INTEGRATING DAILY CO₂ CONCENTRATIONS IN SWAT-VSA TO EXAMINE CLIMATE CHANGE IMPACTS ON HYDROLOGY IN A KARST WATERSHED

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HIGHLIGHTS

- We used SWAT-VSA to assess the effects of climate change with rising CO₂ on the water balance of a karst basin.
- For future climate, SWAT-VSA with rising CO₂ yielded 7.1% less ET and 6.3% more runoff than standard SWAT-VSA.
- Rising CO₂ also affected variable source areas, with greater ET declines and runoff increases in the wettest soils.
- Findings suggest CO₂ effects on water balance should be included in future climate change studies with SWAT-VSA.

ABSTRACT. *Characterizing the effects of climate change on hydrology is important to watershed management. In this study, we used SWAT-VSA to examine the effects of climate change and increasing atmospheric CO₂ (CO₂) on the water balance of Spring Creek watershed, a mixed land-use karst basin in the Upper Chesapeake Bay watershed. First, we modified the stomatal conductance and leaf area index (LAI) routines of SWAT-VSA's Penman-Monteith evapotranspiration (ET) procedure and enabled the model to accept daily CO₂ data. Using downscaled climate projections from nine global climate models (GCMs), we then compared water balance estimations from baseline SWAT-VSA against two modified versions of SWAT-VSA. One SWAT-VSA version integrated daily CO₂ levels (SWAT-VSA_CO2), while another version added flexible stomatal conductance and LAI routines (SWAT-VSA_CO2+Plant) to the dynamic CO₂ capacity. Under current climate (1985–2015), the three SWAT-VSA models produced generally similar water balance estimations, with 51% of precipitation lost to ET and the remainder converted to runoff (10%), lateral flow (9%), and percolate (30%). For future climate (2020–2065), water balance simulations diverged between baseline SWAT-VSA and the two modified SWAT-VSA models with CO₂. Notably, variable stomatal conductance and LAI routines produced no detectable effects beyond that of CO₂. For the 2020–2065 period, baseline SWAT-VSA projected ET increases of 0.7 mm year⁻¹, while SWAT-VSA models with CO₂ suggested that annual ET could decline by approximately -0.4 mm year⁻¹ over the same period. As a result, the two CO₂-based SWAT-VSA models predicted streamflow increases of almost 1.6 mm year⁻¹ over the 2020–2065 period, which were roughly double the streamflow increases projected by baseline SWAT-VSA. In general, SWAT-VSA models with CO₂ effects produced 22.4% more streamflow in 2045–2065 than the SWAT-VSA model without CO₂. Results also showed that adding daily CO₂ to SWAT-VSA reduced ET in wetter parts of Spring Creek watershed, leading to greater runoff losses from variable source areas compared to baseline SWAT-VSA. Findings from the study highlight the importance of considering increasing atmospheric CO₂ concentrations in water balance simulations with SWAT-VSA in order to gain a fuller appreciation of the hydrologic uncertainties with climate change.*

Keywords. Carbon dioxide, Climate change, Hydrologic model, Water balance, Watershed.

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Understanding the hydrologic effects of atmospheric CO₂-induced climate change is critical to watershed management (Chien et al., 2013; Musau et al., 2015; Neupane and Kumar, 2015; Wang et al., 2017; Yang et al., 2019b). Human activities have increased atmospheric CO₂ concentrations (CO₂) from around 278 ppm prior to the Industrial Revolution to almost 412 ppm as of 2019 (Keeling et al., 2001). The added CO₂ has enhanced the Earth's greenhouse effect and brought about a global temperature rise of roughly 1°C (IPCC, 2014;

Jay et al., 2018) over the course of the 20th century. Assuming a “business as usual” emissions trajectory, CO₂ levels could reach 1,370 ppm by the end of the 21st century (Van Vuuren et al., 2011), leading to a global temperature increase of 3.7°C (2.8°C to 4.8°C) relative to pre-industrial climate (Riahi et al., 2007; Moss et al., 2010; Van Vuuren et al., 2011; IPCC, 2014). The principal hydrologic response to higher global temperatures has been a marked intensification of the global water cycle (Huntington, 2006; Durack et al., 2012; Masaki et al., 2014), which is evidenced by changes in hydrologic responses like precipitation, evapotranspiration (ET), and runoff. Given that additional climate warming projected throughout the 21st century is likely to yield even greater degrees of hydrological intensification (Thackeray et al., 2018; Giorgi et al., 2019), it is important to estimate the effects of these changes on the water balance.

Terrestrial ET is a major component of the Earth’s water balance, returning roughly 60% of precipitation to the atmosphere (Oki and Kanae, 2006). Because transpiration accounts for 80% to 90% of these terrestrial ET losses (Jasechko et al., 2013), understanding how key climatic and atmospheric variables affect plant-water relationships is particularly relevant to studies of the water balance (Katul et al., 2012). Among climatic variables, air temperature is often regarded as a significant driver of atmospheric water demand (Allen et al., 1998), while precipitation largely determines the amount of soil water available for ET (Chang and Jung, 2010). Thus, in regions with increasing temperature and precipitation due to climate change, ET would generally be expected to increase. The amount of CO₂ in the atmosphere is also rising with climate change, and changing CO₂ levels are likely to influence two competing plant physiological processes that dictate ET. In one instance, elevated CO₂ can increase stomatal resistance, which reduces the transpiration component of ET (Wullschlegel et al., 2002; Leakey et al., 2009; Katul et al., 2012; Pan et al., 2015). In the other, increased CO₂ also stimulates plant growth, thereby increasing the surface area of transpiring leaves (leaf area index, LAI), which then enhances ecosystem ET (Norby and Zak, 2011; Katul et al., 2012). Given the potential offsetting effects of rising CO₂ on ET, there has been great interest in evaluating the significance of these processes alongside changes in precipitation and temperature in global and regional scale models of the water balance.

To date, the significance of CO₂ on ET and watershed runoff has largely been examined at the global scale using mechanistic land-surface models. Modeling studies by Gedney et al. (2006, 2014), Betts et al. (2007), Cao et al. (2010), and Gopalakrishnan et al. (2011) associated increasing trends in continental runoff with CO₂-induced stomatal closure that reduces the transpiration component of ET. For instance, Betts et al. (2007) estimated that a doubling of CO₂ could increase river runoff by 6% relative to pre-industrial levels. Elsewhere, the significance of CO₂-induced runoff changes has been disputed by Huntington (2006), as well as in other large-scale modeling studies conducted by Piao et al. (2007), Gerten et al. (2008), Leuzinger and Körner (2010), and McCabe and Wolock (2011). These modeling studies have generally shown that increasing precipitation and land use change better explained 20th century trends in

ET and runoff. Still, recent research by Lian et al. (2018) indicates that CO₂ is expected to be a key determinant of stomatal controls on ET rates, especially in temperate regions where transpiration greatly exceeds evaporation (Jasechko, 2018). Thus, higher CO₂ levels could significantly enhance watershed runoff in temperate regions. To address this, watershed modeling studies in temperate regions need to better integrate the potential effects of rising CO₂ in studies of climate change impacts on ET and runoff (Qi et al., 2019).

