ABSTRACT

Title of Thesis: THE IMPACT OF CLIMATE CHANGE ON AGRICULTURAL CRITICAL SOURCE AREAS (CSAS) AND BEST MANAGEMENT PRACTICES (BMPS) IN EASTERN MARYLAND

Jaison Randall Renkenberger, Master of Science, 2015

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Chesapeake Bay jurisdictions are required to develop Watershed Implementation Plans (WIPs) to reduce Non-Point Source (NPS) pollution by sediment, nitrogen, and phosphorus, and meet EPA Total Maximum Daily Loads (TMDLs) for water quality. This study quantifies the potential impacts of climate change on Critical Source Areas (CSAs) and Best Management Practice (BMP) efficiencies, two keys to WIP success, in an agricultural watershed in Maryland. The SWAT model was calibrated for the watershed and subjected to climate scenarios SRES B1, A1B and A2, over mid- and end-century time horizons. Simulation results predict that changed precipitation patterns will produce at least a doubling of CSA areas within the watershed and that, with BMPs designed for current climate, TMDLs will be exceeded by a factor of up to 2.4. For WIPs to be robust against climate

change, BMPs must be designed for future climate and community-based, participatory implementation strategies are needed.

THE IMPACT OF CLIMATE CHANGE ON AGRICULTURAL CRITICAL SOURCE AREAS (CSAs) AND BEST MANAGEMENT PRACTICES (BMPS) IN EASTERN MARYLAND

by

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DEDICATION

To all the circumstances, good and bad, that brought me here.

Jessica, thank you for being the everything I needed.

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CHAPTER 1: BACKGROUND AND LITERATURE REVIEW

This thesis investigates the implementation of land-based water quality Best Management Practices in a small agricultural subwatershed of the Chesapeake Bay watershed under changing climate. The research is intended as a contribution to meeting the federally mandated water quality standards in the Chesapeake Bay. This chapter introduces the regional context, the research objectives, the study site, and relevant previous work.

1.1 INTRODUCTION: THE CHESAPEAKE BAY

The Chesapeake Bay is the largest and most productive estuary in the United States ("Discover the Chesapeake," n.d.). Concern regarding the Bay's water quality is both and environmental and economic. Nutrient pollution and excessive erosion from tributaries within the ~165,000 km^2 Bay basin enter tidal waters and negatively impact the estuarine ecosystem. Efforts to improve water quality have been extensive but have had limited progress. Lack of progress is a direct result of increased urbanization, population and deteriorating stormwater infrastructure. Due to this lack of progress and the Bay's ecological and economic significance, President Barack Obama issued an executive order calling for a federal strategy that would protect and restore the Chesapeake Bay watershed (EPA, 2010; Executive Order No. 13,508, 2009). For this reason the EPA began working with Bay states and jurisdictions to establish reduction goals for nutrient pollution and excessive erosion of sediment. In 2010 the Environmental

Protection Agency (EPA) issued the first iteration of the Chesapeake Bay Total Maximum Daily Load (TMDL) under the authority of the Clean Water Act (CWA) (EPA, 2010). The TMDL requires that Total Nitrogen (TN), Total Phosphorus (TP) and Total Suspended Sediment (TSS) loads be reduced to improve water quality in the Bay. More importantly, the TMDL requires all six Bay states (New York, Pennsylvania, Maryland, West Virginia, Virginia, and Delaware) and the District of Columbia (D.C.) to establish Watershed Implementation Plans (WIPs) that detail how they intend to meet TMDL goals (EPA, 2010). Additionally, the EPA added two-year WIP milestones to TMDL regulations to ensure accountability. All in all, the Bay TMDL calls for Bay states and jurisdictions to complete restoration activities and meet WIP milestones by 2025 and includes a total reduction of TN by 25% (capped at 185.9 million pounds), TP by 24% (capped at 12.5 million pounds), and TSS by 20% (capped at 6.45 billion pounds).

1.2 RESEARCH: MOTIVATION, NEEDS AND OBJECTIVES

The EPA's TMDL call for Bay states and jurisdictions to create WIPs and meet TMDL milestones gives each jurisdiction the power to determine which watershed management measures will be used and how they will be implemented. Unfortunately, that power comes with the immense responsibility of determining which land management practices are the most cost-effective. To aid policy makers, the scientific community has developed and explored, over time, various land management techniques that are highly effective at controlling excessive runoff of eroded sediment and nutrients. These highly effective land management practices, termed Best Management Practices (BMPs), differ by land use (Dressing, 2003). Additionally, the scientific community has

been developing methods to target problematic land areas, Critical Source Areas (CSAs) or “hotspots”, in watersheds and explore how climate change might exacerbate and or cause additional problems in the future.

The Bay’s immense surface area, around 165,000 km^2, requires policy makers to use the latest developments in watershed modeling and science to be cost-effective in the planning, targeting and implementation of BMPs that will ensure that the Bay meets TMDL requirements now and in the future. For long term success scientists and engineers also need to consider climate change’s possible impacts on land management activities within the Chesapeake Bay basin -- a consideration not currently held by the majority of policy actions for water quality improvement in the Chesapeake Bay basin.

This study focuses on 1) quantifying and characterizing expected changes in watershed Critical Source Areas (CSAs) with respect to climate change, and 2) quantifying the impact of climate change on the effectiveness of BMPs for an agricultural watershed within the Chesapeake Bay. These focus areas are expressed in terms of the following objectives in this thesis, corresponding to two manuscripts submitted for publication (Renkenberger et al., 2015a, 2015b). The supporting tasks listed under each objective are described in the corresponding chapters.

Objective #1: Determine the impact of climate change on Critical Source Area identification in a Maryland watershed

Supporting tasks include:

- Calibrate SWAT Hydrologic Model

- Define and identify Critical Source Areas (CSAs) for Surface Runoff (SurQ), Total Suspended Sediment (TSS), Total Nitrogen (TN) and Total Phosphorus (TP)
- Quantify watershed response at the land surface and watershed outlet to climate change
- Determine effects of climate change on Critical Source Areas (CSAs)

Objective #2: Quantify the effectiveness of Best Management Practices under changing climate in a Maryland watershed

Supporting tasks include:

- Identify land areas that are critical sources for more than one target pollutant i.e., Critically Dense Areas (CDAs)
- Simulate implementation of BMPs on CDAs
- Calibrate BMP parameters using Non-CSA Targets

Study Area

The study area, the 298 km^2 Greensboro Watershed, lies within the larger Choptank watershed (USGS HUC 02060005) located on the Delmarva Peninsula. Figure 1 shows the Greensboro watershed, in green, lying at the eastern–most part of the Choptank (red) where it shares boundaries with Maryland and Delaware. The subwatershed has mixed land uses where the majority includes agriculture. Additional details for the study area are given in Chapters 2 and 3 and Renkenberger et al. (2015a).

The study period begins 1-Jan-1990 and ends 31-Dec-2010, for a total of 21 years. The calibration period starts 1-Jan-1990 and ends 31-Dec-2004 for a total 15 year calibration period (3 year warm-up). The validation period runs from 1-Jan-2005 to 31-Dec-2010 for a 6 year validation period (2 year warm-up).

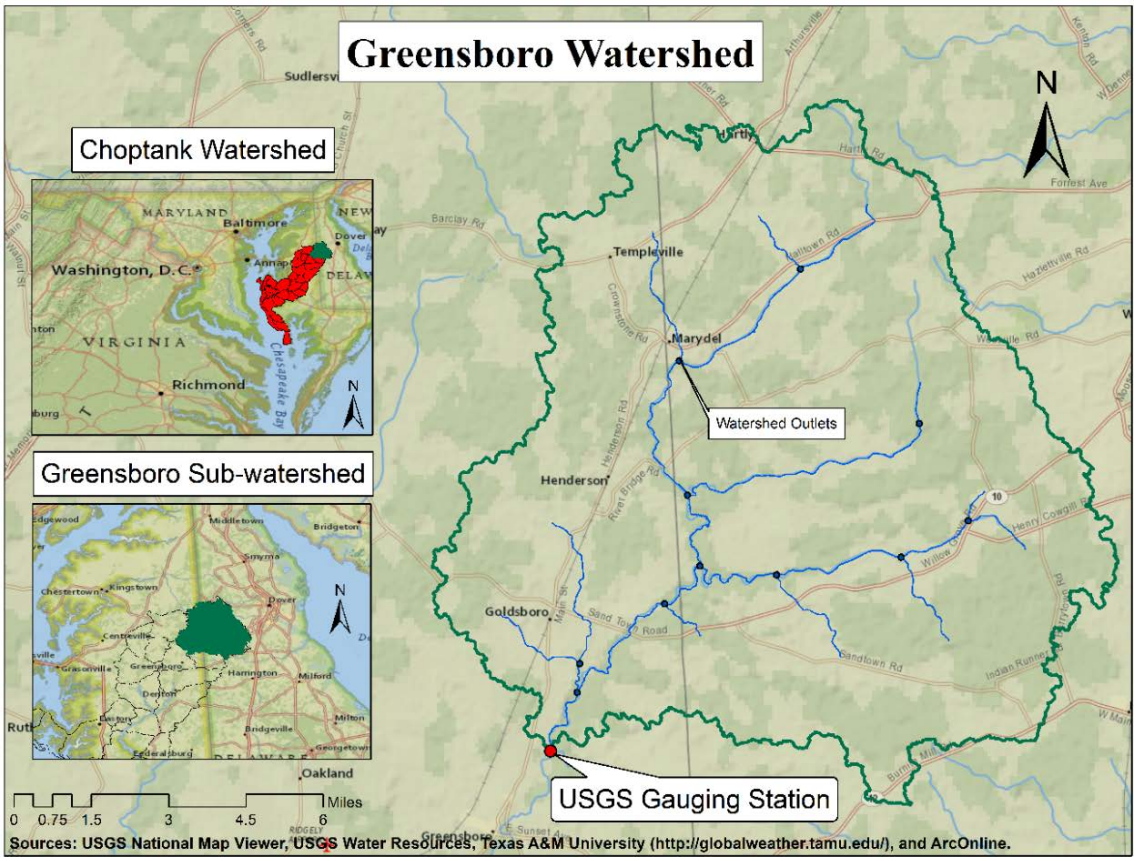


Figure 1: Study Area - The Greensboro Watershed Within the Choptank (USGS HUC 02060005) (Renkenberger et al., 2015a)

Overview

To support the motivation and knowledge needed to justify and investigate each primary objective, this chapter contains a literature review discussing basic Watershed Science, Watershed Modeling Science, their integration into Watershed Assessment and

finally a discussion of state-of-the-art modeling tools and applications. Chapter 2 provides additional detail for analysis supporting each objective. Chapters 3 and 4 are standalone investigations of the primary objectives. Chapter 3 explores climate change impacts on CSA identification and Chapter 4 explores climate change impacts on BMP effectiveness. Chapter 5 offers a summary conclusion and details possible future investigations from the work presented here.

1.3 WATERSHED SCIENCE

Watersheds are complex systems that include natural and man-made interactions. Our key objectives require us to model these systems these systems accurately if we are to seek useful insight for the questions we pose and the hypotheses we test. To support our objectives it is necessary to have a fundamental understanding of how watersheds work, the role nutrients play in watershed health, how best management practices interact with watershed components and finally how climate change affects watersheds.

Watershed Components

A watershed can be described as all the land area that drains water to a single point. This point could be along a small stream for a small watershed or it can be a large body of water, like the Chesapeake Bay, for a relatively large watershed. However, a watershed is much more than any single hydrologic definition can provide. Breaking down a watershed into its primary components and basic processes is useful for understanding and predicting how changes in the past, present and future might impact the watershed in part or as a whole. For the Chesapeake Bay TMDL, targeting watershed

components and their processes under the context of nutrient pollution allows for the tracing and prediction of nitrogen, phosphorus and sediment movement within the watershed and their loadings at the watershed outlet. These primary components include physical, biological, chemical, and social processes (Powledge, 2006). Understanding each is crucial to accurate modeling of these processes.

The physical components of a watershed are largely characteristics of the land surface, the shallow subsurface and their interactions with weather and climate. Figure 2 depicts the hydrologic cycle's primary processes. Weather and climate first control the volume, distribution (e.g. intensity and duration) and type (e.g. snow and rain) of precipitation on the land surface. Land use, land cover, topography and soil properties all control how precipitation is partitioned and moved within the hydrologic cycle. For example, if we were to compare observations from an agricultural watershed experiencing a 2-yr storm to an urban one, we could expect the agricultural area to have less total surface runoff and more infiltration, evapotranspiration, lateral flow, shallow aquifer recharge and deep aquifer recharge than the urban area. Additionally, comparing the same storm in a forested area versus a heavily sloped grassland, we would expect the forested area to capture and dissipate more precipitation energy and contribute less flow and thus experience less erosion of sediment from stream bank areas (Gregory, 2011; Neitsch et al., 2011).

