Modeling non-point source pollution in surface water under non-stationary climates and land uses

THESIS

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Abstract

Non-point source (NPS) pollution causes widespread impairment to surface water in the United States and can potentially impact human health and safety. Nutrient NPS pollution from agriculture is one of the most damaging and widespread non-point source problems in surface water.

Due to the complexity of the processes that govern it, the spatial and temporal extent of nutrient NPS pollution can be difficult to assess and quantify. The use of physically based computer modeling allows us to represent the various physical and chemical cycles that control the amount of pollutant loading that ultimately ends up in a stream.

A simulation of the Upper Big Walnut Creek (UBWC) watershed in central Ohio was set up using the Soil and Water Assessment Tool (SWAT) 2012 model and the ArcSWAT GIS interface. Calibration was performed for the portion of the watershed above the USGS stream gauge 03228300 and calibrated parameters were extended to the entire watershed. The simulation was calibrated for 2000-2004 and validated for 2005-2009 with prediction efficiencies of 0.62 and 0.74, respectively.

Four sets of experiments were performed. The first of these, a sensitivity analysis, was undertaken to understand the influence of selected SWAT variables and their assumptions on the watershed’s hydrologic and nutrient cycles. The other sets of experiments examined the effects of climate change, agricultural management change, and the combination thereof on the UBWC.

Climate change simulations used input downscaled from output of the Climate Model Intercomparison Project (CMIP5) multi-model dataset. This input consisted of two climate scenarios representing different emissions pathways for 2006-2100, downscaled with quantile mapping and regression techniques.
The agricultural management change experiments used a stationary climate in conjunction with four scenarios representing potential avenues of change within the UBWC. These included a reference scenario reflecting the watershed’s current management, a reference scenario with cover crops, a cash grain rotation scenario, and a cash grain rotation scenario with cover crops.

Lastly, coupled management change/climate change simulations were performed. The management component of these simulations used the four scenarios previously developed. Climate change was simulated using the SWAT built-in weather generator as a source of weather inputs. The statistics used to run the weather generator were calculated from the quantile mapping downscaled input used in the first climate change experiment.

Downscaled Representative Concentration Pathway (RCP) 4.5 and RCP 8.5 climate scenarios both predict increased temperatures throughout the year and increases to early spring precipitation. As a result of the temperature increases, crop planting and harvest dates occur earlier in the year, shifting the watershed hydrologic cycle. Residue mineralization, tile nitrogen, and sediment losses are also affected. Overall, climate change was found to reduce NPS pollution loading, however, decreases in streamflow may negate these reductions by increasing the concentration of NPS pollutants. Management practices such as the changes in rotation and application of cover crops studied may also become necessary to ensure protection of human health and the environment.
Dedication

This document is dedicated to my family.
Acknowledgments

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Vita

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Civil Engineering
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1 Introduction

Water resources are under worldwide attack from climate change, land use change, invasive species, and chemical inputs [Carpenter et al., 2011]. Potentially hazardous effects of these factors can vary widely. While climate change threatens to reduce the quantity of water available in some locales [Vörösmarty et al., 2000], wetter areas such as the Midwestern United States are more vulnerable to chemical inputs such as agricultural and suburban fertilizers, municipal sewage, and runoff from urban areas. Shown below are the top five causes of impairment to streams and rivers in the US as of 2009 [USEPA, 2014]:

![Bar chart](chart.png)

**Figure 1.1.** Top five causes of impairment to stream and river miles in the US, 2009 (PCBs refer to polychlorinated biphenyls).
In general, water pollutants are characterized by their method of emission as either point- or non-point source (NPS), where point source emissions have a discrete conveyance or point of entry into the environment (e.g. a stack, drainage pipe, etc.) and NPS emissions are spatially distributed and cannot be attributed to a single point (e.g. runoff, atmospheric deposition). Diffuse or NPS pollution is predominant among chemical inputs in terms of its effects on water quality, and represents perhaps the most significant threat to water quality in the United States today [EPA, 2009]. Four of the five top contributors to stream and river pollution shown in Error! Reference source not found. are released primarily through NPS (pathogens, sediment, nutrients, and PCBs), and oxygen depletion is often an indirect result of elevated nutrient concentrations [Rabalais et al., 2002]. Depending on the area, many other NPS contaminants threaten surface water quality, including salt, heavy metals, and acidity. In urban centers (especially those with older infrastructure), combined stormwater and wastewater sewer systems can lead to overflows and pollution of local streams and rivers with untreated waste [Moffa, 1997]. Cities also contain large numbers of cars, which can become mobile sources of air pollution [Faiz et al., 1996], leading to deposition of nitrogen and other problems. Large impervious areas and short peak runoff times mean contaminants have little opportunity to be adsorbed by soil or transformed by natural processes prior to reaching waterways.

While urban NPS pollutants have an undoubtedly significant impact on water quality, agriculture is the greatest overall source of impairment to rivers and streams and the third-greatest source of impairment to lakes, reservoirs, and ponds today [EPA, 2009] and excess nitrogen and phosphorus are the largest component of this impairment. These nutrients have the ability to negatively impact wildlife, water quality, and water aesthetics [Carpenter et al., 1998]. This impairment comes most frequently in the form of eutrophication, in which algal growth depletes water oxygen levels and kills fish and other organisms. Taste and odor problems in drinking water can also occur as a result of excess algae growth. Certain species of algae can additionally release toxins into water, making it unsafe to drink or even touch. At high levels, nitrogen also has negative effects
on human health and the environment. Nitrate-nitrogen concentrations greater than 10 mg/L (the EPA-legislated maximum contaminant level) can cause methemoglobinemia, a condition potentially fatal to infants. Elevated nitrogen concentrations also contribute to water acidification as well as potentially increased cancer risks to humans over long periods of time [Camargo and Alonso, 2006].

In Central Ohio, the Upper Big Walnut Creek Watershed (UBWC) is a primarily agricultural watershed that is experiencing increasing pressure from adjacent urban areas. Many of the NPS-related issues discussed above are relevant to this watershed and will be the focus of this study. A map of the UBWC in relation to the state of Ohio is shown below in Figure 1.2:
Figure 1.2. Position of the UBWC watershed in relation to the state of Ohio.

The UBWC is part of the farmland of the Midwest region which supplies a great deal of the nation and world’s food. The population of the United States and the world are respectively expected to reach 400 million and 9,500 million shortly before the year 2050 under a medium fertility scenario [UN, 2012]. Food production must also increase to keep pace with this trend, and additional strain on natural resources will also result due to the increased demand for feedstocks and fuel. As a result, it is important to study how this area will be affected by future changes in climate and land use. Additionally, Midwestern nutrient loading is also the primary cause of the large hypoxic zone at the mouth of the Mississippi Delta [Goolsby et al., 2001]. Furthermore, while the Gulf and Chesapeake dead zones are prominent, the number of hypoxic areas resulting from NPS nutrient pollution has greatly increased in the past twenty years [Diaz and Rosenberg, 2008]. Issues such as these have far reaching impacts on the environment as well as the economy and underscore the importance of reductions in nutrient loading.

Problems resulting from NPS pollution are not limited to the United States. A 2011 study conducted by the United Kingdom’s Centre for Hydrology and Ecology found that nitrogen non-point pollution alone costs Europe between 190 and 950 billion dollars per year in impairment to human health, surface water, and air quality [Sutton et al., 2011]. In southern Asia, riverine export of nitrogen and phosphorus is estimated to have increased by approximately two teragrams per year between 1970 and 2000, and may increase even more in the future [Seitzinger et al., 2010].

The extent and severity of nutrient NPS impacts are controlled by complex climatic and chemical processes. Biogeochemical cycles (in particular, the nitrogen and phosphorus cycles) control the magnitude of loading to these bodies, and are also themselves influenced by hydrologic processes. Processes such as precipitation and runoff dictate the amount of contaminants transported to surface water due to the high solubility of both nitrate and phosphate. As these factors are closely linked with hydrologic processes, weather patterns that impact soil moisture levels, subsurface flow, temperature, and precipitation are of interest.
Given the impact that hydrology has on the fate and transport of nutrients, changes in climate such as increased temperature or precipitation have the potential to significantly alter current levels of NPS pollution. Many of the major engineering and planning decisions made in the past century regarding water resources have assumed that the past climate record is representative of the future, and water resources management choices have been made accordingly (e.g. sizing of reservoirs, capacity and technology choices at water treatment plants, etc.). This assumption of events varying within a fixed range is referred to as stationarity. There is growing evidence that historical data may no longer be relied upon for such decisions, as human influence on the climate may render assumptions of stationarity invalid in the near future.

A non-stationary climate has the potential to affect many aspects of the hydrologic cycle. As a result, relaxing the assumption of climate stationarity creates uncertainty in how the nutrient loading resulting from biogeochemical cycles may change in the future, due to the non-linear relationship between nutrient fate, transport, and climate variables. Several investigators have demonstrated that assumptions of stationarity may no longer be reasonable for some areas within the United States [Mauget, 2003; Villarini et al., 2013]. Mauget [2003] examined trends in several climate variables and found that significant departures from stationarity have already occurred in the forms of high temperatures and increases in runoff and precipitation. Another study by Villarini et al. [2013] examined 447 rain gauges with at least 50 years of records across the central United States and found increases in the number of days with heavy rainfall. Similar examination of 1061 stations from the Historical Climatology Network by DeGaetano et al. [2009] suggests that the recurrence interval of storms has decreased by 20% for the eastern United States (i.e., a 50 year storm is now a 40 year storm). Furthermore, Global Circulation Model (GCM) analysis of the late 20th century aligns with these trends [Milly et al., 2007]. This validation of current models on past climate increases confidence in future projections of runoff changes [Milly et al., 2007].

The scientific community has achieved consensus that the Earth’s climate is changing as a result of human actions [Doran and Zimmerman, 2009; Oreskes, 2004]. The IPCC’s Fifth Assessment Report (AR5), released in 2012/2013, features more
quantified language that indicates increased levels of certainty in the probability of change as well as the identification of the factors causing it. There is now high confidence that the amount of precipitation in the northern hemisphere has increased since 1951 [IPCC, 2014]. Temperature has also increased significantly; each of the preceding three decades has had warmer surface temperatures than any since measurements have been recorded [IPCC, 2014].

General climate change may be nearly certain, however, predictions about the local impact of this change can vary greatly due to the spatially and temporally variable nature of climate, as well as different assumptions built into predictive models [R T Watson et al., 1998]. Furthermore, complex feedback mechanisms operate within hydrologic and biogeochemical cycles, causing difficulty in assessing how changes in climate variables will affect cycle output [Bony et al., 2006]. For example, Melillo et al. [2002] examined the effects of increased soil temperature on the nitrogen and carbon cycles within a small tract of the Harvard Research Forest. The soil was heated with buried cables for over 10 years while soil and tree carbon storage was monitored. In the heated plots, soil was found to lose carbon from microbial respiration compared to non-heated plots. However, heating of the soil also increased mineralization of unavailable forms of nitrogen into plant-available forms. The increased nutrient levels within the soil stimulated tree growth, leading the authors to estimate that the resulting change in carbon uptake by the trees equaled that lost by the warmer soil. Examples such as these serve to illustrate the complex and interdependent nature of the interactions between the environment and biogeochemical cycles.

Land use change presents an additional obstacle when assessing the future of NPS pollution. This change will continue to shape the nation’s surface well into the 21st century. Population is increasing in the United States and urban and suburban areas are expanding [Brown et al., 2005]. The effects of climate and land use change on the hydrologic cycle and nutrient loading also have varied in magnitude and direction in previous research. Both increases and decreases in nutrient loading and streamflow have been predicted, dependent on the size, climate, and land use of the catchment. Analysis of these differing results is presented in Sections 4 and 5.
As a result of these diverse challenges, modeling using coupled hydrologic and biogeochemical models is often the best way to answer questions about how nutrient loading will change in the future. Advances in remote sensing, computing availability, and structure of hydrological models afford greater opportunities to modelers than ever before [Singh and Woolhiser, 2002]. Numerical models and their ability to simulate the previously described processes offer the potential to quantitatively assess the sometimes contradictory outputs of hydrological and biogeochemical processes, allowing scientists and watershed managers to arrive at conclusions that can guide resource management within their watersheds.

Several potential outcomes can be hypothesized for possible climate-induced changes in nutrient NPS pollution output in the study watershed. For instance, export of nitrogen from agricultural tile drainage is a strong contributor to NPS nutrient problems in the Gulf of Mexico [Goolsby et al., 2001]. The UBWC is extensively tiled, and as precipitation is expected to increase for the Midwest in the future [IPCC, 2014], it is not unrealistic to believe that tile nitrogen export could increase greatly over the course of the 21st century for the UBWC and similar watersheds, exacerbating an already difficult environmental situation. Projected temperature increases along with potentially wetter soils could also result in a more vigorous nutrient cycle, increasing the amount of nitrate available for export. Expanding growing seasons of crops offer a potential counter to these increases due to their reduction of nitrogen sources and transport through nutrient and water uptake. Given these competing factors, the goal of this study is to ascertain the magnitude and direction of changes to agricultural NPS for the UBWC, as extensively tiled Midwestern watersheds have been unfairly neglected in such studies. Through application of climate change and land use change scenarios to the highly agricultural UBWC, it is hoped that this work will not only identify the controlling factors of NPS pollution in the future but also offer insight into how pollution may be mitigated through the application of management strategies.

The two major objectives of this work are defined as follows:
Objective 1: To assess potential climate-induced changes in NPS pollution for the UBWC watershed.

This objective will be achieved through application of the Soil and Water Assessment Tool (SWAT), a combined hydrologic and biogeochemical model, to the UBWC watershed. Simulations of future climates will utilize two IPCC AR5 Representative Concentration Pathway (RCP) scenarios, 8.5 and 4.5, to represent the range of potential climate change, while use of an ensemble of GCM inputs will avoid over-reliance on any one set of assumptions or biases present in a single GCM. Comparison between two downscaling techniques used to adapt GCM output to the scale of the UBWC will also allow determination of the future scenarios’ sensitivity to different downscaling methods, enabling more confidence in the simulation outcomes.

Objective 2: To test agricultural management strategies for the UBWC watershed in order to counteract potential increases in NPS pollution.

To achieve this objective, a change in the watershed’s crop rotation to incorporate one-third winter wheat will be tested, as will application of rye cover crops between harvest and planting of the watershed’s corn and soybean crops. These management scenarios will be compared with current management under present and future climates in order to determine their appropriateness for not only reducing current levels of watershed NPS pollution but whether their effectiveness is lessened or enhanced in the future as well.
2 Hydrologic Modeling

2.1 Introduction to Hydrologic Modeling

Hydrologic models refer to sets of equations that allow a user to represent a watershed and the complex systems they contain. Such representations can enable modelers to obtain valuable information regarding a watershed and its responses quickly and cheaply without difficult field experiments.

Several broad terms are used to describe hydrologic models and models in general, including “physically-based”, “lumped”, or “distributed”. Physically-based refers to the nature of the relationships used within the model. If a model utilizes fundamental physical equations derived from the interactions between parameters with variables that are directly measurable (e.g. the Green-Ampt infiltration model, Penman-Monteith potential evaporation, etc.) it is described as physically-based. In contrast, empirical models such as Manning’s formula or the curve number infiltration method make use of extensive experimental data in order to define relationships between parameters.

Section 2.1.1 describes two common measures of goodness of fit between observed and simulated data that will become relevant when making comparisons between hydrologic models or different data inputs. Also, in addition to being described as physically-based or empirical, models are further classified based on their representation of a watershed. Section 2.1.2 details these model structures and their potential effects on model data requirements and simulation results.

2.1.1 Assessment of Model Performance

Several measures of fit are often used to evaluate hydrologic model performance, including percent bias (PBIAS), the ratio of root mean squared error to standard deviation (RSR), and the Nash-Sutcliffe efficiency coefficient (NSE) [Nash and Sutcliffe, 1970].
Of these statistics, PBIAS and NSE are often referred to in this study due to their frequent use in the hydrologic literature [Moriasi et al., 2007] as a basis of comparison between studies. The NSE was calculated using the formula below [Nash and Sutcliffe, 1970]:

**Equation 2.1. Nash-Sutcliffe Coefficient of Efficiency (NSE)**

\[
NSE = 1 - \frac{\sum_{t=1}^{T}(Q^t_o - Q^t_m)^2}{\sum_{t=1}^{T}(Q^t_o - \overline{Q}_o)^2}
\]

Where \( Q^t_o \) is the observed streamflow at timestep \( t \), \( Q^t_m \) is the modeled streamflow at timestep \( t \), and \( \overline{Q}_o \) is the mean of all observations.

NSE values were compared with those in similar studies to determine the quality of simulations in this research. Within hydrologic modeling, the range of satisfactory NSE values varies depending on the process being simulated and its timestep, with higher values expected for larger timesteps and easier-to-simulate processes, or processes with wider availability of data. For example, NSE values of 0.5 to 0.7 are considered satisfactory for monthly streamflow calibration while values of 0.3 to 0.5 are acceptable for monthly nutrient loading predictions.

The PBIAS statistic is another common measure of fit used to assess model performance. PBIAS is calculated using the following equation [Moriasi et al., 2007]:

**Equation 2.2. Percent Bias (PBIAS)**

\[
PBIAS = \left[ \frac{\sum_{i=1}^{n}(Y^{obs}_i - Y^{sim}_i)}{\sum_{i=1}^{n}(Y^{obs}_i)} \right] \cdot 100
\]

Where \( Y^{obs}_i \) is the observed value at timestep \( i \), \( Y^{sim}_i \) is the simulated value at timestep \( i \).

Goodness of fit measures are most often used to compare the results of calibrations and therefore become more relevant in the Results and Discussion section of this research. However, the PBIAS and NSE statistics are introduced here due to the fact
that whether to use a particular model input or not (i.e. higher resolution inputs or more inputs such as precipitation gauges) is often justified according to the effect of using that input on a simulation’s NSE or PBIAS. As such, these goodness of fit measures are relevant throughout the body of this work.

2.1.2 Lumped and Distributed Approaches: Pros and Cons

In general, hydrologic models are categorized as either “lumped” or “distributed”. Lumped models employ average values to represent watershed processes, and can be useful for generally representing a variable of interest. For instance, one commonly used lumped model, the Sacramento Soil Moisture Accounting model (SAC-SMA) [Burnash and Singh, 1995] is frequently used by the National Weather Service as a tool to forecast potential flooding. In contrast to the simplicity of lumped models, distributed models seek to capture as much spatial and temporal variability as possible in both model inputs and watershed characteristics.

Challenges exist for both approaches. While simple to apply, lumped models are frequently an oversimplification of reality and may require extensive calibration that may render model parameters outside ranges of meaningful physical interpretation [Abbott et al., 1986], or unfit for application to ungauged basins [Koren et al., 1999]. Conversely, distributed models face the danger of over-parameterization, in that several combinations of different parameter sets can yield the same result [Kirchner, 2006]. As a consequence of their finer resolution, distributed models additionally have more intensive data requirements; however, increasing availability of relevant Geographic Information System (GIS) spatial data has helped to address this issue [Smith et al., 2004].

SWAT [Arnold et al., 1998] is the model chosen for this research and so it will be used as an example here. SWAT employs an approach to modeling in which the watershed area is first split into subbasins. Within subbasins, hydrologic response units (HRUs) are defined and are assumed to have homogenous slope, soil, and land use. Subbasins retain their spatial relationship to one another while HRUs are lumped together. This method is more computationally efficient and requires less (and a lower resolution of) input data. Therefore, SWAT is considered a semi-distributed model, as
opposed to either a fully distributed or a lumped model. Furthermore, SWAT has the ability to become more lumped or distributed depending on the resolution of its input data and user-specified criteria that determine the number and general size of HRUs.

A significant criticism of SWAT is that it does not incorporate spatial referencing below the sub-basin level (HRU outputs are “lumped” for the sub-basin) [Arnold et al., 2013]. SWAT and other hydrologic models are frequently used to identify critical areas to target in NPS pollution reduction plans, and such small-scale spatial uncertainty can potentially cloud the effects of changes in management practices [Arnold et al., 2010]. In this study, the investigators examined four representations of watershed flow routing, including the current HRU method, in order to examine potential improvements in referencing. HRU, lumped, catena, and distributed grid methods were tested. Similar NSE goodness of fit coefficients were observed for the four methods during calibrated periods (ranging from 0.63-0.67), indicating that the methods generally produced the same surface flow. The distributed grid method created significantly more detailed spatial output; however, it was found to require approximately a factor of 500 times greater amount of simulation run time, making it impractical to run except on supercomputers.

Conversely, while SWAT may not represent physical reality as well as some fully distributed models, there is frequently a lack of longer time-series data to calibrate and validate these models [Panagopoulos et al., 2011]. Fully distributed models also can require much greater spatial and temporal resolution in input data [Liu et al., 2012] and successful calibration at the watershed outlet does not ensure accurate simulation of internal processes solely because the model is distributed [Refsgaard, 1997]. Improvements in these technologies are still necessary in order to take full advantage of the benefits they offer.

2.2 Model Choice

Numerous hydrologic modeling frameworks have been developed and used to study agricultural NPS pollution. These include the Agricultural Policy Extender (APEX) [Williams et al., 2008], the Hydrological Simulation Program FORTRAN (HSPF) model [Bicknell et al., 2001], the previously-introduced SWAT model, the Agricultural Non-
Point Source Pollution Model (AGNPS) [Young et al., 1989], and the Agricultural Drainage and Pesticide Transport (ADAPT) model [Chung et al., 1992]. While they have much in common, each model was designed with a specific purpose in mind and has applications for which it is better suited. Several comparison studies have sought to characterize these applications. For example, the HSPF model is able to simulate a multitude of water pollutants in widely varying climate and conditions but has intense data requirements [Daniel et al., 2011]. SWAT has been found to outperform HSPF in with regards to simulation of nutrient loading, perhaps due to HSPF’s lack of detailed representation of agricultural management practices [Saleh and Du, 2004]. SWAT was designed specifically for use in agricultural watersheds. In an agricultural watershed in Indiana, SWAT was found to better simulate streamflow vs. AnnAGNPS in that it realized more consistent results and a smaller degree of overprediction [Heathman et al., 2008]. A similar comparison study of SWAT to AnnAGNPS also resulted in better predictions of nutrient loading by SWAT; however, the better performance was attributed to simulation of in-stream nutrient transformations rather than streamflow [Parajuli et al., 2009].

SWAT can also easily simulate agricultural best management practices in that diverse parameters can be adjusted to account for the effects of a variety of practices. For instance, in order to represent grassed waterways within a watershed, Arabi et al. [2008] modified the Manning’s roughness coefficient to represent the type of vegetation grown in the waterway, as well as the channel width, depth, and cover factor. The level of detail available for factors affecting agriculture enabled this modification, indicating one reason why SWAT is considered to be an appropriate model for simulating the results of management operations.

Table 2.1 below lists various common NPS models and their relative strengths
Table 2.1. General description of common hydrologic/NPS models and their uses.

<table>
<thead>
<tr>
<th>Model</th>
<th>Description</th>
<th>Strengths/Purpose</th>
</tr>
</thead>
<tbody>
<tr>
<td>RZWQM (Root Zone Water Quality Model)</td>
<td>Physically-based, one-dimensional crop root zone model</td>
<td>Examining soil nutrients, water, pesticides, and their interactions with crops</td>
</tr>
<tr>
<td>HSPF (Hydrological Simulation Program Fortran)</td>
<td>Lumped water quality model, hourly timestep</td>
<td>Hydrologic cycle and water quality modeling</td>
</tr>
<tr>
<td>AnnAGNPS (Annualized Agricultural Non-Point Source) Model</td>
<td>Semi-distributed, cell-gridded, simulates water, soil, sediment, and nutrient interactions</td>
<td>Simulating sediment and nutrient transport from agricultural watersheds, BMP evaluation</td>
</tr>
<tr>
<td>ADAPT (Agricultural Drainage and Pesticide Transport)</td>
<td>Combined hydrology, erosion and pesticide transport model</td>
<td>Examining the effects of subsurface drainage on water quality</td>
</tr>
<tr>
<td>SWAT (Soil and Water Assessment Tool)</td>
<td>Physically-based, semi-distributed daily time step model simulating water and nutrient cycles</td>
<td>Studying water cycle, management practices, and nutrient loading from agricultural watersheds</td>
</tr>
<tr>
<td>EPIC (Erosion-Productivity Impact Calculator)</td>
<td>Physically based simulator of processes affecting soil erosion and plant growth</td>
<td>Determining impacts of erosion on soil, examining nutrient and water stress</td>
</tr>
<tr>
<td>APEX (Agricultural Policy Extender)</td>
<td>Extension of EPIC to cover multiple fields or small watersheds</td>
<td>Determining impacts of erosion on soil, examining nutrient and water stress for farms and small watersheds</td>
</tr>
</tbody>
</table>
The UBWC is a predominantly agricultural watershed. For these reasons, the Soil and Water Assessment Tool (SWAT) was chosen to model the complex interactions between climate, land use, and the hydrologic and biogeochemical processes.

2.3 The SWAT Model

SWAT is a watershed-scale, semi-distributed, physically-based daily time step model developed by the United States Department of Agriculture (USDA) Agricultural Research Service (ARS) [Arnold et al., 1998]. First developed in the early 1990s, it combines and expands upon elements of earlier ARS models including Chemicals, Runoff, and Erosion from Agricultural Management Systems (CREAMS) [Knisel, 1980], the Erosion-Productivity Impact Calculator (EPIC) [Williams and Singh, 1995], the Simulator for Water Resources in Rural Basins (SWRRB) [Williams et al., 1985], and Groundwater Loading Effects on Agricultural Management Systems (GLEAMS) [Leonard et al., 1987]. SWAT has proven to be an effective instrument for estimating streamflow and nutrient loading in diverse catchments [Abbaspour et al., 2007b; Gassman et al., 2006]. SWAT was created to study agricultural watersheds in particular, making it well-suited to the UBWC.

In general, SWAT works by dividing a watershed into subunits known as Hydrologic Response Units (HRUs) by similar soil types, land uses, and slopes. A single soil type, land use, and slope value is approximated for each HRU. The model is forced using a prescribed or generated weather time series, and a water balance is performed for each HRU. The HRU-level balance that was found to account for all major water pathways modeled in this research is shown below:

Equation 2.3. Major Components of SWAT HRU-Level Water Balance

\[ (SF_i - SM_i) + (SW_i - SW_{i-1}) \]

\[ = P_i - (ET_i + Q_{\text{runoff},i} + Q_{\text{lat},i} - Q_{gw,i} + Perc_i + Q_{\text{tile},i}) \]

Where \( SF_i \) and \( SM_i \) are the monthly snowfall and snowmelt for the monthly timestep \( i \), \( SW_i \) and \( SW_{i-1} \) are the current and previous months’ soil water levels, \( P_i \) is the monthly precipitation, \( ET_i \) is the monthly evapotranspiration, \( Q_{\text{runoff},i} \) is the monthly
runoff contribution to streamflow, $Q_{lat,i}$ is the monthly lateral flow contribution to streamflow, $Q_{gw,i}$ is the groundwater contribution to streamflow, $Per c_i$ is the amount of water exiting the bottom of the soil column, and $Q_{tile,i}$ is the monthly tile contribution to streamflow. All units are given in millimeters over the watershed’s area.

After computing this water balance, the outputs of biogeochemical cycles are calculated for each HRU and summarized at the subbasin level. Resulting amounts of nutrients, water, and pesticides are distributed through a routing process. For water, routing is performed using either the Muskingum or variable storage [Williams, 1969] methods. Further detail on hydrologic, nutrient, and other processes is provided in the relevant sections below.

Due to the large number of input files required to run SWAT, an ArcGIS interface named ArcSWAT was created by the developers of SWAT in order to facilitate simulation setup and modification. SWAT has been modified over time to incorporate improvements; major recent releases of updated SWAT versions have occurred in 2005, 2009, and 2012. The 2012 version of SWAT was used for this research.

### 2.4 Land Uses within SWAT

Land use within a watershed can have a significant effect on the magnitude of nutrient loading to surface water [Jordan et al., 1997] as well the hydrologic cycle. Land use within SWAT affects a diverse array of processes such as sediment calculations, vegetation parameters, and water interception values. It also affects fertilization application values.

One of the most important ways SWAT simulates the hydrologic response of different land use is by changing the Soil Conservation Service (SCS) curve number if the SCS curve number method is used for infiltration.

Land use additionally influences several other important watershed processes. SWAT assumes an albedo value based on the land use type, which is used in the calculation of net solar radiation and soil temperature. In turn, the soil temperature affects the output of the nitrogen and phosphorus cycles. The partitioning of evapotranspiration between the soil and plants is also influenced by the amount of biomass and residue.
covering the land surface, which also depends on the land use. Because agricultural, forested, and low-density urban/residential are three of the largest land uses in the UBWC watershed, their treatment within SWAT is described in detail below.

2.4.1 Agriculture – Row Crops and Hay

Runoff and infiltration processes are important with any land use. In general, croplands are assigned curve numbers based on the presence or absence of surface residue, the type of crop that is growing, and whether they are contoured or terraced. The user also has the option of specifying a crop (e.g. corn, soybeans, wheat) in order to use growth parameters for that particular species. For example, the generic “AGRR” row crops land use classification, set as default for agricultural land, uses values for corn.

Plant growth is highly sensitive to temperature. To determine the progress of a plant’s life cycle, a measure of mean temperature commonly called heat units (or degree-days) is often used. One heat unit is defined as a daily mean temperature of one degree higher than a base temperature. Heat units can be plant-specific if the base temperature for a plant is used or generic if another base temperature is used such as 0º C or 32º F. SWAT calculates the heat units required for plants to begin growth and reach maturity based on the species associated with the given land use. Heat unit scheduling is further described in Section 2.8.1. The simulation additionally compares the optimal and base growing temperatures listed for the crop in the SWAT database with the daily temperature in order to determine if the plant is in a stress condition. This affects nutrient uptake as well as biomass yield and leaf area index (LAI).