The Soil and Water Assessment Tool (SWAT) has been widely used in temperate regions to evaluate the effects of climate change on watershed hydrology (Jha et al., 2006; Lin et al., 2012; Chien et al., 2013; Luo et al., 2013; Van Liew et al., 2013; Chattopadhyay and Jha, 2014; Panagopoulos et al., 2015; Wang et al., 2017). While SWAT provides three options for simulating ET (Hargreaves, Priestly-Taylor, and Penman-Monteith) (Neitsch et al., 2011), only the Penman-Monteith equation (Walter et al., 2001) explicitly accounts for the physiological effects of CO₂ on ET using the method developed by Easterling et al. (1992) and Stockle (1992). Even so, CO₂ is often held constant at a baseline value of 330 ppm unless otherwise specified in SWAT (Sun et al., 2013; Panagopoulos et al., 2015; Bosch et al., 2018; Xu et al., 2019). To remedy this issue, a growing number of studies have assessed the effects of increased CO₂ on hydrologic simulations (Jha et al., 2006; Ficklin et al., 2010; Arias et al., 2014; Butcher et al., 2014; Gabriel et al., 2016), while other studies have enabled the Penman-Monteith ET routine to accept dynamic CO₂ time series (Wang et al., 2017) and improved its stomatal conductance and LAI routines to account for different vegetation types (Eckhardt and Ulbrich, 2003; Wu et al., 2012; Luo et al., 2013). In essence, projected increases in runoff with climate change have tended to be greater in SWAT models that accounted for rising CO₂ relative to SWAT models that ignored this effect, as the modified SWAT models have generally predicted greater reductions in ET that occurred in response to decreased stomatal conductance. Models with rising CO₂ produced 8% to 30% more runoff than models that ignored this effect (Ficklin et al., 2009; Arias et al., 2014; Butcher et al., 2014). Moreover, allowing CO₂-induced changes in stomatal conductance and LAI to vary by vegetation type has provided greater insight into the relative effects of these competing processes on ET predictions in SWAT (Wu et al., 2012) and other hydrologic models (Niu et al., 2013).

In this study, we used SWAT-VSA to examine the potential effects of climate change and increasing CO₂ on the water balance of Spring Creek watershed, a mixed land-use karst watershed situated in the Upper Chesapeake Bay region of the northeastern U.S. The SWAT-VSA model (Easton et al., 2008; Fuka and Easton, 2016) uses the topographic wetness index (TWI) (Beven and Kirby, 1979) to better account for the variable source area hydrology that typifies sloping watersheds of the Upper Chesapeake Bay. We incorporated the modified stomatal conductance and LAI routines of Wu et al. (2012) into SWAT-VSA’s Penman-Monteith ET procedure and enabled the model to accept a daily time series of CO₂. To the best of our knowledge, this is the first study to add this capability to the Penman-Monteith equation in SWAT-VSA. We used a previously

calibrated and validated version of SWAT-VSA for Spring Creek watershed (Amin et al., 2017) to evaluate the effects of climate change on watershed hydrology using downscaled climate projections from nine global climate models (GCMs). We then compared the baseline version of SWAT-VSA (Amin et al., 2017) against two modified SWAT-VSA models: one that integrated daily CO₂, and a second version that added flexible stomatal conductance and LAI routines to the dynamic CO₂ capability. The objectives of the SWAT-VSA modeling study were twofold: (1) quantify the effects of dynamic CO₂ and variable stomatal conductance and LAI routines on the water balance of Spring Creek watershed under current and future climatic conditions and (2) determine the significance of CO₂-induced water balance changes on runoff generation by variable source areas in Spring Creek watershed. Findings from the study highlight the importance of considering dynamic CO₂ in water balance simulations with SWAT-VSA in the Upper Chesapeake Bay region.

MATERIALS AND METHODS

STUDY AREA

Spring Creek watershed encompasses 370 km² in the Ridge and Valley physiographic province of the northeastern U.S. and is a subwatershed of the Chesapeake Bay watershed (fig. 1). Elevations in Spring Creek watershed range from 183 m above sea level in valleys to 305 m above sea level on the ridges (Fulton et al., 2005). The ridges in Spring Creek watershed are underlain by sandstone and shale geologic formations, whereas the valley floor consists of karst limestone and dolomite. The limestone and dolomite formations contain a network of depressions and sinkholes that capture surface water and recharge underlying carbonate aquifers that supply springs and streams (Fulton et al., 2005). Soil catenas in the watershed generally support variable source area hydrology, with infiltration excess overland flows occurring principally in well-drained upland settings and saturation excess overland flows confined mainly to lower landscape positions with poorly drained soils (Fulton et al., 2005; Buda and DeWalle, 2009).

The climate of Spring Creek watershed is temperate and humid. Monthly mean temperatures assessed in State College, Pennsylvania, ranged from -6.6°C in January to 27.8°C in July (PSC, 2014). Thirty-year climate normals (1981-2010) for State College indicate that annual precipitation averages 1,006 mm, with monthly precipitation distributed relatively evenly throughout the year (Durre et al., 2013). Annual streamflow at the Milesburg USGS gauging station averages roughly 554 mm based on 30 years of discharge data (1981-2010). A simple water balance calculation (annual mean precipitation minus annual mean streamflow) suggests that the annual average ET in Spring Creek watershed was 452 mm, representing ~45% of the annual precipitation.

Spring Creek watershed contains a mixture of land use types, with 43% of the land area classified as forest, 34% as agriculture, and 23% as urban land based on the National Land Cover Database (Homer et al., 2015). Agricultural lands, including cropland and pasture, are mainly found in limestone valleys with well-drained soils. Rotations on croplands include corn, winter wheat, small grain, soybeans, beans, and hay. The valley floor also holds most of the urban development in Spring Creek watershed. Forests, which include a mixture of deciduous and coniferous species, are mainly found on the sandstone ridges (Fulton et al., 2005).