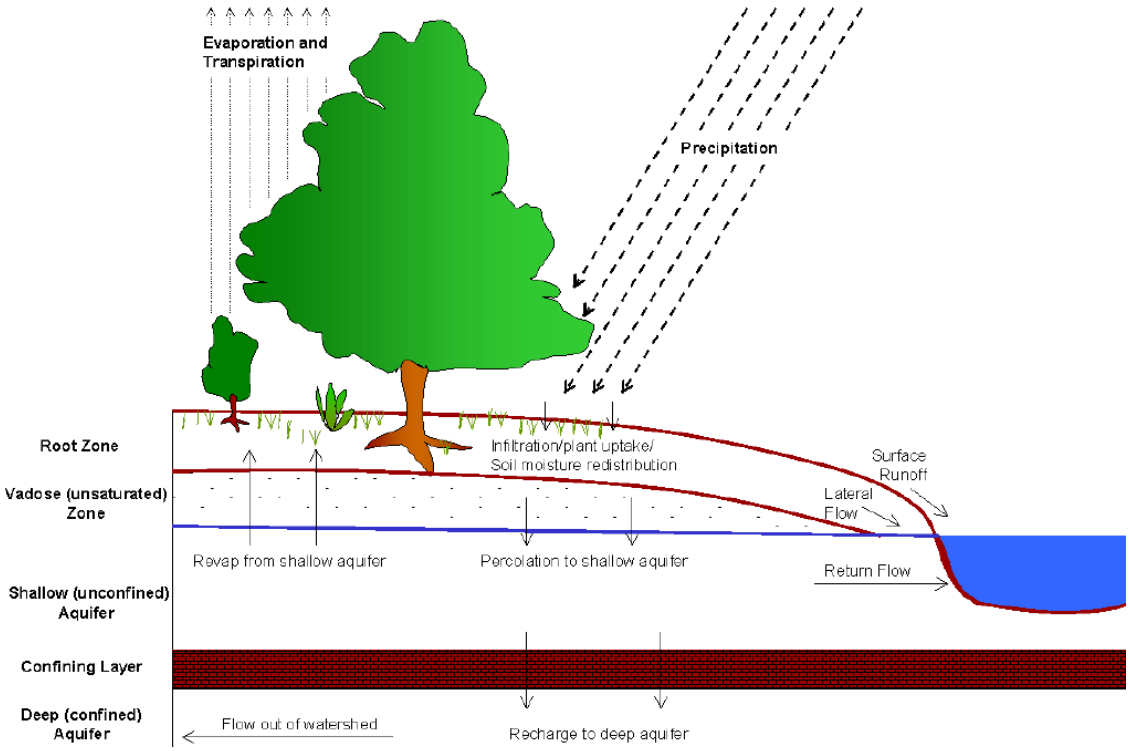
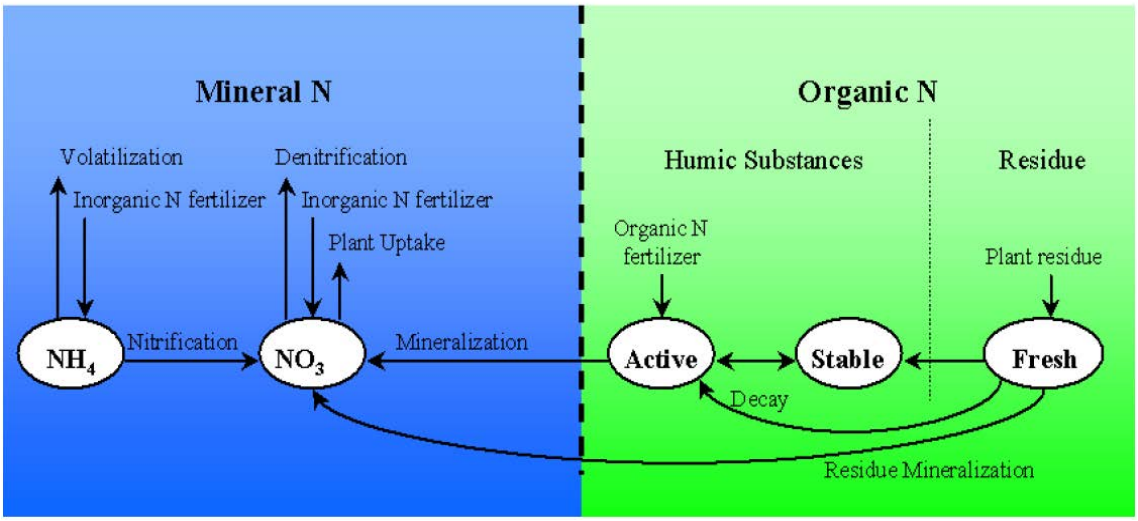


Figure 2: The Hydrologic Cycle (Neitsch et al., 2011)

Chemical processes are another major component of watersheds. With respect to the Bay TMDL, the chemical processes of greatest interest to scientists and policy makers are excessive release of plant nutrients via point (e.g. waste water treatment plants, poultry farms and etc.) and non-point sources. Of these sources, non-point sources are the most difficult to control because these pollutants come from all of a watershed's land surface. Normally nutrients enter and are recycled within a watershed's nutrient cycle naturally. For example, each autumn, leaves and other organic matter decay, shown as plant residue in Figure 4 (Top and Bottom), releasing plant nutrients back into the soil to be taken up again during the spring and summer growing seasons. This cyclical process is homeostatic until nutrients enter the cycle artificially. This occurs when humans apply

organic and inorganic fertilizers to crops and sodded open spaces (e.g. lawns, golf courses and etc.) to maximize growth potential and aesthetics (Morris, 1991). These artificial inputs are depicted in Figure 3 as organic and inorganic N and P fertilizer. However, growth potential and aesthetics are not negatively impacted by over application of nutrient fertilizers, which encourages excessive use and results in the over accumulation of these plant nutrients on areas where they are applied (Mueller & Helsel, 2013). Permanent removal of these nutrients from their respective cycles within a watershed is primarily by plant uptake and then crop harvesting (Figure 3). Additionally, nitrogen can also be removed from the watershed by volatilization and denitrification processes (Figure 3). These chemical processes, and ultimately the chemical component of a watershed, are largely dependent on physical ones and they should be considered together. This is because the energy in flowing water picks up loose organic matter and transports it within a watershed. Soluble forms of each nutrient are moved similarly when absorbed into water flowing over a watershed's surface and subsurface.

NITROGEN



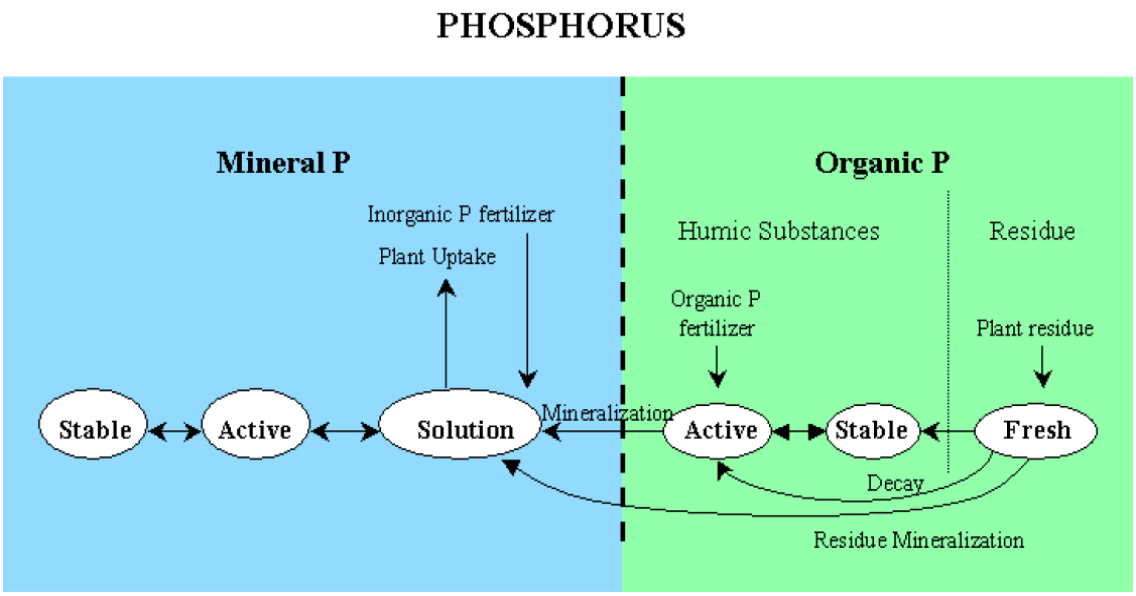


Figure 3: Nitrogen (Top) and Phosphorus (Bottom) Cycles (Neitsch et al., 2011)

The biological component of a watershed is fundamentally supported, and thus affected, by the physical and chemical components of a watershed. The biological watershed component includes all the living organisms in a watershed. Because these organisms depend on physical and chemical processes, they can serve as important indicators of watershed health or disequilibrium. Poor health comes as a result of imbalance and or instability among a watershed's primary components. With this knowledge, various indices have been developed for fish, benthic macroinvertebrates and other aquatic life to assess watershed health (Arocena, 2007; Gaiser et al., 2006). These indicators are important for TMDL development as they shed light on, and help scientists predict, what characteristics make a healthy watershed and, more specifically, what concentrations of nitrogen and phosphorus are sustainable for a particular body of water.

The last, and most often over looked component, are the socioeconomic and fundamentally human aspects of a watershed. Unfortunately, we tend to separate our roles in a watershed from other watershed components and overlook them for philosophical and ideological reasons outside the scope of this study. Regardless, humans are just as fundamental as other watershed components because we directly depend on and impact the physical, chemical and biological dimensions of a watershed (Powledge, 2006). We influence these systems with infrastructure and development; which affects topography, soil and land cover; application of organic and inorganic fertilizers (nitrogen and phosphorus) on crops and sodded open spaces which impact stream, lake and bay health; and we influence biology through deforestation, stream channelization, dam construction and other development which removes the physical habitat that biological organisms depend on for food, shelter and survival. Often forgotten is our dependent relationship with a watershed and its healthy natural systems. Humans cause environmental and water quality degradation, as described above, but also depend on a watershed's components for food and shelter, or "ecosystem services" (Powledge, 2006). Ecosystem services provide humans with food, clean water, abundant water, flood control, precious metals, material resources and many others. Ultimately, when we discuss the social or human component of a watershed, we are speaking not only to human environmental degradation but also to the willingness of people to help or contribute to a sustainable relationship with the natural environment.

Nutrient Pollution

Nutrient pollution refers to a nutrient mass imbalance within a watershed system. This imbalance, most often a mass accumulation, is a direct result of anthropogenic factors that benefit from excessive artificial insertion of nutrient fertilizers into a watershed's nutrient cycles (Mueller & Helsel, 2013; Rabalais et al., 2000). In the Chesapeake Bay basin, stormwater runoff picks up and carries these nutrients from land surfaces to streams, rivers and finally the Bay. When excessive nutrient input occurs, the resulting nutrient chemical imbalance is defined as "eutrophication" (Art, 1993; *Eutrophication*, 1969). The plant nutrients, nitrogen and phosphorus, are important for the growth of aquatic plant life, such as Submerged Aquatic Vegetation (SAV). When there is excessive release of nitrogen and phosphorus nutrients to water bodies, aquatic ecosystems are thrown out of balance and exacerbate eutrophication (Rabalais et al., 2000). Excessive nutrients in aquatic systems stimulate the growth and life cycle of microscopic plant life, algae (Figure 4). As algal growth becomes excessive, the resulting layer of microscopic plant life can cover the water's surface and block sunlight for SAV, which is important for supplying dissolved oxygen and pollutant removal (Mueller & Helsel, 2013). As algae reach the end of their life cycle, they sink and decay along the floor of the water body (Figure 4). Decomposer bacteria increase in population as a result of an influx of food, dead algae, and deplete dissolved oxygen by aerobic decomposition. Oxygen influx from SAV and the air-water interface is overwhelmed by microbial depletion resulting in hypoxic conditions or "Dead Zones" (Rabalais et al., 2000).