2.4.2 Urban/Residential Low-Density

Residential areas are often assigned higher curve numbers that reflect their greater coverage with impervious surfaces. The validity of such impervious area assumptions relies on the accuracy of the input data. In areas with large lots, these assumptions of imperviousness can be too high, leading to shorter modeled times to peak runoff than occur in reality; smaller lots than indicated would have the opposite effect. SWAT is unable to make these small distinctions with the most commonly used National Land
Cover Database (NLCD) inputs, so urban areas of different densities are treated the same with regards to infiltration and runoff.

Runoff is not the only watershed process impacted by the presence of urban areas. Nutrient loading from urban land uses is calculated either with a build-up/wash-off model or a regression model which takes into account total storm rainfall, drainage area, and impervious area. Under the build-up/wash-off model, the density of residential area affects the amount of solids build-up that is assumed to occur on curbs. Because these solids are assumed to contain mineral (nitrate) and organic nitrogen and phosphorus, the density of residential development can affect the nutrient loading from urban areas.

2.4.3 Forest

Treatment of forested areas within SWAT depends on the species composition and the type of forest (deciduous vs. evergreen, wetland vs. dry). The most common forest designation in the UBWC, “FRSD”, refers to deciduous forests and uses values for oak trees.

Forested land uses have important effects on the hydrologic and nutrient cycles in SWAT. In forested areas, SWAT calculates evaporation of water intercepted in the canopy before it calculates additional evaporation from vegetation and the soil. The presence of trees also affects yearly biomass and residue calculations – 30% of the new biomass each year is converted to residue. This affects nutrient loading from forested areas: organic nitrogen (N) in the top 10 mm is set as a fraction of this residue which can in turn mineralize into plant-available N.

SWAT also assumes trees to have the maximum allowed root depth for their particular species and soil. In watersheds with shallow groundwater, this can potentially allow trees to remove water from aquifers.

SWAT is limited in its treatment of forested areas by the resolution and capabilities of its input data. For instance, there is a significant difference (15 units) in curve numbers between forested areas with <50% ground cover and >75% ground cover. Classification accuracy of forested areas has been found to be approximately 80% [Wickham et al., 2013], consequently, it is likely that this distinction is too fine to be sensed by a satellite
with current levels of technology. It would furthermore be impractical to manually compensate for these discrepancies in larger watersheds.

### 2.5 Soil within SWAT

Soil impacts almost all processes within a watershed. Its representation is critical to the function of any hydrologic model. SWAT groups soil characteristics into two categories: physical and chemical. Chemical inputs are optional while most physical characteristics are required \([Arnold \textit{et al.}, 2013]\). Examples of physical characteristics include bulk density and porosity. The chemical characteristics that SWAT uses are generally initial values of nutrients and pesticides present in soil.

Physical information is specified for several layers in the soil profile. Data regarding a soil layer’s clay, silt, sand, and rock fragment content is required, as is the depth of that layer and its hydraulic conductivity. For the top layer, soil albedo must be specified, as well as the Universal Soil Loss Equation (USLE) \([Wischmeier and Smith, 1965]\) soil erodibility factor. The minimum necessary data is contained within the State Soil Geographic (STATSGO2) and Soil Survey Geographic (SSURGO) \([NRCS, 2013]\) soil databases.

Resolution of soils data can have a significant effect on the accuracy of simulation results \([Geza and McCray, 2008]\). \textit{Geza and McCray} [2008] found that STATSGO (scale: 1:250,000) data lumped soils with low infiltration together with those with higher infiltration. When SSURGO (scale of 1:12,000) data was used with the same watershed, the formerly lumped areas with low infiltration capacity were separated into different HRUs and the overall runoff of the simulation increased, also affecting nutrient and sediment loading. Streamflow goodness of fit between observed and simulated output was also affected by the soils data used. \textit{Geza and McCray} [2008] also noted that the uncalibrated NSE value of the simulation was better using STATSGO data, while the SSURGO-parameterized simulation was found to have a significantly higher NSE after calibration. For this research, SSURGO soils data was preferred over STATSGO soils data in order to obtain greater spatial detail at the HRU level.
2.5.1 Infiltration

SWAT users have the option of selecting one of two methods to model the infiltration of water into the soil profile. The first option, the Green-Ampt Mein-Larson method, is a modification of the Green-Ampt [1911] method. Mein and Larson [1973] developed a two-stage infiltration model to address situations in which rainfall intensity is initially above the saturated conductivity of the soil but below the infiltration capacity, and changes to a state where the infiltration capacity is below the rainfall intensity. In this model, the Green-Ampt equation is applied after runoff begins. Constant intensity of rainfall until the start of runoff is assumed. The Green-Ampt equation is given as follows:

\[
\text{Equation 2.4. Green-Ampt Infiltration}
\]

\[f_p = K_s \left[ 1 + \left( M_d \cdot \frac{S}{F} \right) \right]
\]

where \(f_p\) [cm/s] is the infiltration capacity of the soil, \(K_s\) [cm/s] is the saturated conductivity, \(M_d\) [volume/volume] is the initial moisture deficit, \(S\) [cm] is the capillary suction at the wetting front, and \(F\) [cm] is the cumulative infiltration from the beginning of the event (Mein and Larson, 1973). Infiltration prior to runoff is calculated using the following equation [Mein and Larson, 1973]:

\[
\text{Equation 2.5. Green-Ampt Infiltration Prior to Runoff}
\]

\[F_s = \frac{S_{av} \cdot M_d}{\left( \frac{I}{K_s} \right) - 1}
\]

Where \(S_{av}\) [cm/s] is the average capillary suction at the wetting front, and \(I\) [cm/s] is the rainfall intensity. Several assumptions are necessary for the application of this model. Green Ampt infiltration assumes a sharp wetting front, one-dimensional infiltration, and that the soil above the wetting front is completely saturated. As each parameter of the Green-Ampt method is ostensibly related to a measurable soil characteristic, it is considered a physically-based model of infiltration, in theory making it applicable without calibration to any watershed with sufficient data [Wilcox et al., 1990].
The second option available to model infiltration within SWAT is the curve number method. The curve number method was developed in the 1950s by researchers at the Soil Conservation Service and has since been widely used in a number of NPS hydrologic models including AGNPS [Young et al., 1989] and GLEAMS [Leonard et al., 1987]. In contrast to the Green-Ampt Mein-Larson method, the curve number method operates on a daily time step. The method is defined using three key equations, the first of which is:

**Equation 2.6. Runoff Predicted by Curve Number**

\[
Q = \frac{(R_{day} - I_a)^2}{(R_{day} - I_a + S)}
\]

Where \( Q \) [mm] is defined as the runoff or overland flow, \( R_{day} \) [mm] is the daily rainfall depth, and \( I_a \) [mm] is the initial abstraction, or the amount removed by storage, interception by the plant canopy, and infiltration before runoff begins [Neitsch et al., 2011]. \( S \) [mm] is defined as the soil moisture retention after runoff begins.

The next equation introduces the curve number. The curve number takes physical soil properties, antecedent moisture conditions, and land use into account [Neitsch et al., 2011], and is defined as ranging from 0 (completely pervious) to 100 (completely impervious). Soil moisture retention is given as a function of the curve number:

**Equation 2.7. Curve Number Soil Moisture Retention**

\[
S = \frac{1000}{CN} - 10
\]

Where \( CN \) is the curve number. Using a common approximation of 0.2*S for the initial abstraction simplifies Equation 2.6 into:

**Equation 2.8. Simplified Curve Number Runoff**

\[
Q = \frac{(R_{day} - 0.2S)^2}{(R_{day} - 0.8S)}
\]
Previous work by the SCS has defined curve numbers for different land uses/land covers, hydrologic conditions, and NRCS soil groups. SWAT uses this information for each HRU as well as the soil’s condition to determine the curve number for the day.

To determine the initial curve number of a soil, soils within SWAT are grouped into one of four groups (A, B, C, D) or three dual classes (A/D, B/D, C/D) defined by the NRCS that give information about how the soil behaves with regards to infiltration [Neitsch et al., 2011]. These classes are arranged in order of infiltration potential, with “A” class soils having the greatest infiltration and “D” class soils the least. The dual classes exist to characterize soils that have different properties in drained and undrained conditions. For example, a soil could have “D” class properties but tile drains may enable it to act as an “A” class with regards to infiltration. An example of the curve number lookup table used in SWAT is given below.

Table 2.2. Example of land use initial curve number table, based on land use type, soil group, and hydrologic condition (antecedent moisture levels)

<table>
<thead>
<tr>
<th>Land Use</th>
<th>Hydrologic Soil Group</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Hydrologic Condition</td>
</tr>
<tr>
<td></td>
<td>A</td>
</tr>
<tr>
<td>Impervious (parking lots,</td>
<td>NA</td>
</tr>
<tr>
<td>roofs)</td>
<td></td>
</tr>
<tr>
<td>Paved streets and roads</td>
<td>NA</td>
</tr>
<tr>
<td>1/8 acre residential lots</td>
<td>NA</td>
</tr>
<tr>
<td>Woods Poor</td>
<td>45</td>
</tr>
<tr>
<td>Woods Fair</td>
<td>36</td>
</tr>
</tbody>
</table>
Both of the available infiltration methods have benefits and drawbacks; however, one study concluded that no significant improvement in SWAT model results is achieved through use of one over the other [King et al., 1999]. The researchers set up a SWAT simulation for the heavily instrumented Goodwin Creek Watershed in Mississippi and compared the two methods. The Green-Ampt Mein-Larson method better represented the average flow but yielded higher variability than the curve number method, which tended to underestimate flow. One important conclusion of this work was that the Green-Ampt Mein-Larson method is not appropriate for larger watersheds due to their slower response to precipitation. Subsequent work by Kannan et al. [2007] found the curve number method to more effectively model runoff. Both studies examined very small catchments on the order of approximately ten square miles. As such, data availability was less of a concern than it would be for a larger watershed.

For this work, long-term simulations utilized the SCS curve number method. Because the Green-Ampt method operates at a sub-daily timestep, the Green-Ampt method is better used to model single events rather than long simulations for which high-resolution data may not be available [King et al., 1999]. Furthermore, use of the Green-Ampt Mein-Larson method necessitates more extensive soils data (with regards to soil composition and hydraulic conductivity) than the curve number method [King et al., 1999]. Previous work has also suggested that the curve number method is better suited to agricultural watersheds [Ponce and Hawkins, 1996] as the original curve number values were developed using small agricultural research watersheds [Hawkins, 2009]. Taking into consideration the agricultural nature of the UBWC as well as the lack of nearby high-resolution rainfall data, the curve number method was chosen for this research.

2.5.2 Soil Moisture

Due to its effects on plant growth as well as evapotranspiration and runoff, soil moisture is an important consideration in any hydrologic model. SWAT simulates important groundwater processes such as percolation, lateral flow, and revap (movement of shallow aquifer groundwater to moisture-deficient unsaturated zone in soil through capillary action).
Soil moisture processes that most affect plants occur near the surface in the soil column. SWAT calculates the plant available water for each layer as the difference between the soil layer water content minus the soil layer water content at the permanent plant wilting point. The permanent wilting point is defined in SWAT as the soil moisture content at which a plant loses turgor pressure in its cells, wilts, and cannot recover. Wilting point is estimated as the moisture content at a soil water matric potential of -1.5 MPa for all plants. Due to the different physical and structural characteristics of soil (e.g. clay is able to hold more water than sand) plant available water is strongly influenced by soil type.

Percolation of water to succeeding soil layers is another important soil moisture process. SWAT calculates percolation when the soil water content exceeds its field capacity, and the amount of percolation is calculated separately for each soil layer. Once water leaves the lowest soil layer, it enters the vadose zone and becomes classified as recharge. This method assumes a uniform soil moisture level across the HRU. As HRUs generally vary in size from tenths of a hectare to hundreds of hectares, this assumption is not representative of actual conditions. Potential errors exist in the form of runoff, percolation, or plant available water over- or underestimation due to this assumption.

Using a finer-scale Digital Elevation Model (DEM) and a higher number of HRUs in a simulation may lessen the likelihood of these potential errors, as HRUs would be smaller in area and their average values would be more reflective of reality. However, unless one is interested in the relative contribution of small areas to the water balance or overall crop yields, this may introduce unwanted and cumbersome simulation complexity. Easton et al. [2008] adopted a strategy in which an extra topographic criteria was added to the HRU formation simulation setup step such that areas with shallow water tables were better grouped together into HRUs. Because these areas were common within their study watershed, the addition of this step significantly improved nutrient export estimations. This was a technique specific to that type of watershed, but if modelers know of a watershed characteristic (outside of soil, slope, and land use) that would improve HRU delineation within their watershed, adding an additional defining step may prove to be beneficial.
2.5.3 Soil Temperature

SWAT calculates soil temperature based on a modification of the method proposed by Carslaw and Jaeger [1959], which calculates soil temperature at depth based on the average annual soil temperature, the amplitude of surface fluctuations in temperature, the day of the year, damping depth, and an angular frequency term. Several of these variables rely on soil heat capacity and thermal conductivity, for which data is not readily available [Neitsch et al., 2011]. Accordingly, an altered method is used which only requires the previous day’s soil temperature, the average annual air temperature, the current day’s surface soil temperature, and the depth of the layer within the soil profile.

Soil temperature in SWAT is lagged in that it is calculated as a function of the previous day’s soil surface, bare soil temperatures, and ground cover (plants, residue, or snow). Mean soil temperatures are calculated daily at the soil surface and also the center of each soil layer. The nitrogen and phosphorus cycles are affected by soil temperature by means of a temperature cycling factor (see Equation 2.14). In both the nitrogen and phosphorus cycles, mineralization and decomposition do not occur below the freezing temperature and are functions of temperature and soil water content. Movement of water between soil layers also does not occur below 0º C. As with soil moisture, uniform soil temperature is assumed across a HRU.

2.6 Slope within SWAT

ArcSWAT allows up to five slope classes to be defined within a SWAT simulation. These classes define which slope percentages will be grouped together and averaged. For instance, assume three slope classes were defined for a simulation: 0% to 5% slope, 5% to 10% slope, and >10% slope. These classes signify that all slopes from 0% to 5%, 5% to 10%, etc., within a subbasin will be averaged together. Whenever the model encounters a slope, it will assign it to the class that it fits in within the subbasin and use the average value for that class.

Adjustment of the number and division of slope classes to fit a watershed’s topography may be necessary in order to achieve realistic simulation output. For instance, Setegn et al. [2010] examined the effects of different slope class discretization on
simulated sediment output for an Ethiopian watershed. It was found that use of multiple slope classes with relative narrow definitions (0-1, 1-3, 3-5, and >5) resulted in the most accurate monthly prediction of sediment loading, as compared to use of a single averaged slope class or multiple broad slope classes (0-5, 5-10, 10-15, and >15). In light of this, and based on the similar decision to use the high resolution SSURGO dataset, multiple slope classes of 0-1, 1-2, 2-4, 4-8, and >8 were used in the simulation setup.

One disadvantage of SWAT’s assumption of average slopes for an entire HRU is that it ignores the effects of microtopography within a watershed. Infiltration rates and hydraulic conductivity vary and depend on the length of the hillslope [Dunne et al., 1991], and as one hillslope length is assumed per HRU, such variability cannot be accounted for in SWAT. However, as with other spatially varying processes, taking a more distributed approach would require greater input data resolution as well as increased simulation run time.

2.7 Tile Networks

Agricultural tile systems consist of perforated ceramic or plastic pipes placed in fields at regular intervals, generally 10-30 meters [Panuska, 2011] and at a depth of approximately one meter. In poorly drained soils, these systems can greatly increase crop yields, as well as limit erosion and its associated phosphorus loss [USEPA, 2012]. Development of preferential flow pathways within the soil can also potentially create a “shortcut” that permits pollutant-laden water to rapidly enter streams and lakes with little soil remediation [Jaynes et al., 2001]. Due to slow water travel times in poorly draining soils, a wet area several hundred feet from a drainage ditch could take days or longer to drain, assuming no removal of water through evaporation or transpiration. Tile drains place a channel approximately one meter away from the surface, creating a potential that draws water downward and enables more rapid drainage.

Because of their significant effect on soil moisture levels, incorporating tile drainage systems into hydrologic models can greatly improve simulation accuracy and is important in heavily tiled watersheds [Du et al., 2005; Green et al., 2006]. For this reason SWAT2005 and later versions have been modified to allow tile drainage. Tile systems
can be simulated at the HRU level within SWAT. Three parameters are required: depth of tile system, the lag time between water entering the tile system and exiting into surface water, and the time it takes the soil to drain to field capacity.

Several other models also allow simulation of tile drainage, including DRAINMOD [Skaggs, 1978], ADAPT [Chung et al., 1992], and RZWQM [Ahuja et al., 2000]. While these models do simulate tile drainage, they are generally used for narrower purposes than SWAT, and it is more beneficial to compare SWAT with models such as AnnAGNPS (continuous version of AGNPS, [Young et al., 1989]) or HSPF [Bicknell et al., 2001]. A general sketch of several of these models is provided in Section 2.7.

Depending on the climatic and physical characteristics of a study watershed, inclusion of a tile routine may help improve streamflow predictions. In one study, Singh et al. [2005] found that SWAT’s tile drain simulation might have contributed to slightly improved streamflow results over HSPF during low flows in an extensively tile-drained Midwestern watershed. While the HSPF simulation in the study was set up to mimic tile drainage by adjusting the parameters that govern subsurface flow, soil water was not removed as quickly as in reality, resulting in significantly overestimation of streamflows during low flow periods. Also contributing to this effect were smaller estimates of evapotranspiration by HSPF which ultimately led to surplus soil water and ensuing base flow during low flow periods. Another study of a tile-drained Iowa watershed [Green et al., 2006] demonstrated the benefits of including tile routines in SWAT, in that incorporating tile drainage improves the partitioning of the water balance in tiled watersheds, as runoff would be overestimated without tile. Models without tile drainage may attribute nutrient loss to runoff or percolation to groundwater, when it is actually a result of leaching through to the tile drains. Furthermore, some natural attenuation of nitrate occurs in groundwater and riparian zones [Ranalli and Macalady, 2010]; accordingly, misrepresenting the nutrient pathways could affect the amount of loading predicted, potentially leading to erroneous conclusions in management simulations. For these reasons, simply including a tile drainage scheme in a hydrologic model is a step in the right direction.
2.8 Management and Conservation Practices

Agricultural management and conservation practices can greatly influence the magnitude of nutrient loading into surface water [Randall and Mulla, 2001]. Management and conservation practices are broadly defined and can refer to crop rotation, types of tillage, timing and amount of fertilizer application, and many others. SWAT allows users to define these and other practices at the subbasin and HRU levels in its management input files. Management practices can also be specified for a given land use, soil, or slope type. They can be then extended to all or some HRUs depending on user specifications. The management practices described below are those most important to this study: heat unit scheduling, tillage, crop rotation, and fertilization.

2.8.1 Timing of Operations - Heat Unit Scheduling

Timing of management operations (especially fertilizer application) can affect the amount of nutrient loading in surface water [Rejesus and Hornbaker, 1999]. In SWAT, management operations can start on a specified day of the year or at a given number of heat units, normalized by the number of heat units required to reach maturity for the crop being simulated.

In many locations, predicted climate change is expected to increase the average temperature, which will affect the duration of the growing season. Indeed, there is significant evidence that average length of the growing season worldwide has increased regionally approximately 10-20 days within the last few decades [Linderholm, 2006; Menzel and Fabian, 1999]. Using heat unit scheduling is beneficial for climate change simulations, as well as modeling year-to-year variability in climate, because it is able to compensate for changes in the growing season. With heat unit scheduling, land cover begins growing when the temperature is sufficiently warm, which mimics actual farming practices.

In contrast, specifying a given date to start planting or fertilizer application is inflexible, and these operations will occur at the same time every year, regardless of actual weather conditions. For this reason all simulations in this study used heat unit scheduling.
2.8.2 Tillage

Tillage refers to the mechanical mixing of soil with an implement. It redistributes nutrients, plant residue, and bacteria throughout the shallow soil profile, and can also serve to disrupt weeds or mix fertilizer into soil. Soil temperature is also affected by tillage operations. There is strong evidence that excessive or misapplied tillage operations can negatively affect soil quality [Karlen et al., 1994] resulting in lower soil carbon and microbe content. Tillage operations are spatially varying, changing as a result of farmer preferences, soil type, and the type of crop grown. For these reasons, it is important to account for the effects of tillage, especially in an agriculturally-focused model such as SWAT.

Within SWAT, tillage affects the amount of surface residue left from decaying organic matter. Furthermore, the biogeochemical cycling calculations made by SWAT take nutrient distribution in different soil layers into account, which are greatly affected by the mixing efficiencies of the tillage implement specified. For example, if a tillage implement has a mixing efficiency of 50%, and there is 10 kg of residue on the surface, there will be 5 kg of residue remaining on the surface and 5 kg distributed among the lower layers to the mixing depth of the tillage implement after the operation is complete.

Additionally, the soil organic matter decomposition rate in SWAT is directly proportional to a tillage tool mixing factor which is a function of the type of tillage operation specified. This factor is calculated as follows:

**Equation 2.9. Tillage Tool Mixing Factor**

\[ f_{tool} = 1 + (3 + 5e^{-5.5clay}) \left( \frac{f_{cm}}{f_{cm} + e^{1-2f_{cm}}} \right) \]

Where \( clay \) refers to the percentage of clay content in the soil, and \( f_{cm} \) is the cumulative mixing efficiency. \( f_{tool} \) is calculated daily; a cumulative value for the mixing efficiency is used to allow \( f_{tool} \) to slowly return to its base value of 1, as would occur in reality during soil settling.

The soil organic matter (SOM) decomposition rate \( (k_s) \) is calculated as follows:
Equation 2.10. Soil Organic Matter Decomposition Rate

\[ k_s = k_x f_{tool} f_E \left( \frac{S_C}{S_{CC}} \right)^\beta \]

Where \( k_x \) is the maximum apparent SOM decomposition rate, \( f_E \) is the combined temperature, aeration, and soil moisture factor, \( S_C \) is the soil organic carbon content, \( \beta \) is 0.50, and \( S_{CC} \) is the reference soil organic carbon. As an example of how \( f_{tool} \) affects \( k_s \), assume a soil has a clay content of 20%, and a tillage implement with a mixing efficiency of 0.75. With these values, the maximum \( f_{tool} \) value is 3.58, which more than triples the before-tillage SOM decomposition rate (all other factors held constant). While the other variables may enhance or mitigate this difference, this example shows that tillage can have a significant effect on soil biogeochemical cycling.

Many farmers within the US have switched to no-till farming in order to minimize erosion, loss of organic matter, and other detrimental effects of tillage \([Havlin et al., 1990]\). Even though no-till practices leave the soil undisturbed, decomposition of crop residue throughout the soil column can be enhanced by the activities of soil fauna such as earthworms, which can pull residue from the surface deeper within the soil profile \([Kladivko, 2001]\). These activities are simulated in SWAT through the no-till mixing operation, which mixes the soil with an efficiency of 0.05 to 25 mm deep, and the biological mixing operation, which occurs to a depth of 300 mm with a mixing efficiency of 0.20 at the end of every calendar year.

Different tillage implements mix the soil to different depths and have different mixing efficiencies. SWAT includes a database of common tillage implements and their mixing efficiencies. A sampling of information from this database is shown below in Table 2.3 \([Neitsch et al., 2011]\).
Table 2.3. Sample of tillage information from built-in SWAT tillage database.

<table>
<thead>
<tr>
<th>Implement</th>
<th>Tillage Code</th>
<th>Mixing Depth</th>
<th>Mixing Efficiency</th>
</tr>
</thead>
<tbody>
<tr>
<td>Duckfoot cultivator</td>
<td>DUCKFTC</td>
<td>100 mm</td>
<td>0.55</td>
</tr>
<tr>
<td>Field cultivator</td>
<td>FLDCULT</td>
<td>100 mm</td>
<td>0.30</td>
</tr>
<tr>
<td>Furrow-out cultivator</td>
<td>FUROWOUT</td>
<td>25 mm</td>
<td>0.75</td>
</tr>
<tr>
<td>Marker (cultivator)</td>
<td>MARKER</td>
<td>100 mm</td>
<td>0.45</td>
</tr>
<tr>
<td>Culti-mulch Roller</td>
<td>CULMULCH</td>
<td>25 mm</td>
<td>0.25</td>
</tr>
</tbody>
</table>

The EPIC model [Williams and Singh, 1995] also contains a tillage component. Like SWAT, it assumes a mixing efficiency and distributes nutrients and crop residue accordingly after an operation is performed. EPIC goes further than SWAT, however, by changing the bulk density of the soil after tillage and has it return to the undisturbed bulk density value after an amount of infiltration occurs, dependent on the soil type and the depth of the tillage operation [Williams et al., 1984]. This helps EPIC take bulk density into account as a stress factor in its root growth calculations, whereas SWAT simply assumes a set percentage of biomass goes to root development, varying between 40% for new plants and 20% for mature plants. While perhaps not applicable to many cases, the inclusion of a bulk density value might help better model management practices in areas that have soils with density values that could inhibit root growth.

2.8.3 Crop Rotation

Crop rotation is a practice frequently utilized by farmers in order to increase yields and avoid soil nutrient depletion. It is also used to control erosion [Logan, 1990]. SWAT allows crop rotation patterns to be defined on a yearly basis, with timing of planting, harvest, and kill operations specified by the day of year or heat units. Operations schedules reset and begin again at the end of the last year in the schedule.

Much of the land within the UBWC watershed follows a corn-soybean or soybean-soybean-corn rotation, dependent on economic factors. Table 2.4 shows the crop
composition of Delaware County (which comprises the majority of the UBWC watershed) from 2009 to 2013.

**Table 2.4.** Crop distribution of Delaware County, Ohio from the National Agricultural Statistics Service (NASS) database, 2009-2013.

<table>
<thead>
<tr>
<th>Year</th>
<th>Corn %</th>
<th>Soybean %</th>
<th>Wheat %</th>
<th>Other</th>
</tr>
</thead>
<tbody>
<tr>
<td>2009</td>
<td>33%</td>
<td>57%</td>
<td>8%</td>
<td>2%</td>
</tr>
<tr>
<td>2010</td>
<td>38%</td>
<td>56%</td>
<td>4%</td>
<td>2%</td>
</tr>
<tr>
<td>2011</td>
<td>35%</td>
<td>57%</td>
<td>6%</td>
<td>2%</td>
</tr>
<tr>
<td>2012</td>
<td>39%</td>
<td>55%</td>
<td>3%</td>
<td>3%</td>
</tr>
<tr>
<td>2013</td>
<td>42%</td>
<td>52%</td>
<td>4%</td>
<td>4%</td>
</tr>
</tbody>
</table>

### 2.8.4 Fertilization/Auto-fertilization

Unless fertilization operations are specifically defined, SWAT automatically applies fertilizer to HRUs with plants (e.g. hay, other agricultural land uses) based on heat unit scheduling or application date specification if the user so chooses. Fertilizer type and the fraction of fertilizer applied to the top 10 mm of soil can be specified [Arnold et al., 2013]. The fraction of fertilizer applied in the top 10 mm is important because it determines the amount of nutrients that can potentially interact with surface runoff. The amount of nitrogen that plants uptake is exponentially decreasing with depth, so fertilization additionally affects the nutrients available to plants. Several fertilizer types are available in the SWAT database, including popular commercial fertilizers, elemental nitrogen or phosphorus, urea, or manure for several different species of livestock.

SWAT auto-fertilization is initiated at a specific date or fraction of potential heat units and will apply fertilizer if it determines plants are undergoing nitrogen stress, up to a user-specified maximum for total yearly application and single amount application.
Automatic fertilization is the default setting, with fertilization occurring when nitrogen stress would cause plants to achieve less than 75% of potential growth. Automatic fertilization with phosphorus also occurs at the same threshold, but at an amount equivalent to one-seventh of the mass of nitrogen fertilizer that would be applied under nitrogen stress conditions. Total yearly values of N and P automatically applied are given in the output summary file for the watershed.

The auto-fertilization routine contains oversimplifications in that producers are not able to easily determine nitrogen stress and efficiently apply uniform amounts of fertilizer over the entire extent of their fields. Therefore, in watersheds where fertilizer data exists it may be wiser to use those values. These simplifications are useful, however, in allowing the simulated crops to reach realistic levels of biomass and corresponding levels of evapotranspiration, arriving at more accurate partitioning of water balances. Fertilization data and timing is also difficult to obtain on a field by field basis for some watersheds.

### 2.9 Precipitation within SWAT

Due to the spatially varying nature of precipitation, it is frequently necessary to provide precipitation input data for more than one location within a watershed. In SWAT, rain gauges are assigned at the subbasin level. The method chosen for rain gauge assignment must be considered carefully, as different techniques have been shown to influence simulation output [Cho et al., 2009]. Furthermore, with large gaps existing in many datasets and scarcity of measurements of some necessary input variables (e.g. humidity, wind speed), choosing generated or observed precipitation values as simulation input also becomes an important consideration [Harmel et al., 2000]. SWAT provides methods to either generate or supply measured precipitation to a simulation.

#### 2.9.1 Observed Precipitation

Incorporating observed precipitation information into simulations is essential for model calibration and validation or simply studying past conditions in a watershed. Up to
18 rain gauges can be added to a SWAT simulation, which can contain up to 5400 records of precipitation (300 per file).

Rain gauges can be assigned at the sub-basin level either manually or automatically. ArcSWAT 2012 uses the gauge latitude and longitude coordinates in the user-defined gauge locations table to calculate the distance from the centroid of each sub-basin to the nearest gauge, which is then assigned to that sub-basin. This method works best when there are multiple rainfall stations.

Alternate strategies of gauge assignment exist, but are not currently available in ArcSWAT. Cho et al. [2009] used SWAT to investigate the effects of three precipitation assignment methods (centroid, Theissen polygon, and inverse-distance weighting) on accuracy of streamflow, and found that the centroid method works best when the simulation’s subwatershed delineation matches the density of precipitation gauges (i.e. increasing gauge density will not improve simulation unless those gauges can be assigned to the subbasins they represent). When subbasin density did match gauge density, no significant differences were observed in streamflow simulation accuracy between the three methods.