DESCRIPTION OF SWAT-VSA

SWAT is a physically based, semi-distributed watershed model that simulates physical processes governing the water balance, as well as fate and transport of various chemical constituents (Arnold et al., 1998; Neitsch et al., 2011). SWAT predicts the impacts of land management and weather on water yield and quality. Additionally, SWAT simulates the physiological development of plants and predicts their growth and yield. In SWAT, the basic unit of simulation is the hydrologic response unit (HRU), which is a discrete land area defined by the coincidence of soil type, slope, and land use (Arnold et al., 1998; Neitsch et al., 2011). SWAT simulates overland flow using the Soil Conservation Service curve number (CN) (USDA-NRCS, 2004) or the Green-Ampt infiltration (Green and Ampt, 1911) methods;

Figure 1. Maps showing (a) location of Spring Creek watershed within the Upper Chesapeake Bay basin and (b) distribution of major land cover classes within Spring Creek watershed.

most SWAT simulations employ the CN method for its ease of use, relative accuracy, and few data requirements (King et al., 1999; Ficklin and Zhang, 2013).

SWAT-VSA improves on SWAT's representation of spatially variable saturation excess runoff processes in the landscape by incorporating topographically driven soil moisture capacity into the HRU representation (Easton et al., 2008). Instead of spatially defining HRUs as is done in standard SWAT, SWAT-VSA spatially defines HRUs based on the coincidence of soil type, TWI, and land use. An automated ESRI ArcMap toolbox called Topo-SWAT (Fuka, 2013; Fuka and Easton, 2016) is used to initialize SWAT-VSA. Topo-SWAT first generates ten wetness classes of equal area based on the TWI values (Beven and Kirkby, 1979; Collick et al., 2015). Wetness class 1 represents the bottom 10% of TWI values having the lowest runoff potential, and class 10 represents the upper 10% of TWI values having the highest runoff potential. Next, the Topo-SWAT toolbox overlays the wetness classes with the FAO digital soil map of the world (FAO, 2007) to define a combined wetness index soil layer for the watershed. Topo-SWAT then distributes hydrologically based soil values across the wetness index soil layer, with initial CN and available water content (AWC) values (Appendix A; all appendices are available at <http://doi.org/10.6084/m9.figshare.15029082>) expressed as a function of watershed storage (S); S is a watershed-scale parameter that is estimated using meteorological and hydrological observations (see Appendix B for Spring Creek results). The Topo-SWAT initialization procedure enables SWAT-VSA to distinguish areas of the landscape according to moisture status and runoff potential (Easton et al., 2008).

MODIFICATIONS TO SWAT-VSA

Modifications to the SWAT-VSA model generally followed the approach of Wu et al. (2012). CO_2 input is required to run all versions of SWAT, including SWAT-VSA, when the Penman-Monteith method is selected for ET estimation (Neitsch et al., 2011). In SWAT-VSA, the ASCE Penman-Monteith reference equation (Walter et al., 2001) is used to estimate PET. A surface resistance term described as the resistance to water vapor flow through the vegetation leaves (Monteith, 1965) is included in the ASCE Penman-Monteith reference equation and is estimated using equation 1:

$$rs_t = \frac{1}{0.5LAI_t g_l [(1+p) - p(\text{CO}_2/330)]} \quad (1)$$

where

rs_t = surface resistance on day t (s m^{-1})

LAI_t = leaf area index on day t (Jensen and Allen, 2016)

g_l = leaf conductance at $\text{CO}_2 = 330$ ppm (s m^{-1}) (Rosenberg et al., 1983)

p = plant-specific leaf conductance reduction coefficient (fraction)

CO_2 = atmospheric CO_2 concentration on day t (ppm).

Equation 1 accounts for changes in CO_2 over time, which enables an assessment of changing CO_2 on plant-water relationships. SWAT-VSA uses 40% as a constant value for leaf

conductance reduction across all plant types. To account for potential variations in the reduction of leaf conductance, Wu et al. (2012) adopted the approach of Eckhardt and Ulbrich (2003) and proposed a flexible leaf conductance reduction coefficient (p) that replaced the default value of 40%. In addition to the potential reduction in leaf conductance, Wu et al. (2012) also suggested that the maximum LAI be modified based on the type of vegetation in each selected HRU, in accordance with Eckhardt and Ulbrich (2003) and the findings reported by Ficklin et al. (2010). Equation 2 calculates the maximum daily LAI based on CO_2 and accounts for the potential impact of CO_2 on LAI. The value of the maximum modified LAI determines the value of LAI used in equation 1:

$$LAI_{m,\text{CO}_2,t} = LAI_m [(1-q) + q(\text{CO}_2/330)] \quad (2)$$

where

$LAI_{m,\text{CO}_2,t}$ = maximum modified LAI for day t

LAI_m = maximum LAI at $\text{CO}_2 = 330$ ppm (as supplied in the model input crop data file)

q = coefficient of LAI increase (fraction).

SWAT-VSA uses a modification of radiation use efficiency (RUE, eq. 3) to estimate specific plant growth response to solar radiation (Stockle et al., 1992; Neitsch et al., 2011), while accounting for CO_2 :

$$RUE_t = \frac{100\text{CO}_2}{[\text{CO}_2 + \exp(r_1 - r_2\text{CO}_2)]} \quad (3)$$

where

RUE_t = radiation use efficiency (10^{-1} g MJ^{-1})

r_1 and r_2 = RUE shape coefficients determined at 330 and 660 ppm CO_2 , respectively (fraction)

SWAT-VSA computes PET and RUE using a fixed CO_2 value provided by the user in the subbasin input files. The input CO_2 can be changed by the user to accommodate the simulated watershed and time frame of interest (e.g., Ficklin et al., 2010). However, this is a one-time change at the debut of a simulation, and the CO_2 value remains static throughout the simulation. To account for daily fluctuations and temporal changes in CO_2 , and to accurately capture increasing CO_2 trends over multiple decades, we modified SWAT-VSA to read a daily time series of CO_2 covering the period of simulation. When fixed CO_2 is simulated (i.e., no CO_2 time series is supplied), the modified SWAT-VSA (SWAT-VSA_ CO_2) employs the default fixed CO_2 value provided in the subbasin files. In addition, we modified the leaf conductance and maximum LAI as suggested by Wu et al. (2012), where specific values of p and q were selected for each HRU based on the vegetation cover.

VEGETATION-SPECIFIC LEAF CONDUCTANCE REDUCTION AND LAI INCREASE COEFFICIENTS

Values of leaf conductance reduction and LAI increase coefficients (p and q , respectively) were obtained from Wu et al. (2012) and other studies in the literature and are summarized in table 1. Generic values of p and q (40% and 37%, respectively) were used when literature values were unavailable. Although Morison and Gifford (1983) found that the

Table 1. Distribution of land uses in Spring Creek watershed and corresponding coefficients of leaf conductance reduction and LAI increase that were applied to these land use categories.

