Special Report on Emissions Scenarios (SRES) A2 scenario, assuming to reach $CO_2$ concentration of 850 ppm by the end of this century (Najjar et al., 2009). The lower value of 590 ppm (the average of 330 and 850 ppm) was considered to be the level of $CO_2$ concentration around the middle of this century.

Hydrol. Earth Syst. Sci. Discuss., doi:10.5194/hess-2017-178, 2017
Manuscript under review for journal Hydrol. Earth Syst. Sci.
Discussion started: 19 April 2017




[Insert Table 4. Climate sensitivity scenarios developed by modifying baseline values]

### 2.5.2 Climate change scenario

A GCM-based scenario is the most commonly used method for assessing future climate change impact (Mearns, 2001). We downloaded projected climate data (e.g., daily precipitation and maximum and minimum temperature) from the World Climate Research Program (WCRP; bias corrected and downscaled) and the Coupled Model Intercomparison Project3 (CMIP3) climate projection archive (http://gdo-dcp.ucllnl.org/downscaled_cmip3_projections/). Five GCM data under the IPCC SRES A2 scenario were downloaded (Table A2), because the A2 scenario indicates the highest value of $CO_2$ concentration among available $CO_2$ emission scenarios in CMIP3. To be consistent with the period of the baseline data (1999 – 2014), 16-year future data (2083 – 2098) including a 2-year warm-up period were used. Similar to the baseline scenario, humidity, wind speed, and solar radiation values were generated using the SWAT built-in weather generator owing to data unavailability. We assumed $CO_2$ concentration for the future period as 820 ppm, as that is a specified $CO_2$ concentration under SRES A2 scenario in CMIP3 (Meehl et al., 2007). We compared simulated water and nitrate budgets from the baseline simulation with the ensemble mean of those from simulations with five GCMs because substantial variations existed among the GCM projections (Shrestha et al., 2012; Van Liew et al., 2012). The range of changes in simulated outputs was represented with the ensemble mean to show overall responses of watershed hydrological processes to climate change (Shrestha et al., 2012; Van Liew et al., 2012).

### 2.6 Analyses of simulation outputs

Simulated outputs were summarized at multiple temporal scales (e.g., monthly, seasonal, and annual). Annual averages of stream flow, ET, and nitrate loads were calculated to investigate changes in water and nitrate budgets in response to climate sensitivity and change scenarios. The response of crop growth to climate variability and change was also analyzed to show the effects of modified crop biomass on hydrology and N cycle. For comparative analyses between two watersheds, simulated outputs were summarized seasonally for climate sensitivity scenarios (i.e., summer (April – September) and winter (October – March)) and monthly for the climate change scenario. Water and nitrate yields were calculated to identify key landscape characteristics greatly affecting nitrate loads under climate sensitivity scenarios. Note that water and nitrate yields indicate the summations of water and nitrate fluxes transported from lands to streams by surface runoff, lateral flow, and groundwater flow. All simulation outputs were normalized by total watershed size.

We conducted two statistical analyses to demonstrate whether significant differences existed between simulation outputs by climate conditions (baseline vs. climate sensitivity and change scenarios) and watershed characteristics (TCW vs. GW). Two t-tests widely used for demonstrating significant effects of climate change and study site characteristics on hydrologic variables (e.g., water and nitrate budgets) were utilized in this study (Ficklin et al., 2010 and 2013; Lee et al., 2016). A paired sample t-test was performed to compare outputs from climate sensitivity and change scenarios to the baseline scenario at individual watersheds. A two-sample t-test was used to determine whether the differences between the two watersheds were significant.

## 3 Results and Discussions

### 3.1 Model calibration and validation

Monthly simulations for stream flow and nitrate loads were compared with corresponding observations (Figure 3). Results show that simulated monthly stream flow were in good agreement with observations, but simulated peak stream flows were underestimated relative to observations. This underestimation was attributed to the inherent limitations of SWAT model; it does not account for intensity and duration of the precipitation (Qiu et al., 2012). Previous studies conducted in this region have also predicted peak flows beyond the uncertainty band mainly due to model limitation, though the overall simulation results well replicated the actual observations (Yeo et al., 2014; Lee et al., 2016). Simulated nitrate loads were also well matched well actual observations and the uncertainty band (shown as green in Figure 3) captured most observations in the two watersheds. Overall, model performance measures fulfilled "good" or "very good" criteria for stream flow and at least "satisfactory" for nitrate loads (Table 5). These results demonstrated that the calibrated model replicated actual conditions reasonably well, and it was able to predict hydrologic variables under different modeling scenarios (Moriasi et al., 2007; Arnold et al. 2012).

[Insert Figure 3. Simulated and observed monthly stream flow and nitrate loads for (a & b) TCW and (c & d) GW during calibration and validation periods]

[Insert Table 5. Model performance measures for monthly stream flow and nitrate loads]

### 3.2 Responses to climate sensitivity scenarios

#### 3.2.1 Water and nitrate budgets

14-year averages of annual hydrologic variables under the baseline and climate sensitivity scenarios are represented in Figure 4. Elevated $CO_2$ concentration (590 and 850 ppm) and precipitation increase (11 and 21 %) led to significant increases in annual stream flow and nitrate loads by 50 % and 52 % for TCW and 43 % and 33 % for GW, respectively, relative to the baseline scenario (*p-value* < 0.01) (Figure 4). Elevated $CO_2$ concentration lowered plant's stomatal conductance, resulting in a decrease in ET of 30 % and thereby increases in stream flow and nitrate loads (Figure 4). Precipitation increase resulted in a direct increase in stream flow, leading to increased nitrate loads. Compared to the baseline scenario, a temperature increase of 5 °C significantly reduced annual stream flow and nitrate loads by 12 % and 13 % for TCW and 11 and 13 % for GW (*p-value* < 0.01), respectively, due to intensified ET (Figure 4).

Changes in crop growth under climate sensitivity scenarios had great impacts on water and nitrate budgets. Although precipitation increase resulted in the greatest increase in annual stream flow, annual nitrate loads were greater under elevated $CO_2$ concentration (Figure 4ab), due to increased crop biomass (Figure 5a). Elevated $CO_2$ concentration stimulated crop growth by decreasing water demand and increasing radiation use efficiencies (Abler and Shortle, 2000; Parry et al., 2004). For example, simulated corn and soybean biomass increased from 1.5 and 0.9 (baseline concentration of 330ppm) to 1.6 and 1.3 ($CO_2$ concentration of 850 ppm) $Mg{\cdot}ha^{-1,}$ respectively (Figure 5a). Increased crop biomass left greater residue, which contributed to increasing nitrate level through mineralization (Lee et al., 2016). Our simulation results indicated that mineralized nitrate under elevated $CO_2$ concentration increased by 16 % for TCW and 15 % for GW, compared to the baseline values (Figure A3). Increased crop residue resulted in greater nitrate loads under elevated $CO_2$ concentration in comparison to precipitation increase. In contrast, temperature increase led to lower crop biomass than the baseline value, due to increased heat stress (Figure 5b). Lower biomass reduced remaining crop residue and subsequently reduced mineralized nitrate by 15 % compared to the baseline value. Reduction of mineralized nitrate contributed to decreased nitrate loads in conjunction with intensified ET.

[Insert Figure 4. 14-year average of annual hydrologic variables under the baseline and climate sensitivity scenarios at the watershed scale]

[Insert Figure 5. The responses of crop biomass growth to elevated $CO_2$ concentration, temperature increases]

### 3.2.2 Comparative analyses

For the purpose of comparing the two watersheds in response to climate sensitivity scenarios, 14-year averages of seasonal water and nitrate yields were calculated (Figure 6). Both elevated $CO_2$ concentration and precipitation increase led to greater water and nitrate yields for the two watersheds during winter and summer seasons, compared to the baseline scenario. However, the seasonal pattern of nitrate yield differed between the two watersheds. Wintertime water yield was greater than summertime value for both watersheds, which was consistent with the seasonal pattern of nitrate yield for GW. However, summertime nitrate yield was greater than wintertime value for TCW. This was because of the difference in percent agricultural lands between TCW (54.0 %) and GW (36.1 %). Increased water yield could accelerate the export of nitrate added to the watersheds through fertilizer activities mainly occurred during summer seasons. Accordingly, increased water yield caused by elevated $CO_2$ concentration and precipitation increase induced considerable increase in summertime nitrate yield by ~ 62.5 % for TCW, while moderately increasing it by ~ 35.6 % for GW, which is dominated by forest instead of croplands, when compared with the baseline values.