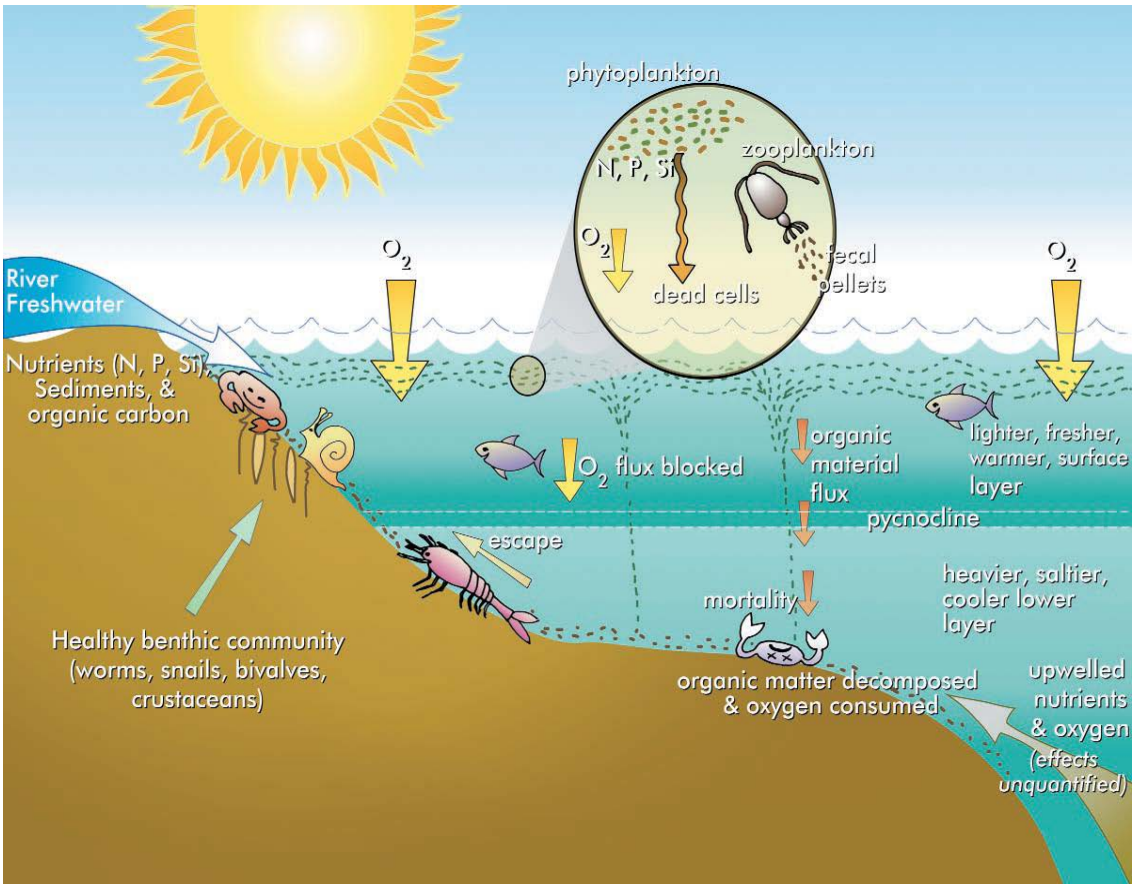


Figure 4: Eutrophication and the development of hypoxic conditions in aquatic habitats by nutrient pollution (Rabalais et al., 2000)

Best Management Practices (BMPs)

In agricultural watersheds BMPs are often employed to prevent and manage excessive erosion and release of nutrients to downstream areas. Unmanaged nutrients and sediments are carried downstream and can result in ecosystem instability, catastrophic eutrophication and hypoxic conditions in the receiving water body (as discussed above). For best crop yields and long term land use, farmers need to apply nutrient fertilizers to maximize plant growth and replenish what was lost in plant uptake. This poses a challenge of careful mass balance between nutrient input and output. Often when

agricultural land is poorly or minimally managed, nutrients accumulate and are washed off or (if soluble) washed through the soil and carried downstream during precipitation events. To prevent damage to soil, land area and receiving water bodies, structural and non-structural BMPs can be implemented to reduce environmental stress and damage (Dressing, 2003). BMPs are categorized as structural and non-structural. Examples of structural BMPs include: livestock fencing along streams, grassed waterways, filter strips, strip cropping, riparian buffers, diversion dikes and many others (Dressing, 2003). Non-structural BMPs include: no tillage, residue management, nutrient management plans, cover crops, pretreatment of Concentrated Animal Feeding Operation (CAFO) discharges and many others (Dressing, 2003). Each BMP offers farmers ways to manage the release of nutrients and prevent soil erosion by limiting or recycling plant nutrients and or by holding and dissipating the energy of flowing water.

Implementing BMPs in agricultural areas is often a complex undertaking because it is largely driven by socioeconomic factors which are notoriously difficult to quantify (Baumgart-Getz et al., 2012). These factors are social in that they involve individual farmers, large corporations, local and the federal government and economic in that BMPs are costly to implement and take up space impacting profit margins (Baumgart-Getz et al., 2012). Currently, the most profound driver of land use change for agriculture in the Chesapeake Bay watershed is environmental protection, especially nutrient pollution. Because BMPs are often costly, many cost sharing programs have been established to help farmers pay for and implement BMPs. However, the rate of BMP adoption has thus far been slow and may result in Bay jurisdictions missing WIP milestones resulting in federally imposed fines (EPA, 2010). To help shed light on this problem, a meta-analysis

of several farmer targeted demographic studies by Baumgart-Getz et al. (2012) identified significant and insignificant socioeconomic factors controlling farmer BMP adoption. Significant factors that influence BMP adoption include: age (younger is better), invested capital, total income, percent income from farming, farm size, knowledge of non-point source pollution (NPS) programs, and connectivity to federal and local agencies as well as citizen organizations (Baumgart-Getz, 2012). Factors that were deemed insignificant to BMP adoption were: formal education, perception of environmental quality, risk aversion to BMPs, farming experience, and knowledge of how agriculture impacts environmental quality as well as the consequences of a degraded environment.

The highlighted example study by Baumgart-Getz et al. (2012) should supply scientists, engineers and policy makers with a very important perspective when working to achieve TMDL targets for the Chesapeake Bay. Simply put, BMP adoption and implementation are as physical and they are social. To drive BMP adoption, policy makers need to be aware of limitations and capacity at the level of individual farms. Targeting farmers that are more likely to adopt BMPs can add an important dimension of efficiency to WIP efforts. For those farmers that may not be able to implement BMPs or make important land use decisions, policy makers and environmental managers should continue to provide additional tools, programs and support networks to help encourage farmers to plan for climate change and respond to nutrient reduction mandates (Baumgart-Getz, 2012).

Watersheds and Climate Change

The primary objectives of this study are centered on the uncertainty introduced by climate change. Climate change and its impacts have been under investigation by the Intergovernmental Panel on Climate Change (IPCC) and three working groups since the early 1990's (IPCC Working Group III, 2000; Pachauri, Mayer, & IPCC, 2015). The primary forcers of present day climate change are anthropogenic sources of CO_2 and related greenhouse gasses (GHGs) (Pachauri et al., 2015). Due to an overall increase of GHGs in the atmosphere, greater portions of outgoing longwave radiation (infrared or heat energy) are absorbed and redirected or re-radiated back to the earth's surface by the earth's atmosphere, resulting in a "greenhouse" warming effect (Pachauri et al., 2015). While GHGs in the atmosphere cause global climate change, their terrestrial sources are ultimately responsible for increases in atmospheric GHG concentrations. The primary drivers of atmospheric CO_2 concentrations are demographic change, social and economic development and the rate and change of technological development (IPCC Working Group III, 2000). The IPCC Working Group III (2000) utilized land and atmospheric models incorporating various predictions in population, technological advance and other worldwide socioeconomic factors to develop 40 unique Special Report on Emissions Scenarios (SRES) (IPCC Working Group III, 2000). Because no single outcome can be said to be more likely than another, Working Group III (2000) harmonized these SRESs into groups, then families and then finally 4 storylines, including SRES A1, A2, B1 and B2. Whether for climate modeling or watershed modeling, SRESs can be used to help support policy actions under a variety of socioeconomic assumptions. Utilizing the higher order SRES storylines, modelers, such as watershed modelers, can capture the widest

ranges of possibilities and reduce assumption specificity for climate predictions and ultimately land management actions (IPCC Working Group III, 2000; Pachauri et al., 2015).

Water is the driving force in any watershed, however, water movement and spatial distribution over the land surface are driven by the physics that govern the distribution of heat energy on earth (Pachauri et al., 2015). As GHGs trap and make heat energy more available, the oceans and atmosphere must move more energy. Over a long period of time this manifests itself as a permanent change in weather or a climate change (Pachauri et al., 2015). Ecosystem function and type rely on a relatively stable climate. For watersheds this means a stable range of temperatures as well as precipitation volume, intensity and distribution. When these ranges change, especially rapidly, ecosystems become stressed and are more vulnerable to problems such as flooding, excessive erosion and eutrophication. These considerations are important for targeting CSAs and implementing BMPs that will improve water quality. If water quality improvement efforts are to be successful in the future, scientists and policy makers need to take into account how climate change might cause additional stress to watersheds and their ecosystems atop the stress already levied by urban development and agriculture (Pachauri et al., 2015; Powledge, 2006).

1.4 WATERSHED MODELING SCIENCE

Most simply, a model can be defined as a representation of a system or process. Models can represent natural or man-made systems and generally attempt to accurately simulate and predict a system's outputs. Models are "forced" or driven with data about

the system or process that is being modeled, i.e. state variables (Shirmohammadi, Montas, & Bergstrom, n.d.). To "build" a model we need to (1) identify and scientifically characterize the system's components or system parameters, (2) develop the logic and science that connects or relates a model's components from input to output and (3) calibrate the model to sufficiently match observations (Shirmohammadi et al., n.d.). In addition to building and calibrating a representative model, we must also consider appropriate use and what elements might dictate what "appropriate use" means (Abbaspour, 2015; Shirmohammadi et al., n.d.).

Development

In this study we define a watershed model as one that simulates a watershed's spatial and temporal outputs including: physical, chemical and biological components. Most systems, watersheds included, can be simplified and represented by the traditional "black-box" model. Already defined earlier, we know that the primary components, also termed as system parameters, in a watershed are physical, chemical, biological and social. Since the vast majority of watershed models do not include a social component (Moriasi et al., 2012), we will focus on the other components. All components reside within the "Black Box" of the Black-Box Model. Within the Black Box, components are broken into sub-components and are connected by established theoretical and or empirical relationships (science and logic) (Shirmohammadi et al., n.d.). Fortunately, the science and logic that connect these components together have been already explored. Relationships between physical, chemical and biological components have been built into "uncalibrated" models. Modelers can then calibrate and use the model to answer

questions and test hypotheses within their study areas. An uncalibrated model is the amalgamation of system parameters or watershed components connected by theoretical and or empirical relationships. A model is calibrated by systematically altering relational parameters between components and subcomponents to improve simulation accuracy. This process can be done manually or by using one of many numerical optimization methods. A model is "complete" after calibration and validation, but completion is often a subjective consideration of statistical analysis (Shirmohammadi et al., n.d.).

Figure 5: Black Box Model

Appropriate Use

Much time and research has gone into developing various kinds of watershed models. As a result of variety and purpose, using a model appropriately can be a unique challenge as it requires a deep understanding of a model's elements. A lack of understanding of a model's spatial, temporal and relational elements can result in erroneous conclusions and possibly damaging policy actions.

Spatial and temporal uncertainty are inherent to all data a modeler will use to establish system parameters and input state (driving) variables (Shirmohammadi et al., n.d.). It is important to understand that uncertainty is an inherent characteristic of

observed data, and because model input is fundamentally connected to model output, observational errors are propagated and appear in simulated variables (Abbaspour, 2015).

In addition to spatial and temporal uncertainty, modelers must also consider the theoretical and empirical relationships that tie inputs to outputs, that is, model uncertainty. Theoretical relationships are ones that can be universally applied and are true no matter what the application might be (Shirmohammadi et al., n.d.). An example might be gravity and its relationship to mass. This theoretical relationship is true everywhere on earth. However, theoretical relationships often pose a challenging data requirement to sufficiently capture a system's spatial and temporal heterogeneity for simulation accuracy (Shirmohammadi et al., n.d.). Empirical relationships are ones that are defined by collected data, i.e. regression models (Shirmohammadi et al., n.d.). They are more flexible in that the need for extensive spatial and temporal data can be sacrificed, but at the cost of wide application as they are defined for, or fit to, data of a particular area and or time scale (Shirmohammadi et al., n.d.). Ultimately, model uncertainty is imposed on simulated variables when data requirements are not met with theoretical relationships and or when empirical models are used outside the scope of their definition.

The final step in the modeling process is model evaluation. This involves comparing simulated and observed signals using standard regression, dimensionless statistics, error indices and or graphically. Legates and McCabe (1999) recommend that reported statistics for hydrologic models include at least one dimensionless statistic, error index, information about standard deviation and graphical technique. Reporting several statistics is important because each statistic may make incorrect assumptions about the data being analyzed. For example, slope and y-intercept are a common analysis, often

given in equation and graphical form. However, this method reflects the assumption that observed and simulated signals are linearly related (Willmott, 1981). Additionally, this assumption leads to the assumption that measured data are error free and that all the error is contained in the simulated values (Willmott, 1981). This is never the case. Other types of statistics offer modelers various perspectives on the data they are analyzing. Dimensionless statistics are useful to report because they allow modeler to compare results between models. Additionally, dimensionless statistics allow modelers to compare different models developed for the same study area (Legates & McCabe, 1999). The importance of standardized guidelines for model evaluation is best illustrated by the Conservation Effects Assessment Project Watershed Assessment Study (Duriancik et al., 2008). The CEAP-WAS seeks to quantify the environmental benefits of conservation practices supported by the USDA in the 2002 Farm Bill, also known as the Farm Security and Rural Investment Act (Duriancik et al., 2008). To best quantify the benefits of conservation practices between models of different types, a standardized method of evaluation would give policy makers additional data points for each practice's performance and track long term trends.