Land Use	Basin Portion (%)	Canopy Resistance Coefficients	
		Stomatal Conductance Reduction (p , %)	Stomatal Area Index Increase (q , %)
SWAT generic	-	40 ^[a]	37 ^[b]
Type and subtype			
Forest	43.3		
Mixed	0.8	21 ^[c]	14 ^[b]
Deciduous	41.1	24 ^[c]	7 ^[b]
Coniferous	1.5	8 ^[c]	7 ^[b]
Agriculture (pasture and crop lands)	35.0		
C3 ^[d]	23.5	24 ^[f]	15 ^[f]
C4 ^[e]	11.3	29 ^[f]	25 ^[f]
Other	0.2	26.5 ^[g,h]	20 ^[g]
Grazing lands	0.1		
Urban	21.2	- ^[i]	-
Water	0.3	- ^[i]	-

^[a] From Morison (1987).

^[b] From Pritchard et al. (1999).

^[c] From Medlyn et al. (2001)

^[d] Alfalfa, apple, hay, vegetables, beans, oats, papaya, pasture, rye, soybean, barley, canola, and wheat.

^[e] Corn and sorghum.

^[f] From Wand et al. (1999).

^[g] From Eckhardt and Ulbrich (2003).

^[h] From Luo et al. (2013).

^[i] Urban and water did not receive specific p and q values.

sensitivity of leaf conductance of C3 and C4 plants was reduced as CO₂ increased, these substitutions were conducted under the assumption that leaf conductance and LAI varied linearly over the selected range of CO₂ values.

SWAT-VSA SETUP AND PERFORMANCE ASSESSMENT

The calibrated and validated standard SWAT-VSA model of Spring Creek watershed (with CO₂ = 330 ppm, p = 0.4, and q = 0.37) described by Amin et al. (2017) was used as the baseline conditions for this study. Briefly, Amin et al. (2017) used a 10 m digital elevation model (DEM) from the National Elevation Dataset (USDA-NRCS, 2006), which is hosted on the USDA-NRCS Geospatial Data Gateway, to discretize Spring Creek watershed into subbasins and HRUs. Soil data descriptions were obtained from the FAO digital soil map of the world (FAO, 2007). Cropland rotations were based on seven years (2008–2014) of data from the Cropland Data Layer (Han et al., 2012) and from the 2011 National Land Cover Database (Homer et al., 2015). The Penn State Agronomy Guide (PSU, 2015) was used as a source for the determination of agricultural operations, and land management was represented in eight-year rotations based on the typical agricultural practices specific to Spring Creek watershed between 2008 and 2015. A 0% deletion threshold was used to ensure the representation of all land cover types in the final discretization of the watershed, which yielded 8,754 HRUs.

Additional details regarding the model calibration and corroboration are provided by Amin et al. (2017). In brief, the standard SWAT-VSA was calibrated and validated against daily stream discharge observed at the USGS gauging stations at Milesburg and Axemann (fig. 1). The

calibration was conducted over the period 2002–2007 against observed stream discharge data from both stations using a manual trial-and-error method incorporating adjustment of one parameter at a time based on visual and analytical evaluations. Parameters influencing the simulation of runoff, lateral flow, baseflow, and percolation were adjusted throughout the calibration process (Appendix A and Appendix C). The sensitivity of the parameters was evaluated using sequential uncertainty domain parameter fitting (Abbaspour et al., 2015). In this study, we verified the performance of standard SWAT-VSA over 2002–2015 against observed stream discharge data from the USGS gauging station at Milesburg and confirmed performance of the TWI classes. In addition to the evaluation against stream discharge, we further compared SWAT-VSA's ET estimates against ET from remotely sensed products, including the MODIS Global Evapotranspiration product and the Operational Simplified Surface Energy Balance (SSEBop) (Mu et al., 2011; Senay et al., 2013; Running et al., 2017).

CLIMATE INPUTS

Daily weather data, including precipitation (mm), temperature (°C), wind speed (m s⁻¹), solar radiation (MJ m⁻²), and relative humidity (fraction), were primarily obtained from NOAA's State College weather station using the Global Historical Climatology Network (GHCN) daily portal (Menne et al., 2012). Weather data obtained from the Chesapeake Community Modeling Program and the Pennsylvania State Climatologist (CCMP, 2015; PSC, 2014) were used to infill missing data from the NOAA State College weather datasets.

Representative Concentration Pathways (RCPs) are standardized greenhouse gas emissions scenarios that are used worldwide to explore the potential impacts of climate change (Van Vuuren et al., 2011). Under RCP 8.5, which is the high-emissions scenario referred to as the “business as usual” pathway, concentrations of atmospheric greenhouse gases reach nearly 1,370 ppm CO₂-eq by the end of the 21st century (Van Vuuren et al., 2011). Given that observed greenhouse gas emission trends have not deviated much from the RCP 8.5 scenario (Manning et al., 2010), we used outputs based on RCP 8.5 from nine GCMs (Appendix D) of the Coupled Model Intercomparison Project 5 (CMIP5) archive (Taylor et al., 2012). Using climate projections from nine different GCMs allowed us to capture the potential range of future climate conditions in Spring Creek watershed. Asynchronous regional regression models (Stoner et al., 2013) were used to statistically downscale gridded daily projections of precipitation (mm), minimum and maximum temperature (°C), wind speed (m s⁻¹), and solar radiation (MJ m⁻²) to point-scale datasets using the NOAA GHCN station at State College as the reference location. The projected data covered the period 1950–2100. Observed CO₂ data were not available for Spring Creek watershed. Therefore, for current climate conditions, we derived a daily CO₂ time series using observed data from NOAA's Carbon Tracker (Peters et al., 2017) for Argyle (Maine), Park Falls (Wisconsin), and Grifton (North Carolina) between 1999 and 2016, a time period during which daily CO₂ data were comparable across all three locations (Appendix E). The selection of these stations

was based on their proximity to Spring Creek watershed and the availability of long-term continuous CO₂ data. For future climate conditions, we generated a daily CO₂ time series by interpolating between the global CO₂ values projected under RCP 8.5 (IPCC, 2014).

SCENARIOS

The modified conductance equation developed by Stockle et al. (1992), which is used in the Penman-Monteith routine of SWAT, is only valid for CO₂ between 330 and 660 ppm (Li et al., 2019). Based on the notion that the canopy conductance response to CO₂ may be strongly nonlinear when CO₂ exceeds 660 ppm (Islam et al., 2012), we decided to end our simulations in 2065, which appears to be the year that CO₂ levels are projected to reach 660 ppm (IPCC, 2014). As such, three modeling scenarios were simulated over the period from 1980-2065 (with a five-year warmup period):

1. Baseline SWAT-VSA: standard model with static CO₂; CO₂ = 394 ppm was selected (instead of the default 330 ppm) to better represent CO₂ in Spring Creek watershed by the early 21st century.
2. SWAT-VSA_CO2 integrates a daily (dynamic) time series of CO₂.
3. SWAT-VSA_CO2+Plant: integrates a daily (dynamic) time series of CO₂ along with changes in the plant routines, including flexible stomatal conductance and LAI parameters.