[Insert Figure 6. 14-year average of seasonal hydrologic variables under the baseline and climate sensitivity scenarios at the watershed scale]

Temperature increase reduced summertime water and nitrate yields by 18.5 % and 27 % for TCW and 13.9 % and 20.2 % for GW, respectively, mainly due to increased water loss by ET (Figure 6). Wintertime water yield also decreased for the two watersheds, but changes in wintertime nitrate yield differed between two them. A decrease of 9.5 % in wintertime nitrate yield was found for GW, but wintertime nitrate yield increased by 1.6 % for TCW (Figure 6b), due to modified crop growth patterns and contrasting soil characteristics between the two watersheds. Temperature increase most likely drove summer crops to reach maturity earlier than the baseline (Figure 5b). Once mature, the crops stopped consuming soil water and nitrate, subsequently increasing soil water content and nitrate leaching (Figure A4). Nitrate leached into groundwater was discharged to streams through groundwater flow during winter seasons. TCW showed increased nitrate leaching of 1.0 kg $N \cdot ha^{-1}$ compared to GW, due to a higher rate of soil infiltration. Different leaching rates between TCW and GW soils led to a greater increase in wintertime nitrate flux transported by groundwater flow (NGWQ) for TCW (0.21 kg $N \cdot ha^{-1}$) compared to GW (0.16 kg $N \cdot ha^{-1}$) (Figure 6b). However, intensified ET reduced wintertime water flux transported by surface runoff (SURQ) and nitrate flux transported by surface runoff (NSURQ) for the two watersheds. Because the majority of water fluxes was transported by groundwater flow for TCW and surface runoff for GW (Figure 6a), a decrease in SURQ led to a substantial reduction of wintertime NSURQ for GW (0.45 kg $N \cdot ha^{-1}$) and less reduction for

Hydrol. Earth Syst. Sci. Discuss., doi:10.5194/hess-2017-178, 2017
Manuscript under review for journal Hydrol. Earth Syst. Sci.
Discussion started: 19 April 2017

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Discussions

TCW (0.12 kg N·ha$^{-1}$), compared to the baseline (Figure 6b). Therefore, both increased NGWQ and decreased NSURQ during winter seasons collectively led to an increasing pattern of wintertime nitrate yield for TCW and a decreasing pattern for GW, compared to the baseline scenario.

### 3.3 Responses to the climate change scenario

#### 3.3.1 Comparison of climate data (baseline vs. climate change scenario)

The monthly averages of mean temperature and cumulative precipitation under the baseline scenario were compared with the ensemble means of five GCMs (Figure 7). Projected temperature was constantly higher than the baseline value throughout the year with the increase rate of 3.8 – 5.5 °C (Figure 7a). Compared to the baseline, projected precipitation was greater from January to March, but lower or similar during other months (Figure 7b). Monthly cumulative precipitation was up to 31 mm greater in January and up to 44 mm lower in October, in comparison to the baseline. Note that the annual average of mean temperature increased from 13.9 °C (baseline) to 18.4 °C (projection), and the annual average of cumulative precipitation decreased from 1220 mm (baseline) to 1160 mm (projection).

[Insert Figure 7. Monthly average of (a) mean temperature and (b) cumulative precipitation for the baseline (2001 – 2014) and future (2083 – 2098) periods]

#### 3.3.2 Water and nitrate budgets

Baseline hydrologic variables (e.g., stream flow, ET, and nitrate loads) are compared with the ensemble means of simulated outputs in Table 6. Relative to the baseline scenario,

Hydrol. Earth Syst. Sci. Discuss., doi:10.5194/hess-2017-178, 2017
Manuscript under review for journal Hydrol. Earth Syst. Sci.
Discussion started: 19 April 2017



annual stream flow and nitrate loads significantly increased by 40 % and 39 % for TCW and 24 % and 24 % for GW (*p-value* < 0.01), respectively. These increasing patterns were mainly caused by decreased ET resulting from elevated $CO_2$ concentration of 820 ppm, considering that both precipitation decrease and temperature increase contributed to reducing stream flow and nitrate loads. Elevated $CO_2$ concentration reduced ET by 34 % for TCW and 32 % for GW (Table 6). In addition, warmer temperature led to the early maturity of crop biomass (Figure 8) and thereby early termination of water and nutrient uptake by crops, contributing to increasing stream flow and nutrient loads.

[Insert Table 6. 14-year average of hydrologic variables under the baseline and climate change scenarios]

[Insert Figure 8. Crop biomass growth under the baseline and climate change scenarios: (a) corn and (b) soybean]

It should be noted that the standard version of SWAT tends to overestimate the effect of $CO_2$ on the reduction of ET (Eckhardt and Ulbrich, 2003). Maximum leaf area index (LAI) is assumed to be constant regardless of variation in $CO_2$ concentration in SWAT. However, maximum LAI is known to increase with increasing $CO_2$ concentration (Eckhardt and Ulbrich, 2003). In addition, the degree of reduction in stomatal conductance varies by plant species, which also is not taken into account in SWAT. Another model simplification, which increases uncertainty, is the application of the same reduction rate to all plants. For example, C3 crops (soybean and wheat) are known to have less reduction in stomatal conductance with rising $CO_2$ concentration compared to C4 crops (corn) (Ainsworth and Rogers, 2007). Both factors could contribute to overestimating the reduction of ET and resultant increase in stream flow and nitrate loads (Eckhardt and Ulbrich, 2003). Our results might overestimate $CO_2$ effects on streamflow and nitrate loads relative to the effects of precipitation and temperature changes. However, this study attempted to demonstrate how watershed hydrological processes would respond to the combined effects of potential changes in $CO_2$ concentration, precipitation, and temperature. Therefore, our results provided feasible changes in water and nitrate budgets under potential climate change.

### 3.3.3 Comparative analysis

Responses of the two watersheds to the climate change scenario were compared using the monthly averages of water and nitrate yields in Figure 9. Relative to the baseline, projected water yield was greater over the year with the range of relative change between 14 and 99 % for TCW; however GW showed a decrease in water yield by 14 % in June and 6 % in October, mainly due to different soil characteristics. For example, substantial reduction of precipitation on two months (June and October) greatly decreased SURQ for both watersheds (Figure 9ab). Surface runoff is the major water pathway in GW and therefore reduction of SURQ resulted in lower water yield compared to the baseline value on two months.

Projected nitrate yield was greater than the baseline value throughout the year for both watersheds. The increased rate of nitrate yield differed between TCW (0.24 – 0.87 kg $N \cdot ha^{-1}$) and GW (0.03 – 0.35 kg $N \cdot ha^{-1}$) due to contrasting land use and soil characteristics (Figure 9cd). First, the larger percentage of croplands in TCW led to considerable nitrate export derived from fertilizer activities compared to GW with less percent croplands. This was because increased water yield by elevated $CO_2$ concentration and precipitation increase promoted the export of nitrate in soil profile. For example, nitrate yield increased by 0.87 kg $N \cdot ha^{-1}$ for TCW and 0.35 kg $N \cdot ha^{-1}$ for GW in April, when fertilizer application occurred, compared to the baseline.

Second, different soil characteristics resulted in greater reduction of nitrate yield in GW and less in TCW in response to precipitation decrease in and temperature increase. Due to contrasting soil characteristics, the major nitrate transport occurred by groundwater flow for TCW and surface runoff for GW. Therefore, precipitation decrease and temperature increased that greatly reduced SURQ led to a greater reduction of NSURQ for GW (0.6 kg N·ha$^{-1}$) than for TCW (0.1 kg N·ha$^{-1}$ over the year. Note that NGWQ increased for both watersheds due to elevated $CO_2$ concentration. Lastly, increased nitrate loss by denitrification contributed to lower nitrate yield in GW (dominated by poorly-drained soils) where higher denitrification is expected, compared to TCW (dominated by well-drained soils). Increased soil water content by elevated $CO_2$ concentration provided conducive conditions (i.e., anaerobic) for denitrification. Compared to the baseline, GW and TCW showed increased nitrate (removed by denitrification) of 3.5 and 0.3 kg N·ha$^{-1}$ under the climate change scenario, respectively. Eventually, GW lost 8.5 kg N·ha$^{-1}$ more nitrate flux via denitrification than TCW under the climate change scenario.

[Insert Figure 9. 14-year average of monthly water and nitrate yields under the baseline and climate change scenarios]

## 4 Implication

The key results of this study can suggest important future tasks towards improving our understanding of climate change impacts on nutrient loads into the CBW. Analysis of climate variability and change impacts on watershed hydrological processes illustrated the close relationship between agricultural activities and future nitrate export in the watershed dominated by croplands, due to excessive export of nitrate from fertilizer application. Changes in crop growth are likely to alter current agricultural activities and associated nitrate loads. Under the climate change scenario, maximum summer crop biomass decreased and the growth cycle of summer crops was shortened due to warmer temperature (Figure 8). To adapt to warmer temperature, early planting of summer crops could be suggested to increase crop production in the future. For example, when planting dates were shifted 10 days earlier, corn and soybean yields increased on average of 0.01 and 0.04 $Mg \cdot ha^{-1}$ (Figure 8). Woznicki et al. (2015) also predicted that planting 10 days earlier contributes to increasing corn yield in southwest Michigan under climate change. However, early planting and associated fertilizer application might lead to increased nitrate export because increased precipitation during early spring could result in considerable export of nitrate from fertilizer application. In addition, fertilizer use would increase in the future due to reduced corn yield compared to the baseline (Figure 8), which potentially increases nitrate loads. Less water demand caused by elevated $CO_2$ concentration might require less irrigation demand. Therefore, it is crucial to investigate potential agricultural activities under climate change to accomplish targeted crop yield (e.g., shift of planting date and fertilizer addition) and their effects on nitrate loads.