2.9.2 Generated Precipitation

The daily precipitation data required to drive SWAT is not always available for the location or time period being studied. Many datasets also contain large gaps. To compensate for lacking data, SWAT can generate rainfall amounts using its built-in weather generator WXGEN [Williams et al., 1985]. These amounts can be daily or sub-daily and are simulated according to either a skewed or exponential distribution based on the user’s specification and the relevant location-specific precipitation data. The skewed distribution is set as default. One study [Watson et al., 2005] tested three models of rainfall generation: skewed, exponential, and a modified Daily and Monthly mixed distribution (DMMm) that is not included in SWAT. 83 years of precipitation were simulated using each method and compared to observed precipitation data within the study watershed. After statistical analysis, the skewed and DMMm distributions were found to more effectively represent the observed mean and standard deviations of daily
and monthly rainfall than the exponential distribution. Based on the results of this paper, the skewed distribution was chosen for rainfall generation.

Missing precipitation values in observed precipitation records are generated according to the distribution specified, as well as the proximity of the subbasin to the nearest station in SWAT’s weather statistics database.

2.10 Other Simulated Climate Variables

Apart from precipitation and temperature, SWAT also has the ability to generate solar radiation, relative humidity, and wind speed. SWAT can additionally simulate some variables while using measured values for others if necessary. Solar radiation, relative humidity, and wind speed were generated in all work conducted in order to enable use of the Penman-Monteith potential evapotranspiration method described in the following section.

2.11 Evapotranspiration Methods – Penman-Monteith

SWAT currently supports three methods for calculating potential evapotranspiration: Penman-Monteith, Priestley-Taylor, and Hargreaves. Penman-Monteith is set as the default method and was used in all UBWC simulations in order to allow future analysis of changes in plant stomatal conductance. After analyzing streamflow output of three SWAT simulations using each method, Wang et al. [2006] found no statistically significant difference between results obtained for a Minnesota watershed. Kannan et al. [2007] conducted a comparison of the Hargreaves and Penman-Monteith methods in a small English catchment, which indicated that use of the Hargreaves method allowed at least as good results as Penman-Monteith with regards to streamflow. Based on this review and the similarity of the UBWC to the watersheds in Wang et al. [2006] and Kannan et al. [2007]., the two other methods, Hargreaves and Priestly-Taylor, were not considered as alternatives and so are not described here.

The Penman-Monteith combination equation is the most complex of the three evapotranspiration methods offered by SWAT. It is regarded as the most physically based of the options, and as such is expected to work well without calibration, as opposed to the
simpler Hargreaves method. The Penman-Monteith equation is used to describe potential evapotranspiration for a well-watered system, and requires solar radiation, air temperature, relative humidity, and wind speed. Several assumptions are necessary for the application of this equation: well-watered plants, neutral atmospheric stability, and a logarithmic wind profile. The equation is given as follows [Neitsch et al., 2011]:

**Equation 2.11. Penman Monteith Potential Evapotranspiration**

\[
\lambda E_t = \frac{\Delta(H_n - G) + \gamma K_1 \left( 0.622 \cdot \lambda \cdot \frac{\rho_{air}}{P} \right) \cdot (e_z^0 - e_z_0)}{\Delta + \gamma \cdot (1 + \frac{r_c}{r_a})} 
\]

Where \( \gamma \) is the psychrometric constant [kPa°C], \( H_n \) is the net solar radiation [MJ m\(^{-2}\) d\(^{-1}\)], \( G \) is the net heat flux to the ground [MJ m\(^{-2}\) d\(^{-1}\)], \( r_a \) is the aerodynamic resistance [s m\(^{-1}\)], \( r_c \) is the canopy resistance [s m\(^{-1}\)], \( e_z^0 \) is the saturation vapor pressure at height \( z \) [kPa], \( e_z \) is the vapor pressure at height \( z \) [kPa], \( \rho_{air} \) is the density of the air [kg/m\(^3\)], \( P \) is the atmospheric pressure [kPa], and \( K_1 \) is a dimensional coefficient with a value of 8.64*10\(^4\) for \( u_z \) in m/s. \( G \) is assumed to be zero.

Few evaluations of the SWAT version of the Penman-Monteith method have been undertaken. However, Licciardello et al. [2011] performed a comparison of the SWAT Penman-Monteith method with the version recommended by the Food Agricultural Organization (FAO) titled FAO-56 P-M, and found that the SWAT Penman-Monteith method underestimated potential ET, leading to overestimation of watershed runoff values. It is possible, however, that this result was a consequence of the study area, which was a Mediterranean watershed with dry soils and short, intense rainfall characteristics.

**2.12 Nutrients - Nitrogen**

Nutrients in soil and water affect both water quality and crop/plant growth. SWAT performs nitrogen and phosphorus calculations in order to determine biomass yields, states of nutrient stress, and the amount and partitioning of nutrient loading to surface waters. Only nitrogen and phosphorus are considered; other nutrients such as potassium, while essential for plant growth, are not calculated in SWAT. The following
diagrams from the SWAT 2009 Theoretical Documentation [Neitsch et al., 2011] illustrate the nitrogen cycle as simulated in SWAT.

**Figure 2.1.** The nitrogen cycle as simulated by SWAT. Five pools of nitrogen are defined: nitrate, ammonium, fresh organic N, humic stable organic N, and humic active organic N. Inputs from fertilization and rain can go directly into the nitrate and ammonium pools. Nitrogen leaves the soil through denitrification, leaching, uptake by plants, and ammonia volatilization.
As shown in Figure 2.2, SWAT defines five pools of nitrogen in the soil: nitrate, ammonium, fresh organic N, humic stable organic N, and humic active organic N, and calculates movement of nitrogen between them. Nutrients applied to the soil start in the fresh pool of nitrogen, as does plant residue.

Initialization is the first step in nitrogen calculations. Nitrogen in the ammonium pool is initially set to zero. In the nitrate pool, soil NO3 levels are first initialized based on the soil layer’s distance from the surface, with near surface layers receiving the most and the rest an exponentially decreasing amount. The following equation \([\text{Neitsch et al., 2011}]\) describes this initialization:

\[
NO_{3\text{conc,z}} = 7 \cdot exp \left( \frac{-z}{1000} \right)
\]

Where \(NO_{3\text{conc,z}} \) [kg/ha] is the nitrate concentration in a specific layer, and \(z \) [m] is the depth of that layer. The remaining organic N pools (fresh, active, and stable) are initialized differently. The amount of N in the fresh pool is set to zero except in the top 10 mm layer, where it is calculated as 0.15% of the initial surface residue. The amount of
humic nitrogen in the soil is calculated based on the assumption of a 14:1 ratio of organic carbon to nitrogen as follows:

**Equation 2.13. Initialization of Soil Humic Nitrogen**

\[
or gN_{\text{hum,ly}} = 10^4 \times \left(\frac{or gC_{ly}}{14}\right)
\]

Where \(or gN_{\text{hum,ly}}\) is the total humic organic nitrogen in the soil layer, and \(or gC_{ly}\) is the organic carbon concentration within the same layer. Of the total humic organic nitrogen calculated, 2% is appropriated to the active pool and the remaining 98% to the stable pool.

Decomposition, mineralization, and immobilization are important processes affecting nitrogen pools within the soil. These three processes are treated in detail in Sections 2.12.2 and 2.12.3 below. As immobilization is simply negative mineralization, it is also governed by the mineralization equations of Section 2.12.3. General factors relevant to both processes are presented in Section 2.12.1.

### 2.12.1 General Factors

Factors that incorporate the effects of temperature and soil water levels on decomposition are calculated as follows.

**Equation 2.14. Nutrient Cycling Temperature Factor**

\[
\gamma_{\text{tmp,ly}} = 0.9 \times \frac{T_{\text{soil,ly}}}{T_{\text{soil,ly}} + \exp[9.93 - 0.312 \times T_{\text{soil,ly}}]} + 0.1
\]

Where \(T_{\text{soil,ly}}\) is the temperature of the soil layer for the day. It is important to note that at temperatures below freezing, this factor equals 0.1.

The SWAT nutrient equations also take soil water content into account, as shown by the following equation:

**Equation 2.15. Nutrient Cycling Water Factor**

\[
\gamma_{\text{sw,ly}} = \frac{SW_{ly}}{FC_{ly}}
\]
Where $SW_{ly}$ is the soil water content in a layer, and $FC_{ly}$ is the field capacity of that layer. The minimum value of this factor is 0.05.

### 2.12.2 Decomposition

Decomposition refers to the decay of residue into its constituent organic components. The equation below governs the decomposition of residue within SWAT [Neitsch et al., 2011]:

**Equation 2.16. Nitrogen Decomposition, Fresh Pool**

$$N_{dec,ly} = 0.2 \cdot \delta_{ntr,ly} \cdot orgN_{frsh,ly}$$

Where $N_{dec,ly}$ refers to the amount of nitrogen decomposed from the fresh N pool [kg N/ha], $\delta_{ntr,ly}$ is a residue decay rate constant, and $orgN_{frsh,ly}$ is the amount of N in the fresh pool.

Temperature and soil moisture drive nutrient decomposition, mineralization, and immobilization. Temperature and moisture factors which dictate the rate of these processes are calculated in this manner:

**Equation 2.17. Residue Decay Rate Constant**

$$\delta_{ntr,ly} = \beta_{rSd} \cdot \gamma_{ntr,ly} \cdot (\gamma_{tmp,ly} \cdot \gamma_{sw,ly})^{1/2}$$

Where $\beta_{rSd}$ is the mineralization rate coefficient for organic residue nutrients, $\gamma_{ntr,ly}$ is the nutrient cycling residue composition factor for the soil layer, and $\gamma_{tmp,ly}$ and $\gamma_{sw,ly}$ are the temperature and water nutrient cycling factors for the layer.

### 2.12.3 Mineralization and Immobilization

Mineralization converts organic nitrogen unavailable to plants into forms they can use. Immobilization refers to the opposite reaction; it converts plant-available forms of inorganic nitrogen into unavailable organic nitrogen. SWAT uses net mineralization algorithms adapted from the PAPRAN model [Seligman and Keulen, 1981] that combine mineralization and immobilization.
Nitrogen mineralization or immobilization is calculated from two pools: the humus active organic nitrogen pool and the fresh residue pool. Equation 2.18 describes the overall mineralization from the humus active organic nitrogen pool.

**Equation 2.18. Mineralization, Active Organic Pool**

\[
N_{\text{mina},ly} = \beta_{\text{min}}(\gamma_{\text{tmp},ly} * \gamma_{\text{wy},ly})^{1/2} \times \text{org}N_{\text{act},ly}
\]

Where \(\beta_{\text{min}}\) is a rate coefficient specific to the humus active organic N pool, \(\gamma_{\text{tmp},ly}\) and \(\gamma_{\text{wy},ly}\) are the temperature and water nutrient cycling factors from Equation 2.14 and Equation 2.15, and \(\text{org}N_{\text{act},ly}\) is the amount of nitrogen in the active organic pool [kg N/ha]. Mineralization from the fresh residue pool is calculated differently. Equation 2.19 below describes the amount of N mineralized from the fresh residue pool, and Equation 2.20 describes the calculation of the residue decay rate constant.

**Equation 2.19. Mineralization, Fresh Residue Pool**

\[
N_{\text{minf},ly} = 0.8 \times \delta_{\text{ntr},ly} \times \text{org}N_{\text{frsh},ly}
\]

Where \(\delta_{\text{ntr},ly}\) is the residue decay rate constant, \(\text{org}N_{\text{frsh},ly}\) is the amount of nitrogen in the fresh pool. The residue decay rate constant is calculated as follows:

**Equation 2.20. Nitrogen Residue Decay Rate Constant**

\[
\delta_{\text{ntr},ly} = \beta_{\text{rsd}} \gamma_{\text{ntr},ly}(\gamma_{\text{tmp},ly} \times \gamma_{\text{sw},ly})^{1/2}
\]

Where \(\beta_{\text{rsd}}\) is the rate coefficient for mineralization of fresh residue, \(\gamma_{\text{ntr},ly}\) is the layer nutrient cycling residue composition factor, and \(\gamma_{\text{tmp},ly}\) and \(\gamma_{\text{sw},ly}\) are the temperature and soil water nutrient cycling factors, respectively.

### 2.12.4 Nitrification

Nitrification refers to the steps of the conversion process of ammonium to nitrate. It can be a significant source of nitrate when ammonium fertilizers or fertilizers that transform easily into ammonium (e.g. urea) are applied. Ammonia volatilization is an important pathway of nitrogen loss that must also be considered if urea or ammonium
fertilizer is applied to soil [Neitsch et al., 2011]. SWAT uses a combination of the methods of Reddy et al. [1979] and Godwin et al. [1983] to simulate these processes.

Nitrification and volatilization are only assumed to occur if the temperature of a soil layer is greater than 5°C. The nitrification and volatilization processes within SWAT have their own temperature and soil water factors, which are calculated as follows:

**Equation 2.21. Nitrification/Volatilization Temperature Factor**

\[
\eta_{\text{tmp,ly}} = 0.41 \times \left( \frac{T_{\text{soil,ly}} - 5}{10} \right)
\]

**Equation 2.22. Nitrification/Volatilization Soil Water Factor**

\[
\eta_{\text{sw,ly}} = \frac{SW_{\text{ly}} - WP_{ty}}{0.25 \times (FC_{ty} - WP_{ty})} \quad \text{if } SW_{\text{ly}} < 0.25 \times FC_{ty} - 0.75 \times WP_{ty}
\]

\[
\eta_{\text{sw,ly}} = 1.0 \quad \text{if } SW_{\text{ly}} \geq 0.25 \times FC_{ty} - 0.75 \times WP_{ty}
\]

Where \( SW_{\text{ly}} \) is the soil water content of a given layer, \( WP_{ty} \) is the wilting point water content of the layer, and \( FC_{ty} \) is the field capacity of the layer. Calculation of the amount of nitrogen volatilized also depends on a depth factor:

**Equation 2.23. Volatilization Depth Factor**

\[
\eta_{\text{midz,ly}} = 1 - \frac{z_{\text{midz,ly}}}{z_{\text{midz,ly}} + \exp[4.706 - 0.0305 \times z_{\text{midz,ly}}]}
\]

where \( z_{\text{midz,ly}} \) is the depth from the soil surface to the middle of the soil layer [mm].

After calculation of the nitrification/volatilization-specific temperature and soil water factors, nitrification and volatilization regulators are defined as the product of the environmental factors:

**Equation 2.24. Nitrification Regulator**

\[
\eta_{\text{nit,ly}} = \eta_{\text{tmp,ly}} \times \eta_{\text{sw,ly}}
\]
Equation 2.25. Volatilization Regulator

\[ \eta_{vol,ly} = \eta_{tmp,ly} \ast \eta_{midz,ly} \ast \eta_{cec,ly} \]

Where \( \eta_{cec,ly} \) is the volatilization cation exchange factor, assumed to have a constant value of 0.15. After determining the necessary environmental factors, the amount of nitrogen lost to nitrification or volatilization is calculated according to Equation 2.26:

Equation 2.26. Ammonium Lost to Nitrification/Volatilization

\[ N_{nit|vol,ly} = NH_{4ly} \ast (1 - \exp[-\eta_{nit,ly} - \eta_{vol,ly}]) \]

Where \( NH_{4ly} \) is the ammonium in layer ly [kg], and the other factors are the same as previously defined. The partitioning between nitrification and volatilization is then calculated based on the product of Equation 2.26 and a nitrification fraction calculated from the following equation:

Equation 2.27. Fraction of Ammonium Partitioned to Nitrification

\[ fr_{nit,ly} = 1 - \exp[-\eta_{nit,ly}] \]

Where \( fr_{nit,ly} \) is the fraction of ammonium partitioned to nitrification. The remaining fraction is assigned to volatilization.

2.12.5 Denitrification

Denitrification is simulated in each layer when the soil water nutrient factor (Equation 2.15) crosses a default threshold of 1.10. Below this threshold, no denitrification is assumed to occur. Equation 2.28 describes the calculation of denitrification for each soil layer.

Equation 2.28. Denitrification for Individual Soil Layers

\[ N_{denit,ly} = NO_{3ly} \ast (1 - \exp[-\beta_{denit} \ast \gamma_{tmp,ly} \ast \sigma g_{C,ly}]) \]
Where $N_{denit,ly}$ is the nitrogen lost to denitrification [kg N/ha], $NO3_{ly}$ is the amount of nitrogen in the soil layer [kg N/ha], $\beta_{denit}$ is the denitrification rate coefficient, $\gamma_{tmp,ly}$ is the nutrient temperature cycling factor, and $orgC_{ly}$ is the organic carbon in the layer.

One study [Pohlert et al., 2005] has suggested that the soil moisture threshold for denitrification is too low, leading to excessive removal of nitrogen. There is also evidence that the simulation of nitrate concentrations could be improved in SWAT by extending the denitrification simulation to aquifers with anaerobic conditions and riparian areas near streams, as concentrations have been shown to be overpredicted in several instances [Glavan et al., 2011]. However, that may require more extensive hydrogeologic data regarding near-stream aquifers than may be commonly available, making it impractical for all but the most intensive of studies.

### 2.12.6 Other Sources of Nitrogen

An additional source of nitrogen is atmospheric deposition. Users are able to specify a watershed-wide deposition value for wet and dry ammonium and nitrate in kg/ha/yr. A concentration of nitrate in rainwater can also be specified. By default, SWAT assumes all rain contains 1 mg/L of nitrate. Deposition values, however, are set to zero by default because data rarely exists to verify them, as was the case in the UBWC.

Lastly, SWAT simulates nitrogen fixation by legumes when soil levels are insufficient to meet plant nutrient requirements. This nitrogen is directly incorporated into the plants’ biomass and never enters the soil.

### 2.13 Nutrients: Phosphorus

Phosphorus calculations are performed in a similar manner as nitrogen calculations. Six different pools of phosphorus are assumed in the soil: mineral stable, active and solution phosphorus, and organic stable, active, and fresh phosphorus.
Unlike nitrogen, phosphorus concentrations are initialized at 5 mg/kg for all soil layers. Partitioning of humic organic phosphorus is calculated based on an assumed ratio of humic organic phosphorus to humic organic nitrogen.

### 2.13.1 Decomposition

Decomposition refers to the breakdown of organic residue into its organic components. To simulate this process, SWAT uses the mineralization algorithms of Jones et al. [1984]. As with decomposition of residue into its organic nitrogen components, the decomposition process relies on the temperature and water cycling factors presented in Equations 2.7 and 2.6.
In the decomposition process, carbon to nitrogen and carbon to phosphorus ratios are first calculated:

**Equation 2.29. Organic Residue C:N Ratio**

\[
\varepsilon_{C:N} = \frac{0.58 \times rsd_{ly}}{orgN_{frsh,ly} + NO3_{ly}}
\]

Where \(rsd_{ly}\) is the amount of organic residue in the layer [kg/ha], \(orgN_{frsh,ly}\) is the fresh organic N in the layer [kg/ha], and \(NO3_{ly}\) is the amount of nitrate in the layer [kg/ha].

**Equation 2.30. Organic Residue C:P Ratio**

\[
\varepsilon_{C:P} = \frac{0.58 \times rsd_{ly}}{orgP_{frsh,ly} + P_{solution,ly}}
\]

Where \(rsd_{ly}\) is the amount of organic residue in the layer [kg/ha], \(orgP_{frsh,ly}\) is the fresh organic P in the layer [kg/ha], and \(P_{solution,ly}\) is the amount of phosphorus in solution in the layer [kg/ha].

After determination of the organic residue C:N and C:P ratios, a nutrient cycling residue composition factor is determined as the minimum of three options.

**Equation 2.31. Nutrient Cycling Residue Composition Factor**

\[
\gamma_{ntr,ly} = \min \left\{ \exp \left[ -0.693 \times \frac{(\varepsilon_{C:N} - 25)}{25} \right], \exp \left[ -0.693 \times \frac{(\varepsilon_{C:P} - 200)}{100} \right] \right\}
\]

Determination of this factor allows the calculation of the decay rate constant for organic residue, which is a function of the temperature, soil water, and nutrient cycling residue composition factors.
Equation 2.32. Organic Phosphorus Decay Rate Constant
\[
\delta_{ntr,ly} = \beta_{rsd} Y_{ntr,ly} (Y_{tmp,ly} Y_{sw,ly})^{1/2}
\]

After calculation of the decay rate constant, decomposition from the fresh organic residue pool can be calculated.

Equation 2.33. Decomposition from Fresh Organic Pool
\[
P_{dec,ly} = 0.2 * \delta_{ntr,ly} * org P_{frsh,ly}
\]

Where \( P_{min,ly} \) is the amount of phosphorus decomposition from the fresh organic residue pool [kg/ha], and other variables are as previously defined.

2.13.2 Mineralization and Immobilization

Mineralization is calculated from the humus active organic P pools and the residue fresh organic P pools. Using the previously calculated nutrient cycling temperature, soil water, and residue composition factors, phosphorus mineralization can be calculated in the following manner:

Equation 2.34. Phosphorus Mineralization
\[
P_{min,ly} = 0.8 * \delta_{ntr,ly} * org P_{frsh,ly}
\]

Where \( P_{min,ly} \) is the amount of phosphorus mineralization in the layer from the fresh organic residue pool [kg/ha], and other variables are as previously defined.

2.14 Nutrient In-Stream Transformation and Routing

Nutrients enter surface water by leaching, tile pathways, and transport via runoff. Only nutrients in the top 10 mm of the soil column are available for transport in runoff. In larger watersheds (with time to concentration greater than one day), nutrients entering surface water through runoff and lateral flow are lagged along with the water entering the main channel.

Once nutrients reach the stream, various nutrient transformation and settling processes are optionally simulated using the QUAL2E model [Brown and Barnwell, 1987] which is incorporated into SWAT. These in-stream nutrient transformation
processes are simulated by default, including death of and nutrient uptake by algae, nutrient settling, nitrification, volatilization, and diffusion of nutrients from bed sediments.

Before estimating any in-stream nutrient transformations, the daily water temperature for the reach must be calculated. It is a function of the daily average air temperature and is described as follows:

**Equation 2.35. Water Temperature**

\[
T_{\text{water}} = 5.0 + 0.75 \times T_{\text{av}}
\]

Water temperature is nearly universal in the calculation of coefficients for in-stream nutrient transformation and exerts a significant influence on the nutrient cycle output.

**2.14.1 Nitrogen Transport**

As nitrate (NO\textsubscript{3}-) is negatively charged, and many soils in agricultural areas are negatively charged, there is little anion exchange capacity available to adsorb nitrate. Consequently, nitrate is easily leached into surface water [Di and Cameron, 2002]. Moreover, the negative charge of nitrate also serves to exclude the molecule from the portion of soil water closest to the soil particle, reducing the travel time of nitrate in soil water [Neitsch et al., 2011]. Because nitrate nitrogen is the most significant contributor to nutrient pollution, its transport is discussed here in depth. Organic nitrogen is not as significant as it must undergo mineralization to be available as a significant source of N for plant uptake [Näsholm et al., 2009].

To determine the amount of nitrate that is transported by percolation, lateral flow, and runoff, the concentration of mobile nitrate in water in all soil layers is first calculated according to the following equation [Neitsch et al., 2011]:

**Equation 2.36. Determination of Mobile Nitrate Concentration**

\[
\text{conc}_{\text{NO}_3, \text{mobile}} = \frac{NO_{3y} \left( 1 - \exp \left(\frac{-w_{\text{mobile}}}{(1 - \theta_e) \times SAT_{ly}}\right)\right)}{w_{\text{mobile}}}
\]
Where \( NO_{3ly} \) is the amount of nitrate in the soil layer [kg/ha], \( w_{mobile} \) is the amount of mobile water in the soil layer [mm], \( SAT_{ly} \) is the saturated water content of the soil layer [mm], and \( \theta_e \) is the fraction of the porosity in the soil from which anions are excluded. Mobile water in the top 10 mm of the soil layer includes runoff, percolation, and lateral flow, while mobile water in deeper layers solely consists of percolation and lateral flow.

Once the concentration of nitrate in the water within a soil layer is determined, the relative amount of nitrate going to each pathway is partitioned according to the following equations [Neitsch et al., 2011]. Nitrate in runoff is calculated as follows:

**Equation 2.37. Calculation of Nitrate Lost to Runoff**

\[
NO_{3surf} = \beta_{NO3} \times conc_{NO3, mobile} \times Q_{surf}
\]

Where \( \beta_{NO3} \) is the nitrate percolation coefficient and \( Q_{surf} \) is the surface runoff generated on the given day. Nitrate lateral flow in the top soil layer is calculated in a similar fashion:

**Equation 2.38. Soil Layer Contribution to Nitrate in Lateral Flow, Top 10 mm of Soil**

\[
NO_{3lat,ly} = \beta_{NO3} \times conc_{NO3, mobile} \times Q_{lat,ly} \text{ for top 10 mm of soil column}
\]

**Equation 2.39. Soil Layer Contribution to Nitrate in Lateral Flow, Lower Layers**

\[
NO_{3lat,ly} = conc_{NO3, mobile} \times Q_{lat,ly} \text{ for all lower layers}
\]

Where \( NO_{3lat,ly} \) is the amount of nitrate transported out of the layer in lateral flow [kg N/ha], \( \beta_{NO3} \) is the nitrate percolation coefficient, and \( Q_{lat,ly} \) is the total lateral flow within the layer [mm].

Unlike lateral flow, percolation is calculated in the same manner for all soil layers:
Equation 2.40. Nitrate Percolation

\[ \text{NO}_{3\text{perc,ly}} = \text{conc}_{N03,\text{mobile}} \times w_{\text{perc,ly}} \]

Where \( w_{\text{perc,ly}} \) is the amount of water that percolates to the underlying soil layer.

2.14.2 Nitrogen Transformation

Inorganic nitrogen concentrations can decrease through algae uptake or increase through mineralization of organic nitrogen through the process of conversion to ammonia, nitrite, and lastly nitrate. Organic nitrogen concentrations can decrease through mineralization or settling with sediment, or increase with decay of algae.

Equation 2.41. Change in Stream Organic Nitrogen

\[ \Delta \text{org}N_{\text{str}} = (\alpha_1 \times \rho_a \times \text{algae} - \beta_{N,3} \times \text{org}N_{\text{str}} - \sigma_4 \times \text{org}N_{\text{str}}) \times TT \]

Where \( \alpha_1 \) is the fraction of algal biomass that is nitrogen [mg N/mg algal biomass], \( \rho_a \) is the local respiration or death rate of algae [day\(^{-1}\) or hr\(^{-1}\)], \( \text{algae} \) is the algal biomass concentration at the beginning of the time period specified, \( \beta_{N,3} \) is the hydrolysis rate constant for the conversion of organic N to ammonia [day\(^{-1}\) or hr\(^{-1}\)], \( \text{org}N_{\text{str}} \) is the in-stream organic N concentration at the beginning of the time period specified, \( \sigma_4 \) is the organic nitrogen settling rate coefficient [day\(^{-1}\) or hr\(^{-1}\)] , and \( TT \) is the flow travel time in the reach segment [days or hours].

Equation 2.42 governs the decrease in organic N through conversion to ammonia:

Equation 2.42. Hydrolysis of Organic N to Ammonia

\[ \beta_{N,3} = \beta_{N,3,20} \times 1.047^{(T_{\text{water}} - 20)} \]

Where \( \beta_{N,3} \) is the local rate constant for hydrolysis of organic nitrogen to ammonia [day\(^{-1}\) or hr\(^{-1}\)], \( \beta_{N,3,20} \) is the local rate constant for hydrolysis of organic nitrogen to ammonia at 20º C [day\(^{-1}\) or hr\(^{-1}\)], and \( T_{\text{water}} \) is the mean water temperature [days or hours].

Equation 2.43 describes the adjustment of the organic nitrogen settling rate coefficient to the temperature of the stream:
Equation 2.43. Organic Nitrogen Settling Rate Coefficient

\[ \sigma_4 = \sigma_{4,20} \times 1.024^{(T_{\text{water}} - 20)} \]

Where \( \sigma_{4,20} \) is the local organic nitrogen settling rate coefficient at 20º C [day\(^{-1}\) or hr\(^{-1}\)].

Equation 2.44. Change in Ammonium Concentration

\[ \Delta \text{org}N_{\text{str}} = (\alpha_1 \times \rho_a \times \text{algae} - \beta_{N,3} \times \text{org}N_{\text{str}} - \sigma_4 \times \text{org}N_{\text{str}}) \times TT \]

Unlike ammonium and nitrate, nitrite is not taken up by algae, so its concentration depends solely on the rate of conversion of ammonium to nitrite and the conversion of nitrite to nitrate.

Equation 2.45. Change in Nitrite Concentration

\[ \Delta \text{org}N_{\text{str}} = (\beta_{N,1} \times \text{NH}_4_{\text{str}} - \beta_{N,2} \times \text{NO}_2_{\text{str}}) \times TT \]

Where \( \beta_{N,1} \) is the rate constant for the oxidation of ammonium, and the other parameters are the same as previously defined.

Equation 2.46. Change in Nitrate Concentration

\[ \Delta \text{NO}_3_{\text{str}} = (\beta_{N,2} \times \text{NO}_2_{\text{str}} - (1 - f_{\text{NH}_4}) - \alpha_1 \times \mu_a \times \text{algae}) \times TT \]

Where \( \beta_{N,2} \) is the rate constant for the biological oxidation of nitrite to nitrate, and the other parameters are the same as previously defined.