DATA ANALYSIS

Predicted daily discharge and monthly ET, runoff, lateral flow, and percolation amounts for Spring Creek watershed were aggregated to annual (calendar year), seasonal (winter: DJF; spring: MAM; summer: JJA; fall: SON) amounts by GCM and scenario. Model ensemble means were calculated by taking the arithmetic mean of all the model results across all time scales (annual and seasonal) and scenarios. The standard error of periodical means accounted for inter-annual variability for single model means and inter-annual as well as inter-model variability for ensemble model means. Three time periods of 21 years separated by four-year periods (1985-2015, 2020-2040, and 2045-2065) were considered for analysis. The percent annual and seasonal changes between time periods were estimated by GCM as well as for the model ensemble means. Mann-Kendall and Theil-Sen slope methods (Helsel and Hirsch, 2002) were used to assess trend significance and estimate rates of change for the current (1985-2015) and future (2020-2065) periods. Generalized linear models (McCulloch and Searle, 2000) were used to compare trends between scenarios. Potential changes in runoff and ET patterns with climate change were also assessed according to land use type and TWI class using the water balance results for each HRU in Spring Creek watershed. These analyses were conducted in the R environment (R-Core-Team, 2016) using the Agricolae package (de Mendiburu, 2016).

RESULTS AND DISCUSSION

SWAT-VSA PERFORMANCE

The standard SWAT-VSA model with calibrated parameters (Appendix A and Appendix C) predicted daily and monthly stream discharge reasonably well over the period 2002-2015 and maintained TWI class variations. Daily and monthly predictions over the corroboration period (2002-2015) were “satisfactory” according to watershed-scale model calibration standards recommended by Moriasi et al. (2015) (NSE = 0.6 and 0.7, and R² = 0.7 and 0.8 for daily and monthly predictions, respectively; table 2). The model also captured most of the peak discharges, although some degree of underestimation was noted for the largest storm-flow events (Appendix F). Baseflow was slightly overpredicted, resulting in overall negative Pbias values (-7.9% and -7.7% for daily and monthly discharges). These results satisfactorily fit those reported by Amin et al. (2017).

Monthly ET values predicted by SWAT-VSA were compared to monthly ET values estimated using remote sensing methods by MODIS and SSEBop (fig. 2). The predicted monthly ET was generally in agreement with the remotely sensed ET estimates. SWAT-VSA-predicted monthly ET values tend to be lower than the remotely sensed ET (as illustrated by the regression slopes), especially during the warm season when ET values are highest.

Annual ET in Spring Creek watershed ranged from 443 to 588 mm (average = 528 ± 14 mm) over the period 1985-2015, amounting to ~51% of annual precipitation. Annual ET was approximately 517 mm (443 to 571 mm) during dry

Table 2. Model performance statistics summarizing the comparison of observed and simulated streamflow for Spring Creek at Milesburg, Pennsylvania, for 2002-2015.

Evaluation	Mean Discharge (m ³ s ⁻¹)		NSE	Pbias (%)	R ²
	Observed	Simulated			
Daily	6.67	6.14	0.56	-7.90	0.70
Monthly	6.67	6.15	0.68	-7.70	0.77

Figure 2. Scatterplot of monthly remotely sensed versus simulated ET for Spring Creek watershed for 1985-2015.

years (precipitation < 30th percentile of 1985-2015 observations) and roughly 525 mm (485 to 588 mm) during wet years (precipitation > 70th percentile of 1985-2015 observations). After accounting for ET losses in Spring Creek watershed, residual precipitation was then converted to runoff (10%), lateral flow (9%), and percolate (30%). Mean soil moisture content across the basin varied between 1,400 mm and 1,725 mm, and the annual discharge and soil moisture content varied with precipitation in contrast to ET.

Special attention was given to runoff prediction in Spring Creek watershed, as its karst character necessitated some adjustments to runoff-related parameters that deviated from those typically used in modeling non-karst basins. For instance, the CN and AWC values provided in Appendix A are the final input values used to represent the ten TI classes in the Spring Creek model after initialization with Topo-SWAT, input of detailed local land management, and watershed-specific calibration. It is important to note that the CNs derived from the Topo-SWAT initialization do not reflect the effects of land management, historical climate, subsurface characteristics, or other factors that might affect streamflow variability during the calibration phase. During model calibration, CNs are further adjusted to account for these factors. In our study, adjusted CNs following calibration spanned a tighter range from 35.0 to 47.5 (mean = 43.3). We believe that a number of hydrogeological, soil, and land use factors can account for the tighter range of unusually low CNs that were obtained following calibration; we explore these factors below.

From a hydrogeological perspective, Spring Creek watershed is unique from other watersheds in which SWAT-VSA and Topo-SWAT have been applied, for two reasons. First, the contributing groundwater watershed is at least 22% larger than the surface watershed (Wood, 1980). Second, the watershed is underlain by karst with sinkholes and frequently losing streams; many of these losing streams re-enter elsewhere as springs (O'Driscoll and DeWalle, 2006). Major springs entering the surface watershed boundary were included as point sources, but the incoming water would not be included in classical calculations of watershed storage. Additionally, lateral flow times were lagged and FAO soil depths were increased to match SSURGO depths in order to adequately represent the sustained spring discharges and groundwater contributions.

Conditions in karst watersheds like Spring Creek push the use of the CN beyond the conditions for which it was initially designed. Moreover, agricultural rotations in Spring Creek watershed consist largely of grasslands, alfalfa, and no-till row crops with winter cover. Thus, CNs determined through the VSA calculations were lower than the standard USDA-NRCS suggestions for soils in hydrologic groups B and C. Low CN values of 30 to 40 have also been found to best describe runoff conditions in karst Mediterranean regions (Efstratiadis et al., 2014; Merheb et al., 2016; Savvidou et al., 2018). The upper range of CNs in this study, seen in row crop areas on minimal slopes in Spring Creek watershed, is roughly consistent with the lower range of CNs used by Collick et al. (2015) and Fuka et al. (2016) on minimal slope agricultural areas in non-karst basins. The AWC profile values in Spring Creek watershed increase steadily from

46.21 to 174.07 mm across the ten TI classes. However, because soil depths were also varied throughout Spring Creek watershed to mimic soil storage and abundant lateral subsurface water movement, the resultant changes in AWC fractions (mm mm^{-1}) were minimal.