Climate change-driven modifications indicated a potential overall increase in nitrate export. Therefore, the importance of conservation practices aimed at N mitigation would be even more critical in the future. Comparative analyses of hydrological processes between two watersheds with different physical characteristics provided insights regarding effective water quality management under climate change. The control of nutrients in manure or fertilizer would be more critical for reducing nitrate export from a watershed dominated by croplands where nitrate loads substantially increased under climate change, due to fertilizer application. Winter cover crops would be more valuable to mitigate agricultural nitrate yield during winter seasons, considering the projected increase in future wintertime precipitation. In a watershed dominated by poorly-drained soils, wetland restoration would be well positioned to enhance denitrification (McCarty et al., 2014). In addition, the conservation/maintenance of prior converted croplands is also necessary for increased nitrate loss by denitrification. However, there is still a great uncertainty regarding whether current conservation practices would be adequate to mitigate increased nitrate loads by climate change (Woznicki and Nejadhashemi, 2012). The performance of conservation practices under climate change conditions should be further examined.

## 5 Summary and Conclusion

Water quality degradation by human activities on agricultural lands is a great concern in the Coastal Plain of the CBW. This degradation is expected to worsen in the future under climate variability and change. However, there is limited information about how climate change will influence hydrology and nutrient cycles. This study used SWAT model to simulate the impacts of potential climate variability and change on two adjacent watersheds in the Coastal Plain of the CBW. Climate sensitivity scenarios were developed to represent potential climate variability (e.g., increases in $CO_2$ concentration, precipitation, and temperature) based on the previous study (Najjar et al., 2009). Using five GCM data, the climate change scenario was prepared to depict future climate conditions. We performed comparative analyses between two watersheds to show how key landscape characteristics influence the watershed level response to climate variability and change.

Our simulation results showed that water and nitrate budgets in two watersheds in the Coastal Plain of the CBW were significantly sensitive to climate variability and change. Compared to the baseline scenario, a precipitation increase of 21% and elevated $CO_2$ concentration of 850 ppm resulted in increases in stream flow and nitrate loads of 50 % and 52 %, respectively. A temperature increase of 5.0 °C reduced stream flow and nitrate loads by 12 % and 13 %, respectively. Under the climate change scenario, annual stream flow and nitrate loads increased by 40 % and 39 %, respectively, compared to the baseline scenario. Contrasting land use and soil characteristics led to different patterns of nitrate yield between two watersheds. The watershed with a larger percent croplands indicated increased nitrate yield of 0.52 kg $N \cdot ha^{-1}$ compared to the one with less percent croplands under the climate change scenario, due to increased export of nitrate derived from fertilizer. Nitrate flux transported via surface runoff (NSURQ) was more susceptible to precipitation and temperature changes, in comparison to nitrate flux transported via groundwater flow (NGWQ). Accordingly, the poorly-drained watershed, where NSURQ accounts for the majority of nitrate yield, indicated less increase in nitrate yield due to considerable reduction of NSURQ in response to precipitation decrease and temperature increase under the climate change scenario, compared to the well-drained one, where NGWQ accounts for the majority of nitrate yield. Increased nitrate loss by denitrification also contributed to less increase in nitrate yield in the watershed dominated by poorly-drained soils compared to one dominated by well-drained soil. Based on our results, we suggest that increased implementation of conservation practices, such as nutrient management planning, winter cover crops, and wetland restoration and enhancement, is necessary to mitigate variations in nitrate loads caused by climate change. These findings should help watershed managers and regulators to establish climate change adaptation strategies for mitigating water quality degradation in this region.

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Manuscript under review for journal Hydrol. Earth Syst. Sci.
Discussion started: 19 April 2017


Hydrology and Earth System Sciences
Open Access
Discussions

**List of Tables**

**Table 1.** Soil properties and land use distribution of Tuckahoe Creek Watershed (TCW) and Greensboro Watershed (GW) (adapted from Lee et al. (2016))

**Table 2.** List of SWAT model input data

**Table 3.** List of calibrated parameters

**Table 4.** Climate sensitivity scenarios developed by modifying baseline values

**Table 5.** Model performance measures for monthly stream flow and nitrate loads

**Table 6.** 14-year average of hydrologic variables under the baseline and climate change scenarios

Hydrol. Earth Syst. Sci. Discuss., doi:10.5194/hess-2017-178, 2017
Manuscript under review for journal Hydrol. Earth Syst. Sci.
Discussion started: 19 April 2017

Hydrology and Earth System Sciences
Open Access
Discussions

**Table 1.** Soil properties and land use distribution of Tuckahoe Creek Watershed (TCW) and Greensboro Watershed (GW) (adapted from Lee et al. (2016))

| Land use | TCW | GW |
|---|---|---|
| Agriculture | 54.0 % [69.5% / 30.5 %] | 36.1 % [32.8% / 67.2 %] |
| Forest | 32.8 % | 48.3 % |
| Pasture | 8.4 % | 9.3 % |
| Urban | 4.2 % | 5.6 % |
| Water body | 0.6 % | 0.7 % |
| Hydrologic soil groups (HSGs) | TCW | GW |
| A | 0.3 % | 3.1 % |
| B | 55.8 % | 22.4 % |
| C | 2.2 % | 4.2 % |
| D | 41.7 % | 70.3 % |

Note: Values in parenthesis [], denote the proportion of well-drained soils (HSG-A&B) and poorly-drained soils (HSG-C&D) used for agricultural lands, respectively.

**Table 2.** List of SWAT model input data

| Data | Source | Description | Year |
|---|---|---|---|
| DEM | MD-DNR | LiDAR-based 2 meter resolution | 2006 |
| Land use | USDA-NASS | Cropland Data Layer (CDL) | 2008 - 2012 |
| | MRLC | National Land Cover Database (NLCD) | 2006 |
| | USDA-FSA-APFO | National Agricultural Imagery Program digital Orthophoto quad imagery | 1998 |
| | US Census Bureau | TIGER road map | 2010 |
| Soils | USDA-NRCS | Soil Survey Geographical Database (SSURGO) | 2012 |
| Climate | NCDC | Daily precipitation and temperature | 1999 - 2014 |
| Stream flow | USGS | Monthly stream flow | 2001 - 2014 |
| Water quality | USGS and CBP | Daily grab nitrate samples | 2001 - 2014 |

Note: MD-DNR: Maryland Department of Natural Resources, USDA-NASS (National Agricultural Statistics Service), MRLC: Multi-Resolution Land Characteristics Consortium, USDA-NRCS (Natural Resources Conservation Service), USDA-FSA-APFO (Farm Service Agency-Aerial Photography Field Office).

**Table 3.** List of calibrated parameters

| Parameter | Variable | Description (unit) | Range | Calibrated value | |
|---|---|---|---|---|---|
| | | | | TCW | GW |
| CN2[#] | Stream flow | Curve number | -50 - 50 % | -30 % | 0% |
| ESCO[#] | | Soil evaporation compensation factor | 0 - 1 | 1 | 0.95 |
| SURLAG[#] | | Surface runoff lag coefficient | 0.5 - 24 | 0.5 | 0.5 |
| SOL_AWC[#] | | Available water capacity of the soil layer (mm H2O·mm soil$^{-1}$) | -50 - 50 % | - 10% | - 1% |
| SOL_K[#] | | Saturated hydraulic conductivity (mm·hr$^{-1}$) | -50 - 50 % | 50 % | 49 % |
| SOL_Z[#] | | Depth from soil surface to bottom of layer (mm) | -50 - 50 % | -20 % | -31 % |
| ALPHA_BF[#] | | Base flow recession constant (1·days$^{-1}$) | 0 - 1 | 0.07 | 0.051 |
| GW_DELAY[#] | | Groundwater delay time (days) | 0 - 500 | 120 | 45 |
| GW_REVAP[#] | | Groundwater “revap” coefficient | 0.02 - 0.2 | 0.10 | 0.02 |
| RCHRG_DP[#] | | Deep aquifer percolation fraction | 0 - 1 | 0.01 | 0.05 |
| GWQMN[#] | | Threshold depth of water in the shallow aquifer required for return flow to occur (mm) | 0 - 5000 | 1.9 | 1.0 |
| CH_K2[#] | | Effective hydraulic conductivity (mm·hr$^{-1}$) | 0 - 150 | 0 | 20 |
| CH_N2[#] | | Manning coefficient | 0.01 - 0.3 | 0.29 | 0.021 |
| NPERCO[†] | Nitrate | Nitrogen percolation coefficient | 0.01 - 1 | 0.5 | 0.2 |
| N_UPDIS[†] | | Nitrogen uptake distribution parameter | 5 - 50 | 50 | 50 |
| ANION_EXCL[†] | | Fraction of porosity from which anions are excluded | 0.1 - 0.7 | 0.59 | 0.6 |
| ERORGN[†] | | Organic N enrichment ratio for loading with sediment | 0 - 5 | 4.92 | 4.1 |
| BIOMIX[†] | | Biological mixing efficiency | 0.01 - 1 | 0.01 | 0.01 |
| SOL_NO3[§] | | Initial NO3 concentration in soil layer (mg N·kg$^{-1}$) | 0 - 100 | 11.23 | 0 |
| CDN[$] | | Denitrification exponential rate coefficient | 0 - 3.0 | 0.3 | 1.8 |
| SDNCO[$] | | Denitrification threshold water content | 0.1 - 1.1 | 1.0 | 1.0 |

* refers to a default value. The ranges of parameters with superscripts (#, †, §, $) were adapted from Gitau and Chaubey (2010), Yeo et al. (2014), Seo et al. (2012), Neitsch et al. (2011), respectively.