2.14.3 Phosphorus Transport

The common forms of phosphorus in the soil are much less soluble than nitrate. Erosion was historically thought to supply the bulk of phosphorus to surface water [Sharples et al., 1993], however, the presence of preferential flow pathways in the soil also can lead to significant phosphorus losses in many instances [Heathwaite and Dils, 2000].
For phosphorus, SWAT calculates loadings to the stream of organic P, mineral P, and P from groundwater. These are calculated in kg/ha and added for each HRU. Organic and mineral phosphorus reach surface water through two pathways: transportation in runoff alone and attached to sediment eroded by runoff. Transportation of mineral phosphorus in runoff is calculated as follows:

**Equation 2.47. Transportation of Mineral Phosphorus in Runoff**

\[
P_{\text{surf}} = \frac{P_{\text{solution,surf}} \cdot Q_{\text{surf}}}{\rho_b \cdot \text{depth}_{\text{surf}} \cdot k_{d,\text{surf}}}
\]

Where \(P_{\text{surf}}\) is the amount of mineral phosphorus removed by runoff [kg/ha], \(P_{\text{solution,surf}}\) is the amount of phosphorus in solution in the top 10 mm soil layer [kg/ha], \(Q_{\text{surf}}\) is the amount of surface runoff on a given day [mm], \(\rho_b\) is the bulk density of the top 10 mm soil layer [Mg/m\(^3\)], \(\text{depth}_{\text{surf}}\) is the depth of the surface layer (a constant 10 mm), and \(k_{d,\text{surf}}\) is the ratio of soluble phosphorus in the top soil layer to the concentration of soluble phosphorus in runoff.

Transportation of mineral and organic phosphorus is calculated as a function of sediment yield, HRU area, concentration of phosphorus attached to sediment, and a phosphorus enrichment ratio in Equation 2.48:

**Equation 2.48. Transportation of Mineral and Organic Phosphorus Attached to Sediment:**

\[
sedP_{\text{surf}} = 0.001 \cdot \text{concsed}_P \cdot \frac{sed}{\text{area}_{\text{hru}}} \cdot \varepsilon_{P:sed}
\]

Where \(\text{concsed}_P\) is the concentration of phosphorus attached to sediment in the top 10 mm soil layer [g P/metric ton of soil], \(sed\) is the sediment yield of the HRU on a given day, \(\text{area}_{\text{hru}}\) is the area of an HRU, and \(\varepsilon_{P:sed}\) is an enrichment ratio that describes the concentration of phosphorus in the transported sediment relative to that of the soil surface layer.

Calculation of phosphorus leaching is limited in SWAT. Unlike nitrogen, phosphorus is only assumed to travel from the top soil layer (first 10 mm) into the next,
meaning that no leaching of soluble phosphorus occurs from the soil profile to groundwater. This also means that SWAT does not calculate tile phosphorus losses, which are significant in the UBWC. SWAT does allow specification of a phosphorus concentration within the shallow aquifer and groundwater flow, but this was not done due to the absence of data on such concentrations.

2.14.4 Phosphorus Transformation

Inorganic phosphorus concentrations can decrease through algae uptake or increase through mineralization of organic phosphorus or diffusion from the streambed sediments. Organic phosphorus concentrations can decrease through mineralization or settling (due to the association of organic phosphorus with sediment) or increase through the breakdown of algae.

The change in stream organic phosphorus is calculated similarly to the change in stream organic nitrogen:

**Equation 2.49. Change in Stream Organic Phosphorus**

\[
\Delta \text{orgP}_{str} = (\alpha_2 \ast \rho_a \ast \text{algae} - \beta_{P,A} \ast \text{orgP}_{str} - \sigma_5 \ast \text{orgP}_{str}) \ast TT
\]

Where \(\alpha_2\) is the fraction of algal biomass that is phosphorus [mg P/mg algal biomass], \(\beta_{P,A}\) is the rate constant for mineralization of organic phosphorus, \(\text{orgP}_{str}\) is the organic phosphorus concentration at the beginning of the day or hour, and \(\sigma_5\) is the rate coefficient for organic phosphorus settling [day\(^{-1}\) or hr\(^{-1}\)].

**Equation 2.50. Adjustment of Organic Phosphorus Mineralization Rate**

\[
\beta_{P,A} = \beta_{P,A,20} \ast 1.047^{(T_{\text{water}} - 20)}
\]

Where \(\beta_{P,A}\) is the local organic nitrogen settling rate coefficient at 20\(^\circ\) C [day\(^{-1}\) or hr\(^{-1}\)].

**Equation 2.51. Adjustment of Organic Phosphorus Settling Rate**

\[
\sigma_5 = \sigma_{5,20} \ast 1.024^{(T_{\text{water}} - 20)}
\]

Where \(\sigma_5\) is the local organic nitrogen settling rate coefficient at 20\(^\circ\) C [day\(^{-1}\) or hr\(^{-1}\)].
Equation 2.52. Change in Inorganic Soluble Phosphorus

\[
\Delta solP_{str} = \left( \beta_{P,4} \text{ or } gP_{str} + \frac{\sigma_2}{1000 \times depth} - \alpha_2 \times \mu_a \times algae \right) \times TT
\]

Where \( \sigma_2 \) is the sediment source rate for soluble P [mg P m\(^{-2}\) day\(^{-1}\) (or hour\(^{-1}\))], \( depth \) is the depth of water in the channel, and \( \mu_a \) is the local growth rate of algae.

Like the mineralization and settling rates, the sediment source rate for inorganic phosphorus must also be adjusted to reflect the water temperature.

Equation 2.53. Adjustment of Sediment Source Rate

\[
\sigma_2 = \sigma_{2,20} \times 1.074^{(T_{water,-20})}
\]

Where \( \sigma_2 \) is the sediment source rate for soluble P [mg P m\(^{-2}\) day\(^{-1}\) (or hour\(^{-1}\))].

2.14.5 Summary

For this research, in-stream nutrient transformations were simulated using the described QUAL2E model incorporated into SWAT. These transformations include losses due to settling and gains from streambed sediment sources, as well as chemical transformations that mineralize organic sources of N and P, making them available to algae for uptake and potentially influencing eutrophication. Decay of dead algae also releases mineral N and P to the stream.

As nutrient NPS pollution is the focus of this study, these transformations are necessary to obtain a more complete picture of the actual amount of loading at the watershed outlet. These processes are strongly dependent on water temperature, which is a function of daily average temperature and as such will change for the UBWC under future climate scenarios. This makes simulation of in-stream processes even more important for comprehensive consideration of the factors that drive potential changes in future NPS pollution.

2.15 Sediment Processes

To calculate sediment losses, SWAT utilizes the Modified Universal Soil Loss Equation [Arnold et al., 1995] (MUSLE) developed by Williams et al. [1975]. The
MUSLE is based on the USLE of Wischmeier and Smith [1965]. As Equation 2.54 shows, calculated soil loss is a function of HRU area, runoff, soil properties, land cover and management, and topography.

**Equation 2.54. Modified Universal Soil Loss Equation**

\[
\text{sed} = 11.8 \cdot (Q_{surf} \cdot q_{peak} \cdot \text{area}_{hru})^{0.56} \cdot K_{USLE} \cdot C_{USLE} \cdot P_{USLE} \cdot LS_{USLE} \cdot CFRG
\]

Where \(\text{sed}\) is the daily sediment yield [tons], \(Q_{surf}\) is the volume of surface runoff [mm], \(q_{peak}\) is the peak runoff rate \([\text{m}^3/\text{sec}]\), \(\text{area}_{hru}\) is the area of the HRU [ha], \(K_{USLE}\) is the USLE soil erodibility factor (set at a constant 0.013 ton/ha), \(C_{USLE}\) is the USLE cover and management factor, \(P_{USLE}\) is the USLE support practice factor, \(LS_{USLE}\) is the USLE topographic factor, and \(CFRG\) is the coarse fragment factor.

\(P_{USLE}\) and \(LS_{USLE}\) are functions of management practices designed to reduce soil losses from sloping areas and watershed topography. These factors do not change between the simulations in the research and so are not further discussed here. Of the factors that comprise the MUSLE, the most important for the purposes of this study is \(C_{USLE}\). \(C_{USLE}\) describes the ratio of soil loss under the specified conditions compared with a corresponding loss calculated for clean-tilled, continuously fallow land. This factor takes into account the effects of canopy and residue cover in reducing the energy of raindrops, runoff, and the resulting erosion. \(C_{USLE}\) is calculated as follows:

**Equation 2.55. USLE Cover and Management Factor**

\[
C_{USLE} = \exp\left(\ln(0.8) - \ln(C_{USLE,mn})\right) \cdot \exp[-0.00115 \cdot rsd_{surf}] + \ln[C_{USLE,mn}]
\]

Where \(C_{USLE}\) is the USLE cover and management factor, \(C_{USLE,mn}\) is the minimum value for the cover and management factor for the land cover simulated, and \(rsd_{surf}\) is the residue on the land surface [ton/ha].

Different values of \(C_{USLE,mn}\) for different land covers are provided in the SWAT crop database. Some of these factors are presented in Table 2.5 below.
Table 2.5. Minimum USLE cover and management factors for different land use types

<table>
<thead>
<tr>
<th>Land Cover Type</th>
<th>$C_{USLE, mn}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Corn</td>
<td>0.200</td>
</tr>
<tr>
<td>Soybeans</td>
<td>0.200</td>
</tr>
<tr>
<td>Winter Wheat</td>
<td>0.030</td>
</tr>
<tr>
<td>Hay</td>
<td>0.003</td>
</tr>
<tr>
<td>Rye</td>
<td>0.030</td>
</tr>
</tbody>
</table>

According to Equation 2.55, higher values of $C_{USLE, mn}$ cause higher values of $C_{USLE}$, resulting in higher soil loss predicted for different land covers. This indicates that differences in this variable must be carefully considered when accounting for the effects of changes in crop rotations and land cover.

As Equation 2.55 also shows, the presence of residue on the land surface can also result in changes to the amount of sediment erosion. Because $C_{USLE, mn}$ is constant for a given land cover, changes in residue during the plant growing season are dictated entirely by decomposition. The rate equation for residue decomposition is given in Equation 2.56 below:

**Equation 2.56. Rate Equation for Residue Decomposition**

$$\frac{dR_c}{dt} = I_{RC} - f_E k_R R_c$$

Where $R_c$ represents the amount of residue in the residue pool, $I_{RC}$ is the input of residue from harvest or harvest and kill operations, $f_E$ is the combined effect of the soil temperature factor, moisture factor, and aeration factor, and $k_R$ is the optimum decay rate constant for residue. $f_E$ is calculated as follows:
Equation 2.57. Combined Soil Temperature, Moisture, and Aeration Factor for Residue Decomposition

\[ f_E = (f_T f_W f_o)^{f_p} \]

Where \( f_T \) is the soil temperature factor, \( f_W \) is the soil moisture cycling factor, \( f_o \) is the soil aeration factor, and \( f_p = 0.67 \).

The reliance of the residue decomposition equations on the soil temperature and soil moisture factors previously discussed in Section 2.12.1 illustrates that sediment losses may be sensitive to changes in precipitation and temperature due to climate change. For instance, if the mean soil temperature factor were to increase, sediment losses may be enhanced as a result of the increase in \( C_{USLE} \) caused by faster decomposition of residue. The interconnected nature of these processes indicate that both land cover and climate changes have the potential to affect sediment loss, and as such will be important when evaluating the outcomes of this research.
3 Experimental Setup

3.1 Field Site: The Upper Big Walnut Creek

The Upper Big Walnut Creek (UBWC) watershed, located in central Ohio, covers an area of 190 square miles (492 km$^2$) and contains diverse land uses, soil type. It is a part of the Upper Scioto Watershed, which ultimately drains into the Ohio River. Hoover Reservoir, situated in the southern portion of the watershed, supplies drinking water to over 700,000 people within the Columbus metropolitan area. The reservoir is approximately 3,000 acres in area and contains approximately 60,130 acre-feet of storage at full capacity [USGS, 1997]. In addition to its use as a drinking water source, Hoover Reservoir is also an important recreation area within the watershed and is frequently utilized by fishermen, boaters, and birdwatchers.
Figure 3.1. Position of the UBWC watershed in relation to the state of Ohio.

### 3.1.1 Agriculture and Other Land Uses

Land use has a significant impact on watershed hydrology because it greatly affects runoff, infiltration, evapotranspiration, and other important processes. As of 2011, the majority of the watershed’s land (54%) is used for row crop agricultural production. Additional area is devoted to hay production (12% in 2011). Deciduous forest also covers a significant percentage of the watershed.
Figure 3.2. Land uses in UBWC watershed (National Land Cover Database, 2006). Predominant land uses include deciduous forest (FRSD), agriculture/row crops (AGRR), hay, and urban low-density (URLD). Other land uses present include evergreen forest (FRSE), mixed evergreen and deciduous forest (FRST), wetlands (WETN), forested wetlands (WETF), water (WATR), urban industrial (UIDU), urban medium and high densities (URMD, URHD), shrubland and herbaceous grassland (RNGB and RNGE), and barren land (SWRN).
A breakdown of the major land uses provided by the NLCD within the watershed is given in Table 3.1 below. Although more than a dozen different NLCD-defined land uses are present in the watershed, the four listed below comprise more than 95% of the total watershed area. The dominant land use overall is agriculture.

### Table 3.1. Major land uses within the Upper Big Walnut Creek watershed, 1992-20011.

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Agriculture Row Crops</td>
<td>52.3%</td>
<td>53.5%</td>
<td>54.3%</td>
<td>53.5%</td>
</tr>
<tr>
<td>Hay</td>
<td>21.4%</td>
<td>12.0%</td>
<td>11.8%</td>
<td>11.8%</td>
</tr>
<tr>
<td>Forest</td>
<td>24.5%</td>
<td>26.9%</td>
<td>26.8%</td>
<td>26.7%</td>
</tr>
<tr>
<td>Low Density Residential</td>
<td>0.5%</td>
<td>5.1%</td>
<td>5.4%</td>
<td>5.5%</td>
</tr>
<tr>
<td>Other</td>
<td>1.3%</td>
<td>2.5%</td>
<td>1.7%</td>
<td>2.5%</td>
</tr>
</tbody>
</table>

Land use within the UBWC has not remained static in the face of population growth in the surrounding area. It is important to note that the forested and row-crop areas within the watershed have remained relatively constant in size, and that most of the change in land use has been a result of declining hay cultivation. The percentage of low-density residential land has also increased by a factor of ten from over a period of 14 years, indicating the occurrence of suburbanization. The Mid-Ohio Regional Planning Commission projects further increases in suburban land area by the year 2050.

### 3.1.2 Watershed Climate

The UBWC exhibits a humid continental climate characteristic of much of the Midwest, with warm to hot summers and cold winters. Analysis of National Oceanic and
Atmospheric Administration (NOAA) National Climatic Data Center (NCDC) daily and hourly precipitation statistics observed from 1971 to 1991 at the nearby Centerburg weather station indicate a mean yearly precipitation value of 1,035 mm and a standard deviation of 159 mm. Rainfall occurs mainly in the summer, but is also significant in spring. Figure 3.3 below shows the long-term mean monthly accumulations of rainfall with standard deviations for Centerburg, Ohio from 1965-1994 calculated from NCDC data.

**Figure 3.3.** Monthly mean rainfall accumulations and standard deviations of monthly mean rainfall accumulations for Centerburg, OH (near UBWC watershed), 1965-1994. Data was obtained from NCDC database (does not include missing data points).
3.1.3 Terrain

Elevation in the watershed ranges from 248 to 433 meters above sea level, with a mean elevation of 328 meters. Higher elevations are concentrated in the northeastern portion of the watershed. The watershed has moderate slope overall. For simulation purposes similar slopes were grouped into five different classes: 0-1%, 1-2%, 2-4%, 4-8%, and greater than 8%. The total area of the watershed in the first three of these classes was almost equally distributed, as shown below in Figure 3.3. Figure 3.4 shows an elevation map of the watershed using data obtained from the USGS National Elevation Dataset.

![Slope Class Breakdown, UBWC Watershed](image)

**Figure 3.4.** Breakdown of slopes within UBWC watershed by user-defined classes, calculated from one arc-second DEM from the USGS National Elevation Dataset
3.1.4 Soil

Soils are an important factor to consider when studying any watershed as they affect drainage, infiltration, runoff, and innumerable other processes. The STATSGO soils database lists five major soil groups within the UBWC, as shown below in Figure 3.6:
Figure 3.6. STATSGO soil dataset (scale:1:250,000) with the major UBWC soil groups overlaid on a SWAT-delineated UBWC watershed subbasin and stream map. The STATSGO database simplifies the watershed into 5 major soil types, compared to 117 using the SSURGO database.

At a resolution of 1:10,000, the SSURGO soils database provides much higher resolution than STATSGO. According to the SSURGO soils database, the UBWC watershed contains 117 different soils types, of which six types comprise approximately 63% of the watershed’s area. The dominant six soil types within the SSURGO database
are Bennington silt loam (BeA, BeB), Centerburg silt loam (CeB), Pewamo (PwB), and Cardington silt loam (CaB, CdB). The relative percentage of watershed area that each of the six most prevalent soils cover is shown in Figure 3.7 below.

![SSURGO Soils Type Breakdown, UBWC Watershed](image)

**Figure 3.7.** Major soil types within the UBWC watershed, as defined by the NRCS SSURGO soils database. Soil types include Bennington silt loam (BeA, BeB), Centerburg silt loam (CeB), Pewamo (PwB), Cardington silt loam (CaB), and CdB.

One of the most vital characteristics of any soil is its drainage properties. The NRCS classifies soils into seven different types of drainage category: excessively drained, somewhat excessively drained, well drained, moderately well drained, somewhat poorly drained, poorly drained, and very poorly drained. Three of the major soils within the watershed (Pewamo silty clay loam, Bennington silt loam, and Cardington loam) are in general classified as poorly draining. Consequently, agricultural tile drainage systems...
have been installed in much of the UBWC watershed in order to facilitate agricultural production. Coverage of tile networks is expanding to the north. Fields with tile drains installed (circa 2006) are indicated below in Figure 3.7.

**Figure 3.8.** Distribution of tiled fields in UBWC watershed (circa 2006). Data provided by the Delaware County Soil and Water Conservation District.
3.2 Model Setup

While extensive documentation of required input file parameters is readily available, manually creating the hundreds to potentially thousands of input files needed to run SWAT could be time-consuming and may increase the likelihood of mistakes within those files. For this reason, the ArcSWAT Geographic Information System (GIS) interface was used to set up a simulation of the UBWC watershed. ArcSWAT creates many of the necessary SWAT input files using user-supplied rasters of relevant watershed characteristics. At a minimum, ArcSWAT requires elevation, land use, and soils raster inputs. While information regarding crop distributions and tile drainage characteristics is not strictly required by SWAT, it was determined to be relevant to the study watershed and was therefore utilized. Incorporation of these inputs into the simulation is described below.

3.2.1 Elevation & Subbasin Delineation

One arc-second elevation data supplied by the National Elevation Dataset within the U.S. Geological Survey National Map Viewer platform was used as a Digital Elevation Map (DEM). ArcSWAT uses the elevation data provided by the DEM to delineate a stream network within the watershed as well as the watershed’s boundaries and subbasins within the watershed. ArcSWAT additionally uses the DEM to group land into slope classes (i.e., 0% to 1% slope, 1% to 10% slope, etc.). To define Hoover Reservoir within the simulation, outlets were placed where the individual reaches met the reservoir. A reservoir point was added at the outlet, and the delineation was completed. Outlets were also placed at the mouths of eight 12-digit Hydrologic Unit Code watersheds within the UBWC in order to enable direct comparison of simulation results with observed data.

3.2.2 Land Use and Soils Setup

After the delineation step of model setup, land use, soils, and slope for the simulation were defined. The area’s land use was taken from the 1992 [Vogelmann et al., 2001], 2001 [Homer et al., 2004] and 2006 [Fry et al., 2011] datasets available in the
NLCD. Usage of NLCD data introduces some uncertainty; recent work has found the land use classification accuracy to be 78% for the NLCD 2006 [Wickham et al., 2013]. The soils layer was defined using the STATSGO and SSURGO databases (discussed briefly in Section 3.1.4).

Input rasters were re-projected into the UTM North American Datum (NAD) 1983 Zone 17N format. Slope classes are created after land use and soils definition and are then considered along with the land use and soils layers in defining HRUs for the simulation.

### 3.2.3 HRU Thresholds

After the soils, land use, and slope data layers are defined, criteria for HRU formation within the subbasins must be defined. The HRU threshold definition step in model set-up with ArcSWAT is extremely important to the overall simulation. It sets the minimum percentage of sub-basin area (from 0-100%) at which a soil, slope class, or land use type has to cover to merit formation of an additional HRU. For example, defining an HRU threshold of 0% creates an HRU for every unique combination of land use, soil type, and slope class within a subbasin. In contrast, setting HRU thresholds at their maximum creates no additional HRUs within subbasins, and the HRU characteristics become the dominant soil type, slope, and land use of the subbasin.

For this work, the HRU thresholds were set at 10% for land use, soils, and slope, in order to obtain more detailed spatial information on HRU level output. This resulted in a total of 1,617 HRUs for the watershed. Increased thresholds and their corresponding level of detail can have their benefits: Mamillapalli et al. [1996] noted increasing model simulation accuracy with finer HRU definitions, and a point of diminishing returns beyond which accuracy did not increase further. Similar tests were conducted in this research. The results of these tests are presented in Table 8.4 in Section 8.1.

### 3.2.4 Crop Distribution and Characterization

Crops present within the watershed have a significant effect on nutrient loading due to the differences between species in nutrient uptake and fertilizer requirements. As
such, accurate characterization of the location and distribution of crops in a watershed model is an important consideration. Some SWAT studies in agricultural watersheds (e.g. Wu et al. [2012]) have used agricultural GIS data to quantify crop distributions, frequently from the National Agricultural Statistics Service’s (NASS) Cropland Data Layer mapping system. Based on five years of NASS crop distribution data for Delaware County (presented in Table 2.4) the watershed crop distribution was assumed to be 67% soybeans and 33% corn.

To attempt to match the HRU crop type to the watershed crop distribution, a 2006 (corresponding with the year of the land use inputs) Cropland Data Layer map was intersected with HRU-level data in order to determine the extent of soybean production. However, because the Cropland Data Layer has a 30 by 30 meter pixel resolution and due to the spread-out nature of HRUs, this method indicated that soybeans were present in each HRU. As this was clearly not a realistic assumption, the Land Use Refinement module within SWAT was used to split agricultural HRUs into 67% soybeans and 33% corn. Alternate schemes such as random assignment of land use to HRUs may introduce unintended effects of soil or slope characteristics (i.e. if more nutrient-intense crops like corn are placed on poorly draining soil or greater slopes NPS loading to surface water may increase). For example, a formerly 150 hectare HRU of agricultural land in the 2-4% slope class would be split into three 50 hectare HRUs in the 2-4% slope class. Making the 67%-33% assumption also allowed for the implementation of a crop rotation that would maintain a constant crop breakdown across the watershed.

3.2.5 Adjustment of Plant Heat Units

SWAT provides default values for the number of heat units to maturity for every plant listed in its database. Although these values are often acceptable, they must be carefully reviewed during model setup in order to verify their appropriateness for the study watershed. For instance, the default value for heat units to maturity for soybeans is 1800 heat units. At the Centerburg weather station near the UBWC, records indicate only approximately 1500 heat units for corn [Ohio State University Extension, 2014]. Soybeans have a higher base growing temperature than corn, so the mean number of heat
units available for soybeans in a given year is even less. This means when using default values for soybean heat units to maturity, the soybeans on average never reach maturity and are therefore harvested and killed at the end of the year, leading to unrealistic assumptions for late-season ground cover, changes in evapotranspiration, and potential effects on simulated nutrient uptake. To address these issues, the mean number of heat units in the soybean growing season was calculated based on the mean heat units between the time 50% of the crop was planted and the time that 50% of the crop was harvested for the period of 1971-1990. The dates for 50% completion of planting and harvesting dates were obtained from a five year average of 1994-1998 data provided by farmers to the NASS. A sensitivity test using different values of heat units to maturity was conducted for soybeans and is located in Section 8.4.3.

Heat units to maturity of other plants simulated (fescue, hay, forest) were adjusted such that their LAI and biomass qualitatively matched that of which would be expected for seasonal differences in the UBWC (i.e. spring growth and late fall senescence). The default values and the adjusted values used in the simulations are provided below in Table 3.2.
Table 3.2. Approximate default plant heat units to maturity provided by SWAT database for each plant simulated in the UBWC, with adjusted values based on the 1971-1990 mean heat units in the growing season. Mean heat units for 1971-1990 were used due to that period’s selection as the baseline for future comparison in this research. The growing season was defined as the date from which 50% of the crop was planted to when 50% of the crop was harvested, using a five year average of 1994-1998 provided by the NASS Ohio Agricultural Statistics Crop and Weather Report historical data. The 1994-1998 period was selected because it was the closest period of data available to the baseline 1971-1990 period. Season start and end date information was not available for deciduous forest, hay, and fescue. Therefore, these plants used values calculated from the same length of growing season as corn, adjusted for their respective base temperatures.

<table>
<thead>
<tr>
<th>Plant Name</th>
<th>Default Heat Units to Maturity (°C)</th>
<th>Adjusted Heat Units (°C)</th>
<th>Base Growing Temperature (°C)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Corn</td>
<td>1284</td>
<td>1284</td>
<td>8.0</td>
</tr>
<tr>
<td>Soybeans</td>
<td>1800</td>
<td>1050</td>
<td>10.0</td>
</tr>
<tr>
<td>Winter Wheat</td>
<td>1565</td>
<td>1565</td>
<td>0.0</td>
</tr>
<tr>
<td>Deciduous Forest</td>
<td>1518</td>
<td>1260</td>
<td>10.0</td>
</tr>
<tr>
<td>Hay</td>
<td>1478</td>
<td>880</td>
<td>12.0</td>
</tr>
<tr>
<td>Fescue</td>
<td>1800</td>
<td>2860</td>
<td>0.0</td>
</tr>
</tbody>
</table>

3.2.6 Climate Data

In order to simulate uncommonly available climate inputs such as solar radiation or wind speed, weather stations must be defined for the simulation. ArcSWAT contains over 15,000 built-in weather station locations with statistics in the continental US. While these default values were not used for precipitation and temperature, wind speed, relative humidity, and solar radiation values were generated based on these statistics. Statistics
can be used from several time periods, including 1960-2010, 1960-1990, 1980-2010, and 1990-2006. 1990-2006 was chosen as it was closest to the time period of interest.

After simulation setup, parameters provided by the City of Columbus, Ohio regarding the volume of Hoover Reservoir at several stages were incorporated into the simulation. Although SWAT allows simulation of basic reservoir management, the reservoir was assumed to be uncontrolled.

3.2.7 **Tile Drainage Data**

Tile coverage was simulated for the watershed, based on information supplied by the Delaware County Soil and Water Conservation District. At first, GIS data regarding the distribution of tile drains (shown in Figure 3.8) was intersected with a map of the SWAT-generated HRUs to identify only those agricultural areas with tile drains for tile simulation. This analysis concluded that 299 out of 309 agricultural HRUs overlapped with tiled fields. As a result, tile drainage was assumed for all agricultural areas as a simplification.

In the UBWC watershed, the most common depth at which tile drains are placed is one meter; this value was assumed for all tiled HRUs. The DEP_IMP (depth to impervious layer) parameter was also changed for HRUs with tile to imitate the characteristics of a perched water table that tile drainage creates. Data for the water lag time from the tile drains to streams and time to drain to field capacity was unavailable for the watershed. These values can significantly impact streamflow simulation and were therefore included in the automated calibration process described in Section 8.1.

3.2.8 **Effects of Data Input Scale and Resolution**

Many of the previous works within the SWAT literature examine catchments on the basin scale. As the watersheds studied increase in size, the simulation complexity can grow and results may vary based on data availability and other site-specific factors [Bosch et al., 2011]. One study found that increased soil map and DEM resolution has a significant effect on runoff, sediment, and nitrate prediction accuracy [Vincent Chaplot, 2005]. Similar work by Chaubey et al. [2005] also confirmed the sensitivity of
streamflow and sediment loading to resolution of DEM inputs to SWAT. In Chaubey et al. [2005], the authors evaluated seven different DEM resolutions and found that resolution impacted runoff and streamflow predictions, which in turn affected erosion and changes in phosphorus concentrations associated with sediment loading.

Resolution of precipitation data also has a pronounced effect on simulation quality and uncertainty. Chaplot et al. [2007] experimented with different rainfall inputs and found that rain gauge concentration has an important effect on simulations with regards to runoff and sediment predictions. This study discussed the concept of a threshold for the number of rain gauges at which simulation accuracy did not improve with additional gauges. The thresholds were found to be different for the two study watersheds as well as runoff and sediment predictions.

Strauch et al. [2012] experimented with four precipitation input methods in a SWAT simulation with the objective of accounting for uncertainty in precipitation inputs. Simulations were run using the only available raingauge for the study watershed, a smoothed version of that data, Theissen polygons incorporating gauges outside the watershed, and data from the Tropical Rainfall Measuring Mission (TRMM).

Based on review of these studies, a DEM with a moderate resolution of one arc-second was chosen for the watershed. Different numbers and locations of precipitation gauges were used to force simulations, and the uncalibrated NSE values were examined. Three precipitation gauges (the maximum available given the constraints of streamflow data needed for calibration) were chosen as a result. SSURGO data was utilized to allow for finer spatial detail of simulation outputs. A more in depth discussion of the input resolution tests conducted and their results is presented in Section 8.1.
Climate Change and Hydrologic Modeling

NPS pollution is a serious problem facing water quality within the United States. Recent assessments of American waterways have indicated that five of the six top sources of river and stream impairment are NPS [Brown and Froemke, 2012]. As previously defined, NPS pollution is that which does not originate from a discrete source such as a stack or drain pipe. It is spatially distributed and is caused by many inputs, leading to challenges in its regulation and abatement.

Due to the proximity of the Midwest to the Great Lakes, previous agricultural NPS pollution mitigation efforts have focused on phosphorus reduction, as eutrophication has been found to be phosphorus-limited in most freshwater lakes [Schindler et al., 2008]. However, focusing on reducing phosphorus only can cause problems downstream where systems may be nitrogen-limited [Conley et al., 2009], such as in oceans or estuaries.