BASELINE AND MODIFIED SWAT-VSA SIMULATIONS OF HISTORICAL (1985-2015) WATER BALANCE IN SPRING CREEK WATERSHED

We found no significant differences in historical simulations of the water balance in Spring Creek watershed among the three versions of SWAT-VSA tested in this study (Appendix G and Appendix H). For instance, baseline SWAT-VSA predicted significant increases in annual ET of 2.9 mm year^{-1} ($p = 0.01$) for 1985-2015. This modeled ET trend was consistent with remotely sensed ET observations from MODIS and SSEBop, showing that actual ET increased by 4.1 ($p = 0.01$) and 5.4 mm year^{-1} ($p = 0.30$), respectively, for 2000-2015. Annual water balance calculations (e.g., Huntington and Billmire, 2014) using observed precipitation and stream discharge data for Spring Creek watershed also showed that annual ET increased by roughly 4.7 mm year^{-1} . Notably, SWAT-VSA_CO2 and SWAT-VSA_CO2+Plant predicted slower ET increases of 2.4 and 2.5 mm year^{-1} , respectively. Even so, a comparison of ET trends across all three models using generalized linear methods showed no significant differences. In terms of annual discharge, all three versions of SWAT-VSA predicted increases in flow (Appendix G and Appendix H), with baseline SWAT-VSA predicting a streamflow increase of 0.4 mm year^{-1} , and SWAT-VSA_CO2 and SWAT-VSA_CO2+Plant predicting flow increases on the order of 0.8 mm year^{-1} over the 1985-2015 simulation period. Although the rates of discharge increase were not significantly different among the three models, the streamflow increases simulated by SWAT-VSA_CO2 and SWAT-VSA_CO2+Plant were consistent with discharge observations at the USGS gauging at Milesburg, which revealed flow increases of about 0.9 mm year^{-1} for 1985-2015. Overall, the addition of dynamic CO₂ and variable stomatal conductance and LAI routines to SWAT-VSA did not have appreciable effects on the water balance prediction in Spring Creek watershed under 1985-2015 conditions.

FUTURE CLIMATE (2020-2065) *Climate Change Projections for Spring Creek Watershed*

In Spring Creek watershed, downscaled climate projections from the nine GCMs suggest that 21st century climate will be increasingly warmer and wetter on average, which is consistent with recent regional (Hayhoe et al., 2007, 2008) and national climate change assessments (Easterling et al., 2017). For instance, in terms of annual precipitation, the 2020-2040 period is expected to be 6% $\pm$ 2% wetter than 1995-2015; in 2045-2065, annual precipitation is anticipated to increase by 9% $\pm$ 2% relative to 1995-2015 climate (fig. 3a). From a seasonal perspective, winter precipitation is likely to increase the fastest, with precipitation rising by 7.4 $\pm$ 1.5 mm decade^{-1} between 2000 and 2100. Relative to 1995-2015, annual mean temperatures in Spring Creek

Figure 3. Projected changes in precipitation, temperature, and atmospheric CO₂ concentration for Spring Creek watershed from 1950 to 2100 under the RCP 8.5 emissions scenario. Dashed lines represent the mean response across the nine GCMs used in this study. Solid lines show locally estimated scatterplot smoothing (LOESS).

watershed are expected to be $1.0^{\circ}\text{C} \pm 0.01^{\circ}\text{C}$ (mean $\pm$ standard error) warmer in 2020–2040 and $2.6^{\circ}\text{C} \pm 0.01^{\circ}\text{C}$ warmer in 2045–2065 (fig. 3b). In accordance with previous studies, summer temperatures in Spring Creek watershed will likely warm the fastest, with warming trends averaging $0.7^{\circ}\text{C decade}^{-1}$. In addition to temperature and precipitation increases, CO₂ levels are also expected to continue rising into the 21st century. By the 2040s, CO₂ will likely be 80 ppm higher than in the 2010s, representing an increase of $20.8\% \pm 0.1\%$. Beyond the 2040s, the rate at which CO₂ increases is likely to accelerate even further, reaching $54.4\% \pm 0.1\%$ above the 2010s level by the 2070s (fig. 3c).

Baseline SWAT-VSA Simulations of Water Balance in Spring Creek Watershed under Climate Change

The effects of climate change on the water balance of Spring Creek watershed (fig. 4, Appendix I, and Appendix J) were initially examined using baseline SWAT-VSA, which lacked dynamic CO₂ and variable stomatal conductance and LAI routines. In terms of ET, baseline SWAT-VSA suggested that annual ET in Spring Creek watershed would rise slightly from 540 mm in 1995–2015 to 572 mm in 2045–2065, an increase of $6.0\% \pm 0.8\%$ (fig. 4). Given that CO₂

and plant routines were invariant in baseline SWAT-VSA, annual ET increases were largely attributed to increases in annual air temperature and precipitation. Notably, the largest ET increases of $18.2\% \pm 2.6\%$ and $18.3\% \pm 1.2\%$ were projected in the winter and spring months, respectively, with fall actually exhibiting a decrease in ET of $13.1\% \pm 1.6\%$ by 2045–2065. Despite projections for increases in annual ET, baseline SWAT-VSA results still indicated increases in annual runoff ($15.7\% \pm 4.1\%$), lateral flow ($14.0\% \pm 2.7\%$), and percolation ($11.8\% \pm 3.2\%$) in Spring Creek watershed between 1995–2015 and 2045–2065 (fig. 4). Collectively, the increasing trends in runoff generation and percolation led to a $13.0\% \pm 3.0\%$ increase in discharge from 460 mm in 1995–2015 to 520 mm in 2045–2065 (fig. 4). In particular, eight of the nine GCMs yielded projected increases in discharge in Spring Creek watershed using baseline SWAT-VSA, with the strongest flow increases projected for the winter months when increases in precipitation were also projected to be the largest. As such, the effects of increasing ET on the water balance of Spring Creek watershed were more than offset by increasing precipitation using baseline SWAT-VSA.

Results from the baseline SWAT-VSA simulations in Spring Creek watershed were generally consistent with other water balance modeling studies in the Mid-Atlantic and Northeast regions of the U.S. that did not account for the effects of CO₂. For instance, Wagena et al. (2018) used SWAT-VSA to model climate change impacts in a headwater tributary to Mahantango Creek in east-central Pennsylvania. Relative to 1975–1998, SWAT-VSA suggested that ET could increase by 8% in 2045–2068, leading to a 0.7% decline in streamflow at the watershed outlet. Despite the different time periods that were assessed, the findings of Wagena et al. (2018), at least with regard to ET changes, mainly agreed with the ET projections made with baseline SWAT-VSA in Spring Creek watershed. In a broader analysis of climate change impacts across the Susquehanna River drainage, Wagena et al. (2018) also projected a 5% increase in ET from 1990–2014 to 2041–2065. However, the Susquehanna River study indicated that riverine discharge could increase by 5% over the same time frame. Elsewhere in the Mid-Atlantic region, a SWAT modeling study by Lee et al. (2018) in the Tuckahoe Creek and Greensboro watersheds, both tributaries to the Choptank River on the Delmarva Peninsula, suggested that increases in precipitation and temperature with climate change could increase ET by 1% to 9% between 1999–2014 and 2083–2098. Consistent with the aforementioned studies, regional modeling by Cherkauer et al. (2003) using the Variable Infiltration Capacity (VIC) model indicated that climate change could increase ET in the Northeast U.S. by as much as 8% between 1961–1990 and 2035–2064 due to increases in precipitation and temperature. Taken together, the results of our study with baseline SWAT-VSA and similar studies in the Mid-Atlantic and Northeast U.S. suggest increasing ET rates with climate change when dynamic changes in atmospheric CO₂ are not explicitly simulated.