Hydrol. Earth Syst. Sci. Discuss., doi:10.5194/hess-2017-178, 2017
Manuscript under review for journal Hydrol. Earth Syst. Sci.
Discussion started: 19 April 2017



**Table 4.** Climate sensitivity scenarios developed by modifying baseline values

| Scenario | Percent increase of precipitation (%) | Absolute increase of temperature (°C) | Replacement of $CO_2$ (ppm) |
|---|---|---|---|
| Baseline | 0 | 0 | 330 |
| 1 | 0 | 0 | 590 |
| 2 | 0 | 0 | 850 |
| 3 | 11 | 0 | 330 |
| 4 | 21 | 0 | 330 |
| 5 | 0 | 2.9 | 330 |
| 6 | 0 | 5.0 | 330 |

**Table 5.** Model performance measures for monthly stream flow and nitrate loads

| Period | Variable | Stream flow | | Nitrate loads | |
|---|---|---|---|---|---|
| | | TCW | GW | TCW | GW |
| Calibration | NSE | 0.723** | 0.686** | 0.623* | 0.702** |
| | RSR | 0.523** | 0.556** | 0.610* | 0.542** |
| | P-bias (%) | -5.8*** | -3.2*** | -9.8*** | -4.1*** |
| Validation | NSE | 0.674** | 0.790*** | 0.604* | 0.567* |
| | RSR | 0.566** | 0.454*** | 0.624* | 0.652* |
| | P-bias (%) | 17.8** | 13*** | -5.6*** | -12.1*** |

Model performances were rated based on the criteria of Moriasi et al. (2008); * Satisfactory, ** Good, and *** Very Good; Satisfactory ($0.5 < NSE \leq 0.65$, $0.6 < RSR \leq 0.7$, and $\pm 15 \leq$ P-bias $< \pm 25$), ** Good ($0.65 < NSE \leq 0.75$, $0.5 < RSR \leq 0.6$, and $\pm 10 \leq$ P-bias $< \pm 15$), and *** Very Good ($0.75 < NSE \leq 1.0$, $0.0 < RSR \leq 0.5$, P-bias $< \pm 10$).

Hydrol. Earth Syst. Sci. Discuss., doi:10.5194/hess-2017-178, 2017
Manuscript under review for journal Hydrol. Earth Syst. Sci.
Discussion started: 19 April 2017



**Table 6.** 14-year average of hydrologic variables under the baseline and climate change scenarios

| Variables | TCW | | | GW | | |
|---|---|---|---|---|---|---|
| | Baseline | Projection | Relative change (%) | Baseline | Projection | Relative change (%) |
| Stream flow ($m^3 \cdot s^{-1} \cdot ha^{-1} \cdot 10^4$) | 1.5 | 2.1 (1.6 – 2.7) | 40 | 1.7 | 2.1 (1.6 – 2.6) | 24 |
| ET ($mm \cdot ha^{-1}$) | 2.7 | 1.8 | -34 | 2.3 | 1.6 | -32 |
| Nitrate loads ($kg\ N \cdot ha^{-1}$) | 12.5 | 17.5 (14.6 – 21.4) | 39 | 5.3 | 6.6 (5.5 – 8.1) | 24 |

Note: Projection stands for the ensemble mean of simulated hydrologic variables with 5 GCMs. The numbers within parenthesis indicates the maximum and minimum values of simulations with five GCM data. Relative change indicates the percent changes in the ensemble mean relative to the baseline value.

Hydrol. Earth Syst. Sci. Discuss., doi:10.5194/hess-2017-178, 2017
Manuscript under review for journal Hydrol. Earth Syst. Sci.
Discussion started: 19 April 2017


**List of Figures**

**Figure 1.** The location of Tuckahoe Creek Watershed (left) and Greensboro Watershed (right)

**Figure 2.** The physical characteristics of Tuckahoe Creek Watershed (left) and Greensboro Watershed (right); (a) land use, (b) hydrologic soil groups, and (c) elevation

**Figure 3**. Simulated and observed monthly stream flow and nitrate loads for (a & b) TCW and (c & d) GW during calibration and validation periods

**Figure 4**. 14-year average of annual hydrologic variables under the baseline and climate sensitivity scenarios at the watershed scale: (a) stream flow and evapotranspiration (ET), (b) nitrate loads, and (c) mineralized nitrate.

**Figure 5.** The responses of crop biomass growth to elevated $CO_2$ concentration, temperature increases: corn (a & b) and soybean (c & d). TMP in (b & d) stands for temperature.

**Figure 6.** 14-year average of seasonal hydrologic variables under the baseline and climate sensitivity scenarios at the watershed scale: (a) water and (b) nitrate yields.

**Figure 7.** Monthly average of (a) mean temperature and (b) cumulative precipitation for the baseline (2001 – 2014) and future (2083 – 2098) periods.

**Figure 8.** 14-year average of monthly water and nitrate yields under the baseline and climate change scenarios. The descriptions of abbreviation are illustrated in the caption of Figure 6.

**Figure 9.** Crop biomass growth under the baseline and climate change scenarios (projection): (a) corn and (b) soybean.

Hydrol. Earth Syst. Sci. Discuss., doi:10.5194/hess-2017-178, 2017
Manuscript under review for journal Hydrol. Earth Syst. Sci.
Discussion started: 19 April 2017