Funds to address water quality problems incurred by NPS pollution are often limited, and have become more limited in recent years with cuts to government programs that subsidize Best Management Practices (BMPs) [Shortle et al., 2012]. Field studies can be time consuming and money intensive. As such hydrologic models are often used to study NPS pollution in order to determine future changes in pollution as well as to discover management practices that are most cost-effective in treating the problem.

Hundreds of studies have been conducted in order to ascertain the direction and magnitude of anthropogenic changes to the Earth’s climate. With the release of the IPCC Fifth Assessment Report in 2013, the consensus among the scientific community is that climate is being affected globally by human activities and will continue to change in the short and long term time scales. Every facet of hydrologic and biogeochemical cycles is intertwined with basic variables such as temperature and precipitation.
As temperature changes, so does the capacity of air to hold water, potentially altering local weather patterns and precipitation characteristics. Potential evapotranspiration may increase or decrease as well, as energy available to drive water into the air varies with the conditions. In areas like the Midwest, warmer winter temperatures may cause less precipitation to fall as snow, leading to changes in discharge patterns as well as the timing and intensity of floods. Processes such as groundwater recharge may also be affected. More intense precipitation results in greater runoff and less infiltration of water into the soil. Figure 4.1 from the IPCC AR5 below shows past and future predictions of the mean global temperature anomaly for the next 100 years.

**Figure 4.1.** IPCC AR5 projected mean global temperature anomaly. Observed data is presented for 1960-2010 with projections extending onward to approximately 2100.
Because changes such as these are occurring much more rapidly than most natural variation in climate cycles, it is important to examine its effects when making long-term decisions about water quality policy or infrastructure.

A great body of research exists that examines links between climate change and streamflow using the SWAT model in diverse watersheds [Eckhardt and Ulbrich, 2003; Ficklin et al., 2012; Ficklin et al., 2009; Franczyk and Chang, 2009; Githui et al., 2009; Guo et al., 2008; Xu et al., 2009; Zhang et al., 2007]. Ficklin et al. [2009] found decreases in evapotranspiration and large increases in streamflow in a heavily irrigated, Mediterranean-climate watershed in California. The streamflow increases were attributed to decreases in evapotranspiration as a result of changes in plant stomatal conductance brought about by the increase in CO₂ concentrations. Zhang et al. [2007] investigated climate change impacts on a Chinese agricultural basin with a mean rainfall of 580 mm/year, predicting a possible increase in streamflow volume of 10%. Githui et al. [2009] also found streamflow to increase under future climate scenarios for an agricultural Kenyan watershed, albeit by different amounts (6% to 115%). Eckhardt and Ulbrich [2003] found minimal increases in streamflow for a mountainous forested German watershed, but that patterns of precipitation might change, resulting in higher wintertime streamflow and less springtime flooding. Gosain et al. [2006] modeled several large river basins across India and in general, found reductions in streamflow and increases in severity of both droughts and floods, dependent on the local climate. Xu et al. [2009] found potential for streamflow increases due to increased precipitation for the rural headwater catchment of the Yellow River basin; however, results were noted as being strongly dependent on the choice of GCM used as simulation input. In a primarily urban watershed in Oregon’s Rock Creek basin, Franczyk and Chang [2009] found that changes in streamflow due to climate change varied seasonally, with wintertime increases and summertime decreases. Further details of these works and their methods are presented in Section 4.2. Taken as a whole, they represent a thorough examination of streamflow response to climate change under a multitude of climates, land uses, and scenarios.
In contrast, however, less work has been done with SWAT to assess the effects of climate change on nitrogen and phosphorus concentrations in surface water \cite{Bouraoui et al., 2002; Bouraoui et al., 2004; Ficklin et al., 2010; Shrestha et al., 2012; Wu et al., 2012}. Bouraoui et al. \cite{2002} studied climate change in a rural northern English catchment (mean yearly precipitation of 870 mm) and found increased nutrient loading in future climate scenarios driven by increased mineralization and losses due to the forecasted increases in precipitation. A different study \cite{Wu et al., 2012} examined nitrate nitrogen (NO$_3$-N) in an agricultural semiarid U.S. basin. As a result of less precipitation predicted in the study region, decreased nutrient loading was estimated, potentially offset, however, by reductions in streamflow that may actually increase in-stream concentrations of NPS pollutants. Bouraoui et al. \cite{2004} studied a forested Finnish watershed with moderate yearly precipitation (657 mm/year), predicting slightly increased nutrient loading compared to a stationary climate under current climate change trends. Another study, Ficklin et al. \cite{2010}, of the agricultural San Joaquin watershed in California, predicted increases in nitrogen and phosphorus loading of 4.2% and 7.8%, respectively, due to CO$_2$ concentration increase alone. While these works have done much to assess future changes to NPS pollution, significantly more work remains to be accomplished in this field of study. For example, due to this range in results of the works previously mentioned and their climate dependence, it is worthwhile to model watersheds that may exhibit different climates and land uses than those previously studied. Previous work has focused on forested catchments \cite{Bouraoui et al., 2004; Eckhardt and Ulbrich, 2003} or arid or semi-arid catchments \cite{S Wang et al., 2008; Wu et al., 2012}. Few SWAT studies have examined primarily agricultural watersheds within the American Midwest, and those that have primarily concentrated on streamflow and the water balance, pesticides \cite{Bekele and Knapp, 2010; Larose et al., 2007; Schilling et al., 2008} or the effects of changes in management practices \cite{O'Donnell et al., 2008}. Furthermore, while agricultural watersheds are a common object of study, previously examined agricultural areas have been dominated by fruit, vegetable, and nut cultivation \cite{Ficklin et al., 2009} or pastureland \cite{Wu et al., 2012}, and not the row crop agriculture predominant in the Midwestern US.
This section will review the methods implemented by previous works to simulate the effects of climate change and comment on their suitability for work in the UBWC. A description of the most up to date IPCC scenarios is also presented, as they will be applied to this research.

4.1 IPCC Fifth Assessment Report (AR5)

In order to obtain realistic predictions, it is essential to run simulations under conditions representative of potential future climates or land uses. Studies that increase some hydrologic or climatic variable by an arbitrary percentage can be valuable as sensitivity analyses, but engineers and scientists often require more rigorous assessments. Grounded by complex evaluations of economic, social, and climatic factors, the IPCC Assessment Reports represent perhaps the most comprehensive attempt to quantify the magnitude and spatial and temporal extent of anthropogenic climate change, and serve as an excellent source of information regarding potential future conditions.

Previous assessment reports created several climate change scenarios that represented a diverse range of potential future economic and emissions conditions. The fifth and most recent assessment report (AR5, 2013) has updated these scenarios and lumped them into four RCPs which are described by the amount of increase in radiative forcing expected (e.g. RCP +2.6 W/m², RCP +4.5 W/m², etc.), where radiative forcing is defined as the difference between the energy reaching Earth and that reflected back into space. The four RCPs include one low range scenario (2.6 W/m²), two moderate scenarios (4.5 W/m² and 6.0 W/m²), and one high range scenario (8.5 W/m²). RCP 4.5 and RCP 8.5 were considered in this research because they had the most complete data availability within the CMIP5 dataset. Those two scenarios are described in further detail below.

4.1.1 RCP 4.5

This scenario assumes that the increase in radiative forcing will stabilize in the year 2100 as a result of emissions controls assumed to be enacted and effectively applied by all nations [Thomson et al., 2011]. A price is placed on common emitted air pollutant
(e.g. CO$_2$, CH$_4$, etc.) corresponding to their warming potential, thereby inducing countries to seek reductions and minimize cost. RCP 4.5 is comparable to the IPCC Special Report: Emissions Scenarios (SRES) B1 scenario presented in previous assessment reports.

RCP 4.5 was developed using the Global Change Assessment Model (GCAM), a fully-integrated economic model that jointly considers land use, hydrology, costs of emissions, and other economic factors. Changes in these variables are updated at 15 year intervals for 14 regions around the world, constrained by trajectories of population growth and trends in productivity of labor [Thomson et al., 2011].

**4.1.2 RCP 8.5**

RCP 8.5 represents the highest emission scenario presented in the AR5. It is a “business as usual” scenario [Riahi et al., 2011] that builds on the population and technological changes of the 20$^{th}$ century. RCP 8.5 is based on the A2 and A2r scenarios presented in AR3 and AR4, respectively, which previously described the higher end of the IPCC potential emissions spectrum. In this scenario, predictions of growth in the world’s population to 12 billion people coupled with assumptions of slow economic growth and insufficient increases in efficiency result in high energy use and demand. Scarcity of currently-utilized fossil fuels also leads to a greater dependence on more polluting sources of energy such as coal, shale oils, and tar sands.

Like the other RCP scenarios, RCP 8.5 was developed using an integrated economic and climate/energy system model. Initial assumptions regarding economic growth, demographic change, technology, and government policies result in population and economic projections. After a downscaling process to adapt the input to a regional level, these projections influence agriculture and forest management practices, which in turn affect greenhouse gas outputs. As these outputs feed back into and modify the initial conditions of economic, demographic, and technological change, the process is repeated. The following figure from Riahi et al. [2011] provides an excellent schematic of the process used to develop RCP 8.5, and the other RCPs in general.
Figure 4.2. Flowchart of RCP 8.5 development process [Riahi et al., 2011]. Initial conditions and guidelines are first defined, incorporating technological, demographic, and governmental policy assumptions. These feed into population and economic projections and are subsequently downscaled to characterize their spatial extent. Results are processed by agricultural and forest models, which are then entered into coupled economic and climate models. The outputs of these coupled models influence the assumptions made at the beginning of the simulated year, and the process begins anew.
4.2 Model Scenario Development - Climate

Several characteristics of the future climate will have a significant impact on the hydrologic cycle, including increased mean temperature, increased volume of precipitation, and elevated atmospheric CO$_2$ concentrations. Various ways exist to incorporate these changes into hydrologic modeling studies. Many of the previously mentioned studies [Bouraoui et al., 2004; Chaplot, 2007; Eckhardt and Ulbrich, 2003; Dix et al., 2009; Githui et al., 2009; Xu et al., 2009] are notable for their methods of future climate scenario development. These works utilized diverse strategies. For example, estimations of the potential change in temperature and precipitation have frequently been created using GCM model output [Githui et al., 2009; Wu et al., 2012; Xu et al., 2009] or other sources of information such as IPCC technical reports [Ficklin et al., 2009; Ficklin et al., 2010]. Sections 4.2.1 and 4.2.2 below detail the processes behind the development of these inputs as well as common concerns or challenges for each method and their implications for this research.

4.2.1 Changing Precipitation and Temperature - Using GCM Predictions

Several studies have used GCM model predictions to develop future scenarios for a variety of land uses and climates [Jin and Sridhar, 2012; Wu et al., 2012; Xu et al., 2009]. GCMs are an attractive source of future climate information because they offer time series data at locations across the globe. However, this data is not often suitable for regional or finer-scale hydrological model input without some modification. GCM simulations are run at a coarse resolution in order to maintain computational efficiency, and there is a discrepancy between this scale and the much smaller scale at which more focused watershed-scale climate change studies are conducted. To adjust for these differences, model output is often “downscaled” by developing mathematical relationships between GCM-simulated historical data and observed data in the study watershed and applying these relationships to future time series. Section 7.2 of this document contains a more in-depth treatment of general downscaling methods as well as those chosen for this research.
Xu et al. [2009] developed four future climate scenarios using downscaled GCM output from four models (CGCM2, CCSR, CSIRO, HadCM3) for the 122,000 km$^2$ headwater catchment of the Chinese Yellow River Basin. Delta change and statistical downscaling techniques were used, which yielded similar general trends but not exact correspondence. GCM model output for the region also agreed on significant increases in maximum and minimum temperature values and smaller increases in precipitation.

In Wu et al. [2012], climate change scenarios were developed using downscaled GCM climate predictions from six models: BCCR-BCM2, CCSM3, CSIRO3.0-Mk, CSIRO-Mk3.5, INM-CM3.0, and MIROC3.2. Downscaling was performed using a modified change factor method set forth by Hay et al. [2011]. Plant stomatal conductance within SWAT was also changed by modifying the air CO$_2$ concentration to simulate the effects that increased CO$_2$ concentrations would have on vegetation.

Githui et al. [2009] developed climate scenarios in several different ways for the 12,709 km$^2$ Nzoia river basin in Kenya. The basin’s land use is mostly agricultural with some dense population centers. Model output of six GCMs (GFDL, ECHAM4, CSIRO, HadCM3, CCSR) and the IPCC AR3 report were used to define a set of scenarios. Downscaling was not performed due to a lack of data needed to develop relationships between the global and watershed scale. A moderate number of rain gauges were used to force the simulation, and high NSE coefficients of 0.76 for the calibration period and 0.74 for the validation period indicated good simulation fit with observed streamflow.

This review led to the choice of an ensemble of six GCMs as a source of future climate data and two downscaling techniques to adapt that data to the UBWC watershed. Wide uncertainty exists in the range of GCM output, and some doubt GCM model accuracy [Koutsoyiannis et al., 2008]. Therefore, we believe that using multiple GCMs and downscaling techniques will help with capturing this uncertainty, as supported by the GCM ensemble methods of Githui et al. [2009], Jin and Sridhar [2012], and Wu et al. [2012]. It also may allow for conclusions that are not GCM choice dependent, as some previous studies [Franczyk and Chang, 2009; Gosain et al., 2006; Hanratty and Stefan, 1998] have relied solely on one GCM as input. While utilization of multiple downscaling techniques is less common [Xu et al., 2009], two are included in this research in order to
provide a basis of comparison with commonly used methods (quantile mapping or QM) and a robust technique (regression) that adequately captures means as well as high daily rainfall variability [Chandler and Wheater, 2002].

4.2.2 Changing Precipitation Patterns and Temperature – Other Methods

While GCM-based methods are perhaps the most commonly used, several other methods for modeling future scenarios are present within the literature. Some studies [V Chaplot, 2007; Ficklin et al., 2009] have used weather generators to develop climate change forcings. Others modified existing time series that exhibited strong to reflect future trends [Bouraoui et al., 2004].

Bouraoui et al. [2004] ran SWAT for 34 years in a watershed in Finland using observed climate data as the climate change scenario. A de-trended version of that data was used as a baseline scenario. Nutrient loading to surface water was found to increase slightly for the observed scenario. The calibration period of 34 years was also longer than most and the NSE value for flow prediction was found to be 0.81, indicating that the simulation was representative of the actual flow.

Chaplot [2007] considered four different levels of increasing rainfall amounts (+10%, +20%, +30%, +40%), along with different sets of CO₂ and temperature increases. Daily rainfall amounts were generated for a 100 year reference scenario, and scaled up by a percentage each year for future scenarios (for example, precipitation was increased by 0.37% per year for the +40% scenario).

Ficklin et al. [2009] utilized a stochastic weather generator (LARS-WG) to create a fifty-year set of precipitation and temperature inputs to examine changes in streamflow under IPPC AR4-inspired estimates of +1.1° C to 6.4° C increases in temperature, 0%, 10%, and 20% increases in precipitation, and changes in CO₂ concentration from 550 ppm to 970 ppm. These changes were represented by increases to the mean statistics used by the weather generator.

Each method by itself contained assumptions or simplifications that may render it unsuitable for unmodified application to the UBWC. For instance, the weather generator method utilized by Ficklin et al. [2009] was beneficial in that it allowed for the
evaluation of a range of variability within a future scenario, lessening the vulnerability of the results to particularly extreme events or time periods. Unfortunately, that method does not allow for examination of trends within the output. Chaplot [2007] addressed this by modifying a generated timeseries input to have a non-stationary mean, but climate variability did not change with this method. To make up for these previous deficiencies, this research will utilize downscaled GCM timeseries input as well as stationary weather generator inputs. This combination of forcings will enable evaluation of any trends or changes in extremes that can be captured only through non-stationary data, while still allowing for longer-term simulations that can demonstrate the full potential variability of climate.
5 Land Use Change

Land use affects watershed response in a multitude of ways. It controls infiltration rates, the amount of runoff generated, and amounts of evaporation and transpiration, affecting the pathways that water takes across the landscape. It also has a significant impact on surface water quality with regards to the types of contaminants that may be present and their quantities [Tong and Chen, 2002].

Land use change within watersheds is common. From the period of 1950-2000, there were significant increases in the area of suburban land across the United States, and the area of agricultural land decreased east of the Mississippi due to improvements in farming technology and abandonment of less productive land [Brown et al., 2005]. Population change also shapes the land surface within a watershed. For example, Delaware County, OH, which comprises the majority of the area of the UBWC watershed, is currently projected to expand from a 2012 population of 181,000 to 282,000 by 2040 [He, 2013]. Much of the current population of Delaware County resides in an area classified as low-density urban land. As such, it is expected that this land use will expand, decreasing the area currently occupied by agriculture. The historical population of the county and future projections for its population is shown in Figure 5.1 below.
Changes in watershed land use are influenced by population growth, shifts in crop planting caused by fluctuating markets, conservation efforts, or myriad other reasons. While land use change may sometimes contribute less than climate change to alterations in the hydrologic cycle [Li et al., 2009], it is still an important factor to consider in any long-term study of a watershed.

As with climate change, a number of studies have focused on the response of streamflow to land use change [Fohrer et al., 2002; Ghaffari et al., 2010; Jha et al., 2010; Schilling et al., 2008]. Others have studied the effects of NPS pollution on lakes under changing land use [Lin et al., 2009]. Section 5.1 below weighs the relative merits of several land use change techniques in order to find those best suited for the UBWC.
5.1 Model Scenario Development – Land Use

Although land use change is common and widespread, it is often difficult to exactly quantify and assess these changes due to the heterogeneity of the land surface and the difficulty of characterizing diverse land uses and their features. The literature reveals a variety of methods that have been used to evaluate the effects of land use change on defined response variables. The studies reviewed focus on SWAT, as it is the model chosen for this research.

In previous works, many investigators have utilized Landsat images to develop watershed land use maps, which are then used in hydrologic modeling frameworks such as SWAT. Ghaffari et al. [2010] examined land use change in a 4,354 km² semi-arid basin in Iran using SWAT. Land use scenarios were defined using Landsat satellite images and old aerial photographs of the study watershed. As only six different land covers were identified, this technique may be more difficult to apply for more diverse or smaller watersheds.

Lin et al. [2009] studied the effects of forest to pasture and urban conversion on nutrient loading to a large lake outside of Atlanta, Georgia. Land use maps of the watershed were developed from the NLCD. Total phosphorus loading increased, as a result of 50% and 225% increases in pasture and urban land use areas respectively from 1992 to 2001.

Two similar studies examined the agricultural aspect of land use change in Midwestern watersheds [Jha et al., 2010; Schilling et al., 2008], with a crop-specific focus. Jha et al. [2010] found conversion of approximately 6% of the Squaw Creek watershed’s area from grassland to row crops potentially increased nitrogen loading to area surface water by 7%-48%. SWAT model results indicated that conversion of certain areas to perennial grasses could potentially significantly decrease watershed nitrogen loading. While this is unsurprising, a key result indicated that conversion of the watershed’s highly erodible lands to perennial grasses would lead to the greatest reduction in nitrogen loading (over converting row crops in the upper basin or converting all rows crops in the floodplain).
Schilling et al. [2008] found SWAT results confirmed correlations between increased acreage planted with corn and observed decreases in watershed evapotranspiration and increases in streamflow. The overall goal of the study was to assess how planting of three potential biofuel crops (corn, warm season grasses, and cool season grasses) would affect the hydrologic cycle and water quality within the watershed. To model expanded corn production, grasslands in the USDA Conservation Reserve program were converted to corn, with several scenarios representing incremental increases in the amount of corn. Grassland scenarios also followed an incrementally increasing strategy. Conversion of highly erodible land to grasslands was found to greatly reduce sediment erosion as well as nitrate-nitrogen and phosphorus loading. In general, water quality was found to improve with expansion of grasslands.

Another method to simulate the effects of land use change involves the recently added SWAT land use update module, described in Pai and Saraswat [2011]. This function allows the user to change the area of one or several HRUs to reflect increases in the size of a specific land use. Several studies have already incorporated non-static land uses into their land use change simulations [Castillo et al., 2014; Koch et al.; Strauch et al., 2013]. While this does allow SWAT users to simulate changing land use, they must alter the size of existing HRUs; new HRUs are not allowed to be created. It is mentioned here to describe a potential avenue of future work on land use change within the study catchment.

Overall, a good scenario definition is essential to a land use change study. Using NLCD data is a popular method of comparing different years’ land use; however, a 14 year span with four data points (1992, 2001, 2006, 2011) is currently available within the UBWC, which creates a limited time frame to draw assumptions about change. NLCD data is also approximately 75% accurate on average, introducing additional uncertainty [Wickham et al., 2013].

Other methods have drawbacks as well. Aerial photographs also are a source of land use change data, but these may require greater amounts of analysis and careful decisions in order to consistently and accurately classify land use. Moreover, SWAT was
developed with NLCD data in mind, and other land use data may not fit well into SWAT categories and land use assumptions as a result.

As a result of this review, it is apparent that for complex watersheds such as the UBWC, predicting land use with aerial photographs is time-consuming and subject to individual interpretation and assumptions that may not be widely applicable. Options like the SWAT Land Use Change (LUC) module offer promise, but may require more land use input data than is currently available to offer more than a general result.

Although land use change in the UBWC is undoubtedly significant, the majority of the watershed will likely retain its agricultural characteristics for some time to come, as shown by the leveling off of the change in low-density urban land shown in Table 3.1. Because agricultural land is one of the largest contributors to NPS pollution, this signifies that shifts in management practices may have a greater effect on NPS pollution than conversion of a small percentage of the land to different purposes. NPS pollution is the focus of this work. Accordingly, scenarios that focus on shifts in types of crops grown and their management will serve as the basis of the land use change presented by this research. An in-depth analysis of the potential avenues of agricultural management change is provided in Section 6.2.
6 Coupled Land Use and Climate Change

Land use change and climate change both have the ability to significantly influence hydrological and biogeochemical cycles. When combined, their effects may offset or exacerbate watershed processes, dependent on local or regional conditions, often making joint examination of these factors an important consideration in a long-term watershed study. There is a relatively small amount of research using SWAT that examines coupled effects of climate and land use change, all of which apply different strategies to assess the coupled interaction [Franczyk and Chang, 2009; Li et al., 2009; Park et al., 2011; Wang et al., 2008; Wilson and Weng, 2011].

6.1 Expansion of Urban/Suburban Areas and Shifts in Agricultural Management

Some studies have combined land use change and climate change predictions in order to obtain a comprehensive picture of future conditions. Wilson & Weng [2011] used Markov chain modeling to forecast land use changes 20 years into the future based on 1990, 2000, and 2010 Landsat images of a mostly urban watershed within the Chicago metropolitan area. Coupling this with climate change simulations forced with downscaled CMIP3 data indicated changes in phosphorus and sediment loadings to area surface waters.

Li et al. [2009] used SWAT to model the effects of land use change on the agricultural Heihe River basin in China. The watershed is moderate in size with an area of 1506 km² and has an elevation change of approximately 1500 meters over its area. Four coupled land use and climate change scenarios were created based on combinations of 1985 and 2000 land use maps and 1981-1990 and 1991-2000 climate. Decreases in runoff were found under the future climate scenarios. These were attributed mainly to climate change rather than land use change. Approximately 3% of the land area changed
in land use from 1985 to 2000 so the results may not be widely applicable.

Wang et al. [2008] used similar combinations of past land uses and climates to examine land use change in a mountainous Chinese watershed. As in Li et al. [2009], past trends in the study area’s climate were used to determine the effect of climate change on the water cycle within the watershed. Land use scenarios included simulation of the complete change of forested area to grassland and vice versa.

Another study [Franczyk and Chang, 2009] primarily focused on alterations to runoff under future climate and several land uses. The authors used statistically downscaled ECHAM model output to study the Rock Creek basin in Oregon, a basin that has undergone rapid expansion of urban areas within the past twenty years. Four land use scenarios were defined for the study area: baseline, compact, sprawl, and planned. Sprawl scenarios were found to cause the greatest absolute change in baseline runoff. Changes in runoff were amplified by combinations of sprawl and climate change scenarios.

Fewer watershed studies have incorporated both non-stationary land use and climate change forcings compared to land use or climate change alone [Franczyk and Chang, 2009; Li et al., 2009; S Wang et al., 2008]. Of these, only one [Wilson and Weng, 2011] focused on a Midwestern watershed with row crops, and it was relatively urban (only 13% agricultural land use in 2010). That study additionally drew conclusions regarding future NPS pollution levels from analysis of single years of simulation in 2010, 2020, and 2030, potentially allowing the results to be influenced by the variation inherent in climatic cycles. Like that of Bouraoui et al. [2004], the methods of Li et al. [2009] and Wang et al. [2008] rely on significant observed trends within a study area’s precipitation record, which is not observed for the UBWC. Wang et al. [2008] additionally used a complete conversion of grassland to forest and the reverse as land use change scenarios, indicating a more general assessment. In comparison, Wilson and Weng [2011] and Franczyk and Chang [2009] developed more rigorous land use change scenarios; however, their methods concerned urban catchments and are therefore not considered to be well-suited to the UBWC.
6.2 Coupled Land Use and Climate Change – Shifts in Agricultural Management

Management has the potential to interact with several aspects of a watershed, the most important of which are soil and water quality. Beneficial effects of crop rotation with regards to disease reduction [Krupinsky et al., 2002; Peters et al., 2003], increases in soil nutrients [Havlin et al., 1990], yields [López-Bellido et al., 1996], and soil quality have been extensively documented [Bullock, 1992]. The positive effects of winter cover crops on soil and water quality have also been assiduously studied [Dabney et al., 2001; Teasdale, 1996]. However, cover crops do not always align with farmer’s economic goals and may not contribute enough N to soil to obviate the need for N fertilizer [Mallory et al., 1998]. As a result, adoption of cover crop practices has been slow. Forage, legumes, or grasses that offer little short-term economic benefit and may have high initial investments [Snapp et al., 2005], as opposed to winter wheat, which can serve as both a cover crop and a cash crop, and is more attractive as a result.

The corn-soybean-winter wheat rotation is common in Ontario, where the wheat serves to improve soil structure, disrupt soybean pathogens and parasites, and reduce soil erosion [Schaafsma, 2002]. As reduced soil erosion and cover crops have been shown to improve water quality, it is possible that similar effects may be observed in the study watershed with changes in the current crop rotation. To evaluate the effects of adding winter wheat to the typical corn-soybean rotation in central Ohio, the operations schedule detailed in Table 6.1 below will be implemented in SWAT.
Table 6.1. Operations schedule used for testing effects of winter wheat inclusion in a corn-soybean Crop Rotation

<table>
<thead>
<tr>
<th>Year</th>
<th>Operation</th>
<th>Timing (Heat Unit Fraction)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Tillage</td>
<td>0.10</td>
</tr>
<tr>
<td>-</td>
<td>Planting (Corn)</td>
<td>0.15</td>
</tr>
<tr>
<td>-</td>
<td>Fertilization (N and P)</td>
<td>0.15</td>
</tr>
<tr>
<td>-</td>
<td>Fertilization (Side Dress N)</td>
<td>0.40</td>
</tr>
<tr>
<td>-</td>
<td>Harvest/Kill</td>
<td>1.20</td>
</tr>
<tr>
<td>2</td>
<td>Planting (Soybeans)</td>
<td>0.10</td>
</tr>
<tr>
<td>-</td>
<td>Fertilization (Limited N, P)</td>
<td>0.15</td>
</tr>
<tr>
<td>-</td>
<td>Harvest/Kill</td>
<td>1.20</td>
</tr>
<tr>
<td>-</td>
<td>Planting (Winter Wheat)</td>
<td>0.90</td>
</tr>
<tr>
<td>-</td>
<td>Fertilization (50% of N, P)</td>
<td>0.01</td>
</tr>
<tr>
<td>-</td>
<td>Remaining 50% of N</td>
<td>0.50</td>
</tr>
<tr>
<td>3</td>
<td>Harvest/Kill</td>
<td>1.20</td>
</tr>
</tbody>
</table>

It is expected that the mean phosphorus export to surface water will be reduced as a result of the reduction in rainfall and runoff energy that cover crops provide. Changes in nitrogen uptake due to plant growth going into the winter may also have the ability to decrease the amount of nitrate available for transport from the soil column. Evaporation could also potentially be increased during these periods, resulting in decreases to the amount of soil water which would decrease tile flow and its large export of nitrate to surface water.

It is important to note the potential effect that increases in CO$_2$ concentration may have on the water cycle. For instance, research has shown that elevated CO$_2$
concentrations decrease stomatal conductance of plants, reducing evapotranspiration and increasing soil moisture [Drake et al., 1997]. Other research has posited that agricultural and pasture areas with be minimally affected by this change due to canopy resistance feedbacks [Field et al., 1995] or that increases in LAI and changes in vapor pressure deficits may more than offset the effects of reduced stomatal conductance [Dieleman et al., 2012]. Due to this conflict in potential effects, changing CO₂ concentrations were not studied here but will be addressed in future research.

The potential effects of climate change on crops have been extensively studied over the past thirty years [J W White et al., 2011]. On the other hand, no study using SWAT (or a similar coupled hydrologic/biogeochemical model) has to our knowledge combined climate change scenarios with shifts in agricultural management practices such as crop rotation or conservation tillage in order to study NPS pollution. The objective of this research is to begin to address this gap in the literature. To address these shortcomings, this research will couple stationary climate forcings developed from downscaled GCM predictions with four generalized management scenarios that represent current and potential changes in land use. The simulations will be forced with the weather generation option available in SWAT, utilizing statistics developed from three periods within the 2006-2100 CMIP5 [Taylor et al., 2012] output of six GCMs.
7 Methods

7.1 Introduction to the Experiments Run

Three avenues of research are presented within this chapter. The first, described in Section 7.2, defines scenarios designed to examine the effects of climate change alone on the UBWC watershed. Section 7.3 introduces and provides extensive detail on three potential agricultural management scenarios set up to test how changes to current management schemes may affect NPS pollution and watershed processes. Lastly, Section 7.4 describes the setup of simulations intended to evaluate the coupled effect of management and climate change on watershed functions.