Summary and Special Considerations

Calibrating and validating a sound watershed model begins with problem identification and then collection of relevant data. Data about system parameters and state variables collected is usually dictated by our current scientific understanding of the watershed system (Shirmohammadi et al., n.d.). A watershed model is complete only after watershed parameters are calibrated and then validated with monitoring data

(Shirmohammadi et al., n.d.). However, even a calibrated model is never a true representation of a watershed due to uncertainties inherent in the observed data and our current scientific understanding of the processes involved. Errors in data and scientific understanding propagate through and are reflected in the form of unexpected outputs (Muñoz−Carpena et al., 2006; Shirmohammadi et al., n.d.).

Modelers should also be aware of model conditionality. Model conditionality concerns appropriate use and refers to the limited applicability of a watershed model after it has been calibrated (Abbaspour, 2015). In addition to limitations imposed by data, modeling processes including: calibration procedure, choice of objective function, objective function weights, initial conditions, boundary conditions and others all contribute to model conditionality (Abbaspour, 2015). For this reason a calibrated model cannot simply be used for any analysis since the calibration and final model is dependent on each step in the modeling process (Abbaspour, 2015). Final parameterization is influenced in many ways during the modeling process. System parameter uncertainty, state variable uncertainty and the many subjective decisions a modeler makes during the calibration process suggest that a single parameter set or parameter solution is not realistic (Abbaspour, 2015). Solutions obtained through calibration or “inverse modeling” are inherently non-unique and this non-uniqueness should be considered during the interpretation of results (Abbaspour, 2015).

1.5 THE ROLE OF WATERSHED MANAGEMENT

Watershed management is the culmination of watershed and modeling science. Watershed modeling plays two important roles in watershed management: 1) significantly reducing the need for monitoring and 2) the ability to experimentally explore the potential costs and benefits of watershed management plans and or actions without affecting the real system (Munoz-Carpena et al, 2006).

As the Chesapeake Bay region's jurisdictions develop their WIPs they need to know the current state or health of the watershed. Unfortunately, monitoring requires many long term in-situ deployments of expensive equipment to be representative of the watershed (Shirmohammadi et al., n.d.). Models reduce this need by incorporating limited data and using the best available science and computational resources to make relatively accurate predictions about unmonitored upstream portions of a watershed. The second step involves simulating management strategies in watershed areas that might achieve TMDL targets. Because socioeconomic resources are limited, it is nearly always less costly to test watershed response to land management actions with a calibrated model than by real world implementation and long term monitoring (Munoz-Carpena et al, 2006).

With calibrated hydrologic models we can ask questions, such as the two primary objectives of this paper, and use watershed models to provide useful information and insight that will aid policy makers. Watershed models become even more valuable when coupled with other models, e.g. social and economic models. As discussed earlier, most watershed models ignore the socioeconomic aspects of a watershed. Utilizing a piecewise logic, socioeconomic models can be coupled with watershed models to answer questions

and test hypotheses on larger scales. For example, the two objectives of this paper explore climate change and the targeting of BMPs to CSAs. These objectives will offer policy makers a way to optimize BMP targeting and selection based on a watershed's physical and chemical components. If a socioeconomic model and data were added to these results, we might be able to more efficiently implement BMPs by targeting specific farmer demographics with a high BMP adoption probability. Again, this is important because agricultural BMP adoption and Bay recovery have been slow. Regardless of what stakeholders want or do, each Bay jurisdiction is subject to EPA mandated TMDL targets, and policy makers must find ways to encourage implementation.

1.6 MODELING APPLICATIONS: SWAT, SWAT-CUP AND OTHER SUPPORTING SOFTWARE

Many watershed models have been developed for a variety of analysis. In addition to hydrologic watershed modeling, additional software tools can further aid in development, calibration and analysis of watershed areas. In the final sections of this chapter the SWAT model, calibration software and other supporting applications are discussed. Table 1 summarizes the software products used for model development, calibration and analysis in this study.

Table 1: Summary of Model Applications and Resources

Software	Purpose	Organization/Link
ArcSWAT	Model development	Texas A&M University http://swat.tamu.edu/software/arcswat/
SWAT	Model development	Texas A&M University http://swat.tamu.edu/software/swat-executables/
ArcGIS	Model Analysis	ESRI http://www.esri.com/software/arcgis

SWAT-CUP	Model calibration	Neprash Technology http://www.neprashtechnology.ca/Downloads.aspx
SWAT Check	Model calibration and analysis	Texas A&M University http://swat.tamu.edu/software/swat-check/
SWAT BFlow	Model calibration	Environmental Systems Inc. http://www.envsys.co.kr/~swatbflow
WHAT	Model calibration	Perdue University College of Engineering https://engineering.purdue.edu/~what/

The Soil and Water Assessment Tool (SWAT)

1.6.1.1 Overview

The Soil and Water Assessment Tool (SWAT) builds on 30 years of work that began with models developed by the USDA's Agricultural Research Service (ARS). SWAT's evolution over time is detailed in Chapter 3. The SWAT model is considered a spatially distributed basin-scale continuous hydrologic and water quality model (Gassman et al., 2007). This model has the power to analyze and make predictions over large geographic areas for long periods of time (decades) and can provide results at a daily time step. This tool models watershed components by land discretization and then by partitioning the hydrologic cycle into a land phase and routing phase (Neitsch et al., 2011).

Spatial data detailing topography, land use and soil type distribution are among the first inputs to the SWAT model and are used to define system parameters. A watershed boundary and streams are drawn from an outlet from topographic information. Stream confluences define subwatershed outlets to draw and define subwatershed boundaries. Each subwatershed is broken down further into discrete land units defined as Hydrologic Response Units (HRUs). Each HRU is a unique combination of slope class,

land use and soil hydrologic group based on topography, land use and soil type (Neitsch et al., 2011).

The land phase within the SWAT model controls how precipitation is partitioned between the hydrologic cycle's primary subcomponents (Figure 1). Land use, soil and topography together control the movement of surface and subsurface water, sediment, nutrients and other pollutant loadings to the main channel defined for each subbasin (Neitsch et al., 2011). Paralleling movement, physical, chemical and biological components within the land phase also determine concentration and mass export for each constituent from each HRU. The final action in the land phase is to move calculated water, sediment, nutrient and other masses to the subbasin's main channel (Neitsch et al., 2011).

Once the land phase completes and moves masses to the main channel, the routing phase begins. The routing phase of the SWAT model defines the movement of water, sediments, nutrients and other pollutants through each subbasin's main channel (Neitsch et al., 2011). Each subbasin channel is further routed to downstream channels and finally to the watershed outlet. Within the routing phase SWAT keeps track of water, sediment and nutrient masses. While in-stream, SWAT simulates natural processes that involve the transformation of nutrients, deposition or erosion of sediment and changes in the volume and energy of flowing water (Neitsch et al., 2011).

1.6.1.2 ArcSWAT and SWAT Outputs

ArcSWAT is a free public domain extension to ESRI's ArcGIS software. As an extension, ArcSWAT makes use of ArcGIS's graphical user interface to provide an easy-

to-use environment to build the initial SWAT model for the study watershed (M. Winchell et al., 2007). ArcSWAT leads users through a step-by-step process to generate SWAT input files specific to a study watershed. Key elements of the tool include: delineation of watershed boundary, subbasins, and HRUs; definition and application of weather data for the study period; initial writing of SWAT input text files; SWAT command file setup; and additional options for watersheds with special characterizes, e.g. ponds, reservoirs, dams, and etc. (Winchell et al., 2007). Once all input output files have been customized to the study area, the user can then use calibration software to modify parameter values, unmeasurable quantities that control physical processes, to match observed data.

SWAT-CUP

1.6.1.3 Overview

The primary calibration tool used for parameter fitting was the SWAT Calibration and Uncertainty Programs (SWAT-CUP) software. SWAT-CUP resides in the public domain and can be used and copied freely. This program features five numerical optimization programs, each of which can utilize eleven different objective functions with the possibility of weighting, and the ability to sub-parameterize by land use, slope classification, subbasin, soil class and others to help preserve natural heterogeneity.

SWAT-CUP interfaces with SWAT input files and outputs as outlined in Figure 5. The modeler begins by inputting the parameters to be estimated in calibration. For example, if the modeler desires to calibrate watershed hydrology then the modeler will inputs SWAT parameters controlling how water is distributed in the surface and

subsurface and routed to the watershed outlet. From this point the program is started and an automated process applies the parameter values to the SWAT files using the SWAT_Edit.exe. SWAT is then run using the new parameter sets and outputs extracted by the SWAT_Extract.exe. Finally, the numerical optimization program chosen calculates the objective function to choose the best parameter set or simulation and suggests a new round of parameter ranges for sampling and simulation.

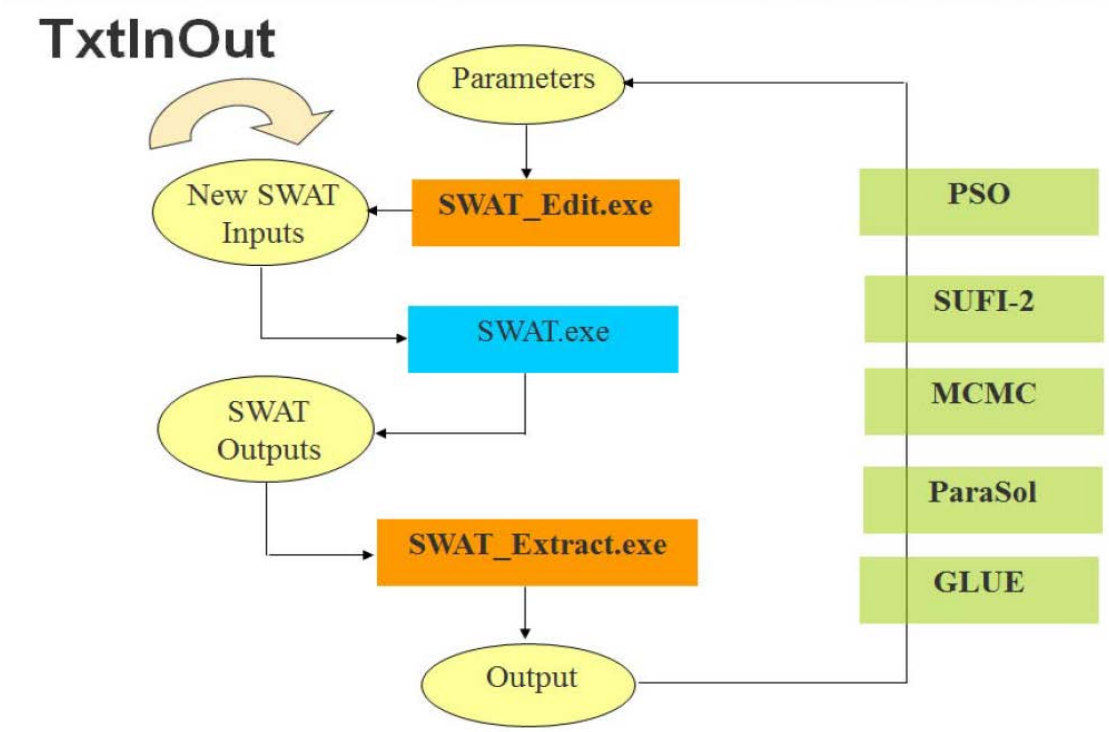


Figure 6: SWAT-CUP Operation (Abbaspour, 2015)

1.6.1.4 Numerical Optimization: SUFI-2

The SWAT-CUP software includes five numerical optimization methods which include: Sequential Uncertainty Fitting Ver. 2 (SUFI-2), Particle Swarm Optimization (PSO), Generalized Likelihood Uncertainty Estimation (GLUE), Parameter Solution (ParaSol), and Markov Chain Monte Carlo (MCMC) (Abbaspour, 2015; Abbaspour et al.,

2004; Yang et al., 2008). Only the SUFI-2 method is described here as it is the most widely used by the SWAT user community and has the most support in the manual and online in the SWAT-CUP forum ("Google Groups - SWAT-CUP").

The SUFI-2 numerical optimization technique operates over a nine step process as described in Abbaspour et al. (2004). To simplify understanding of the SUFI-2 process within the SWAT-CUP graphical user interface, the SUFI-2 process is summarized below in operative steps where user input is the focus.

1.6.1.4.1 USER OPERATION 1: PARAMETER INPUT, OBJECTIVE FUNCTION DEFINITION AND SIMULATION COUNT

J. G. Arnold et al., (2012) recommend performing calibration stepwise beginning with hydrology, then sediment and then nutrients. Starting with parameters related to hydrology only, the user enters the names of the parameters to be calibrated into the par_inf.txt file and then sets maximum and minimum ranges for each based on experience and knowledge (Figure 6). These ranges should be physically meaningful (Abbaspour et al., 2004). After each iteration these ranges are updated and made smaller. Initially, when sufficiently broad ranges are chosen final calibration statistical performance is not significantly impacted i.e., not sensitive (Abbaspour et al., 2004).