Modified SWAT-VSA Simulations of Water Balance in Spring Creek Watershed under Climate Change

Adding a daily time series of CO₂ to the SWAT-VSA model yielded significant changes to water balance

Figure 4. Average percent changes in annual and seasonal ET, runoff, lateral flow, percolation, soil moisture content, and discharge in Spring Creek watershed with climate change, with error bars representing GCMs-years variability. Projected changes in 2020-2040 and 2045-2065 are estimated relative to the 1995-2015 period using baseline SWAT-VSA.

projections under climate change in Spring Creek watershed, with particularly notable effects on the direction and magnitude of ET trends relative to baseline SWAT-VSA (fig. 5 and Appendix K). The added effects of variable stomatal conductance and LAI routines (SWAT-VSA_CO2+Plant) were not significantly different from the SWAT-VSA model that only considered CO₂ effects (SWAT-VSA_CO2). In essence, the principal hydrologic effects were attributed to the addition of dynamic CO₂ to SWAT-VSA and not to the variation of the stomatal conductance reduction (p) and coefficient of LAI increase (q) terms in equations 1 and 2 by plant type. Consequently, we mainly focused on the differences between SWAT-VSA_CO2 and baseline SWAT-VSA. In terms of ET, baseline SWAT-VSA projected an ET increase of $0.7 \pm 0.3 \text{ mm year}^{-1}$ from 2020 to 2065, while SWAT-VSA_CO2 suggested that annual ET in Spring Creek watershed would potentially decline by $0.4 \pm 0.3 \text{ mm year}^{-1}$ over the same time frame. Seasonally, ET declines projected by SWAT-VSA_CO2 were most apparent during the summer and fall months (fig. 5).

Disparities between baseline SWAT-VSA and SWAT-VSA_CO2 affected other facets of the water balance as well. For instance, SWAT-VSA_CO2 projected that soil water storage would increase by 0.5 mm year^{-1} from 2020 to 2065 due in part to the projected decreases in annual ET. In stark contrast, baseline SWAT-VSA projected that soil water storage would decline by 1.5 mm year^{-1} in response to increasing

ET. Even though dynamic CO₂ routines yielded significantly different trends in soil water storage between baseline SWAT-VSA and SWAT-VSA_CO2, we did not see similarly significant effects on runoff, lateral flow, and percolation. However, SWAT-VSA_CO2 generally projected greater increases in runoff, lateral flow, and percolation relative to baseline SWAT-VSA. The collective effects of these trends produced a notable difference in streamflow projections, with SWAT-VSA_CO2 predicting streamflow increases of 1.6 mm year^{-1} during 2020-2065, which were more than double those projected by baseline SWAT-VSA (0.7 mm year^{-1} , fig. 5).

As the aforementioned results demonstrate, integrating increasing CO₂ along with projected changes in precipitation and temperature in SWAT-VSA resulted in reduced ET and enhanced streamflow relative to SWAT-VSA models that did not account for changes in CO₂. These findings strongly indicate that the inclusion of elevated CO₂ in SWAT-VSA stimulated an increase in stomatal resistance that lowered ET rates in Spring Creek watershed, which is an ecosystem-level response that has been widely observed in many CO₂ fertilization experiments (Wullschlegel et al., 2002; Leakey et al., 2009). Indeed, the review by Leakey et al. (2009) suggested that elevated CO₂ levels could reduce ET by 5% to 20% depending on the plant species that was monitored. According to Leakey et al. (2009), the consequent effect of these ET reductions was a notable increase in soil moisture

Figure 5. Theil-Sen slopes showing projected trends (2020-2065) in annual ET, runoff, lateral flow, percolation, soil water, and stream discharge using SWAT-VSA, SWAT-VSA_CO2, and SWAT-VSA_CO2+Plant. Each bar represents the mean trend across all nine global climate models, and the error bars indicate 95% confidence limits of the mean trend slopes. Asterisks indicate significant differences between slopes: 0.1 (*), 0.05 (**), and 0.01 (***).

that would be expected to enhance the generation of watershed runoff, as has been indicated in several modeling studies of continental runoff responses to climate change and increased CO₂ (Gedney et al., 2006; Betts et al., 2007; Cao et al., 2010). Moreover, a recent study by Lian et al. (2018) also reinforced the notion that higher CO₂ levels could reduce the transpiration component of ET, enabling increased watershed discharge, especially in temperate regions like the Mid-Atlantic where transpiration exceeds evaporation. In accordance with these studies, the significantly lower ET rates that were projected by SWAT-VSA in response to increasing CO₂ yielded discernibly increasing trends in soil moisture, runoff, and stream discharge in Spring Creek watershed (fig. 5).

Despite the significance of CO₂ for plant-water relationships and the hydrologic cycle, CO₂ dynamics are not routinely incorporated into watershed models of climate change (Butcher et al., 2014). Still, watershed modeling studies that have accounted for CO₂ generally agree with our SWAT-VSA simulations of Spring Creek watershed. For instance, Johnson et al. (2012) and Butcher et al. (2014) used SWAT to simulate the integrated effects of climate change and CO₂ on the hydrology of 20 U.S. watersheds, which included the Susquehanna River basin in the Mid-Atlantic region. Their results showed that median discharge across all 20

watersheds could be as much as 11% higher relative to SWAT models that held CO₂ constant at present-day levels. In our SWAT-VSA modeling study of Spring Creek watershed, annual mean discharge projections for the 2045-2065 period were 22.4% $\pm$ 3.3% higher when increasing CO₂ was accounted for in the model. In a SWAT modeling study of climate change impacts in the Choptank River basin, Lee et al. (2018) reported that by accounting for elevated CO₂, annual ET could be reduced by up to 30%, with streamflow increasing by roughly 46% as a result. Elsewhere in the U.S., climate change modeling studies by Jha et al. (2006), Ficklin et al. (2009), Wu et al. (2012), Gabriel et al. (2016), and Wang et al. (2017) have also demonstrated that the incorporation of dynamic CO₂ into SWAT reduces ET and enhances streamflow in comparison with SWAT models that do not simulate the effects of CO₂ on plant-water relationships. It is important to note that previous studies have highlighted the potential for SWAT to overestimate the increase in stomatal resistance as a function of dynamic CO₂ (Ficklin et al., 2009; Butcher et al., 2014), which introduces a degree of uncertainty into the magnitude of runoff and streamflow increases due to reduced ET. As such, further research is needed on the ET algorithms in SWAT to more fully comprehend how watershed hydrology could be affected by rising CO₂ and modified precipitation and temperature regimes.