The experiments performed in this research utilize two methods of precipitation input: timeseries and weather generation. Use of timeseries input allows for dynamic precipitation and temperature inputs. The timeseries input utilized in the climate change only simulation set was developed by adapting daily CMIP5 GCM output using two downscaling techniques, regression and quantile mapping. In contrast to timeseries input, generation of climate inputs allows simulations to capture the full spectrum of climate variability and avoid the potential undue influence of any extreme events that may be disproportionately represented in a shorter dataset. For this reason, the agricultural management change only simulations and the coupled management and climate change simulations used forcings supplied by the SWAT weather generator. Representation of future climates was accomplished by modifying the weather generator input files to reflect climate change scenarios, using statistics calculated from the QM downscaled RCP 4.5 and RCP 8.5 inputs.
While the area of specific land use categories (e.g. urban low density, forested, etc.) were held constant for this research, four different sets of management practices were applied to agricultural areas. These sets include a reference scenario intended to represent the current management and crop distribution within the UBWC, a scenario in which winter cover crop of rye is planted between the main crops within the reference rotation, a scenario in which the overall watershed crop rotation switches from a predominantly corn–soybeans rotation to that of corn–soybeans–winter wheat, and a scenario in which rye cover crops are planted between the main crops in the corn-soybeans-winter wheat rotation. Table 7.1 provides a summary of the experiments conducted and their most relevant characteristics, while further details are given in Sections 7.3.1 and 7.3.2.
Table 7.1. Summary table of experiments run to test effects of climate change only, management change only, and coupled climate and management change.

<table>
<thead>
<tr>
<th>Experiment Type</th>
<th>Scenario Name</th>
<th>Periods of Simulation</th>
<th>Climate Forcing</th>
<th>Management</th>
</tr>
</thead>
<tbody>
<tr>
<td>Climate Change Only</td>
<td>RCP 4.5 &amp; RCP 8.5 – QM Downscaling</td>
<td>2006-2100</td>
<td>Downscaled RCP 4.5 &amp; RCP 8.5 timeseries input</td>
<td>Representation of current practices</td>
</tr>
<tr>
<td>Management Change Only</td>
<td>Baseline Climate Reference Mgmt</td>
<td>NA</td>
<td>Generated 1990-2006 climate (from SWAT observed database)</td>
<td>Representation of current practices</td>
</tr>
<tr>
<td></td>
<td>Baseline Climate Reference Mgmt w/ Cover Crops</td>
<td>NA</td>
<td>“ “</td>
<td>Representation of current practices with rye cover crop between cash crops</td>
</tr>
<tr>
<td></td>
<td>Baseline Climate Wheat Mgmt</td>
<td>NA</td>
<td>“ “</td>
<td>Equal corn, soybeans, and wheat cultivation</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Continued
Table 7.1 continued

<table>
<thead>
<tr>
<th>Coupled Management and C.C.</th>
<th>Baseline Wheat Mgmt w/ Cover Crops</th>
<th>Periods 1,2,3: RCP 4.5 and 8.5 Reference Mgmt with Cover Crops</th>
<th>Generated climate from mean statistics of 6 GCMs</th>
<th>Equal corn, soybeans, and wheat cultivation with rye cover crop between cash crops</th>
</tr>
</thead>
<tbody>
<tr>
<td>“ “</td>
<td>NA</td>
<td>Periods 1,2,3: RCP 4.5 and 8.5 Reference Mgmt</td>
<td>Representation of current practices</td>
<td></td>
</tr>
<tr>
<td>“ “</td>
<td>“ “ “</td>
<td>Periods 1,2,3: RCP 4.5 and 8.5 Reference Mgmt with Cover Crops</td>
<td>“ “</td>
<td>Representation of current practices with rye cover crop between cash crops</td>
</tr>
<tr>
<td>“ “</td>
<td>“ “ “</td>
<td>Periods 1,2,3: RCP 4.5 and 8.5 Wheat Mgmt</td>
<td>“ “</td>
<td>Equal corn, soybeans, and wheat cultivation</td>
</tr>
<tr>
<td>“ “</td>
<td>“ “</td>
<td>Periods 1,2,3: RCP 4.5 and 8.5 Wheat Mgmt with Cover Crops</td>
<td>“ “</td>
<td>Equal corn, soybeans, and wheat cultivation with rye cover crop between cash crops</td>
</tr>
</tbody>
</table>
7.2 *Climate Change Only Simulations*

The necessary precipitation and temperature inputs used by SWAT were downscaled from daily output of the World Climate Research Program's (WCRP's) Coupled Model Intercomparison Project phase 5 (CMIP5) multi-model dataset. This dataset is a compilation of many of the world’s leading GCMs run using defined Intergovernmental Panel on Climate Change (IPCC) scenarios based on a spectrum of possible carbon emissions forecasts.

As mentioned previously, climate forcings within a SWAT simulation can be either supplied (observed data) or generated. Using statistics relevant to the study watershed, SWAT’s built-in weather generator WXGEN is able to generate climate forcings. Relative humidity, wind speed, and solar radiation were generated based on statistics developed from 1990-2006 weather data available in the SWAT weather station database due to their unavailability for the UBWC.

To match the resolution of the CMIP5 temperature and precipitation inputs with the scale of the study watershed, downscaling was performed for three precipitation stations located near the UBWC at Centerburg, Mt. Gilead, and Westerville, and for daily maximum and minimum temperature data taken from the same locations in Centerburg and Westerville. Two downscaling methods were tested: delta change and regression. The outputs of these methods are further described in Section 8.2 and Section 8.3.

To study climate change effects on nutrient loading and runoff, the general simulation setup described above in Section 3 was used. For corn, fertilizer was applied as 112 kg/ha elemental N at planting and 56 kg/ha elemental N sidedress (defined as an application of fertilizer between rows of growing crops) in a split application according to a similar study performed in the UBWC by Nair et al. [2011], who utilized total fertilizer amount applications recommended by Vitosh et al. [2000]. Automatic applications of fertilizer under moderate levels of nutrient stress were kept for other simulated plants such as hay and fescue. As described in Section 2.8.4, default automatic fertilization schemes in SWAT apply fertilizer when plants reach a nitrogen stress level that causes actual plant growth to decline to 75% of potential. The heat units to maturity values for each plant were adjusted according to the amount of heat units available in the
UBWC’s growing season (see Section 3.2.5). Furthermore, to avoid the effects of uncertain initial conditions, the first ten years of downscaled precipitation and temperature inputs were duplicated and added onto the timeseries used to force the model to allow the simulation to “warm up”.

7.2.1 CMIP 5 Scenarios Utilized – RCP 4.5 and RCP 8.5

To capture the wide range of uncertainty inherent in future climate predictions, an ensemble of GCMs output from several models within the CMIP5 dataset was used. While validation of individual GCM CMIP5 results on past climate periods indicates general overestimation of warming trends, the model ensemble average is more accurate [Kim et al., 2012], reinforcing the decision to use multiple GCMs.

7.2.2 Downscaling of GCM Data – Quantile Mapping and Regression Methods

In order to run efficiently, GCM models such as those used in CMIP5 must simulate global climate at a coarse resolution of approximately one degree of latitude by one degree of longitude. For finer modeling purposes, this low-resolution data must be downscaled so that it is valid at a much smaller resolution that is appropriate for the study watershed. Downscaling is especially useful in climate change scenarios as it helps to compensate for the “always wet” tendency of GCMs. It also corrects biases towards higher or lower precipitation values that may be present at a larger scale.

A wide variety of downscaling methods exist, many of which have been applied to GCM inputs for use in SWAT. As downscaling procedures can manipulate the timing and magnitude of patterns in precipitation and temperature, the selection of a downscaling technique can have noticeable effects on the final simulation output. The most common of these techniques are change factor (delta change), in which changes in a future climate are projected onto a baseline climate; quantile mapping, in which relationships are developed to match the quantiles of GCM-simulated data to those of an observed data set, and statistical downscaling (SDS), where large-scale climate variables are used as indicators to predict meteorological data at a point. Delta change is discussed here because quantile mapping is considered to be a form of delta change.
Previous work has provided examples of downscaling techniques frequently used for hydrological simulations. For example, Abbaspour et al. [2009] used a change factor methodology to downscale CGCM3 model output for a study of Iran’s water resources, where the mean monthly GCM data was divided by the mean monthly observed data for rainfall and daily amounts were multiplied by the resulting ratio. This method was found to work well for both temperature and precipitation, with the exception of small rainfall events in wet regions and intermediate to large events in dry regions, which were underpredicted and overpredicted, respectively. Wu et al. [2012] also used a change factor methodology, calibrated on a GCM-simulated 1961 to 1990 assumed baseline period. Although this method eliminated potential bias that would be introduced by comparing results of GCM-forced simulations with those forced with observed inputs, no comparison between the 1961-1990 GCM simulations and observed data was given. Xu et al. [2009] used delta change and SDS methods to adapt outputs from four GCM models. When comparing downscaled input to observed input of 1961-1990, the SDS method fared worse in reproducing the duration of dry periods; however, the authors noted greater general confidence in the SDS method due to the simplicity of the delta change method and its direct reliance on often incorrect GCM output. It was also noted that while downscaling is important, the variability between GCMs can be much larger than hydrologic model uncertainty or the difference between downscaled and non-downscaled climate forcings.

Overall, review of the previous work demonstrated good results with both the complex SDS method and simpler procedures such as the change factor method. To further examine differences between downscaling methods, this research utilizes two downscaling methods. The first, a modification of the quantile mapping (QM) method detailed by Teutschbein and Seibert [2012], was used to screen for representative GCMs in order to find candidates for the second, regression-based method. The QM method entails calculating the distributions of temperature and precipitation for both the baseline and GCM data, and scaling the future GCM data appropriately. For instance, the 75th percentile intensity of a storm in the observed data will correspond to that of the GCM data; so when a 75th percentile storm is encountered in the GCM data it is altered to
match the baseline $75^{th}$ percentile storm. Figure 7.1 shows a general illustration of this technique.

**Figure 7.1.** Illustration of the quantile mapping downscaling technique [Walsh, 2011]. The $90^{th}$ quantile of the GCM value is adjusted to match that of the $90^{th}$ quantile observed value.

The three weather stations used as a source of data are in close enough proximity that their temperature and precipitation values are related. Data was resampled according to Wilby *et al.* [2003], in order to maintain these relationships (areal averages) between the three precipitation and two temperature weather stations. Lastly, a bias correction term was introduced for the month of January in order to fix a high mean monthly rainfall value for GCM inputs.

The second downscaling method using in this research was a regression method described by Chandler and Wheater [2002]. This method relates GCM grid-scale
predictors of climate with local observations in order to develop regression functions which are then applied to GCM data.

Along similar lines, a generalized linear model (GLM) was developed using temperature, sea level pressure, geopotential heights, relative humidity, specific humidity, zonal and meridional winds, divergence, and vorticity (a variable describing the spinning motion near a point) as indicators of precipitation and temperature values. The CMIP5 data was interpolated to conform to a 2.5 by 2.5 degree grid in order to match National Center for Environmental Prediction (NCEP) historical GCM data.

### 7.2.3 Final GCM Selection

Data from 17 models was initially downscaled using a preliminary version of the QM technique. These models and the groups that developed them are listed below:

**Table 7.2.** All 17 CMIP5 models used in the preliminary QM downscaling technique and their modeling groups and institutes.

<table>
<thead>
<tr>
<th>Modeling Center (or Group)</th>
<th>Institute ID</th>
<th>Model Used</th>
</tr>
</thead>
<tbody>
<tr>
<td>Beijing Climate Center, China Meteorological Administration</td>
<td>BCC</td>
<td>BCC-CSM1.1</td>
</tr>
<tr>
<td>College of Global Change and Earth System Science, Beijing Normal University</td>
<td>GCESS</td>
<td>BNU-ESM</td>
</tr>
<tr>
<td>Centro Euro-Mediterraneo per I Cambiamenti Climatici</td>
<td>CMCC</td>
<td>CMCC-CM</td>
</tr>
<tr>
<td>Centre National de Recherches Météorologiques/ Centre Européen de Recherche et Formation Avancée en Calcul Scientifique</td>
<td>CNRM-CERFACS</td>
<td>CNRM-CM5</td>
</tr>
<tr>
<td>LASG, Institute of Atmospheric Physics, Chinese Academy of Sciences and CESS, Tsinghua University</td>
<td>LASG-CESS</td>
<td>FGOALS-g2</td>
</tr>
</tbody>
</table>

Continued
As regression downscaling techniques were found to consume time and computing resources, the initial QM downscaling method was used to group GCM inputs that displayed similar future climates. As shown in Figure 7.2, much less variability was witnessed in downscaled temperature compared to downscaled precipitation, which is presented in Figure 7.3. Consequently, models were evaluated on the basis of their precipitation input characteristics, which are presented for RCP 4.5 in Figure 7.3 below. Only 17 of the CMIP5 models were examined, as the remainder lacked the characteristics necessary for the regression downscaling method (e.g. geopotential height).
Figure 7.2. Mean monthly temperature for each of 17 GCMs from CMIP5 RCP 4.5 (2006-2100) dataset, with overall mean of each month plotted at the bottom of the figure for RCP 4.5 (blue) and the 1971-1990 observed temperature (black). Of the GCMs available from CMIP5, these had the information necessary to perform the regression downscaling method described in Section 7.1.3. Minimum and maximum daily temperature values were downscaled using a preliminary version of the quantile mapping technique discussed in Section 7.1.2.
Figure 7.3. Mean monthly precipitation for each of 17 GCMs from CMIP5 RCP 4.5 (2006-2100) dataset, with monthly mean of all models plotted at the bottom of the figure for RCP 4.5 (blue) and the 1971-1990 observed rainfall (black). Of the GCMs available from CMIP5, these had the information necessary to perform the regression downscaling method described in Section 7.2.2. Precipitation values were downscaled using a preliminary version of the quantile mapping technique also discussed in Section 7.2.2.

Upon first examination of the downscaled data in Figure 7.3, the trend most readily apparent is a large increase in precipitation amounts during the first half of the year. To pick GCMs that were representative of a broad range of changes in precipitation, the percent change in precipitation from the baseline 1971-1990 in the first half of the year was examined. Of these 17 GCMs, the six GCM models presented in Table 7.3 were chosen as representative of a spectrum of potential change in precipitation. These models were BCC-CSM1-1, IPSL-CM5A-LR, CNRM-CM5, IPSL-CM5B-LR, MIROC-ESM-CHEM, and Nor-ESM1-M. For reference, the mean changes forecasted by all 17 GCMs for the first six months of the year were increases of 21% and 25%, with standard deviations of 8% and 9% for RCP 4.5 and RCP 8.5 respectively.
Table 7.3. Mean precipitation change for the first six months of the year for both RCP scenarios. These six models were selected based on the degree of their precipitation changes for use in this research. Percent change of QM-downscaled GCM data (obtained from CMIP5 dataset) from baseline observed mean monthly precipitation during the first half of the year for the six GCMs chosen for this study. The first half of the year was chosen due to significant shifts in its precipitation patterns.

<table>
<thead>
<tr>
<th>GCM Name</th>
<th>RCP 4.5</th>
<th>RCP 8.5</th>
</tr>
</thead>
<tbody>
<tr>
<td>BCC-CSM1.1</td>
<td>+35%</td>
<td>+36%</td>
</tr>
<tr>
<td>CNRM-CM5</td>
<td>+18%</td>
<td>+19%</td>
</tr>
<tr>
<td>IPSL-CM5A-LR</td>
<td>+15%</td>
<td>+19%</td>
</tr>
<tr>
<td>IPSL-CM5B-LR</td>
<td>+19%</td>
<td>+22%</td>
</tr>
<tr>
<td>MIROC-ESM-CHEM</td>
<td>+18%</td>
<td>+25%</td>
</tr>
<tr>
<td>NorESM1-M</td>
<td>+6%</td>
<td>+16%</td>
</tr>
</tbody>
</table>

7.3 Land Use/Management Change Only Simulations

To quantify the effects of shifting crop rotations and tillage on water quality, four scenarios were defined: a reference scenario, a reference scenario with a rye cover crop between cash crops, a scenario in which winter wheat replaces a year of soybeans in the default rotation (corn-soybeans-winter wheat), and the corn-soybeans-winter wheat rotation with a rye cover crop planted between the cash crops. Complete details of the scenario management operations including fertilizer application, tillage practices, and planting/harvest heat units are given below.

For these land use change only simulations, climate inputs were generated from the period of 1990-2006 available in the SWAT weather station database.
7.3.1 Reference Scenario

A reference scenario was set up and simulated to provide a basis for comparison. This scenario represents a simplified general pattern of crop rotation and management followed in the UBWC watershed at present. In order to capture the full range of the watershed’s response and avoid under- or overrepresentation of the influence on extreme events, the reference simulation and each succeeding simulation was run for a simulation period of 100 years.

To represent the reference watershed characteristics, a three-year crop rotation of corn–soybeans–soybeans was first defined. The complete operations schedule is provided below in Table 7.4.

Table 7.4. Reference land use change management operations schedule. Year, type of operation, and fraction plant potential heat units achieved at which the operation begins are listed (heat units are defined in Section 3.2.5).

<table>
<thead>
<tr>
<th>Year</th>
<th>Operation</th>
<th>Start Date/Heat Units Fraction</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Till (Chisel Plow)</td>
<td>0.10</td>
</tr>
<tr>
<td>-</td>
<td>Plant Corn</td>
<td>0.15</td>
</tr>
<tr>
<td>-</td>
<td>Fertilization (N and P)</td>
<td>0.20</td>
</tr>
<tr>
<td>-</td>
<td>Fertilization (Side dress N)</td>
<td>0.40</td>
</tr>
<tr>
<td>-</td>
<td>Harvest/Kill</td>
<td>1.2</td>
</tr>
<tr>
<td>2</td>
<td>Plant soybeans</td>
<td>0.10</td>
</tr>
<tr>
<td>-</td>
<td>Fertilization</td>
<td>0.20</td>
</tr>
<tr>
<td>-</td>
<td>Harvest/Kill</td>
<td>1.2</td>
</tr>
<tr>
<td>3</td>
<td>Plant soybeans</td>
<td>0.15</td>
</tr>
<tr>
<td>-</td>
<td>Fertilization</td>
<td>0.20</td>
</tr>
<tr>
<td>-</td>
<td>Harvest/Kill</td>
<td>1.2</td>
</tr>
</tbody>
</table>
Within subbasins, agricultural HRUs were split into 67% soybeans and 33% corn. These HRUs were subsequently assigned the above management schedule starting on year one, two, or three, in order to have the watershed consistently reflect current crop distributions of approximately two-thirds soybeans and one-third corn. Because different HRUs have different soil types and slopes, which HRU is selected for a certain management schedule would have influenced the loading in a given year. Use of the ArcSWAT land use refinement module prevented this complication within simulations.

Default SWAT heat unit fraction values of 0.15 and 1.2 were kept for corn planting and harvest times, but those of soybeans were adjusted qualitatively to 0.10 to represent UBWC soybean growth timing. General farming practices were also considered during definition of the reference scenario. According to USDA-ARS observed data in one subbasin, the side dress application of fertilizer to corn crops generally occurs a month after planting. For the observed temperature data period, one month after planting was found to be approximately 0.40 heat unit fractions.

Tillage is frequently performed as close to the crop planting date as possible in order to minimize the effects of erosion [USEPA, 2013]; as such, tillage was assumed to be performed at 0.10 heat unit fractions, approximately a week before planting in the observed data set. In the UBWC, soil is tilled before corn planting but not before soybean planting [K. King, personal communication, February 27, 2014]. Accordingly, tillage was only scheduled before corn planting.

7.3.2 Cover Crop and Wheat Rotation Scenarios

For the wheat rotation scenario, the winter wheat management schedule was defined as shown in Table 6.1. In this rotation, the corn planting year of the crop rotation remains unchanged from the reference scenario. After the harvesting of soybeans, 50% of Ohio’s winter wheat is planted by October 10 (1994-1998 five year average, [NASS, 1999]). Fertilization of the winter wheat occurs shortly thereafter. To reduce nitrogen losses during the winter, the application of nitrogen fertilizer is split 50-50 between the planting date and the spring.
To simulate the effects of cover cropping practices on the watershed, rye was planted after each cash crop (corn, wheat, or soybeans) and killed before planting of the next year’s crop. The schedule used for this scenario is shown below in Table 7.5:

Table 7.5. Management schedule for the winter wheat rotation with rye cover crops. The timing of each operation is described by the base zero heat units calculated from the start of the year at which it occurs until planting, after which heat units are calculated in terms of the crop’s base growing temperature until the death of that crop. Heat unit concepts are reviewed in Section 3.2.5.

<table>
<thead>
<tr>
<th>Year</th>
<th>Operation</th>
<th>Start Date/Heat Units Fraction</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Kill (rye from Year 3)</td>
<td>0.50</td>
</tr>
<tr>
<td>-</td>
<td>Plant corn</td>
<td>0.15</td>
</tr>
<tr>
<td>-</td>
<td>Fertilization</td>
<td>0.20</td>
</tr>
<tr>
<td>-</td>
<td>Fertilization (Side dress)</td>
<td>0.40</td>
</tr>
<tr>
<td>-</td>
<td>Harvest/Kill</td>
<td>1.20</td>
</tr>
<tr>
<td>-</td>
<td>Plant rye</td>
<td>0.90</td>
</tr>
<tr>
<td>-</td>
<td>Kill rye</td>
<td>0.50</td>
</tr>
<tr>
<td>2</td>
<td>Plant soybeans</td>
<td>0.10</td>
</tr>
<tr>
<td>-</td>
<td>Fertilization</td>
<td>0.20</td>
</tr>
<tr>
<td>-</td>
<td>Harvest/Kill</td>
<td>1.20</td>
</tr>
<tr>
<td>-</td>
<td>Plant winter wheat</td>
<td>0.90</td>
</tr>
<tr>
<td>-</td>
<td>Fertilization (100% of P, 50% of N)</td>
<td>0.90</td>
</tr>
<tr>
<td>3</td>
<td>Fertilization (remaining 50% of N)</td>
<td>0.50</td>
</tr>
<tr>
<td>-</td>
<td>Harvest/Kill</td>
<td>1.20</td>
</tr>
<tr>
<td>-</td>
<td>Plant rye</td>
<td>0.90</td>
</tr>
</tbody>
</table>
7.4 Coupled Climate and Land Use Change

The four management scenarios detailed in the previous section (reference, reference with cover crop, wheat rotation, and wheat rotation with cover crop) were combined with generated weather inputs for three periods within both RCP scenarios to examine the coupled impact of land use and climate change on water quality within the UBWC watershed. Statistics required by the SWAT weather generator (WGN) files were calculated using the WGN macro developed by Gabrielle Boisrame, available on the SWAT website. These calculated statistics are described further in the following section.

For combined land use and climate change simulations, weather statistics were calculated for three periods: of 2006 to 2037, 2038 to 2069, and 2070 to 2100 for both RCP 4.5 and RCP 8.5 inputs.

7.4.1 Weather Generator Inputs

As previously mentioned, SWAT incorporates a built-in weather generator, WXGEN, which can generate climate forcings using statistics relevant to the study watershed. This weather generator was used to simulate RCP 4.5 and RCP 8.5 climate scenarios using the required statistics calculated from the six GCMs used in the QM downscaling method. These statistics include the mean and standard deviation of maximum daily temperature, minimum daily temperature, and monthly precipitation accumulation, as well as the probability of a wet day following a dry day, probability of a wet day following a wet day, and the mean number of days with precipitation in a month.
8 Results and Discussion

8.1 Model Calibration and Validation

Calibration of the SWAT model was an iterative process combining automated and manual techniques. The simulation was first naively parameterized using default values for all values, including agricultural management. Several parameters were then selected based on their potential to influence simulated streamflow, and automated calibration software was used to find values for these parameters that optimized the fit between simulated and observed streamflow as measured by the NSE coefficient. Output values were then examined manually and the parameter ranges were checked to ensure that they met criteria unable to be addressed by the objective function (i.e. some parameter ranges may allow achievement of a high NSE but may negatively influence the simulation in other ways by causing overestimation of low streamflow events, etc.). This method was repeated upon the discovery of and adjustment of other factors that affected the goodness of fit between observed and simulated flow or the realism of other simulated processes. Three variables with limited treatment in the SWAT modeling literature (ESCO, EPCO, and plant heat units to maturity) were singled out due to their significant effects on the hydrologic and plant growth cycles. These three variables are examined further in Section 8.4.

The automated portions of the calibration process were accomplished using the SWAT Calibration and Uncertainty Procedures (SWAT-CUP) 2012 program [Abbaspour et al., 2007a]. SWAT-CUP offers a variety of methods to calibrate parameters, including Generalized Likelihood Uncertainty Estimation (GLUE), Parameter Solution (PARASOL), and others. Of these, the Sequential Uncertainty Fitting (SUFI) 2 method was used. This method is examined in detail in Abbaspour et al. [2007b] and Schuol et al. [2008].
8.1.1 Variables Chosen for Calibration

An initial set of variables was selected for calibration from a review of the SWAT modeling literature [White and Chaubey, 2005] due to their significant influence on factors contributing to streamflow. However, as assumptions changed within the model and non-hydrologic variables were altered (e.g. plant heat units to maturity, which had important implications for the hydrologic cycle as shown in Section 8.4.3) it became evident that additional variables were needed in the calibration. The final set of SWAT model parameters adjusted during the calibration process included:

1. Curve number (CN2): Affects the land surface response to precipitation by partitioning water between infiltration and runoff through assumptions regarding the perviousness of the ground. The curve number method and its implications for infiltration and runoff processes are thoroughly described in Section 2.5.1.

2. Baseflow alpha factor (ALPHA_BF): Controls the rate at which groundwater flow responds to changes in recharge. This variable affects baseflow release to the stream as described by the following equation [Smedema and Rycroft, 1983]:

Equation 8.1. Groundwater Release to the Stream

\[
Q_{gw,i} = Q_{gw,i-1} \cdot \exp[-\alpha_{gw} \cdot \Delta t] + w_{rchrg.sh} \cdot (1 - \exp[-\alpha_{gw} \cdot \Delta t])
\]

Where \(Q_{gw,i}\) is the groundwater flow to the main channel on day \(i\) [mm], \(Q_{gw,i-1}\) is the groundwater flow to the main channel on day \(i-1\) [mm], \(\alpha_{gw}\) is the baseflow alpha factor [days], \(\Delta t\) is the time step [days], and \(w_{rchrg.sh}\) is the amount of recharge entering the shallow aquifer on day \(i\) [mm].

Alpha baseflow factor values of 0.1 to 0.3 indicate slow response to changes in recharge while higher values of 0.9-1.0 represent rapid response [Arnold et al., 2013]. The default value of 0.048 indicates very slow response to changes in recharge. Higher values of the baseflow alpha factor can cause more rapid drop-offs in the contribution of
baseflow to the stream due to their presence in the exponential terms of Equation 8.1. The observed streamflow shown in Figure 8.5 exhibits rapid decreases from high to low values in the summer months. Therefore, inclusion of the baseflow alpha factor in the calibration process was deemed necessary to give the simulation the ability to represent such swift changes.

3. **Groundwater delay time (GW_DELAY):** Sets the delay between when water leaves the soil profile and when it becomes recharge, directly influencing the amount of water available for baseflow. Equation 8.2 below shows this relationship:

\[
R_{w_{\text{chrg},i}} = (1 - \exp[-1/d_{gw}]) \cdot w_{\text{seep}} + \exp[-1/d_{gw}] \cdot R_{w_{\text{chrg},i-1}}
\]

Where \(R_{w_{\text{chrg},i}}\) refers to the amount of water entering the aquifer on day \(i\) [mm], \(d_{gw}\) is the groundwater delay time [days], \(w_{\text{seep}}\) is the amount of water that leaves the bottom of the soil column on day \(i\) [mm], and \(R_{w_{\text{chrg},i-1}}\) refers to the amount of water entering the aquifer on day \(i-1\) [mm].

The default value of the groundwater delay time within SWAT is assumed to be uniform across the watershed and is set at 31 days. As with the baseflow alpha factor, adjustment of the groundwater delay time was found to be critically necessary to simulate the extreme low flows that often occur in the watershed during the summer.

4. **Surface runoff lag coefficient (SURLAG):** Controls lag time between when runoff is generated and when it arrives at the reach. The amount of surface runoff is calculated as follows [Neitsch et al., 2011]:

\[
Q_{\text{surf}} = (Q_{\text{surf}}' + Q_{\text{stor},i-1}) \cdot \left(1 - \exp\left[\frac{-\text{surlag}}{t_{\text{conc}}(i)}\right]\right)
\]
Where \( Q_{surf} \) is the amount of surface runoff that reaches the channel [mm], \( Q'_{surf} \) is the amount of surface runoff generated [mm], \( Q_{stor,i-1} \) is the lagged runoff from the previous day [mm], \( surlag \) is the surface runoff lag coefficient, and \( t_{conc} \) is the time of concentration for the subbasin [hours].

SURLAG varies between 1 and 12, with greater values indicating more rapid release of surface runoff. The default value of 4 for SURLAG allows a moderately slow release of runoff compared with higher values, as shown below in Figure 8.1:

![Figure 8.1](image.png)

**Figure 8.1.** Influence of different values of the surface runoff lag coefficient (SURLAG) on the fraction of runoff released to a stream reach on a given day.

SURLAG was included in the calibration due to this effect on the hydrograph. SURLAG was found to also be an important parameter due to the fact that its influence varies with changes in other parameters. For example, SURLAG was found to have
greater simulation goodness of fit at higher curve number values due to the greater amount of runoff generated by the model.