Once parameter names and allowed ranges have been entered, SWAT-CUP requires definition of an objective function. SWAT-CUP offers users the choice of 11 different objective functions, however, the most commonly used are maximizing the Coefficient of Determination (R^2) and Nash-Sutcliffe Efficiency (NSE) shown as Eqns. 1 and 2 respectively (as defined in Abbaspour, (2015)). Equation 3 defines a variable, g,

which is the sum of more than one weighted objective function (as defined in (Abbaspour, 2015)). It is important to note that objective function choice and weight, for multiple objectives, are all at the discretion of the user.

$$R^2 = \frac{\left[\sum_{i=1}^{n}\left(Y_i^{obs} - \bar{Y}^{obs}\right)\left(Y_i^{sim} - \bar{Y}^{sim}\right)\right]^2}{\sum_{i=1}^{n}\left(Y_i^{obs} - \bar{Y}^{obs}\right)^2 \sum_{i=1}^{n}\left(Y_i^{sim} - \bar{Y}^{sim}\right)^2} \quad (1)$$

$$NSE = 1 - \frac{\sum_{i=1}^{n}\left(Y_i^{obs} - Y_i^{sim}\right)^2}{\sum_{i=1}^{n}\left(Y_i^{obs} - \bar{Y}^{obs}\right)^2} \quad (2)$$

$$g = \sum_j w_j XX_j \quad (3)$$

Where for all equations:
Y_i^{obs} = Observed values at given time step
Y_i^{sim} = Simulated values at given time step
$\bar{Y}^{obs}$ = Observed mean
n = Number of observations
w_j= Weight of jth variable
XX_j= Value of objective function NSE or R^2

Lastly, the user defines the number of simulations desired for the current iteration. Depending on the parameter ranges and number of parameters (Abbaspour et al., 2015) suggest a simulation count, n, of between 300 and 1000 simulations for a single iteration and at least 4-5 iterations.

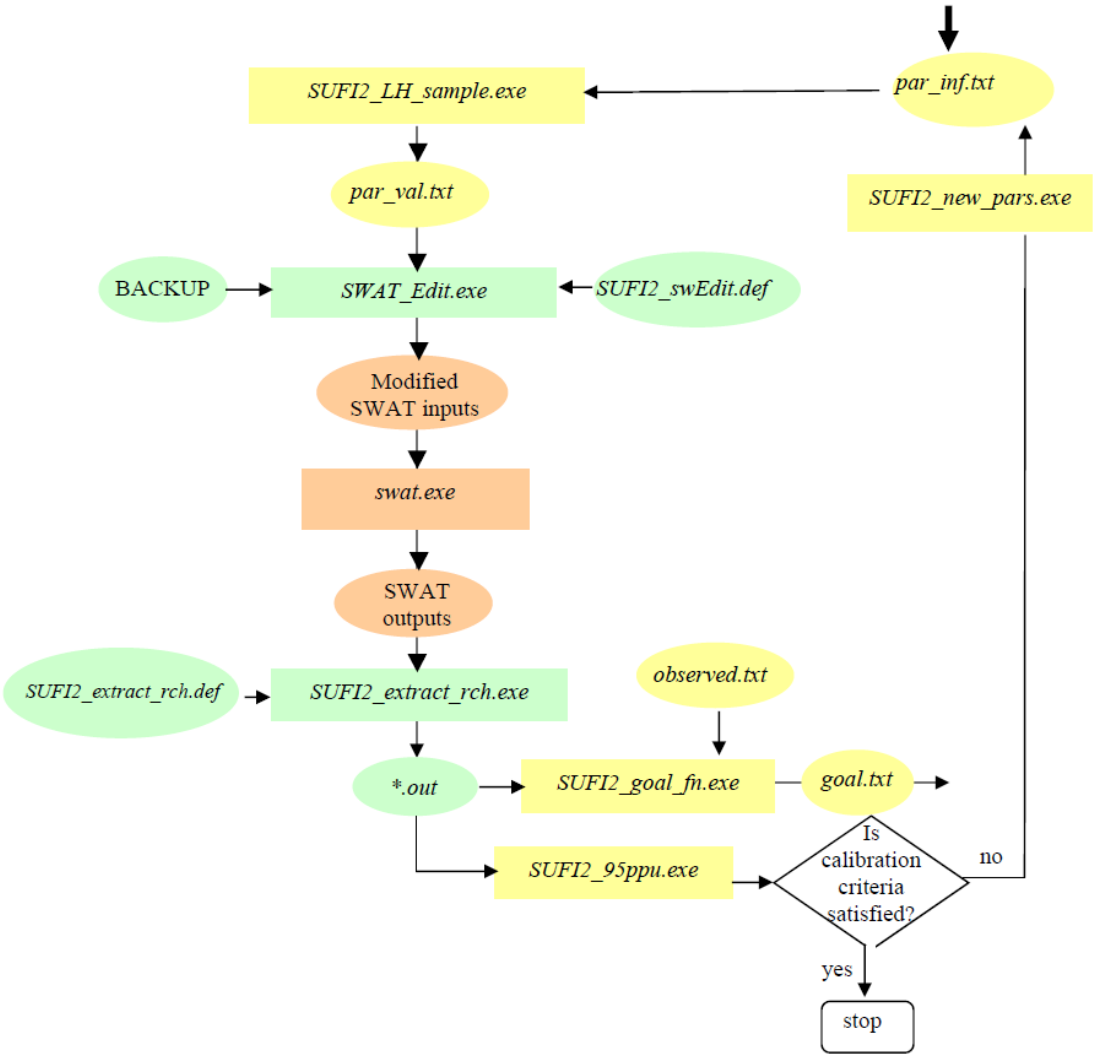


Figure 7: SWAT-CUP with SUFI2 Command Structure (Abbaspour, 2015)

1.6.1.4.2 USER OPERATION 2: PROGRAM EXECUTION AND STATISTIC CALCULATIONS

Execution of the program is simple. The user interface allows the modeler to execute the SUFI-2 program suite together or one at a time (The “one at a time” feature becomes more important for diagnostic and other advanced use of the SWAT-CUP

software). The three SUFI-2 programs include: SUFI2_pre.bat, SUFI2_run.bat and SUFI2_post.bat.

The SUFI2_pre.bat runs the SUFI2_LH_sample.exe subroutine to generate the par_val.txt as shown in Figure 7. The technique used to randomly generate n parameter sets is a stratified sampling technique, Latin Hypercube sampling, which has been proven to be an improvement over the more traditional Monte Carlo sampling technique (Iman et al., 1980; McKay et al., 1979). Briefly, the SUFI2_LH_sample.exe partitions the parameter range for each entered parameter into n equal parts where n is the number of simulations previously defined for the given iteration. The mean of each partition is taken and then randomized among n parameter sets so that each simulation contains a unique parameter set. Once the random pairing process is completed for all parameters, the final action is to write n parameter set combinations to the par_val.txt file to pass to the SUFI2_run.bat program (Abbaspour, 2015).

The SUFI2_run.bat passes each parameter set from par_val.txt file to the SWAT_Edit.exe to modify SWAT input files before each experimental run. After each simulation SWAT outputs are recorded and then rerun with new parameter sets until all user defined simulations have completed. The SUFI2_run.bat process ends and the SUFI2_post.bat program begins.

The majority of the SUFI-2 routine's calculations are performed by the SUFI2_post.bat. The SUFI2_post.bat performs an optional sensitivity analysis (global or one-at-a-time), calculation of objective function and weights, multi-statistic calculations and the 95% prediction uncertainty (95PPU) (Abbaspour et al., 2004).

1.6.1.4.3 USER OPERATION 3: NEXT ITERATION OR END CALIBRATION

At this point SWAT-CUP's automated processes end and the user is provided with statistics and graphical relationships between simulated and observed data, e.g. discharge, sediment, nutrients and etc., for the best simulation or simulation with the maximized or minimized objective function value (maximized for R^2 and NSE). Depending on the value of R^2 and NSE the user can either begin a new iteration or end the calibration.

If statistics are unsatisfactory, for example, NSE value <0.3 for annual mean discharge, the user can start a new iteration with n simulations and follow the three user operations again as defined above. To aid in the calibration process the SUFI2_post.bat routine runs a subroutine that calculates and suggests new smaller parameter ranges centered on the best simulation's fitted parameter values (Abbaspour, 2015; Abbaspour et al., 2004). Beginning a new iteration with new parameter ranges bring the user back to the first user operation.

1.6.1.5 Summary

The SUFI-2 calibration process is summarized above into three phases of user operations. Each operation involves one or more of SUFI-2's nine step process as defined in Abbaspour et al., 2004. While, each simulation runs fixed values, i.e. not a range for a single parameter, Abbaspour et al. (2004 and 2015) repeatedly emphasize that parameter "solutions" are a fitted parameter range. This is because there are many combinations of parameter values in each calibrated parameter range that could produce the same output

signal. Therefore, appropriate use of “fitted” parameters be used and considered with this caution in mind (Abbaspour, 2015).

Supporting Software: ArcGIS, SWAT Check, BFlow and WHAT

Other useful applications that can be used with SWAT or SWAT-CUP include ArcGIS, SWAT Check, BFlow and WHAT. All programs, except ArcGIS, are free and can be found on Texas A&M University (TAMU) SWAT dedicated website (http://swat.tamu.edu/).

The ArcGIS tool developed by Environmental Systems Research Institute (ESRI) is widely used for many purposes. For watershed modeling this tool is valuable for displaying and creating images of spatial data and results.

SWAT Check is a simple to use program, listed under available software on TAMU’s website (Table 1). After placing the program in the folder containing SWAT input output files it can be run to quickly examine watershed hydrology, sediment movement, nutrient cycles, and other watershed characteristics. As described on TAMU’s SWAT website, SWAT check is meant to help novice SWAT modelers during the calibration process by graphically showing watershed components and their processes, as well as offering warnings if parameter values and watershed outputs exceed what is considered to be “reasonable” by program experts and developers.

SWAT BFlow is a baseflow filter program that estimates baseflow and groundwater recharge from historic streamflow records. While it can be used as a stand-alone software package distributed by TAMU’s SWAT website (Table 1), it also has its own website with a Google Map interface where USGS gauging stations and historic data

can be easily retrieved and analyzed. Use of a baseflow filter program is encouraged by both the TAMU SWAT website and (Gassman et al., 2007). SWAT BFlow and similar programs not listed here are used to estimate the baseflow recession constant, ALPHA_BF.gw, for the watershed (Neitsch et al., 2011). Development of BFlow and its use are explored in more detail by Arnold et al. (1999) and Arnold et al. (n.d.).

The last tool to be discussed is the Automated Web Based Hydrograph Analysis Tool (WHAT) (Table 1). This tool uses the algorithm developed for the BFlow filter program and other algorithms based on different techniques. WHAT is used to separate baseflow discharge from surface runoff giving two hydrographs. This is useful when calibrating each component of the hydrograph to have different objective function weights, such as in flood routing research, or to better simulate observed outputs. Development of this tool is further discussed by Lim et al., 2005.

CHAPTER 2: SUPPORTING ANALYSIS FOR MATERIALS AND METHODS

Chapters 3 and 4, corresponding to the two study objectives, are standalone papers intended for journal submission. Each paper contains all critical supporting information for tasks that support meeting its objective. This chapter outlines additional analysis performed to help support or provide perspective on both objectives.

2.1 DATA: AVAILABILITY, SELECTION AND USE

The SWAT model requires several primary inputs to establish system parameters and write the initial input files for the uncalibrated model. Inputs required include: watershed soil, topography, land use, weather and climate variables. Spatial and temporal data characteristics are detailed in Chapter 3. This section provides additional information about the data used and selection process. This is important as required SWAT inputs may be available in different formats and resolutions and contribute similar or different kinds of error to the final calibrated model. Providing additional information about data availability, selection and use allows modelers the opportunity to better determine a model's appropriate use.

Spatial Data

System parameters are set by topographic, land use/cover, and soil data about the study area. This study used publically available online databases of the USGS, USDA and US DOI (NLCD) to build the initial SWAT model (Table 2). Topographic data were chosen to balance resolution and computational resources, i.e. file sizes got too large at

resolutions of less than 10 meters. Land use and land cover data used the 2006 NLCD because the 2011 dataset was not available at the time. Finally, SSURGO was chosen for its relevance (more recent than STATSGO2 data) and finer resolution. These data and their alternatives are given in Table 2.

Table 2: Spatial Data Availability and Use Summary

Data Type	Data Used	Alternatives	Organizations/Links
Topography/DEM	10 Meter (2006)	1 Meter LiDAR 3 Meter 30 Meter	USGS NED EROS Data Center http://ned.usgs.gov http://datagateway.nrcs.usda.gov/
Land Use and Land Cover	30 Meter (2006)	30 Meter (2011)	USDA/NRCS - National Geospatial Center of Excellence http://datagateway.nrcs.usda.gov/
Soils	SSURGO (2012) 1:24,000	STATSGO2 (1994) 1:250,000	USDA/NRCS http://datagateway.nrcs.usda.gov/

Temporal Data

In this study some temporal data required analysis since a single USGS gauging station (USGS 01491000) had multiple options for the selection of TSS, TN and TP. Some options differed only in units of measurement, however, analysis showed significant differences between each, i.e. TSS concentrations in mg/l did not equal TSS in tonnes/day when converted. Fortunately, daily discharge data did not have other formats so it was used to perform analysis and then selection of other time series data. Discussed last is the selection process for weather data.