Impacts of Modified SWAT-VSA on Variable Source Area Hydrology in Spring Creek Watershed

In addition to assessing watershed-scale responses to enhanced CO₂ in SWAT-VSA, we also examined the integrated effects of CO₂ and climate change on the water balance of variably saturated areas in Spring Creek watershed. Projected trends in ET, runoff, lateral flow, and percolation were aggregated across the different wetness classes (i.e., variably saturated areas) for the three different versions of SWAT-VSA over the 2020-2065 simulation period (fig. 6 and Appendix L). In the following discussion, we explore the effects of rising CO₂ on low (class 1), medium (class 5), and high (class 10) wetness classes.

As seen for the watershed-scale results, the differences between baseline SWAT-VSA and SWAT-VSA_CO₂ generally captured the main effects of CO₂ enhancement on water balance trends across the three different wetness classes. In general, baseline SWAT-VSA projected ET increases across all three wetness classes during the 2020-2065 period, with projected ET trends increasing three-fold from drier (0.4 mm year⁻¹) to wetter (1.0 mm year⁻¹) soils. In contrast, SWAT-VSA_CO₂ projected ET declines across all three

Figure 6. Theil-Sen slopes showing projected trends (2020-2065) in annual ET, runoff, lateral flow, and percolation aggregated across three wetness classes for baseline SWAT-VSA, SWAT-VSA_CO₂, and SWAT-VSA_CO₂+Plant. The three wetness classes include: class 1, the bottom 10% of TWI values having the lowest runoff potential, class 5, the middle 50% of TWI values having moderate runoff potential, and class 10, the upper 10% of TWI values having the highest runoff potential. Each bar represents the mean trend across all nine GCMs, and error bars indicate 95% confidence limits of mean trends. Asterisks (***) indicate differences between slopes are significant at $p = 0.01$.

wetness classes (-0.4 to -0.5 mm year⁻¹), with no discernible trend as a function of soil wetness. Disparities in the direction and magnitude of ET projections by wetness class led to noteworthy differences in runoff projections that were most evident in the wettest soil class. For instance, during the 2020-2065 period, SWAT-VSA_CO₂ projected that runoff from the wettest soils could increase by 1.5 mm year⁻¹, while baseline SWAT-VSA predicted runoff increases that were four-fold less for the same soils. Even though the runoff projections were not significantly different between the three versions of SWAT-VSA that were tested, the results indicate that increases in CO₂ could depress ET rates in wetter parts of the landscape, thereby enabling larger amounts of runoff generation relative to models that do not account for CO₂ effects. Indeed, the results from SWAT-VSA_CO₂ suggest that the wettest soils could potentially generate 28% more runoff in 2045-2065 than in 1985-2015 (table 3). As such, these findings suggest that wetter areas of the landscape are likely to play an increasingly important role in streamflow generation if rising CO₂ levels depress ET rates, as suggested by the SWAT-VSA simulation results.

IMPLICATIONS AND CONCLUSIONS

Modifying the SWAT-VSA model to accept daily CO₂ values and variable plant-based parameters in ET subroutines enabled us to examine the integrated effects of increased precipitation, air temperature, and CO₂ on the hydrology of Spring Creek watershed. At the watershed scale, accounting for the effects of increasing CO₂ in SWAT-VSA yielded simulation results with 8% lower annual ET rates in 2045-2065 than SWAT-VSA models that were run with static CO₂ levels. The CO₂-induced ET reductions in SWAT-VSA led to higher projections of soil water storage, runoff, lateral flow, and discharge than would have been realized with SWAT-VSA models that did not account for daily increases in CO₂. These results were concordant with other hydrological modeling studies that have integrated the effects of CO₂ in evaluations of climate change impacts on the water balance. In addition to the watershed-scale assessment, analyses of variable source areas also suggested that wetter areas of Spring Creek watershed would generate higher amounts of runoff (11% higher for the top 10% of TWI values) due to the antagonistic effects of CO₂ on ET. As such, the impacts of a CO₂-enriched atmosphere later in the 21st century have potential to augment runoff generation and pollutant loss from variable source areas of the

Table 3. Mean annual percentage change across nine GCMs in the water balance of three wetness classes in Spring Creek watershed between 1985-2015 and 2045-2065. Results are shown for SWAT-VSA_CO₂.

Component	Wetness Class ^[a]		
	Class 1	Class 5	Class 10
ET	-3	-2	-1
Runoff	+11	+20	+28
Lateral flow	+20	+22	+14
Percolation	+22	+23	+11

^[a] Class 1 = bottom 10% of TWI values having the lowest runoff potential, class 5 = middle 50% of TWI values having moderate runoff potential, and class 10 = upper 10% of TWI values having the highest runoff potential.

landscape. Given the projected changes in surface runoff and pollutant loading, the effectiveness of currently adopted best management practices under future climate scenarios requires further investigation.

At a broader level, our study demonstrates the importance of incorporating the effects of CO₂ into watershed models like SWAT-VSA, especially for simulations that are run in temperate climates (Jasechko, 2018). Given that ET is often the largest term in the water balance of temperate basins, reliable estimation of ET is critical to simulating watershed hydrology in a changing climate (Milly and Dunne, 2011). While our study focused solely on the Penman-Monteith equation with and without the effects of CO₂, there is a need to assess other ET routines in SWAT (Bae et al., 2011; Thompson et al., 2014) alongside the Penman-Monteith equation to provide a fuller appreciation of the uncertainties in the water balance with climate change. Finally, our study only considered CO₂ levels between 330 and 660 ppm, which is the range of CO₂ for which ET predictions by the Penman-Monteith equation are considered valid (Li et al., 2019). As such, our study could only provide water balance projections out to 2065. Future studies of this type should consider the workarounds proposed by Li et al. (2019) and Yang et al. (2019a), which, if integrated into SWAT, would enable the effects of CO₂ to be examined for the higher CO₂ concentrations that are anticipated by the end of the 21st century.

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APPENDICES

The appendices mentioned in the text are available at <http://doi.org/10.6084/m9.figshare.15029082>.

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