5. Plant uptake compensation factor (EPCO): Allows user to adjust distribution of plant water uptake from the soil column with depth. Default values of this variable and their implications for the simulated hydrologic cycle are treated in greater detail in Section 8.4.1.

6. Soil evaporation compensation factor (ESCO): Allows user to adjust distribution of soil water evaporation with depth. Along with EPCO, default values of this variable and their effects on the hydrologic cycle are discussed in Section 8.4.2.

7. Tile drain lag time (GDRAIN): Similar to the SURLAG variable described above, the GDRAIN variable sets the amount of time between water entering the tile system and arrival at the reach (hours).

Tile drainage output is separated from lateral flow in SWAT output, but its travel time is calculated in a similar fashion. The following equation shows the effect of the lag time on the amount of lateral or tile flow arriving at the reach:

**Equation 8.4. Lagging of Lateral and Tile Flow**

\[ Q_{lat} = (Q'_{lat} + Q_{latstor,i-1}) \cdot \left(1 - \exp\left(-\frac{1}{TT_{lag}}\right)\right) \]

Where \(Q_{lat}\) is the daily amount of lateral or tile flow discharged to the main channel [mm], \(Q'_{lat}\) is the amount of lateral flow generated in a subbasin on a given day [mm], \(Q_{latstor,i-1}\) is the lateral or tile flow lagged from previous days [mm], and \(TT_{lag}\) is the lateral or tile flow travel time [days].

When tile flow is being lagged, \(TT_{lag}\) is calculated as follows:

**Equation 8.5. Travel Time of Lagged Tile Flow**
Where \( T_{T_{\text{lag}}} \) refers to the tile drain lag time [hours]. This parameter was included in the calibration due to the large contribution of tile flow to the UBWC’s water balance.

8. **Time to drain tiled areas to field capacity (TDRAIN):** Describes the amount of time required to drain saturated soil in tiled areas to field capacity (hours). If the height of the water table is greater than the depth of the simulated tile drains in the soil column, the amount of water going to tile drainage is calculated as follows:

\[
\text{Equation 8.6. Amount of Tile Drainage}
\]

\[
tile_{wtr} = \frac{h_{\text{wtbl}} - h_{\text{drain}}}{h_{\text{wtbl}}} \cdot (SW - FC) \cdot \left(1 - \exp\left(-\frac{24}{t_{\text{drain}}}\right)\right)
\]

Where \( tile_{wtr} \) is the amount of water going to tile drainage from the soil layer [mm], \( h_{\text{wtbl}} \) is the height of the water table within the soil layer [mm], \( h_{\text{drain}} \) is the height of the tile drain above the simulated impervious zone in the soil column [mm], \( SW \) is the water content of the soil profile [mm], \( FC \) is the water content of the soil profile at field capacity [mm], and \( t_{\text{drain}} \) is the tile drain lag time [hours].

*Arnold et al.* [2013] suggests a value of 48 hours or less; accordingly, 48 hours was used as a starting point for GDRAIN in the automated calibration.

8.1.2 **Automated and Manual Calibration Techniques**

As previously described, the calibration process contained both manual and automated components. To summarize the automated calibration procedure, the user first selects the model parameters they wish to calibrate. An objective function is defined to enable assessment of simulation performance for the desired output variable or variables. Next, maximum and minimum parameter values are defined. Users have the option of either replacing parameters with absolute values or using a percent change method, which preserves spatial variation within the model (e.g. not all areas within the watershed have
tile drainage and using absolute values would replace the tile drainage parameters in all files including those that were set to zero). An uncertainty value is assumed for each parameter, and the simulation is run a large number of times, with input parameters changed each run to reflect the effects of uncertainty. After completion of the model runs, simulated values are compared to observations and the performance of the runs are assessed using measures of fit (e.g. NSE, percent bias). SWAT-CUP provides an assessment of the iteration’s performance and lastly recommends new minimum and maximum values for model parameters. Additional iterations can be performed if desired.

A manual review of variables also occurred between iterations of the automated calibration process in order to reduce bias within the streamflow output. For instance, in one iteration of the calibration process, the parameter ranges suggested by SWAT-CUP were followed exactly with no manual adjustment and a final calibrated NSE value of 0.66 was achieved for the simulation. Plotting the best-fit simulated vs. observed values, however, revealed systematic overprediction of low streamflow months, as shown in Figure 8.2 and by the slope of the best-fit line for the simulated vs. observed streamflow values, which was 0.74. The r² value of the simulated vs. observed streamflow was also low at 0.67. This overprediction was a result of using a high SWAT-CUP recommended value for GW_DELAY of 289 days, which resulted in the long-term release of baseflow to the stream and an inability to simulated the low flows that frequently occur during the summer in the UBWC.
Figure 8.2. Simulated vs. observed streamflow for the upper UBWC above the Sunbury, Ohio USGS stream gauge (03228300) during the calibration period of 2000-2004. Calibrated parameters for this iteration were completely chosen using SWAT-CUP recommendations with no manual adjustment, resulting in a high NSE coefficient but overprediction of low flows.

After two additional iterations of the calibration process and manual constraint of the GW_DELAY parameter, simulation of summer low flows was significantly improved, as shown by the slope of the best-fit line plotted in Figure 8.3 below (0.95). The $r^2$ value of the simulated vs. observed streamflow also improved to 0.72 from its previous value of 0.67.
Figure 8.3. Simulated vs. observed streamflow for the upper UBWC above the Sunbury, Ohio USGS stream gauge (03228300) during the calibration period of 2000-2004. In this iteration of the calibration process, the GW_DELAY variable was only allowed to vary within a lower, narrower range (0-30 days), resulting in better prediction of low flows but a lower overall goodness of fit between observed and simulated values (NSE of 0.63).

Although this parameter set more successfully represented low streamflow months, the calibrated NSE value dropped to 0.63 from 0.66, indicating a potential trade-off between overall simulation goodness of fit and representation of low flows.

Upon discovery of the importance of the ESCO and EPCO parameters, additional automated runs were performed with manual adjustment of the range of EPCO and ESCO values in order to attempt to maintain a high NSE coefficient while also accurately simulating water stress on plants during the summer months. Imposing a low range of
0.0-0.40 on the EPCO variable and limiting ESCO to between 0.93 and 1.0 helped the simulation of plant water stress and enabled more realistic simulation of soil evaporation. These changes, however, also lowered the calibrated NSE value to 0.62. It was also necessary to relax the strict requirements on the GW_DELAY variable to maintain an acceptable NSE value. As Figure 8.4 shows, these adjustments resulted in a return to overprediction of low flows, with a slight improvement over the original iteration (best-fit line slope of 0.77 compared to 0.74). The $r^2$ of simulated vs. observed streamflow also declined to 0.66, approximately matching its original value.
Figure 8.4. Simulated vs. observed streamflow for the upper UBWC above the Sunbury, Ohio USGS stream gauge (03228300) during the calibration period of 2000-2004. In this iteration of the calibration process, ESCO and EPCO were confined to ranges of 0.93-1.0 and 0.0-0.40, respectively. Ranges of GW_DELAY were expanded to attempt to maintain a high NSE value, resulting in a return to overestimation of low streamflow months. In spite of this, the best NSE value achieved between observed and simulated values was 0.62.

Table 8.1 shows a summary of the progression in goodness of fit and error statistics from the start to the finish of the calibration process.
Table 8.1. Goodness of fit and error statistics for five iterations of the SWAT model calibration process followed in this research. The slope column gives the slope of a linear best fit calculated for a plot of simulated vs. observed streamflow.

<table>
<thead>
<tr>
<th>Iteration</th>
<th>Notes</th>
<th>NSE</th>
<th>$r^2$</th>
<th>RMSE</th>
<th>PBIAS</th>
<th>Slope</th>
</tr>
</thead>
<tbody>
<tr>
<td>Uncalibrated</td>
<td>No adjustment of parameters</td>
<td>0.46</td>
<td>0.56</td>
<td>2.0</td>
<td>-13.9</td>
<td>0.77</td>
</tr>
<tr>
<td>1</td>
<td>No manual adjustment of ranges</td>
<td>0.66</td>
<td>0.67</td>
<td>1.58</td>
<td>3.9</td>
<td>0.74</td>
</tr>
<tr>
<td>2</td>
<td>Some reduction of GW_DELAY</td>
<td>0.66</td>
<td>0.69</td>
<td>1.58</td>
<td>-3.0</td>
<td>0.84</td>
</tr>
<tr>
<td>3</td>
<td>Large reduction of GW_DELAY</td>
<td>0.63</td>
<td>0.72</td>
<td>1.64</td>
<td>12.2</td>
<td>0.96</td>
</tr>
<tr>
<td>4</td>
<td>Adjusted plant heat units to maturity to realistic values</td>
<td>0.64</td>
<td>0.66</td>
<td>1.64</td>
<td>-10.2</td>
<td>0.75</td>
</tr>
<tr>
<td>5</td>
<td>Introduction and restriction of EPCO, restriction of ESCO</td>
<td>0.62</td>
<td>0.66</td>
<td>1.67</td>
<td>-10.5</td>
<td>0.77</td>
</tr>
</tbody>
</table>

Overall, the calibration process followed serves to highlight the dangers of unguided automated calibration of models, while underscoring the compromises that must be made between adjustments of individual variables for realism and overall representation of the watershed’s monthly streamflow. The following section provides the final values of the calibrated parameters, introduction of the calibration and validation periods used, and a discussion of the overall performance of the calibrated simulation.

8.1.3 Calibration Results

Exactly ten years of daily precipitation data from Jan. 1st, 2000 to Dec. 31st, 2009 were obtained from the NCDC database for the Westerville and Centerburg stations (NCDC IDs 338951 and 331404) near the watershed to use for SWAT model calibration and validation. The first five years of this data were used to force the simulation during the calibration period, while the second five years of data were used for validation. This timeframe was chosen after examining the available streamflow output to find a period containing high and low flows representative of a range of conditions. Streamflow data
was unavailable before 1988, which also constrained the choice of calibration and
validation periods. In addition to precipitation data, the Westerville and Centerburg
weather stations also had daily minimum and maximum temperature data which was
incorporated into the simulation input. Wind speed, solar radiation, and relative humidity
data inputs were unavailable at those weather stations and were therefore generated in
SWAT.

The simulation was calibrated for monthly average streamflow, using daily output
from the Sunbury, Ohio USGS stream gauge (03228300). Calibration was performed for
the upper 25 subbasins above this stream gauge due to the management of flow at the
watershed outlet. It is important to note that the upper and lower portions of the
watershed are not exactly alike; the upper half of the watershed contains less farmland,
hay, and urban land uses than the lower half. Table 8.2 provides a summary of the land
use characteristics for the year 2006 for the upper and lower subwatersheds.

<table>
<thead>
<tr>
<th>Characteristic (2006)</th>
<th>Upper Subwatersheds</th>
<th>Lower Subwatersheds</th>
</tr>
</thead>
<tbody>
<tr>
<td>Row Crops</td>
<td>53.6%</td>
<td>42.3%</td>
</tr>
<tr>
<td>Hay</td>
<td>11.8%</td>
<td>15.7%</td>
</tr>
<tr>
<td>Forest</td>
<td>26.8%</td>
<td>23.1%</td>
</tr>
<tr>
<td>Low-Density Residential</td>
<td>5.4%</td>
<td>8.7%</td>
</tr>
</tbody>
</table>

While these differences in land use may mean that the lower watershed may be
better represented by its own set of calibrated parameters, the parameters chosen (with
the exception of GDRAIN and TDRAIN) are not specifically relevant to any land use. As
a result, the calibration outcome would likely not be disproportionately affected by the
small differences in land use present between the upper and lower subbasins.
Accordingly, the calibrated values for the upper subbasins were extended to the whole watershed.

Each iteration of the calibration process required approximately four to six sub-iterations of 500 model runs in the SWAT-CUP software, between which parameter ranges were updated according to SWAT-CUP recommendations and manually altered if necessary. The calibrated parameter values given in Table 8.3 below are the product of the final iteration of this process. Ranges shown are based their maximum extent throughout all iterations.

Table 8.3. Final ranges and calibrated values of selected SWAT variables. Units are given where appropriate.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Change Type</th>
<th>Minimum</th>
<th>Maximum</th>
<th>Calibrated Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>CN2</td>
<td>Percent</td>
<td>-25%</td>
<td>+9%</td>
<td>-24.0%</td>
</tr>
<tr>
<td>ALPHA_BF</td>
<td>Replace</td>
<td>0.01</td>
<td>1.0</td>
<td>0.54</td>
</tr>
<tr>
<td>GW_DELAY</td>
<td>Replace</td>
<td>1</td>
<td>250</td>
<td>48 days</td>
</tr>
<tr>
<td>SURLAG</td>
<td>Percent</td>
<td>-75%</td>
<td>+300%</td>
<td>1.14</td>
</tr>
<tr>
<td>ESCO</td>
<td>Replace</td>
<td>0.93</td>
<td>1.0</td>
<td>0.93</td>
</tr>
<tr>
<td>EPCO</td>
<td>Replace</td>
<td>0.00</td>
<td>0.40</td>
<td>0.36</td>
</tr>
<tr>
<td>GDRAIN</td>
<td>Percent</td>
<td>-90%</td>
<td>+50%</td>
<td>22.1 hours</td>
</tr>
<tr>
<td>TDRAIN</td>
<td>Percent</td>
<td>-90%</td>
<td>+50%</td>
<td>25.0 hours</td>
</tr>
</tbody>
</table>

The model was validated using the same USGS stream gauge for the periods of 2005-2009, resulting in a NSE coefficient of 0.74. Observed vs. simulated streamflow data for the calibration and validation periods is presented in Figure 8.5 below.
Figure 8.5. Comparison of mean monthly observed streamflow to simulated streamflow at USGS Gauge 03228300 (Sunbury, OH) for the model calibration and validation periods of 2000-2004 and 2005-2009.

The PBIAS value for the calibration period was -10.5\%, indicating that the simulation tended to overestimate streamflow by 10\% on average. For the validation period, this value improves to -2\%. -2\% is well within the satisfactory range of 25\% recommended by Moriasi et al. [2007].

After calibration, it is important to note that the model slightly overestimates summer streamflow for nearly every year. This is likely a result of the automatic calibration’s increase of the GW_DELAY variable, which regulates the days required for water to enter streamflow from the shallow aquifer. Modifying GW_DELAY from a default value of 31 days to 48 days in the calibration process reduced the model’s ability
to simulate shifts from high to low flows, resulting in overprediction. Overall, as the
summer streamflow overestimation was very small, it was deemed acceptable for the
purposes of this study.

Poor results for other months (e.g. March 2002 with a 42% underprediction,
March 2005 with a 251% overprediction) appear to be a result of the simulation’s three
rain gauges failing to capture the spatial variability of the area’s precipitation. While
other sources of rain gauge data were present in the area, they did not have the
recommended length of 50 years required for the regression downscaling technique. The
choice of calibration and validation period was also limited by the length of the Sunbury
stream gauge’s dataset, which begins in 1988.

Before final model calibration, a series of tests were undertaken on streamflow
data for the years of 1990-1992 to determine the optimal soils data, HRU thresholds, and
number of rain gauges and locations for the simulation. Table 8.4 below provides the
simulation input data and the NSE values achieved using that data.

Table 8.4. Effects on simulation goodness of fit of number of rain gauges used to force a
simulation, quality of soils data (STATSGO or SSURGO), and use of temperature data.

<table>
<thead>
<tr>
<th>Soils Data Type</th>
<th>No. of Rain Gauges</th>
<th>Rain Gauge Locations</th>
<th>Uncal. NSE (20% thresholds)</th>
<th>Uncal. NSE (10% thresholds)</th>
<th>Uncal. NSE (1% thresholds)</th>
<th>NSE with Temp. Stations</th>
</tr>
</thead>
<tbody>
<tr>
<td>SSURGO</td>
<td>1</td>
<td>Centerburg</td>
<td>0.67</td>
<td>0.63</td>
<td>0.62</td>
<td>0.67</td>
</tr>
<tr>
<td>STATSGO</td>
<td>1</td>
<td>Centerburg</td>
<td>0.68</td>
<td>0.66</td>
<td>0.64</td>
<td>0.71</td>
</tr>
<tr>
<td>SSURGO</td>
<td>1</td>
<td>Westerville</td>
<td>0.59</td>
<td>0.55</td>
<td>0.54</td>
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</tr>
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<td>0.41</td>
<td>0.42</td>
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Continued
Contrary to expectations, uncalibrated simulation goodness of fit was found to decrease with higher resolution HRU thresholds. Furthermore, increased resolution of soils data did not improve uncalibrated model goodness of fit. With low-resolution STATSGO data, the fit was minimally better with all numbers of rain gauges compared to simulations using SSURGO data, with uncalibrated NSE values being 0.02 higher on average. Geza and McCray [2008] also noted slightly higher uncalibrated NSE values with STATSGO data, but were able to realize higher final calibrated NSE values using the SSURGO soils dataset. For this research, calibration of the simulations was not performed, so it is unknown which soil input can achieve the best result for the UBWC. Overall, the number and location of precipitation gauges used to force the simulation had the greatest effect on simulation goodness of fit. Adding two climate stations with minimum and maximum daily temperature data also improved simulation goodness of fit.
8.2 Downscaling Results - Precipitation

This section compares the most important characteristics of the downscaled precipitation timeseries, including total yearly precipitation, mean monthly precipitation, and the number of wet days per month.

8.2.1 Total Yearly Precipitation

The observed precipitation data from the 1971-1990 baseline period was found to have a mean total annual precipitation of 1037 mm (Centerburg) and a standard deviation of 158 mm. Both of the scenarios examined in this research exhibit an increase from this value for the period of 2006-2100. For the RCP 4.5 scenario, QM-downscaled yearly total precipitation increases on average over the duration of the 2006-2100 period, with a mid-century maximum that levels off towards the year 2100. The average of the 2006-2039 period (Centerburg, Westerville, Mt. Gilead weather stations) is 1054 mm, compared to an average of 1097 mm and 1083 mm for the 2040-2070 and 2071-2100 periods, respectively. This is a smaller increase than that exhibited by RCP 8.5, which shows averages of 1067 mm for the 2006-2040 period, and 1109 mm and 1140 mm for the 2040-2070 and 2070-2100 periods. Unlike RCP 4.5, RCP 8.5 displays no leveling trend; precipitation totals demonstrate an increasing tendency throughout the entire period. The variation in the downscaled input for CMIP5 is plotted below in Figure 8.6 and Figure 8.7 for each model and scenario to demonstrate the variation between GCM inputs and the overall trend in the ensemble mean.
Figure 8.6. GCM model variation in total yearly precipitation with overall mean plotted in black for the RCP 4.5 (2006-2100) scenario.
Figure 8.7. GCM model variation in total yearly precipitation with overall mean plotted in black for the RCP 8.5 (2006-2100) scenario.

8.2.2 Comparison of Observed Precipitation with Downscaled GCM Data

In addition to future scenarios, GCM simulations of the 1971-1990 period are available from the CMIP5 dataset. The QM downscaling technique applied in Section 7.2.2 was applied to 1971-1990 data for the six selected GCMs in order to reveal any biases present in the QM downscaling technique. Comparison of this data is presented below in Figure 8.8:
Figure 8.8. Comparison of simulated GCM 1971-1990 precipitation for the six selected GCMs with observed 1971-1990 dataset. The values shown in the color matrix are the overall monthly means for the 1971-1990 period, with the observed precipitation for 1971-1990 shown for comparison at the top of the color matrix and as the black line on the plot. The blue line indicates the mean of all six downscaled GCMs, while the red line indicates the difference between the observed mean and the mean of all six downscaled GCMs.

Overall, a good fit exists between the mean of the GCM data and that of the observed dataset with the clear exception of August, in which precipitation is overpredicted by approximately 40 mm. This bias will be taken into account during later analysis of simulation results.

8.2.3 Mean Monthly Precipitation

Figure 8.9 and Figure 8.10 show the mean monthly precipitation inputs for RCP 4.5 and RCP 8.5 scenarios compared to the observed simulation. A significant increase in April precipitation occurs for RCP 4.5. This increase expands to March as well in the RCP 4.5 scenario. With the exception of January, wide variability is seen across GCMs
for both climate change scenarios, especially for the months of March, April, August, and December. This is not unexpected as GCMs were chosen on the basis of their variability to represent a wide range of possible changes to precipitation regimes. Such variability, however, reinforces the decision to use an ensemble of GCMs as simulation inputs.

**Figure 8.9.** QM-downscaled RCP 4.5 mean monthly precipitation (mm) for the entire watershed. The values shown in the color matrix are the overall monthly means for the 2006-2100 period, with the observed precipitation for 1971-1990 shown for comparison at the top of the color matrix and as the black line on the plot. The blue line indicates the mean of all six downscaled GCMs, while the red line indicates the difference between the observed mean and the mean of all six downscaled GCMs.
Figure 8.10. QM-downscaled RCP 8.5 mean monthly precipitation (mm) for the entire watershed. The values shown in the color matrix are the overall monthly means for the 2006-2100 period, with the observed precipitation for 1971-1990 shown for comparison at the top of the color matrix and as the black line on the plot. The blue line indicates the mean of all six downscaled GCMs, while the red line indicates the difference between the observed mean and the mean of all six downscaled GCMs.

The choice of downscaling method also affected mean monthly precipitation, as is shown in Figure 8.11 and Figure 8.12 for the regression-downscaled RCP 4.5 and RCP 8.5 precipitation inputs below:
Figure 8.11. Regression-downscaled RCP 4.5 mean monthly precipitation (mm) for the entire watershed. The values shown in the color matrix are the overall monthly means for the 2006-2100 period, with the observed precipitation for 1971-1990 shown for comparison at the top of the color matrix and as the black line on the plot. The blue line indicates the mean of all six downscaled GCMs, while the red line indicates the difference between the observed mean and the mean of all six downscaled GCMs.
Figure 8.12. Regression-downscaled RCP 8.5 mean monthly precipitation (mm) for the entire watershed. The values shown in the color matrix are the overall monthly means for the 2006-2100 period, with the observed precipitation for 1971-1990 shown for comparison at the top of the color matrix and as the black line on the plot. The blue line indicates the mean of all six downscaled GCMs, while the red line indicates the difference between the observed mean and the mean of all six downscaled GCMs.

Both RCP 4.5 and RCP 8.5 regression-downscaled monthly mean precipitation values differ from their QM-method equivalents. Both downscaling techniques show increases to March and April precipitation values. However, the regression downscaling technique results in decreasing December precipitation values from the baseline 1971-1990 period. This is significantly different than the output of the QM downscaling technique, which resulted in an increase to December precipitation. The regression downscaling method also predicts significant increases to August and September precipitation (October as well for RCP 8.5), while the QM downscaling method only predicted increases to August precipitation in both RCP 4.5 and RCP 8.5. Comparison of the QM-downscaled precipitation for the baseline period to observed data showed that the August increase in precipitation is likely an overprediction, casting into doubt the August, September, and October results of the regression downscaling technique. For this reason,
results from this point forward utilized precipitation and temperature inputs of the QM downscaling technique. While in general the results are similar in capturing an overall increase in yearly precipitation, the techniques disagree widely on several months, indicating the great sensitivity of precipitation predictions to the choice of downscaling method used.

8.2.4 Wet Days

The number of QM-downscaled RCP 4.5 and RCP 8.5 precipitation wet days at the Centerburg weather station are compared to baseline mean monthly wet days in Figure 8.13 below.

![Graph showing wet days per month for RCP 4.5 and RCP 8.5 compared to observed values](image)

**Figure 8.13.** Mean wet days per month for the six downscaled RCP 4.5 and RCP 8.5 GCMs selected compared with the observed 1971-1990 precipitation values.
Several seasonal shifts are apparent. With the notable exceptions of July and August, the number of wet days per month decrease throughout the year for both the RCP 4.5 and 8.5 scenarios. Taken with the forecasted overall increases in total yearly precipitation, this represents an increase in mean daily precipitation amount.

8.3 Downscaling Results - Temperature

8.3.1 Downscaled Temperature Comparison to Baseline

In addition to changes in precipitation patterns, the RCP 4.5 and RCP 8.5 scenarios forecast considerable alterations to existing temperature regimes. Two temperature variables were needed to force SWAT: daily maximum temperature (Tmax) and daily minimum temperature (Tmin). Downscaling these variables separately may lead to instances in which Tmax is greater than Tmin; therefore, Tmax-Tmin/2 and Tmax+Tmin/2 were downscaled and then converted back into their components for the quantile mapping downscaling method.

RCP 4.5 predictions for daily maximum and daily minimum temperature, broken down by month, are presented below in Figure 8.14 and Figure 8.15.
Figure 8.14. Mean monthly maximum temperature presented for the six downscaled GCMs, RCP 4.5 scenario. The values shown are the overall monthly means for the 2006-2100 period, with the observed temperature for 1971-1990 shown for comparison at the bottom of the color matrix and as the black line on the plot. The blue line indicates the mean of all six downscaled GCMs, while the red line indicates the difference between the observed mean and the mean of all six downscaled GCMs.
Figure 8.15. Decadal trends for mean monthly maximum temperature in °C, 1970-2095, QM downscaling method. Observed decades are shown in red. The slope of a linear best-fit line calculated for the trend (degrees per year) is shown in the upper right hand corner for each month.

Figure 8.14 and Figure 8.15 illustrate the overall projected trend for RCP 4.5, which is one of steady warming for the rest of the century.

Just as with precipitation, comparison of the GCM-simulated 1971-1990 period with the observed temperature dataset was undertaken in order to reveal potential biases towards higher or lower temperatures that may influence the RCP 4.5 and RCP 8.5 scenarios. Mean monthly maximum and minimum temperatures were compared and are presented in Figure 8.16 and Figure 8.17:
Figure 8.16. Comparison of simulated GCM 1971-1990 maximum temperature for the six selected GCMs with observed 1971-1990 dataset. The black line indicates observed temperature, the blue line indicates mean of the 6 downscaled GCMs’ monthly maximum temperature, and the red line shows the difference between the two.
Figure 8.17. Comparison of simulated GCM 1971-1990 maximum temperature for the six selected GCMs with observed 1971-1990 dataset. The black line indicates observed temperature, the blue line indicates mean of the 6 downscaled GCMs’ monthly maximum temperature, and the red line shows the difference between the two.

8.4 Parameter Sensitivity

SWAT is a complex hydrologic model that contains thousands of variables. Due to a lack of data, most of these variables are left to their default values. Three of these variables, EPCO, ESCO, and plant heat units to maturity were found to have important impacts on simulation output. General sensitivity analyses using incremental values of these variables were conducted. Relevant output is presented below.

8.4.1 EPCO

As a general rule, plant roots occur more densely near the surface. SWAT simulates the effects of this by assuming plants uptake proportionately more water from shallower soil layers. The EPCO variable allows plants to deviate from this regime and uptake water from deeper layers within the soil profile if needed, with a value of 1.0
indicating removal of water from as deep as necessary and 0.0 indicating strict adherence to the calculated depth distribution. EPCO modifies potential water uptake for a plant from a soil layer as follows:

**Equation 8.7. Effect of EPCO on Plant Water Uptake**

\[ w'_{up,ly} = w_{up,ly} + w_{demand} \cdot epc\]

Where \( w'_{up,ly} \) is the adjusted potential water uptake for layer \( ly \), \( w_{up,ly} \) is the potential water uptake for layer \( ly \), and \( w_{demand} \) is the water uptake demand not met by the above soil layers.

The default value of EPCO assumed by SWAT is 1.0. As this means that plants are able to draw almost as much water as they need from deeper layers, plants were rarely found to undergo water stress using unadjusted EPCO values. Occasional brief dry spells often occur in the UBWC so this assumption is likely unrealistic. Figure 8.18 demonstrates the effect of four different values of EPCO on the simulated water stress days within SWAT.
Figure 8.18. Timeseries of monthly water stress days for the 1971-1990 observed simulation, using four different values for the plant uptake compensation factor (EPCO).

As Figure 8.18 shows, less than one water stress day was simulated for the summer using the default value of EPCO. Decreasing EPCO values show increasingly realistic amounts of water stress days for the UBWC. However, as demonstrated by the monthly evapotranspiration values plotted in Figure 8.19, this decrease does not occur without effects on other facets of the water cycle:
As the value of EPCO decreases, plants are able to pull less water from deeper in the soil. Thus plant evapotranspiration begins to be limited by water availability and is reduced in the hotter summer months due to water stress. This in turn can affect streamflow goodness of fit. After reducing EPCO in the automated calibration process, SWAT-CUP repeatedly suggested higher ranges for EPCO for subsequent iterations. With a high EPCO, water that may otherwise go towards evapotranspiration would stay in the soil column, leading to tile flow or conditions more conducive to runoff. This would tend to result in overprediction of streamflow, as was observed during the calibration process. For this reason a compromise was made between a lower EPCO value and obtaining an acceptable NSE value, resulting in a calibrated EPCO of 0.36.

Seasonal effects of the change in EPCO are seen in Figure 8.19 coinciding with the greatest periods of plant growth within the year. Ideally, EPCO would be adjusted by land cover type, with trees having the greatest value due to the depth and extent of their

Figure 8.19. Monthly mean evapotranspiration for the 1971-1990 observed simulation, using four different values for the plant uptake compensation factor (EPCO).
root systems. Annual plants such as corn and soybean crops would preferably have dynamic values of EPCO that would enable changes in the water uptake with depth as the plant roots develop throughout the growing season. However, this is not currently possible within SWAT, so one value for EPCO was assumed for the entire watershed.