2.1.1.1 TN, TP and TSS Analysis

Data for in-stream TN and TP loads were obtained from the USGS gauging station website (USGS 01491000 Choptank River, 2015.). To avoid the need for multiple objective functions and possible subjective weighting, model calibration utilized TN and TP concentrations instead of the organic and inorganic species of each individually. USGS data offers many codes for or related to each monitored constituent. Using proper USGS codes is important to model accuracy. TN and TP values could be derived from summing N and P species individually or by using USGS calculated TN and TP concentrations. Using the latter, the USGS provides four options that are defined as "filtered" and "unfiltered" TN and TP. The unfiltered specification was chosen after an inquiry with USGS scientists clarified that filtered TN and TP exclude non-soluble organics and or particulates. Thus, unfiltered nitrogen and phosphorus are complete measures of TN and TP (Skrobialowski, 2014).

Similarly, USGS data had two designations for sediment with different units, #80154 and #80155. Assuming that they each would be same when converted might be reasonable, however, this would be a mistake as they are very different. Since no documentation suggested use of one sediment measurement over the other, the choice became a somewhat subjective decision. To remove as much subjectivity as possible, both a graphical and correlation analysis were performed.

Graphical analysis shows that the two USGS sediment data sets, shown in Figure 7, are relatively dissimilar. While some peaks or valleys occur at the same time, only larger trends can be inferred due to different scales and units. The data sets differ especially for the latter half of each time series. While both could be said to have a long

term downward trend, data set #80154 drops off significantly halfway through the time series and becomes even smaller for the latter third. This might be reasonable if, during the time series, there were significant changes in land use, but agricultural landscapes, especially in our study area, tend to change much more slowly than indicated by figure 7. Lastly, considering that the volume and velocity of flowing water contributes directly to erosion, a correlation analysis (Pearson's correlation coefficient or the square root of Equation 1) between sediment concentrations and discharge showed #80155 (0.80) to be a better selection than #80154 (0.5).

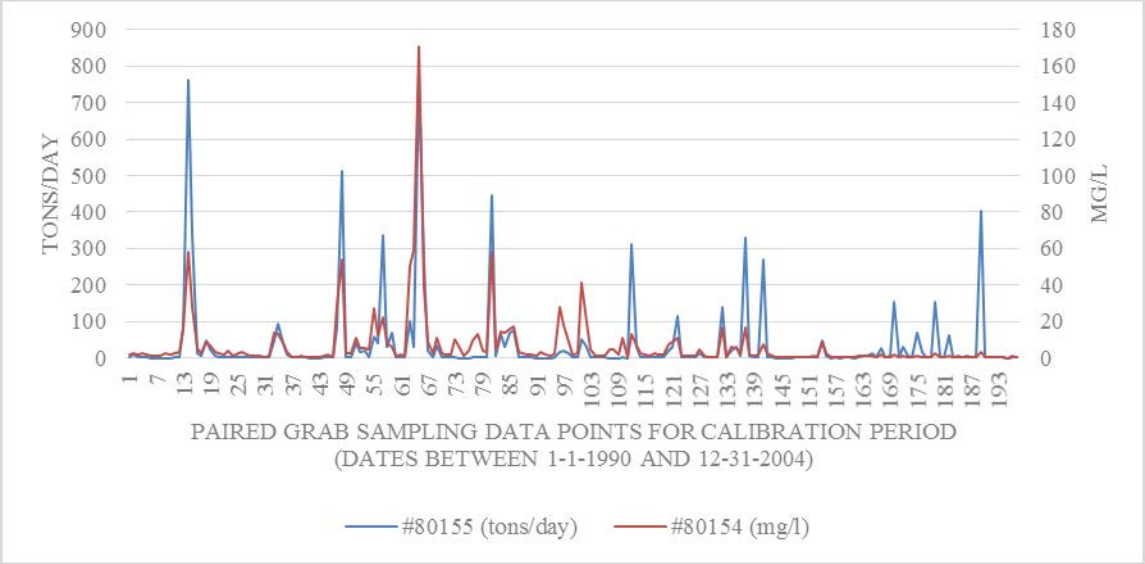


Figure 8: Sediment Analysis of USGS Data (Data not continuous)

2.1.1.2 Weather data

Multiple sources and types of weather data, i.e. precipitation, temperature, wind speed and etc., were available for use. The two primary weather sources considered were data from the National Climatic Data Center (NCDC) and data provided by TAMU's Global Weather Data for SWAT website ("Global Weather Data for SWAT"). TAMU

weather data comes from the NOAA National-Weather-Service (NWS) National Center for Environmental Prediction (NCEP) Climate Forecast System Reanalysis (CFSR) database and is adapted and packaged specifically for SWAT users. The NCDC website also offers NEXRAD weather data, however, these data were not examined due to increased complexity and time limitations.

Data obtained from five physical weather stations via the NCDC website ("National Centers for Environmental Information (NCEI)") and from TAMUs Global Weather Data for SWAT website are listed in Table 3. Data were selected based on optimal length of period of record, coverage, and correlation. Location was also considered but other nearby stations were automatically excluded within both website's mapping interfaces. Table 3 shows all data and sources that were analyzed.

Table 3: Weather Data

Station	**Period of Record/ Coverage**	**Location (Lat,Long)**
Snow Hill 4 Nw Hill GHCND:USC00188380	1916-03-01 to 2014-11-30 96% Coverage	38.2365, -75.3788
Georgetown Sussex Co Airport GHCND:USW00013764	1945-02-01 to 2015-01-23 25% Coverage	38.68917, -75.35917
Millers 4 NE GHCND:USC00185934	1988-03-01 to 2015-01-23 100% Coverage	39.7194, -76.8027
MD Science Center Baltimore GHCND:USW00093784	1998-05-01 to 2015-01-23 98% Coverage	39.2814, -76.6089
Easton GHCND:USC00182700	1893-01-01 to 2008-02-14 74% Coverage	38.74278, -76.06694
TAMU Stations (From NCEP Reanalysis)	1990-01-01 to 2010-12-31 100% Coverage	39.185, -75.938 38.873, -75.625 39.185, -75.625

Note: Table is adapted from Renkenberger et al., 2015a

Weather data were further selected by performing a daily correlation analysis with USGS discharge data. The most correlated stations had a correlation of >0.1 and

included NCDC's Snow Hill Station as well as all three TAMU weather stations shown in Table 4. Ultimately, TAMU data were selected by ease of use, no missing data points and best correlation.

Table 4: Weather Data Correlation Analysis

Station	Discharge Correlation
Georgetown (USW00013764)	-0.001
MD Science Center (USW00093784)	0.002
Easton (USC00182700)	0.012
Millers (USC00185934)	0.052
Snow Hill (USC00188380)	0.119
Tamu A	0.105
Tamu B	0.112
Tamu C	0.101

Climate Data

Climate data includes precipitation, temperature and carbon dioxide (CO_2) concentrations for the baseline study period and future climate scenarios. While sources for climate data were limited, TAMU also provides SWAT users projected future temperature and precipitation data on their website ("Climate Change Data for SWAT (CMIP3)"). Historic and projected CO_2 concentrations were obtained from NOAA's website ("Carbon Dioxide: Projected emissions and concentrations"). Climate data and their sources are discussed in the materials section of chapter 3.

2.2 MODEL CALIBRATION AND VALIDATION

Detailed in this section is additional information regarding calibration and validation presented in additional detail with respect to a similar section in Chapter 3. Tables detailing parameters and additional statistics are presented with brief comments.

Parameterization

Parameter selection was guided by multiple literature sources (Arabi et al., 2008; Arnold et al., 2012; Chu et al., 2004; "SWAT Calibration Techniques," n.d.) and sub parameterized using prior scientific knowledge and understanding. The final calibrated parameter set contain 55 unique parameters; 20, 8, 15, and 11 for hydrology, sediments, TN and TP respectively. Several parameters were broken into groups by land use to maintain spatial heterogeneity (Abbaspour, 2015). In total, the final calibrated model consisted of 77 calibrated parameters. Selected parameters, their descriptions and fitted values are listed in Appendix 1.

Calibration and Validation Statistics: Extended Summary

Calibration and validation of the SWAT model was primarily performed using the SWAT-CUP SUFI-2 software and numerical optimization technique as introduced in Chapter 1 and described in Chapter 3. Appendix 2 contains a more complete statistical reporting of the calibration and validation periods for both investigations. Statistics include daily, monthly and annual values for each calibrated and uncalibrated constituent (i.e., hydrology, TSS, TN and TP).

CHAPTER 3: CLIMATE CHANGE IMPACT ON CRITICAL SOURCE AREA IDENTIFICATION IN A MARYLAND WATERSHED – OBJECTIVE 1

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Abstract

The potential impacts of climate change on Critical Source Areas (CSAs) of surface runoff, sediments, nitrogen and phosphorus were evaluated in an agricultural watershed of the Chesapeake Bay drainage basin, in the US Northeast climate region. The SWAT model was calibrated for the study watershed and used to establish its baseline response and constituent CSAs under current climate. The calibrated model was then subjected to weather time series downscaled from the CMIP3 GFDL CM2.1 Atmosphere-Ocean Global Circulation Model (AOGCM) for IPCC SRES scenarios B1 (low emissions), A1B (medium emissions) and A2 (high emissions) to predict the watershed's response to climate change and identify how constituent CSAs may change under future climate. The utility of targeting Best Management Practices (BMPs) to

CSAs was assessed by computing advantage ratios that relate the fraction of watershed-generated constituents that emanate from CSAs to the fraction of watershed area occupied by these CSAs. Results indicated that, under current conditions, CSAs occupying 11% to 21% of the watershed area contribute 31% to 45% of constituents, corresponding to advantage ratios of 1.5:1 for runoff control and approximately 3:1 for other constituents. Under climate change scenario B1, constituent yields were predicted to increase by factors of 1.5 to 1.8 at the watershed outlet, from an increase in annual rainfall of 25% predicted by the AOGCM, over current conditions. Under scenarios A1B and A2, constituent yields were predicted to increase by factors of 1.8 to 2.3 over current conditions, from an increase of 30% in annual rainfall. The area of runoff CSAs was predicted to more than triple with climate change, leading to negligible advantage of targeting runoff control BMPs to CSAs under future climate. The areas of sediment, nitrogen and phosphorus CSAs were predicted to increase by factors of 2 to 3 with climate change, causing BMP-targeting advantage ratios to decrease from approximately 3:1 (baseline) to 2:1 (future). While advantage ratios for suspended and dissolved constituents remain favorable, even under future climate, the much larger area predicted to be covered by CSAs (2 to 3 times current values) suggests that stakeholder involvement and community-oriented participatory approaches will be increasingly important for achieving Bay TMDLs with climate change.

Keywords.

Climate change, critical source areas, hotspots, NPS pollution, SWAT model, water quality, watershed hydrology

3.1 INTRODUCTION

The Chesapeake Bay is the largest and most productive estuarine ecosystem in the United States but suffers from substantial water quality degradation (Chesapeake Bay Program, 2012). To help improve Bay water quality, President Obama signed Executive Order 13508, established under the authority of the federal Clean Water Act (CWA) of 1972 (Executive Order No. 13,508, 2009), which led the EPA to develop Total Maximum Daily Loads (TMDLs) for total suspended sediment (TSS), total nitrogen (TN), and total phosphorus (TP) for watersheds that drain into the Bay (Garvin and Enck, 2010). Agricultural areas, on Maryland's Eastern shore portion of the Chesapeake Bay basin, have been identified as a potentially important source of suspended solids and nutrients entering the Bay and possibly contributing to eutrophication of the Bay's ecosystem (Mueller and Helsel, 2013). Over the past three decades, significant efforts have reduced point-source pollution loadings of sediments and nutrients going into the Bay (e.g., waste water treatment plants, factory or industry outfalls) but Non-Point Source pollution (NPS) has remained challenging to manage, due to the size and spatial heterogeneity of the Bay's drainage basin. NPS pollution is best tackled by applying Best Management Practices (BMPs) over the landscape (Ritter and Shirmohammadi, 2001). However, land area, time, and monetary resources are limited. For local, county, and state governments to make efficient and effective resource allocations they need to know where especially critical watershed areas are so that they can focus their BMP adoption and implementation efforts there.

Watershed areas that export target pollutants at rates significantly higher than others, within a given watershed, are often termed Critical Source Areas (CSAs), or

hotspots. Strategies for identifying such areas have been explored in many research studies (Chen et al., 2014; Chu et al., 2004; Huaifeng et al., 2010; Huang et al., 2015; Niraula et al., 2013; Sexton et al., 2010; Shang et al., 2012; White et al., 2009; Winchell et al., 2014). These strategies include: Sub-watershed Load Approach (SLA), River/Reach load approach (RLA), River/Reach Concentration Approach (RCA), Sub-watershed Load per Area Approach (SLAA) and HRU Load Approach (HRULA), with the choice of method typically selected based on scope, purpose, target pollutant(s) and tools used in the study (Chen et al., 2014). The use of spatially distributed, physically-based hydrologic models, in conjunction with Geographic Information Systems (GIS) is currently the preferred approach for CSA identification, but simpler indices and loading functions are still applied where advanced tools are unavailable or training is missing (Naraula et al., 2013).