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Discussions

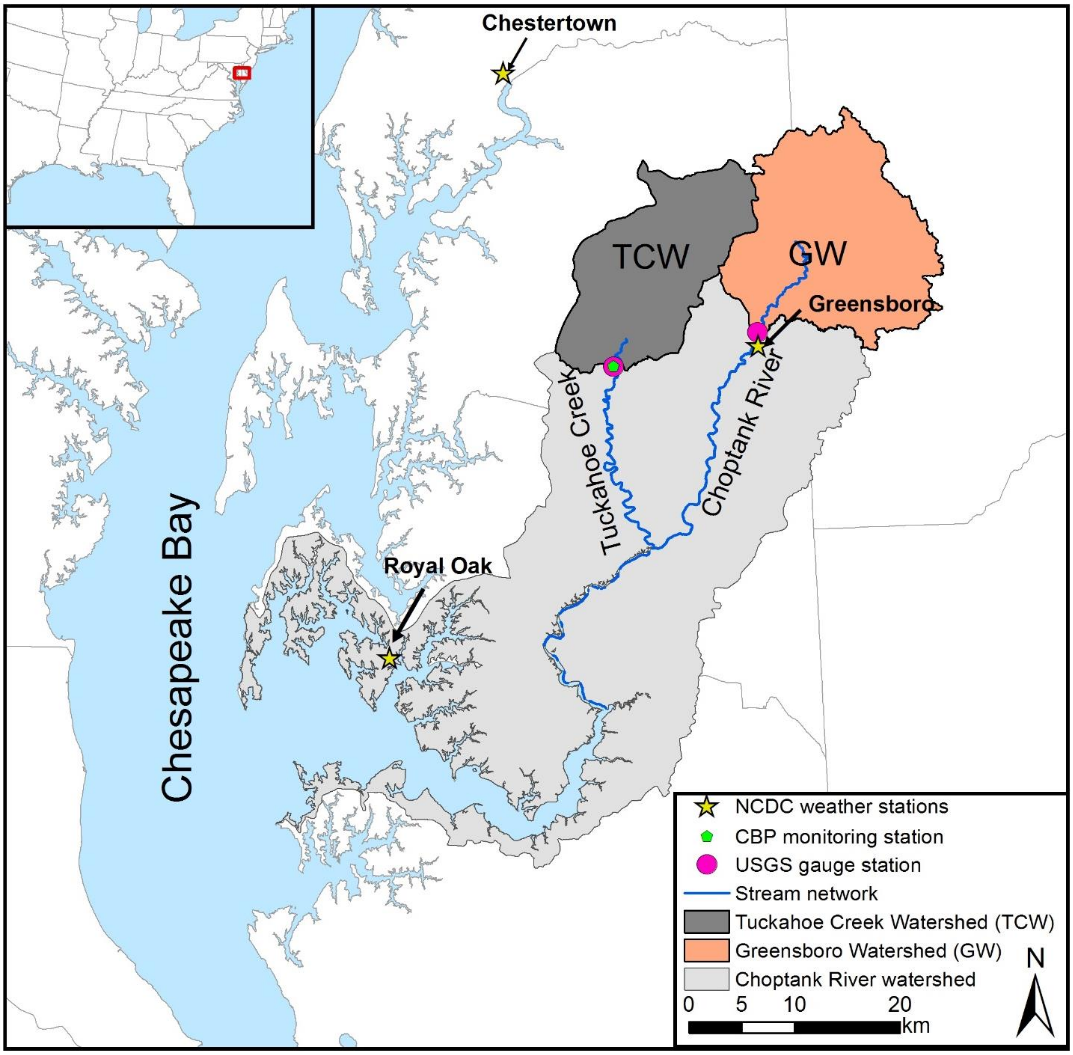
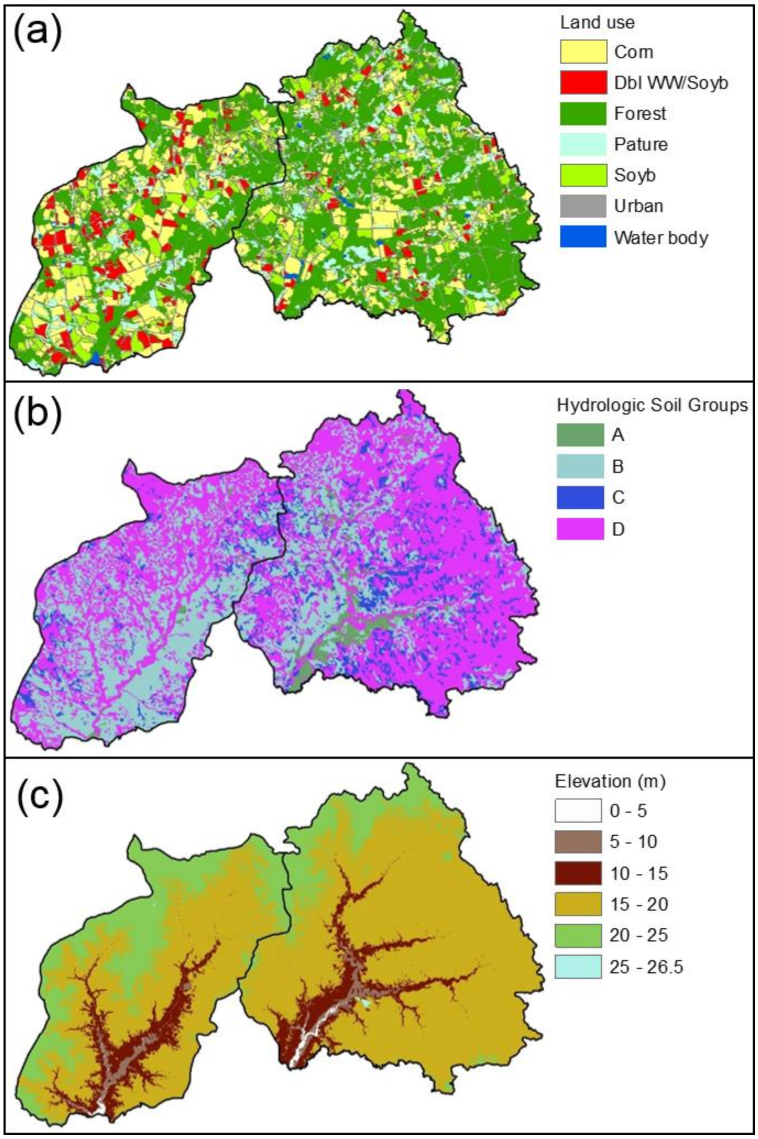



**Figure 1.** The location of Tuckahoe Creek Watershed (left) and Greensboro Watershed (right) (adapted from Lee et al. (2016))

901 


902 **Figure 2.** The physical characteristics of Tuckahoe Creek Watershed (left) and Greensboro
903 Watershed (right); (a) land use, (b) hydrologic soil groups, and (c) elevation (adapted from Lee
904 et al. (2016)).

905 Note: Dbl WW/Soyb stands for double crops of winter wheat and soybean in a year. Hydrologic
906 soil groups (HSGs) are characterized as follows: Type A- well-drained soils with 7.6-11.4 mm/hr
907 (0.3-0.45 inch/hr) water infiltration rate; Type B - moderately well-drained soils with 3.8-7.6
908 mm/hr (0.15-0.30 inch/hr) water infiltration rate; Type C - moderately poorly-drained soils with
909 1.3-3.8 mm/hr (0.05-0.15 in/hr) water infiltration rate; Type D – poorly-drained soils with 0-1.3
910 mm/hr (0-0.05 inch/hr) water infiltration rate (Netisch et al., 2011).

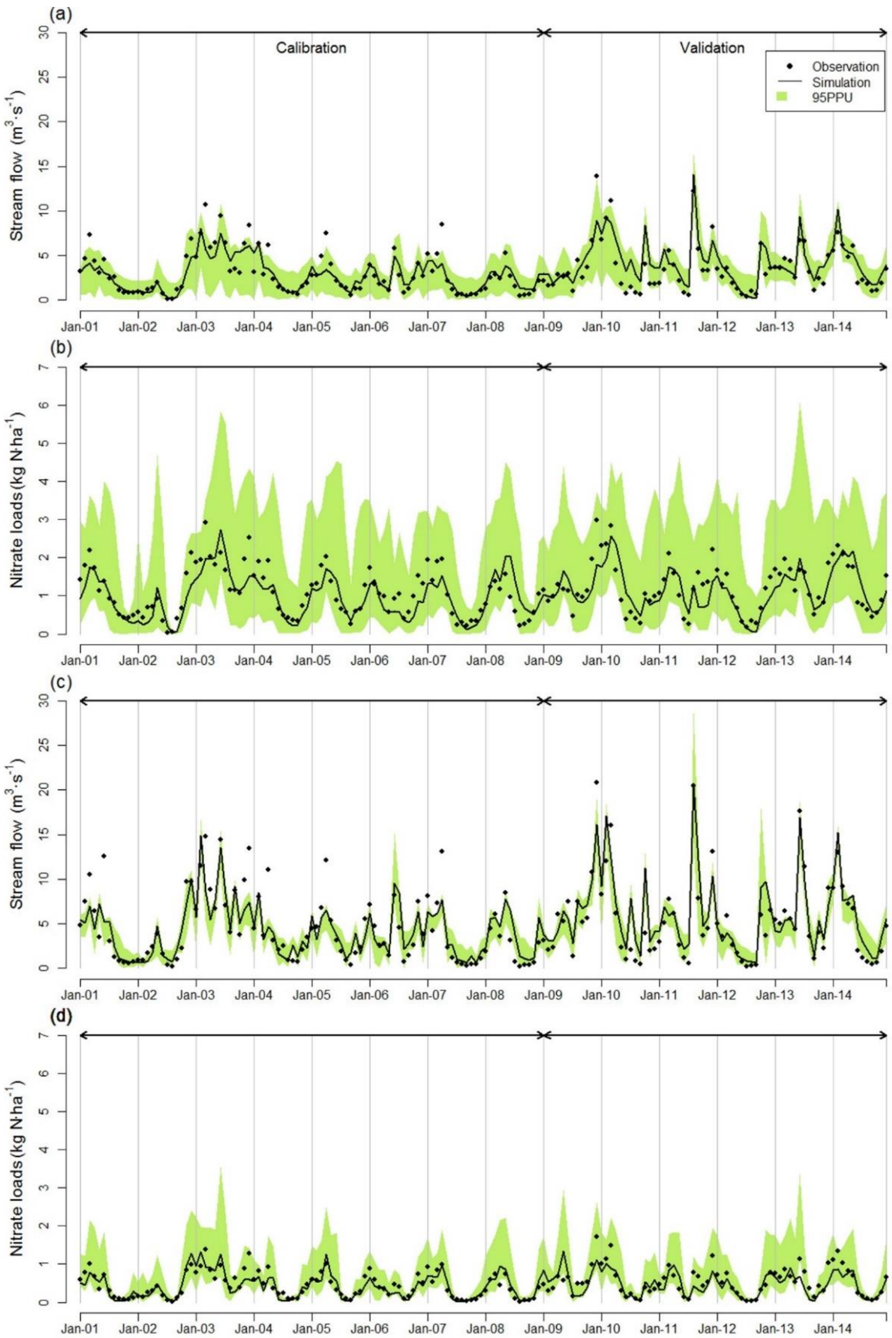



**Figure 3**. Simulated and observed monthly stream flow and nitrate loads for (a & b) TCW and (c & d) GW during calibration and validation periods.