8.4.2 ESCO

Evaporation follows a similar pattern to plant water uptake; it mainly occurs in the upper soil layers. The SWAT variable ESCO (the soil evaporation compensation factor) is similar to EPCO in that it can allow water to evaporate from deeper within the soil column if evaporative demand is not met by the upper layers. Equation 8.8 describes this relationship:

**Equation 8.8. Effect of ESCO on Soil Evaporative Demand**

\[ E_{soil,ly} = E_{soil,zl} + E_{soil,zu} \cdot esco \]

Where \( E_{soil,ly} \) is the evaporative demand for layer \( ly \), \( E_{soil,zl} \) is the evaporative demand at the lower boundary of the soil layer, and \( E_{soil,zu} \) is the evaporative demand at the upper boundary of the soil layer. ESCO ranges from 0 to 1, with the default value of ESCO is set at 0.95, allowing some flexibility to meet the evaporation demand of upper layers. The following figure from the SWAT Technical Documentation illustrates the distribution of different ESCO values and their effects on the evaporative demand distribution with depth.
Figure 8.20. Maximum evaporation as function of the depth in the soil profile for different values of ESCO [Neitsch et al., 2011]. High values result in approximately zero evaporation deeper than 50 mm, while low values reverse the default distribution, allowing large amounts of evaporation from depth.

Modification of ESCO had a significant effect on the amount and timing of simulated evapotranspiration within the year.
Figure 8.21. Monthly mean evapotranspiration for the 1971-1990 observed simulation, using four different values for the soil evaporation compensation factor (ESCO).

Figure 8.21 shows that decreasing ESCO increases evapotranspiration year round, especially during the spring and summer months. ESCO also has a noticeable effect on water stress days:
Figure 8.22. Timeseries of monthly water stress days for the 1971-1990 observed simulation, using four different values for the soil evaporation compensation factor (ESCO).

ESCO can potentially have much greater effects than EPCO on the simulated water balance due to its large effect on evapotranspiration shown in Figure 8.21. However, based on the results of this sensitivity test, it was decided to keep ESCO within a high range during the calibration process in order to maintain representation of soil moisture conditions within more realistic bounds. The final calibrated value of ESCO chosen was 0.93, slightly increasing the ability of layers to meet evaporative demand from the default value of 0.95.

8.4.3 Plant Heat Units to Maturity

Small shifts in plant heat units to maturity values can significantly impact plant growth. To demonstrate this, a sensitivity test was set up in which all UBWC agricultural
land was converted to soybeans. Four decreasing increments of plant units to maturity were tested, beginning with the default value of 1800.

**Figure 8.23.** Monthly mean soybean biomass using several different values of plant heat units to maturity for soybeans.

Figure 8.23 underscores the necessity of adjusting plant heat units to maturity to fit the study watershed. Using the default value of 1800 results in extension of plant growth well past its traditional harvest date. Modification of heat units to maturity values corrects this problem. Failure to address these assumptions can also affect watershed evapotranspiration values, as shown below.
Different values of heat units have a clear effect on evapotranspiration, especially for the month of August which exhibits a difference of over 50 mm of water between 1800 and 1000 heat units to maturity. Failure to account for this factor can therefore affect the water balance, potentially resulting in inaccurate representation of nutrient transport pathways. For example, overpredicted evapotranspiration could leave the simulated soil drier than in reality, reducing tile flow and runoff. NPS pollution would be underpredicted as a result. While not shown here, the heat units to maturity value also controls the simulated land cover in SWAT. In the case tested here, unadjusted heat units to maturity would represent the land cover as soybeans until the kill operation at the end of December, erroneously protecting the land from erosion until January.

8.5 Watershed Effects of Climate Change

Changes to the plant growth cycle, hydrologic cycle, and watershed nutrient cycling were observed under simulated future climates. During the growing season,
plants move the majority of water in the watershed and thus their life cycle strongly influences other watershed parameters. The UBWC’s agricultural nature also ensures that fertilizer and decomposition of crop residue are major drivers behind the watershed’s biogeochemical processes. Effects of climate change on plant growth are therefore presented first, followed by discussions of the alterations to the water and nutrient cycles.

8.5.1 Plant Growth Effects

As described in Section 3.2.5, plants are governed by the accumulation of heat units in the watershed. Crop planting, maturation, and harvest all occur based on watershed temperature. As temperatures become warmer throughout the year, it was expected that plant LAI would respond accordingly and shift to earlier months. This was observed for both the RCP 4.5 and RCP 8.5 scenarios. Figure 8.25 and Figure 8.26 show the variation among the six GCMs in LAI over a comparison of the overall RCP 4.5 and 8.5 LAI means with that of the baseline mean, while Figure 8.27 displays the breakdown in LAI trends for the observed simulation (solid line) compared to the future RCP 4.5 scenario (dashed line).
Figure 8.25. Mean monthly LAI (area/area) for the entire watershed. The values shown in the color matrix are the overall monthly means for the 2006-2100 period for the RCP 4.5 scenario, with the observed simulation LAI for 1971-1990 shown for comparison at the top of the color matrix and as the black line on the plot. The blue line indicates the mean of all six downscaled GCMs, while the red line indicates the difference between the observed mean and the mean of all six downscaled GCMs.
Figure 8.26. Mean monthly LAI (area/area) for the entire watershed. The values shown in the color matrix are the overall monthly means for the 2006-2100 period of the RCP 8.5 scenario, with the observed simulation LAI for 1971-1990 shown for comparison at the top of the color matrix and as the black line on the plot. The blue line indicates the mean of all six downscaled GCMs, while the red line indicates the difference between the observed mean and the mean of all six downscaled GCMs.
Figure 8.27. Mean monthly LAI (area/area) separated by land use. The observed simulation (1971-1990) is presented as a solid line, while RCP 4.5 (2006-2100) is presented as a dotted line.

A similar but more extreme shift in watershed-averaged LAI was observed by Ficklin et al. [2009] for a scenario simulating a mean increase in all annual temperatures of 6.4 degrees C. In that case, the temperature increase caused a shift in the growing season from March-November to November-June. That study watershed is located in California’s Central Valley and likely has much milder winter temperatures, allowing closer to year-round growth under a climate change scenario. For the UBWC, even under the extreme scenario tested, RCP 8.5, temperatures do not increase enough in December through February to allow a shift similar to that seen in Ficklin et al [2009]. LAI follows a set progression that is a function of heat units, so more heat units per day results in a compression of the LAI curve. This can potentially render SWAT’s LAI assumptions to
be unrealistic, as seen in Figure 8.26 where the large increase in temperature causes a peak of LAI in May and a decline throughout the rest of the year.

SWAT’s biomass calculation depends in part on LAI in that more leaf area allows more interception of radiation and more photosynthesis. Consequently, the change in LAI observed in the RCP 4.5 and RCP 8.5 scenarios is likely one of the causes of the overall reduction in watershed biomass seen in Figure 8.28 and Figure 8.29.

**Figure 8.28.** Mean monthly watershed biomass for the six downscaled GCMs, RCP 4.5 scenario. The values shown are the overall monthly means for the 2006-2100 period, with the observed simulation’s biomass for 1971-1990 shown for comparison at the bottom of the color matrix and as the black line on the plot. The blue line indicates the mean of all six downscaled GCMs, while the red line indicates the difference between the observed mean and the mean of all six downscaled GCMs.
Environmental constraints on plant growth calculated in SWAT were also examined, including water, temperature, nitrogen, and phosphorus stress. No significant changes were observed from the reference scenario, indicating that the changes in biomass are largely due to the shift in LAI previously described.

8.5.2 Water Cycle Effects

The main components of the water cycle, including ET, runoff, and streamflow were examined. As Figure 8.30 shows, the summer peak of evapotranspiration shifts a month earlier in the year, as a result of the earlier plant growth shown in Figure 8.25 and Figure 8.28. Evapotranspiration during the other months of the year also increases slightly because of the greater temperatures predicted by RCP 4.5.
Figure 8.30. Mean monthly evapotranspiration for the six downscaled GCMs, RCP 4.5 scenario. The values shown are the overall monthly means for the 2006-2100 period, with the observed simulation’s evapotranspiration for 1971-1990 shown for comparison at the bottom of the color matrix and as the black line on the plot. The blue line indicates the mean of all six downscaled GCMs, while the red line indicates the difference between the observed mean and the mean of all six downscaled GCMs.

This shift in evapotranspiration was expected. Similar outcomes are predicted in the results of Ficklin et al. [2009] and Hanratty et al. [1998]. Less drastic changes are observed in streamflow and tile flow output. Figure 8.31 shows these changes for the RCP 4.5 climate scenario compared to the observed 1971-1990 simulation.
Figure 8.31. Mean monthly tile flow for the six downscaled GCMs, RCP 4.5 scenario. The values shown are the overall monthly means for the 2006-2100 period, with the observed simulation’s tile flow for 1971-1990 shown for comparison at the bottom of the color matrix and as the black line on the plot. The blue line indicates the mean of all six downscaled GCMs, while the red line indicates the difference between the observed mean and the mean of all six downscaled GCMs.
The values shown are the overall monthly means for the 2006-2100 period, with the observed simulation’s streamflow for 1971-1990 shown for comparison at the bottom of the color matrix and as the black line on the plot. The blue line indicates the mean of all six downscaled GCMs, while the red line indicates the difference between the observed mean and the mean of all six downscaled GCMs.

Tile flow is reduced in the RCP 4.5 scenario in the spring months as compared to the baseline simulation due to the shift in plant growth which leads to greater evapotranspiration and removal of water from the soil column (in spite of the increased precipitation forecasted). Increases in both streamflow and tile flow are seen in August as a result of the bias towards higher precipitation values in the QM downscaling technique for that month.

8.5.3 Nutrient Cycle and Transport Effects

The soil temperature and water nutrient cycling factors introduced in Section 2.12.1 were calculated for both downscaled and observed simulations and are presented below in Figure 8.33 and Figure 8.35.
Figure 8.33. Mean monthly nutrient cycling temperature factor (calculated in Equation 2.14) for the six downscaled GCMs, RCP 4.5 scenario. The values shown are the overall monthly means for the 2006-2100 period, with the observed simulation’s nutrient cycling temperature factor for 1971-1990 shown for comparison at the bottom of the color matrix and as the black line on the plot. The blue line indicates the mean of all six downscaled GCMs.
Figure 8.34. Mean monthly nutrient cycling temperature factor (calculated in Equation 2.14) for the six downscaled GCMs, RCP 8.5 scenario. The values shown are the overall monthly means for the 2006-2100 period, with the observed simulation’s nutrient cycling temperature factor for 1971-1990 shown for comparison at the bottom of the color matrix and as the black line on the plot. The blue line indicates the mean of all six downscaled GCMs.
Figure 8.35. Mean monthly soil water factor for the entire soil column (calculated in Equation 2.15) for the six downscaled GCMs, RCP 4.5 scenario. The values shown are the overall monthly means for the 2006-2100 period, with the observed simulation’s soil water factor for 1971-1990 shown for comparison at the bottom of the color matrix and as the black line on the plot. The blue line indicates the mean of all six downscaled GCMs.

A marked increase in the temperature cycling factor is noted for all months when it is not at a minimum. Some variability among individual GCM output exists, but the trend is clearly increasing overall. This is a direct result of increasing soil temperature, which is a function of the previous day’s soil temperature, the average annual air temperature, the current day’s surface soil temperature, and the depth of the layer within the soil profile. The increases in air temperature seen in both the RCP 4.5 and RCP 8.5 scenarios drive this result, which is even more pronounced for the RCP 8.5 temperature cycling factor seen in Figure 8.34.

The soil water factor used within SWAT does not change as much as the temperature factor, however, an increase of roughly 0.1 does occur in August, likely due to the increased precipitation for the month of August (shown in Figure 8.9). This is an
effect of the overprediction of precipitation by the QM downscaling technique noted in Section 8.2.2.

Changes in these factors have the potential to affect water nutrient cycling. For instance, mineralization of residue into $\text{NO}_3$ is strongly influenced by the temperature and soil water cycling factors. Accordingly, we would expect to see increased peak mineralization of residue. This was observed and is shown in Figure 8.36:

**Figure 8.36.** Mean monthly mineralization from the fresh nitrogen pool (residue) to the mineral nitrogen pool for the entire soil column for the six downscaled GCMs, RCP 4.5 scenario. The values shown are the overall monthly means for the 2006-2100 period, with the observed simulation’s mean mineralization for 1971-1990 shown for comparison at the bottom of the color matrix and as the black line on the plot. The difference between the observed 1971-1990 simulation and the 2006-2100 simulation is shown in red.

In the reference simulation, mineralization of residue occurs primarily in the fall with the remaining amount mineralized after temperatures reach sufficient values in the spring. The climate change simulations exhibit a shift in that crop harvest occurs earlier.
Higher temperatures create greater temperature cycling factors allowing more mineralization in the late summer and less in the spring. This frees more nitrogen for transport in tile drainage in September, as precipitation does not increase significantly from the baseline for that month in the RCP 4.5 scenario. This is shown in Figure 8.37. However, as previously described, this increase may be exaggerated as a result of a bias towards higher August precipitation (which also led an increase in the soil water cycling factor).

**Figure 8.37.** Mean monthly tile nitrogen export for the six downscaled GCMs is shown for the QM downscaling method and the RCP 4.5 climate change scenario. The values shown are the overall monthly means for the 2006-2100 period, with the observed simulation’s tile nitrogen export for 1971-1990 shown for comparison at the bottom of the color matrix and as the black line on the plot. The blue line indicates the mean values of all six downscaled GCMs, while the red line indicates the difference between the observed mean values and the mean values of all six downscaled GCMs.
Although precipitation was found to increase for the months of March, April, and May, tile nitrogen export declines. This is a result of the shift in plant uptake of water and nutrients corresponding with earlier planting and maturation of crops discussed previously. This shift allows crops to remove nitrate that would otherwise leach into tile drains, and hinders its transport by lessening tile flow. As illustrated below, even more reductions are seen for the RCP 8.5 scenario:

![Figure 8.38](image)

**Figure 8.38.** Mean monthly tile nitrogen export for the six downscaled GCMs is shown for the QM downscaling method and the RCP 8.5 climate change scenario. The values shown are the overall monthly means for the 2006-2100 period, with the observed simulation’s tile nitrogen export for 1971-1990 shown for comparison at the bottom of the color matrix and as the black line on the plot. The blue line indicates the mean values of all six downscaled GCMs, while the red line indicates the difference between the observed mean values and the mean values of all six downscaled GCMs.

Further reductions may also be achieved by waiting to plant crops until later in May or early June to avoid the high nutrient loss from precipitation in May.
expanded growing season and warmer temperatures may allow later planting to be done without risking frost damage to crops. Currently, corn and soybeans are frequently planted in May or late April, which are among the rainiest periods in the year. The value of this must be tested against the cost of cover crops, which may be needed if bare soil conditions are exposed to the heavy spring rains for longer.

Lastly, sediment loading and its associated sorbed mineral phosphorus is seen to change in the future, as seen for RCP 4.5 in Figure 8.39 and Figure 8.40 and for RCP 8.5 in Figure 8.41 and Figure 8.42. Significant winter increases are seen in sediment and sorbed mineral phosphorus for both scenarios with changes throughout the year in the RCP 8.5 scenario.

**Figure 8.39.** Mean monthly sediment loss for the six downscaled GCMs is shown for the QM downscaling method and the RCP 4.5 climate change scenario. The values shown are the overall monthly means for the 2006-2100 period, with the observed simulation’s tile nitrogen export for 1971-1990 shown for comparison at the bottom of the color matrix and as the black line on the plot. The blue line indicates the mean values of all six downscaled GCMs, while the red line indicates the difference between the observed mean values and the mean values of all six downscaled GCMs.
Figure 8.40. Mean monthly P sorbed to sediment for the six downscaled GCMs is shown for the QM downscaling method and the RCP 4.5 climate change scenario. The values shown are the overall monthly means for the 2006-2100 period, with the observed simulation’s tile nitrogen export for 1971-1990 shown for comparison at the bottom of the color matrix and as the black line on the plot. The blue line indicates the mean values of all six downscaled GCMs, while the red line indicates the difference between the observed mean values and the mean values of all six downscaled GCMs.
Figure 8.41. Mean monthly sediment loss for the six downscaled GCMs is shown for the QM downscaling method and the RCP 8.5 climate change scenario. The values shown are the overall monthly means for the 2006-2100 period, with the observed simulation’s tile nitrogen export for 1971-1990 shown for comparison at the bottom of the color matrix and as the black line on the plot. The blue line indicates the mean values of all six downscaled GCMs, while the red line indicates the difference between the observed mean values and the mean values of all six downscaled GCMs.
Figure 8.42. Mean monthly P sorbed to sediment for the six downscaled GCMs is shown for the QM downscaling method and the RCP 8.5 climate change scenario. The values shown are the overall monthly means for the 2006-2100 period, with the observed simulation’s tile nitrogen export for 1971-1990 shown for comparison at the bottom of the color matrix and as the black line on the plot. The blue line indicates the mean values of all six downscaled GCMs, while the red line indicates the difference between the observed mean values and the mean values of all six downscaled GCMs.

As shown in Section 2.15, sediment losses are a function of land cover, surface residue cover, and runoff. For RCP 4.5, sediment and sorbed mineral P losses increase in December and spring months due to the greater precipitation forecasted by the QM downscaling method (and the resulting increase in runoff). However, in the RCP 8.5 scenario, mean LAI (shown in Figure 8.26) rises and falls more rapidly due to the greater heat units per day caused by warmer temperatures. The harvest and kill operation scheduled for crops is wholly reliant on heat units to set its timing. As a result, the land cover surface is bare, and the quicker decay of crop residue leads to even less mitigation of erosion by land cover and surface residue factors. This result suggests that it may be necessary to grow two crops or adopt a cover crop for the longer period between harvest and planting that would occur with warmer temperatures. The next section shows the
results of tests conducted using cover crops to help avoid that very problem of erosion and sorbed mineral P export.

8.6 Watershed Effects of Land Use Change

This section focuses on the results of the four management scenarios tested with a reference 1990-2006 climate. As detailed in Section 7.3, these scenarios included a representation of current UBWC agricultural practices (Base), current agricultural practices with a rye cover crop between main crops (Base w/ CC), a rotation in which winter wheat replaces half of the watershed soybean area (Wheat), and the wheat rotation previously described with rye as a winter cover crop (Wheat w/ CC).

8.6.1 Driving Factors and Shifts in NPS

All of the simulations discussed in this section used the same generated climate as a forcing. As a consequence, changes in plant growth and the presence or absence of ground cover drove the results seen below. The presence of cover crops created an increase in nitrogen uptake for the months of March and April, as shown in Figure 8.43:
Figure 8.43. Mean monthly watershed nitrogen uptake for the reference climate scenario. Management change scenarios included a representation of current UBWC agricultural practices (Base), current agricultural practices with a rye cover crop between main crops (Base w/ CC), a rotation in which winter wheat replaces half of the watershed soybean area (Wheat), and the wheat rotation previously described with rye as a winter cover crop (Wheat w/ CC)

In addition the increase in March nitrogen uptake for the cover crop scenario,s an increase was also observed for the wheat rotation scenario. Higher peak values occur due to the large uptake of nitrogen during the summer growth period, compared to uptake distributed throughout the spring for wheat.

As expected, a large decrease in sediment loss was noted for scenarios with cover crops compared to the reference scenario. Figure 8.44 shows the monthly mean sediment loss for all four scenarios.
Changes in sediment loss are most noticeable during January, February, March, and April. In the reference scenario, agricultural land corn and soybean crops have no cover for these months, creating the opportunity for significant soil loss. Bare soil conditions in SWAT have the maximum USLE minimum support practice factor ($C_{USLE, mn}$) of 0.5, meaning the largest soil losses occur under bare soil conditions. Inclusion of cover crops or growth of winter wheat over the winter months reduces $C_{USLE, mn}$ to 0.03 for both wheat and rye crops, significantly reducing sediment loss for these months. The wheat and wheat cover crop scenarios both show a spike in sediment loss in June as a result of the winter wheat harvest in that month; however, the winter reductions of sediment loss due to these scenarios more than compensates for this increase.

Tile nitrogen patterns were also found to change, as is seen in Figure 8.45:
The large decrease in loss of nitrogen through tile in the spring months likely occurs as a result of the increased N plant uptake seen in Figure 8.43. Small amounts of uptake for N in November and December are also likely the cause of the small differences in tile nitrogen losses for those months.

Changes in residue mineralization patterns were also expected for the different management change scenarios. An increase in early spring mineralization was anticipated due to the breakdown of the winter cover crops. This effect was observed, as illustrated by Figure 8.46.
Figure 8.46. Monthly mean mineralization of residue for the reference climate scenario.

While a large increase in the mineralization of residue is apparent for the base scenario in April and May, this does not appear to adversely affect tile loss of nitrogen for those two months.

8.7 Coupled Effects of Climate and Land Use Change

Taken alone, climate change and management change were both shown to alter amounts of NPS pollution as well as modify their temporal distribution within the year. The combined effects of these factors are given in the following sections.

8.7.1 Reference Cover Crop Scenario

The addition of winter cover crops to the reference corn-soybean-soybean scenario yielded reductions in winter tile nitrogen loss as well as sediment. Figure 8.47 shows these reductions in sediment loading for the RCP 4.5 climate change scenario.
Figure 8.47. Mean monthly sediment loss for the reference cover crop (corn-soybeans-soybeans rotation with cover crops between) scenario. Climate change effects are shown for RCP 4.5.

Large decreases similar to those seen in the management change only simulations were achieved for January and February; however, December’s high sediment loss was negligibly affected.

Significant reductions in tile nitrogen loading from the climate change only scenario were also observed as a result of the cover crop scenario for the month of April, as is shown in Figure 8.48. These reductions were a result of the increased in watershed nitrogen uptake resulting from growth of the rye cover crop in April, which increased from the reference management scenario by 1.9 kg/ha. This likely explains a great deal of the 0.8 kg/ha decrease in tile N export from the climate change only scenario to the coupled climate change and reference cover crop scenario. Less of a decrease was seen for the RCP 8.5 scenario shown in Figure 8.49 due to the large increase in spring
precipitation in that scenario. Mean nitrogen uptake for the reference cover crop scenario for management only, climate change only, no change, and coupled climate and management change is shown for RCP 4.5 in Figure 8.50.

**Figure 8.48.** Mean monthly tile nitrogen loading for the reference cover crop scenario. Climate change effects are shown for RCP 4.5.
Figure 8.49. Mean monthly tile nitrogen loading for the reference cover crop scenario. Climate change effects are shown for RCP 8.5.
Figure 8.50. Mean monthly nitrogen uptake for the reference cover crop scenario. Climate change effects are shown for RCP 4.5.

8.7.2 Wheat and Wheat Cover Crop Scenarios

The wheat and wheat cover crop scenarios were successful in counteracting increases in NPS pollution and enhancing NPS reductions in the face of climate change, performing better than the cover crop reference scenario with regards to tile nitrogen and sediment loss, especially in December. Tile nitrogen export for the wheat cover crop scenario is shown below in Figure 8.51.
Figure 8.51. Mean monthly tile nitrogen loss for the wheat cover crop (corn-soybeans-wheat rotation with cover crops between) scenario. Climate change effects are shown for RCP 4.5.

Total nitrogen loss through tile was approximately 17.6 kg·ha⁻¹·yr⁻¹ for the reference scenario with no climate or management change. As an effect of the increased winter precipitation predicted for the RCP 4.5 climate change scenario, Figure 8.51 indicates large increases in loss of nitrogen through tile for the months of November and December, with the total yearly export increasing only slightly to 18.4 kg·ha⁻¹·yr⁻¹ kg due to offsetting decreases in March, April, and May. The wheat cover crop scenario was successful in further reducing spring nitrogen loss, as well as partially abating the increased losses in November and December, with a final reduction to 14.8 kg·ha⁻¹·yr⁻¹. While these values are uncalibrated, they represent the general trends that would occur with implementation of the wheat cover crop management scenario.
Similar decreases in sediment loss were also observed and are shown in Figure 8.52 through Figure 8.55 for both the wheat scenario and the wheat cover crop scenario (RCP 4.5 and RCP 8.5):

**Figure 8.52.** Mean monthly sediment loading for the wheat cover crop (corn-soybeans-wheat rotation with cover crops between) scenario. Climate change effects are shown for RCP 4.5.
**Figure 8.53.** Mean monthly sediment loading for the wheat scenario (corn-soybeans-wheat rotation). Climate change effects are shown for RCP 4.5.

**Figure 8.54.** Mean monthly sediment loading for the wheat cover crop (corn-soybeans-wheat rotation with cover crops between) scenario. Climate change effects are shown for RCP 8.5.
Figure 8.55. Mean monthly sediment loading for the wheat cover crop (corn-soybeans-wheat rotation) scenario. Climate change effects are shown for RCP 8.5.

Climate change reduces the benefits of the wheat and wheat cover crop scenarios achieved in January as compared to the decreases seen in the management change only simulations (Figure 8.44), but they are still clearly valuable as they effectively halve the winter sediment loss. The increase in sediment loss for the winter months is also attributable to the higher soil temperature and soil moisture factors (shown in Figure 8.33 and Figure 8.35) causing more rapid breakdown of the fall harvest residue. This increases the USLE cover and management factor calculated in Equation 2.55, resulting in greater end of season sediment losses. Greater sediment decreases are seen for the RCP 8.5 scenario due to a small reduction in springtime runoff.

Potentially negating benefits of declining springtime sediment and nutrient loads, however, is the general decline in streamflow, which may offset the overall N and sediment load reduction by increasing local NPS pollutant concentration. This decline in streamflow is seen below in Figure 8.56:
Overall, streamflow affects local conditions in that it changes the concentrations of NPS pollutants. The changes in local streamflow may not be seen nationally, so conclusions about the wider effects of climate change must be limited to the consideration of the nutrient load that is sent downstream, which was found to decrease. Although there is a predicted increase in streamflow that may dilute the increased winter tile N losses, the doubling of winter tile nitrogen export shown in Figure 8.51 may lead to a decrease in water quality that threatens to impact human health and safety if left untreated. While climate change alone may reduce NPS loading overall, seasonally targeted countermeasures such as winter cover crops may become necessary as changes to the local climate develop into the future.
9 Summary and Conclusions

This study had two overall objectives:

Objective 1: To assess potential climate-induced changes in NPS pollution for the UBWC watershed.

Objective 2: To test agricultural management strategies for the UBWC watershed in order to counteract potential increases in NPS pollution.

9.1 Methods

To accomplish the objectives of this study, a SWAT model simulation was set up for the Upper Big Walnut Creek watershed in Central Ohio to examine the potential impacts of climate and land use change on nutrient loading and the hydrologic cycle. The simulation was calibrated for streamflow from 2000-2004 with an NSE value of 0.62 and validated for the period of 2005-2009 with an NSE value of 0.74, indicating satisfactory prediction of streamflow and the hydrologic processes that drive it.

After calibration, preliminary downscaled CMIP5 climate output was first used as a timeseries input to run a 2006-2100 climate change simulation for 17 separate GCMs. Based on the similarity of model inputs, six GCM models were chosen as being representative of the spectrum of potential output and two downscaling techniques, regression and quantile mapping, were applied to these GCMs’ data to adapt it to the scale of the UBWC.

In addition to the general analysis conducted to determine the set of parameters needed for calibration, more detailed sensitivity analysis was undertaken to demonstrate the effects of changes in SWAT’s ESCO, EPCO, and plant heat units to maturity.
variables due to their pronounced effect on simulation output. Simulated evapotranspiration and biomass outputs were found to be extremely sensitive to values of these three variables, indicating the need for great care to be taken during the model setup process.

Three sets of experiments were then conducted. The first of these used the downscaled GCM timeseries as simulation input to examine the effects of climate change on watershed processes and output. For the second set of experiments, four agricultural management change scenarios were developed to represent potential techniques used to improve water quality. Scenarios tested included a reference simulation, a reference simulation with rye cover crops grown over the winter, a simulation in which winter wheat replaced 50% of the watershed’s current soybean area, and a scenario using the corn-soybeans-winter wheat rotation with rye cover crops between planting. Lastly, the third set of experiments combined climate change with agricultural management change. To simulate future variations in climate, statistics were developed from the timeseries downscaled using the quantile mapping technique. These statistics were used to run the weather generator in SWAT for three periods: 2006-2037, 2038-2069, and 2070-2100.

9.2 Key Findings

Several key findings were obtained as a result of this research:

- **Parameter Sensitivity:** Simulated evapotranspiration and heat stress days were found to be exceptionally sensitive to the SWAT variables ESCO and EPCO (the soil evaporation and plant uptake compensation factors). Plant potential heat units to maturity also were found to strongly influence plant biomass and simulation of land cover, affecting the watershed hydrologic and nutrient cycles.

- **Changes in Precipitation Characteristics:** Downscaling of GCM model outputs for the study watershed revealed potentially greater springtime precipitation as well as significant increases in November and December.

- **Changes in NPS Magnitudes and Temporal Patterns:** Nutrient loading was found to decline overall primarily as a result of shifts in plant growth
earlier in the year, resulting in greater evapotranspiration and decreases in tile flow that allowed less transport of nitrogen. Increased November and December precipitation led to approximately doubled tile nitrogen outputs for those months which may make some form of management change necessary to reduce adverse effects on water quality.

- **Effectiveness of Management Practices in NPS Reduction:** Use of a rye winter cover crop alone and in conjunction with the substitution of a year of winter wheat for soybeans in the commonly practiced corn-soybeans-soybeans rotation was found to greatly reduce the high sediment losses of January and February. The wheat rotation scenario also was effective in counteracting high nitrogen losses in November and December. While climate change alone was found to reduce NPS pollution, use of these management practices may be essential during some months as a result of reductions in streamflow that may increase NPS concentrations.

### 9.3 Future Work

Two important factors were not addressed by this research. The first of these was the effects of increasing CO₂ concentrations on plant growth and stomatal conductance. Two notable climate change sensitivity studies documented decreases in streamflow due to temperature increases and increases in streamflow due to reduction of plant evapotranspiration from increased CO₂ concentrations [Ficklin et al., 2009; Wu et al., 2012]. If the former outcome prevails, increased transport of NPS from elevated streamflow may further complicate the situation. It remains to be seen which effect would dominate in the UBWC watershed.

The second factor not considered is the local issue of land use change. For the purposes of this study, agricultural management change was considered to be the greater influence on NPS pollution. However, development within the UBWC portends change in the magnitude of urban effects on NPS. Further study is recommended in order to determine the directions of these changes and their implications on water quality within the study area.
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