By the end of the century, climate change is expected to cause annual precipitation and storm intensity to undergo substantial increases in the US Northeast climate region, where the Chesapeake Bay drainage basin is located (Melillo et al., 2014). Recent studies in other US regions, where precipitation increases are expected to be of lower magnitude, have shown that increases in streamflow, sediment yield, nitrogen or phosphorus exports of up to 2.5 times their values under current climate, are possible with climate change, depending on geographical location and watershed characteristics (Bosch et al., 2014; Van Liew et al., 2012; Woznicki et al., 2011). Accordingly, one may expect that in the Chesapeake Bay watershed, controlling CSAs identified under current climate may no longer be sufficient to control NPS pollution with future climate change. The expected increases in rainfall may cause such CSAs to expand spatially, for example,

which would require the planning performed assuming a stationary climate to be redone so that planned BMPs would remain effective at meeting Bay TMDLs under future climate. Unfortunately, the potential extent to which the characteristics of Chesapeake Bay CSAs may vary in response to climate change is currently unknown.

The objective of this study is to quantify the expected impacts of climate change on CSAs for Chesapeake Bay watersheds in the US Northeast climate region of the Atlantic Coastal Plain physiographic region. The approach used was first to calibrate a hydrologic and water quality model for a representative study watershed under current climate, and then to apply this model to the simulation of the watershed's response under selected climate change scenarios. The next four sections of this article describe the study watershed, the materials used for the investigation, the methods, and the results.

3.2 STUDY AREA AND STUDY PERIOD

This study is focused on the Greensboro watershed (Figure 1), a 298 km^2 subwatershed of the Choptank River (USGS HUC 02060005) located near the town of Goldsboro, Maryland, and extending over part of Caroline County, MD, and Kent County, DE, on the Delmarva peninsula. The watershed receives an average of 1070 mm of rainfall annually and is typical of mixed land use watersheds in the Atlantic Lower Coastal Plain, with row crops and hay occupying 39% and 10% of its land area, respectively. Other land uses include: forested wetlands (23%), deciduous forests (18%), mixed or evergreen forests (2%) and residential or urban land (6%). The Greensboro watershed is relatively flat with slopes below 1% covering 53% of its area. The distribution of its hydrologic soil groups (HSGs) consists of: A (4%), B (26%), C (50%)

and D (20%). The large fractions of B and C HSGs are expected as the Coastal Plain region is composed of unconsolidated sand, silt and clay sediments (Maryland Geological Survey, 2015). USGS gaging station 01491000, located at the watershed's outlet (latitude 38°59'49.9", longitude 75°47'08.9"), provides continuous monitoring of streamflow along with water quality data from intermittent grab samples. Based on these data, a study period spanning the 15 years beginning on 1-Jan-1990 and ending on 12-31-2004 was selected to represent the watershed's response baseline in this study.

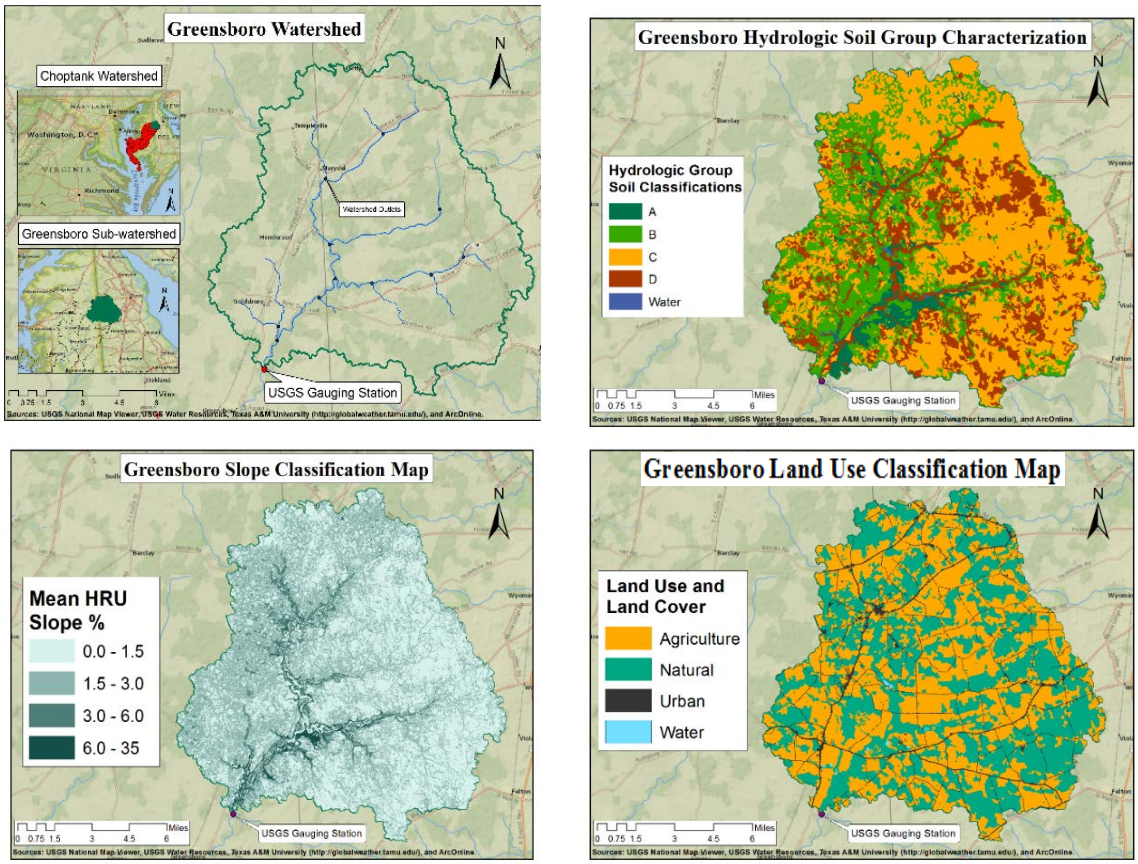


Figure 1. Location (Top Left) and Spatial Characteristics of the Study Watershed

3.3 MATERIALS

Three major groups of materials were used in this study: 1) GIS and modeling software; 2) spatial data; 3) baseline time series; and 4) climate change time series. The GIS and modeling software were used throughout the study, to develop and calibrate the watershed model, analyze outputs under selected climate regimes, and produce maps of the results. The baseline spatial data and time series were used to develop and calibrate the watershed model and to identify baseline CSAs. The climate change time series were used to evaluate the watershed's response to climate change, and to assess the impacts of future climate on CSAs.

GIS and Modeling Software

The key software products utilized in this study are listed in Table 1. The primary program used is the Soil Water and Assessment Tool (SWAT). It is a spatially distributed basin-scale continuous time hydrologic and water quality model with the ability to predict changes in nutrient, sediment, and chemical yields at the watershed outlet and over land elements with simulated management actions and observed or simulated weather data (Arnold et al., 1993). SWAT bases its calculations of runoff and constituent generation, within a watershed, on Hydrologic Response Units (HRUs), which are small land areas representing unique combinations of soil, topography and land use. Constituents generated by HRUs are pooled within an individual sub-watershed and routed through tributaries to the watershed outlet. SWAT is the result of 30 years of research that began with three models developed by the USDA's Agricultural Research Service (ARS): 1) the Groundwater Loading Effects on Agricultural Management Systems (GLEAMS); 2)

Chemicals, Runoff, and Erosion from Agricultural Management Systems (CREAMS), and; 3) Environmental Impact of Policy and Climate (EPIC) (Gassman et al., 2007). These models were first combined into the SWRRB (Simulator for Water Resources in Rural Basins) model, which was designed to simulate impacts of management practices in rural areas in the US. SWRRB was combined with the Enhanced Stream Water Quality (QUAL2E) and Routing Outputs to Outputs (ROTO) models, to add in-stream kinetics and outlet-to-outlet routing functions, forming SWAT.

Table 1: Software Used in Study

Software	Purpose	Source
SWAT	Model Development	Texas A&M University http://swat.tamu.edu/software/swat-executables/
ArcSWAT	Model Development	Texas A&M University http://swat.tamu.edu/software/arcswat/
ArcGIS	Spatial Analysis	ESRI http://www.esri.com/software/arcgis
SWAT-Check	Model Analysis	Texas A&M University http://swat.tamu.edu/software/swat-check/
SWAT-CUP	Model Calibration	Neprash Technology http://www.neprashtechnology.ca/Downloads.aspx
SWAT BFlow	Model Calibration	Environmental Systems Inc. http://www.envsys.co.kr/~swatbflow/USGS_GOOGLE/display_GoogleMap_for_SWAT_BFlow.cgi?state_name=maryland
WHAT	Model Calibration	Purdue University College of Engineering https://engineering.purdue.edu/~what/

The support software for SWAT includes the SWAT Calibration and Uncertainty Programs (SWAT-CUP) which implements several calibration and analysis algorithms, including Sequential Uncertainty Fitting Ver. 2 (SUFI-2), Particle Swarm Optimization (PSO), Generalized Likelihood Uncertainty Estimation (GLUE), Parameter Solution (ParaSol), and Markov Chain Monte Carlo (MCMC) (Abbaspour et al., 2004; Abbaspour,

2013; Yang et al., 2008). It is considered a semi-automated calibration tool and supports an iterative mode where, after each iteration of a user-defined set of simulations, the modeler can alter or change parameters and their ranges before the next iteration. Other support programs include SWAT-check, SWAT Base flow (BFlow) (Arnold and Allen, 1999; Arnold et al., 1995), and the Web-based Hydrograph Analysis Tool (WHAT) (Lim et al., 2005), which support that help with model input verification, base flow extraction and separation of hydrographs produced by SWAT, respectively. The ArcGIS software is a Geographic Information System (GIS) program that is used to store and analyze spatial data and ArcSWAT is an interface program that eases the development of SWAT input files from spatial data layers stored in ArcGIS. These programs are open source and freely available expect ArcGIS which is developed by Environmental Systems Research Institute (ESRI Inc.) and proprietary. They can be run independently of each other, except for ArcSWAT which is a plug-in for ESRI's ArcGIS.

Spatial Data

Spatial data on topography, land use and soils were obtained, for the study area, from publically available online databases of the USGS, USDA and US DOI (NLCD). These data are listed in table 2 along with their characteristics (eg. year, scale, resolution) and specific source. The maps of the study watershed presented earlier in figure 1, and related statistics on the distribution of land uses, soils and slopes, were produced using this dataset and provide further illustration of its characteristics.

Table 2: Spatial Data Used in this Study

Data Type	Characteristics	Source
Topography /	USGS NED 2006 10	USGS NED

DEM	Meter DEM	http://ned.usgs.gov http://datagateway.nrcs.usda.gov/
Land Use / Land Cover	NLCD 2006 30 Meter Shapefile	USDA/NRCS - National Geospatial Center of Excellence http://datagateway.nrcs.usda.gov/
Soils	SSURGO 2012 1:24,000 Shapefile	USDA/NRCS http://datagateway.nrcs.usda.gov/

Baseline Time Series

The sources and characteristics of time series data used for the baseline period of the study (1990-2004) are listed in table 3. Data for stream discharge (SurQ), Total Suspended Solids (TSS), Total Nitrogen (TN) and Total Phosphorus (TP) at the watershed outlet were obtained from the USGS National Water Information System (NWIS) for USGS gaging station 01491000. Weather data were obtained from the NOAA National-Weather-Service (NWS) National Center for Environmental Prediction (NCEP) Climate Forecast System Reanalysis (CFSR) database, as provided by Texas A&M's (TAMU) Global Weather Data for SWAT website ("Global Weather Data for SWAT"). Data from 3 weather stations that surround the watershed, were used to add spatial heterogeneity in rainfall distribution over the relatively large study area.

Table 3: Baseline Time Series Data Used in this Study

Data Type	Characteristics	Source
Discharge (SurQ)	USGS Code: #00060 Points: 4383 daily average (m^3/s)	USGS National Water Information System http://waterdata.usgs.gov/usa/nwis/uv?01491000
Total Suspended Sediment (TSS)*	USGS Code: #80155 (tons/day) Points: 197 grab samples	USGS http://waterdata.usgs.gov/usa/nwis/uv?01491000
Total Nitrogen	USGS Code: #00600 Unfiltered** (mg/l)	USGS http://waterdata.usgs.gov/usa/nwis/uv?0

(TN)*	Points: 224 grab samples	1491000
Total Phosphorus (TP)*	USGS Code: #00665 Unfiltered** (mg/l) Points: 217 grab samples	USGS http://waterdata.usgs.gov/usa/nwis/uv?01491000
Baseline Weather	Stations: 3 Daily rainfall, temperature, relative humidity, solar radiation, and wind speed were used.	TAMU NOAA NCDC Reanalysis product http://globalweather.tamu.edu/

* Sediment and nutrient (TN and TP) data are grab samples taken intermittently during the study period.
** The unfiltered specification indicates that inorganic and organic particles were not filtered.