Note: 95 PPU stands for 95 percent prediction uncertainty.

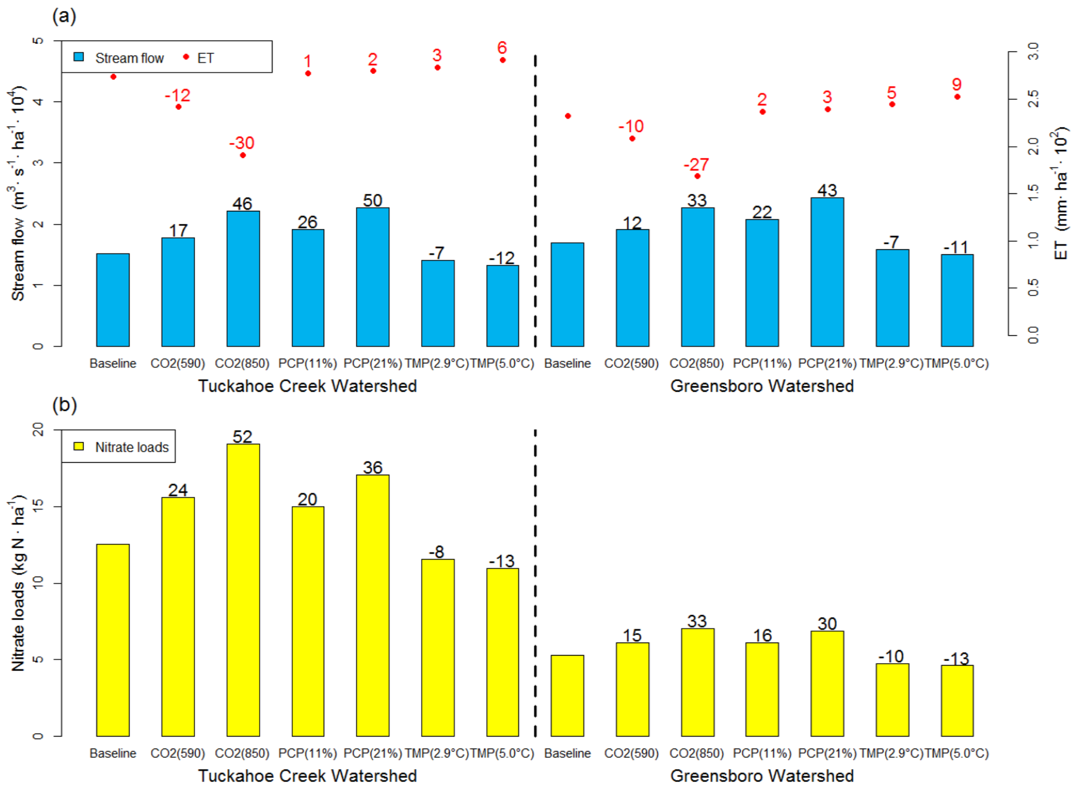



**Figure 4**. 14-year average of annual hydrologic variables under the baseline and climate sensitivity scenarios at the watershed scale: (a) stream flow and evapotranspiration (ET), and (b) nitrate loads.

Note: The red and black numerical values above the bar and the dot graphs, respectively, indicate the relative changes (%) in hydrologic variables for climate sensitivity scenarios relative to the baseline scenario [relative change (%) = (Sensitivity Scenarios – Baseline) / Baseline × 100]. PCP and TMP stand for precipitation and temperature, respectively.

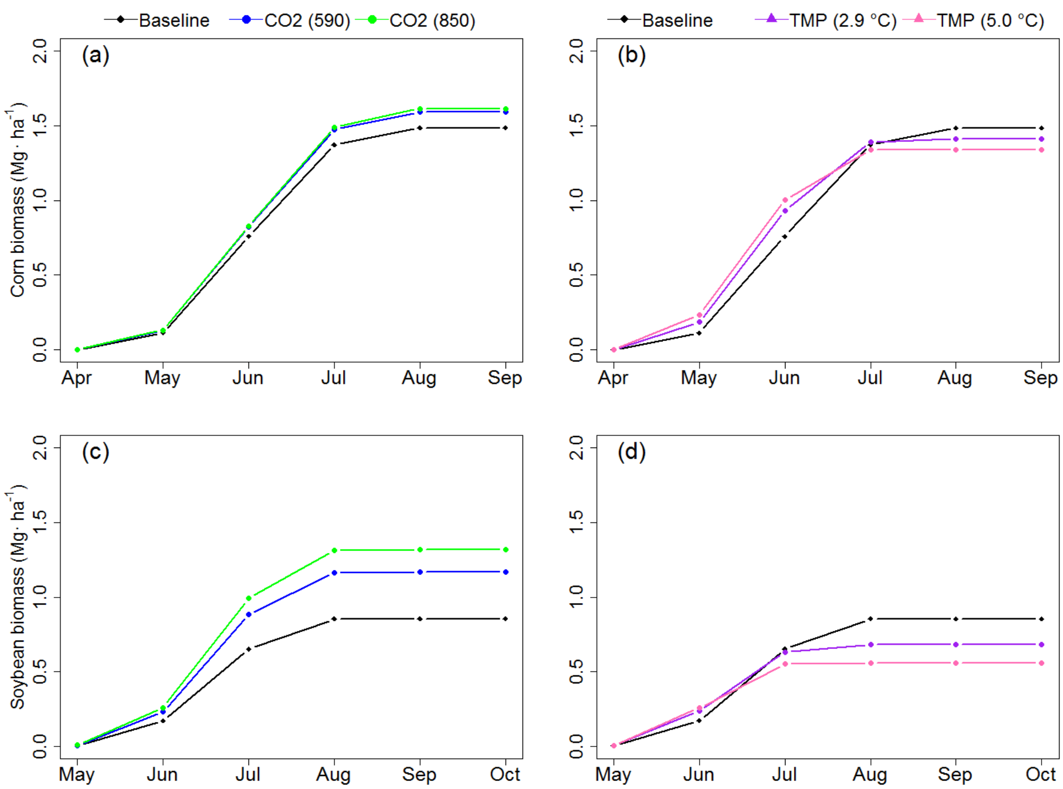



**Figure 5.** The responses of crop biomass growth to elevated $CO_2$ concentration, temperature increases: (a & b) corn and (c & d) soybean.

Note: TMP in the legend of (b) stands for temperature.

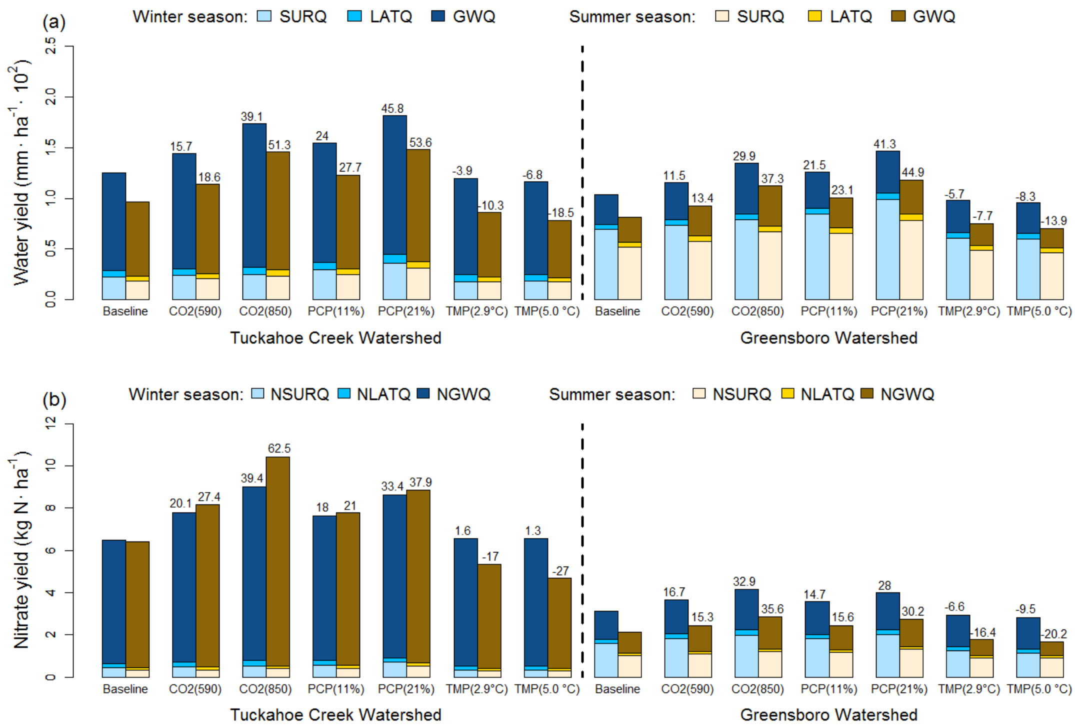



**Figure 6.** 14-year average of seasonal hydrologic variables under the baseline and climate sensitivity scenarios at the watershed scale: (a) water and (b) nitrate yields.

Note: The number on the bar graph indicates the relative changes (%) in hydrologic variables for climate sensitivity scenarios relative to the baseline scenario. Water and nitrate yields indicate the summations of water and nitrate fluxes transported from lands to streams by surface runoff, lateral flow, and groundwater flow. PCP and TMP stand for precipitation and temperature, respectively. SURQ, LATQ, and GWQ indicate water fluxes transported by surface runoff, lateral flow, and groundwater flow, respectively. NSURQ, NLATQ, and NGWQ indicate nitrate fluxes transported by surface runoff, lateral flow, and groundwater flow, respectively.

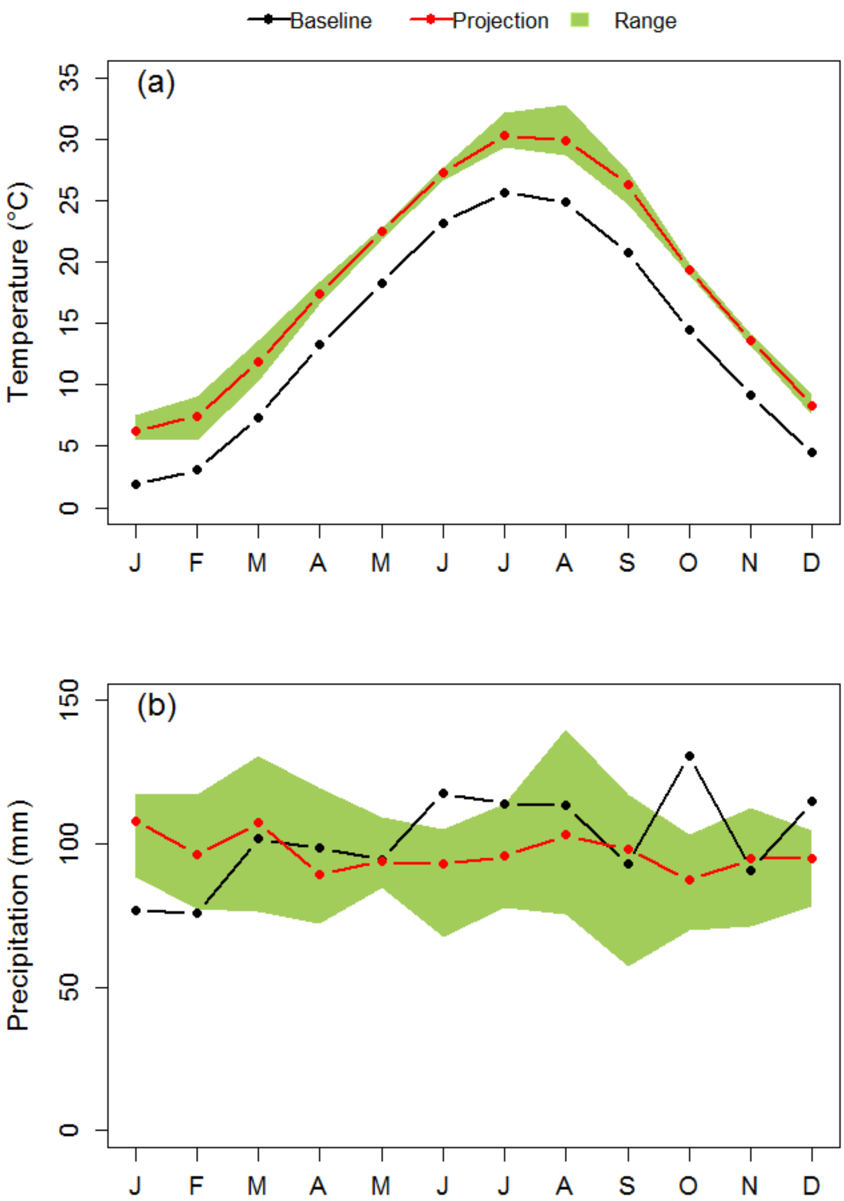
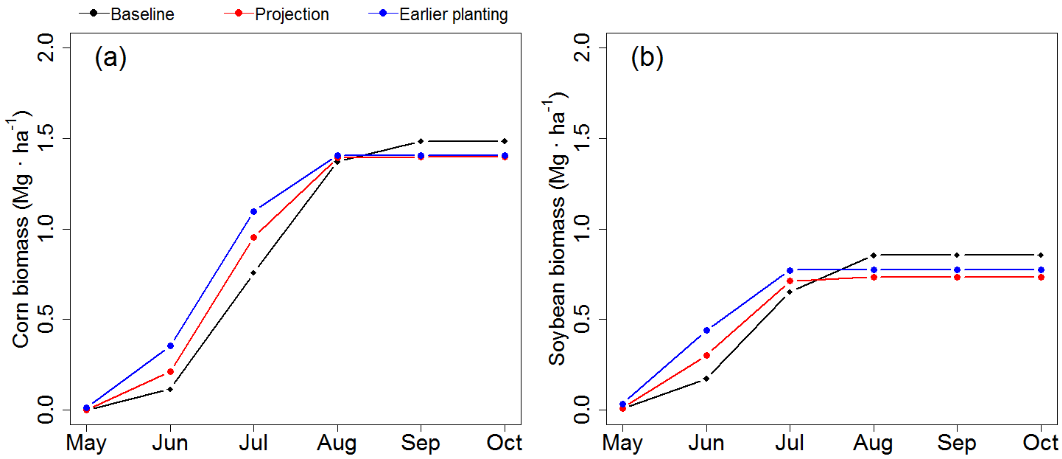



**Figure 7.** Monthly average of (a) mean temperature and (b) cumulative precipitation for the baseline (2001 – 2014) and future (2083 – 2098) periods.

Note: Projection stands for the ensemble mean of five GCM data, and the range stands for the interval between the maximum and minimum values of five GCM data.




957

958 **Figure 8.** Crop biomass growth under the baseline and climate change scenarios: (a) corn and (b)
959 soybean.

960 Note: Projection stands for the ensemble mean of simulated bimoass with 5 GCMs. Earlier
961 planting indicates the ensemble mean of simulated biomass planted 10 days earlier than the
962 original planting dates.

Hydrol. Earth Syst. Sci. Discuss., doi:10.5194/hess-2017-178, 2017
Manuscript under review for journal Hydrol. Earth Syst. Sci.
Discussion started: 19 April 2017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Discussions

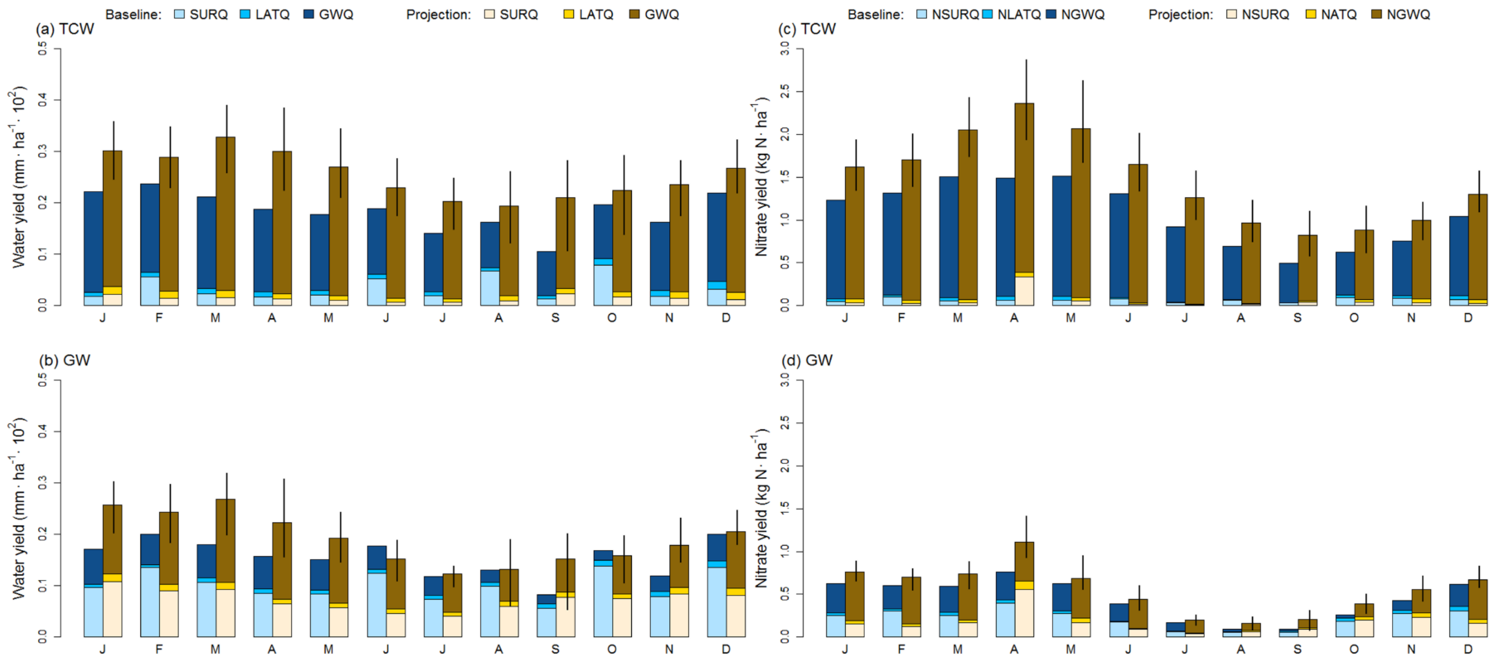


**Figure 9.** 14-year average of monthly water and nitrate yields under the baseline and climate change scenarios.

Note: The descriptions of abbreviation are available in the caption of Figure 6.The black line indicates the interval between minimum and maximum values (water or nitrate yields) of simulation with 5 GCMs.

Hydrol. Earth Syst. Sci. Discuss., doi:10.5194/hess-2017-178, 2017
Manuscript under review for journal Hydrol. Earth Syst. Sci.
Discussion started: 19 April 2017

Hydrology and Earth System Sciences Discussions

**List of Appendices**

**Table A1.** Management schedules for the baseline scenario

**Table A2.** Five GCMs used to the climate change scenario

**Figure A3.** 14-year average of annual mineralized nitrate under the baseline and climate sensitivity scenarios at the watershed scale.

**Figure A4.** Changes in (a & b) soil water content and (c & d) nitrate leaching under temperature increase

Hydrol. Earth Syst. Sci. Discuss., doi:10.5194/hess-2017-178, 2017
Manuscript under review for journal Hydrol. Earth Syst. Sci.
Discussion started: 19 April 2017


**Table A1.** Management schedules for the baseline scenario (adapted from Lee et al. (2016))

| Baseline scenario (no winter cover crop) | | | |
|---|---|---|---|
| Crop | Planting | Fertilizer | Harvest |
| Corn (after corn) | Apr. 30 (no-till) | 157 kg N·ha$^{-1}$ (140 lb N·acre$^{-1}$) of poultry manure on Apr. 20<br>45 kg N·ha$^{-1}$ (40 lb N·ha$^{-1}$) of sidedress 30% UAN on Jun. 7 | Oct. 3 |
| Corn (after Soybean and Double crop soybean) | Apr. 30 (no-till) | 124 kg N·ha$^{-1}$ (110 lb N·acre$^{-1}$) of poultry manure on Apr. 20<br>34 kg N·ha$^{-1}$ (30 lb N·ha$^{-1}$) of sidedress 30% UAN on Jun. 7 | Oct. 3 |
| Soybean | May 20 (no-till) | | Oct. 15 |
| Double crop winter wheat (Dbl WW) | Oct. 10 | 34 kg N·ha$^{-1}$ (30 lb N·acre$^{-1}$) of sidedress 30% UAN on Oct. 8<br>45 kg N·ha$^{-1}$ (40 lb N·acre$^{-1}$) of sidedress 30% UAN on Mar. 1<br>67 kg N·ha$^{-1}$ (60 lb N·acre$^{-1}$) of sidedress 30% UAN on Apr. 5 | Jun. 27 |
| Double crop soybean (Dbl Soyb) | Jun. 29 | | Nov. 1 |

Note: UAN stands for Urea-Ammonium Nitrate. The typical nitrogen content for poultry manure is assumed as 2.8% (Glancey et al., 2012).

**Table A2.** Five GCMs used to the climate change scenario

| Num. | Model | Full name | Abbreviation | Agency |
|---|---|---|---|---|
| 1 | CCCMA CGCM3.1.1 | Canadian Centre for Climate Modelling and Analysis Coupled GCM 3.1.1 | CCCMA | Canadian Centre for Climate Modelling and Analysis, Canada |
| 2 | CNRM CM3.1 | Centre National de Recherches Météorologiques Coupled Global Climate Model, version 3.1 | CNRM | National Center of Meteorological Research, France |
| 3 | GFDL CM2.0.1 | Geophysical Fluid Dynamics Laboratory Climate Model, version 2.0.1 | GFDL | Geophysical Fluid Dynamics Laboratory, United States |
| 4 | IPSL CM4.1 | L'Institut Pierre-Simon Laplace Coupled Model version 4.1 | IPSL | L'Institut Pierre-Simon Laplace, France |
| 5 | MIROC3.2 (medres) | Model for Interdisciplinary Research on Climate | MIROC | Marine-Earth Science and Technology, Japan |

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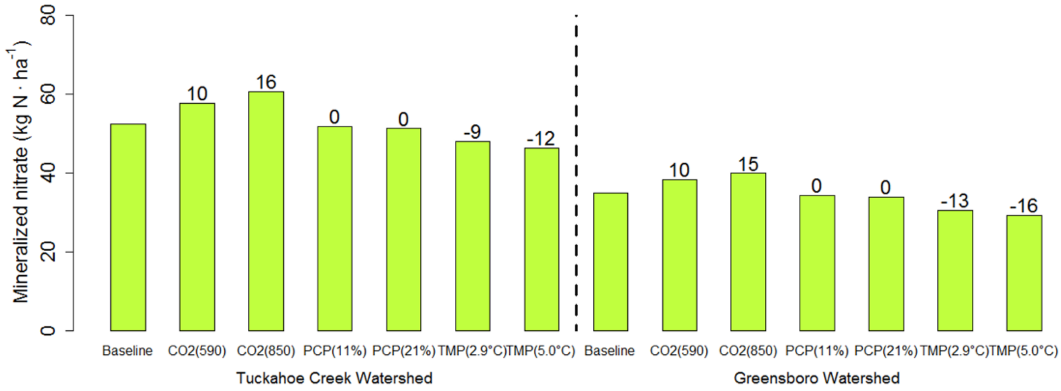


1001

1002 **Figure A3.** 14-year average of annual mineralized nitrate under the baseline and climate
1003 sensitivity scenarios at the watershed scale.

1004 Note: The black numerical values above the bar graph indicate the relative changes (%) in
1005 hydrologic variables for climate sensitivity scenarios relative to the baseline scenario [relative
1006 change (%) = (Sensitivity Scenarios – Baseline) / Baseline × 100]. PCP and TMP stand for
1007 precipitation and temperature, respectively.

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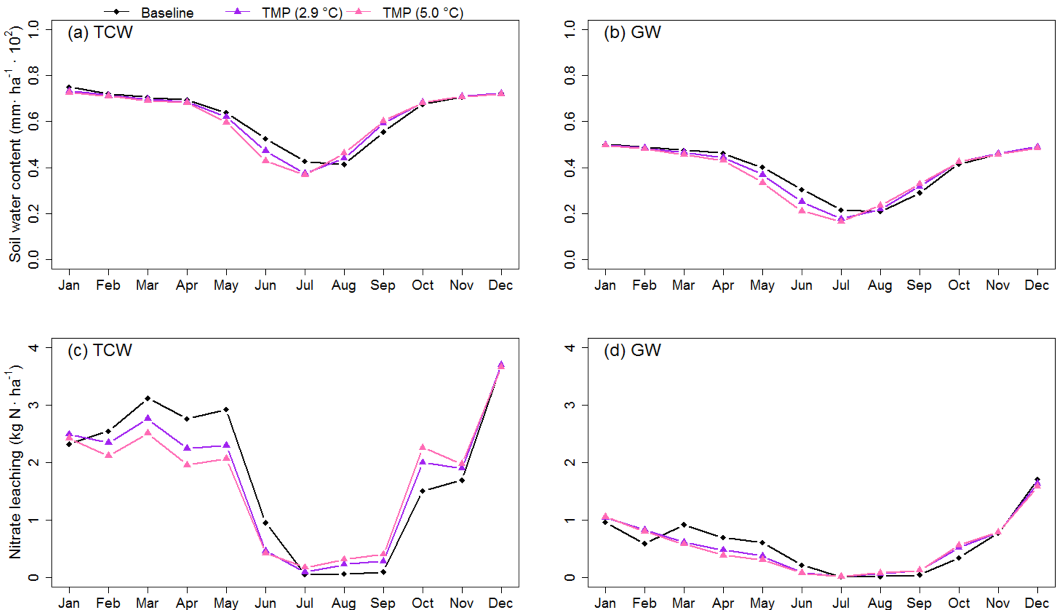
1011 


1012 **Figure A4.** Changes in (a & b) soil water content and (c & d) nitrate leaching under temperature
1013 increase

1014 Note: TMP stands for temperature, respectively.