Climate Change Time series

The climate change time series used in this study are derived from predictions of the Geophysical Fluid Dynamics Laboratory Coupled Model Version 2.1 (GFDL CM2.1) Atmosphere-Ocean General Circulation Model (AOGCM) developed by NOAA (Table 4). The model predicts the global changes in temperature, wind and precipitation that are expected to result from changes in atmospheric CO_2 levels. The global CO_2 levels that drive the AOGCM are averages of predictions by two carbon cycle models adopted by the Intergovernmental Panel on Climate Change (IPCC): ISAM (Integrated Science Assessment Model; Kheshgi and Jain, 2003) and BERN (Joos et al., 2001). Predictions of the GFDL CM2.1 AOGCM are part of the CMIP3 (Coupled Model Intercomparison Project Phase 3) archived by the Program for Climate Model Diagnosis and Intercomparison (PCMDI) at Lawrence Livermore National Laboratory (LLNL) for the United Nation’s World Meteorological Organization’s (UNWMO) World Climate Research Programme's (WCRP) Working Group on Coupled Modelling (WGCM). This AOGCM was selected for its low root mean square error relative to temperature and

precipitation observations (Knutti et al., 2013) and from results of Jha et al. (2006) that suggest it may be more accurate than others for US conditions.

This study uses a downscaled version of the global GFDL CM2.1 predictions, developed for high-resolution hydrologic modeling by a collaborative effort of the World Bank, the Nature Conservancy, Climate Central, and Santa Clara University (Maurer et al., 2014; Meehl et al., 2007). The downscaled data were obtained in SWAT format from the dedicated server at TAMU ("Climate Change Data for SWAT (CMIP3)") for socio-economic development scenarios of the IPCC Special Report on Emission Scenarios (SRES; Nakicenovic and Swart, 2000) that lead to low, medium and high future levels of atmospheric CO_2: scenarios B1, A1B and A2, respectively (Table 4). The B1 storyline is characterized by a world that tends toward a service-based economy and resource efficient. The A1B scenario reflects a balance between fossil and non-fossil fuel sources, in combination with rapid economic and technological growth worldwide. The A2 storyline is one where economies and social boundaries remain heterogeneous into the future and economic and technological growth are slower than for B1 and A1B. Downscaled weather predictions for the study watershed, under these 3 scenarios, were obtained for two future time periods: mid-century (2046-2064) and end-century (2081-2100).

Table 4: Climate Change Time Series Data Used in this Study

Source Model	Data Characteristics	Source

GFDL CM2.1 (Unaltered)	CMIP3 (B1, A1B, A2) Station(s): 1 Modeled Temperature (°C) and Precipitation (mm) Mid Century Points (All SRES): 6940 End Century Points (All SRES): 7280	US Dept. of Commerce / NOAA / Geophysical Fluid Dynamics Laboratory http://globalweather.tamu.edu/cmip
BERN and ISAM (Averaged)	Carbon Dioxide Concentration Projections Present Day: 370 ppmv SRES B1: Mid (484), End (540) ppmv SRES A1B: Mid (527), End (678) ppmv SRES A2: Mid (529), End (766) ppmv	NOAA/IPCC http://www.ipcc-data.org/observ/ddc_co2.html

3.4 METHODS

The work performed to achieve the objectives of this study was separated into four consecutive steps: 1) model calibration for the study watershed under current climate; 2) identification of CSAs under current conditions; 3) evaluation of the study watershed's response to climate change, and; 4) identification of CSAs under future climate.

Model Setup and Calibration

Primary SWAT input data, including topography, land use and soil characteristics for the study watershed and weather data for the study period, were obtained from the previously listed sources. Spatial data were entered into ArcGIS and the ArcSWAT plug-in was used to combine them with time series data to produce SWAT input files. The process entailed identification of the watershed boundary and definition of an effective set of outlet-connected tributaries and corresponding subwatersheds based on area topography. This was followed by intersection of spatial data layers to identify and

characterize HRUs within each sub-watershed. Slope and land use thresholds were set to zero (0% or zero land area) during this process to prevent elimination of infrequent HRUs that may correspond to those unusual combinations of characteristics that lead an HRU to be a hotspot, and to support later map production activities (White et al., 2009). The SWAT model was run with the resulting input files and the output was evaluated with the SWAT-check program to verify the consistency, validity and completeness of the input dataset.

Model outputs and USGS gauging data were input into the SWAT-CUP software to perform model calibration using the Sequential Uncertainty Fitting Ver. 2 (SUFI-2) method (Abbaspour et al., 2004). This method is the most widely used by the SWAT user community, and has the most support both in the manual and in the SWAT-CUP online forum ("Google Groups - SWAT-CUP"). Calibration with SUFI-2 involved a nine-step process that ultimately resulted in a fitted parameter range with suggested single values for best fit parameters. It was performed stepwise by constituent, starting with hydrology, then sediment and finally nutrients, as suggested in the literature (Arnold et al., 2012). The number of simulations per iteration was generally set at 500 and iterations continued until goodness-of-fit statistics stopped improving. Adjustments were made, however, for the optimum use of time and computational resources, as, depending on the number of parameters, a single simulation could take from 10 to 20 minutes. The selection of parameters for the calibration process was based on sensitivity analyses presented in prior literature on SWAT (Sexton et al., 2011; Wang, 2015). Hydrograph and baseflow analysis tools (WHAT and SWAT-bflow) were used at the initial hydrology calibration to

fit a base flow coefficient (ALPHA_BF) and experiment with hydrograph separation and weighting to improve hydrologic statistics respectively.

The calibrated model performance was evaluated using commonly used statistics including: Pearson's correlation coefficient (r), Nash-Sutcliffe Efficiency (NSE, also known as coefficient of determination, R^2, Eq. 3 in Nash and Sutcliffe (1970)), Percent Bias and Mean Square Error (MSE). These are defined in equations 1-4 respectively.

$$r = \frac{\sum_{i=1}^{n}\left(Y_i^{obs} - \bar{Y}^{obs}\right)\left(Y_i^{sim} - \bar{Y}^{sim}\right)}{\sqrt{\sum_{i=1}^{n}\left(Y_i^{obs} - \bar{Y}^{obs}\right)^2 \sum_{i=1}^{n}\left(Y_i^{sim} - \bar{Y}^{sim}\right)^2}} \quad (1)$$

$$NSE = 1 - \frac{\sum_{i=1}^{n}\left(Y_i^{obs} - Y_i^{sim}\right)^2}{\sum_{i=1}^{n}\left(Y_i^{obs} - \bar{Y}^{obs}\right)^2} \quad (2)$$

$$PBIAS = \frac{\sum_{i=1}^{n}\left(Y_i^{obs} - Y_i^{sim}\right)}{\sum_{i=1}^{n}\left(Y_i^{obs}\right)} * 100 \quad (3)$$

$$MSE = \frac{1}{n}\sum_{i=1}^{n}\left(Y_i^{sim} - Y_i^{obs}\right)^2 \quad (4)$$

Where for all equations:
Y_i^{obs} = Observed values at given time step
Y_i^{sim} = Simulated values at given time step
$\bar{Y}^{obs}$ = Observed mean
n = Number of observations

Hydrology statistics were calculated on daily, monthly and annual bases by water year (October 1st – September 30th). Statistics for sediment, TN and TP were calculated annually by calendar year. Recommendations and guidelines for use of these statistics in hydrologic and watershed modeling are discussed by Harmel et al., 2014 and Moriasi et al., 2007. Trend lines were computed by regression between predicted and observed annual values of streamflow, sediment and nutrients, to verify that the calibrated model could replicate the range of values observed for these variables over the study period.

Baseline Critical Source Areas (CSAs)

Outputs from the calibrated SWAT model were used to identify Critical Source Areas (CSAs) under current climate in the study watershed (baseline conditions). Following the nomenclature of Chen et al. (2014) the method used in this study is classified as a HRU Load per Area Approach (HRULA). It is a quantile method in which the HRUs exporting top amounts of surface runoff (SurQ), sediments (TSS), nitrogen (TN) and phosphorus (TP) are separated from the rest of the watershed area and considered to be hotspots (CSAs). Two levels were used to establish these CSAs in the present work: the top 10% and the top 20% of HRUs. These hotspots were identified by (1) recording the total number of HRUs (eg. N_{HRU}) in the SWAT model of the Greensboro watershed; (2) ranking HRUs, separately, by their production of: a) SurQ (mm); b) TSS (Mg/ha); c) TN (Kg/ha), and; d) TP (Kg/ha); and (3) marking the top 10% (i.e. 0.1 x N_{HRU}) of each set of ranked HRUs as the 10% level CSAs and the top 20% of each set (i.e. 0.2 x N_{HRU}) as the 20% level CSAs. Accordingly, four sets of CSAs (one per constituent) were developed for each of the two selected levels. The breakpoint constituent levels, marking the boundary between CSA and non-CSA HRUs, were recorded at both target levels for all constituents, for later use in extending the CSA identification process to climate change conditions. The predicted exports of constituents, on a per HRU basis, were retrieved from the SWAT output file "output.hru" and the corresponding SWAT output variables were combined using equations 5, 6, and 7 to produce the total HRU exports needed for ranking.

$$TSS \quad = (SYLD)\frac{Mg}{Ha} \qquad 5)$$

$$TN \quad = (ORGN + NSURQ + NLATQ + NO3GW)\frac{Kg}{Ha} \qquad 6)$$

$$TP \quad = (ORGP + SEDP + SOLP + P\_GW)\frac{Kg}{Ha} \qquad 7)$$

Where:
TSS = Total Suspended Sediment
TN = Total Nitrogen
TP = Total Phosphorus
OrgN/P = Organic Nitrogen/Phosphorus
NSURQ = Nitrogen in surface runoff

The areal coverage of CSAs (A) and the contribution of CSAs to the total amount of constituents generated by HRUs (E) were tabulated. These values were interpreted in terms of advantage ratios, defined as E:A, which quantify the magnitude of export reductions that may be achieved by focusing remediation resources to CSAs. For a given constituent and target level, a large E:A ratio indicates the possibility of obtaining high water quality returns with low resource investment, by targeting Best Management Practices (BMPs) to CSAs.

Watershed Response to Climate Change

The hydrologic and water quality response of the Greensboro watershed to climate change, was evaluated by using the calibrated SWAT model to simulate its behavior with time series downscaled from the GFDL CM2.1 OAGCM as weather input data. Simulations were performed for the 3 selected climate change scenarios (B1, A1B and A2) with time series representing predicted weather at mid-century and end-century (total of 6 simulations). The predictions of annual streamflow, sediment load, total nitrogen and total phosphorus produced by these simulations were compared, at the watershed outlet, with corresponding results obtained under baseline conditions. These

results were used to identify whether export trends were expected to increase or decrease with changing climate in this watershed, and the degree to which they would do so. Predicted trends in watershed export were compared to the trends in precipitation predicted by the downscaled climate models (driving force) and to the literature to explain and contextualize the results.

Effects of Climate Change on Critical Source Areas (CSAs)

Critical Source Areas (CSAs) were identified by using the HRU-based output of SWAT (file "output.hru") resulting from the simulations of the hydrology and water quality response of the Greensboro watershed to scenarios B1, A1B and A2, at mid- and end-century. These climate change CSAs were extracted at the 10% and 20% levels using the same breakpoint constituent levels established in the baseline CSA analysis (fixed threshold approach). In other words, for each constituent and target level, all HRUs producing more than the breakpoint value established at baseline, for that constituent and target level, are considered hotspots in the predicted watershed response to a given climate change scenario. The amount of watershed area occupied by CSAs and their export contributions were computed for the three climate change scenarios, at mid- and end-century, and compared to baseline results to assess the impact of climate change. The trends in CSA area and export with climate change, from the baseline to the mid- and end-century time points were compared to trends in watershed outlet climate change response, over the same time frame and scenarios, to evaluate the degree to which changes in surface and in-stream responses are consistent with one another. Advantage ratios (E:A) were computed for the climate change CSAs and compared to corresponding

values obtained under current climate to quantify the degree to which the benefits of a CSA-based BMP targeting approach may be degraded, maintained or enhanced for each climate change scenario and constituent in the study area. ArcGIS was used to map the CSAs obtained at the 10% and 20% levels for baseline conditions, and for the climate change scenarios that caused them to change the most, to provide a graphical illustration of the expected impact of future climate on hotspots in the study area.

3.5 RESULTS AND DISCUSSION

Model Setup and Calibration

The data preparation steps resulted in a representation of the study watershed composed of 23 sub-basins and 7705 HRUs, which was then calibrated using the procedure outlined earlier. Discharge predicted at the watershed outlet by the calibrated model is presented in Figure 2 along with observed streamflow and precipitation from one of the three stations used in model. Simulated flows follow observations relatively well at the daily time-step but tend to under predict on days with the largest discharges. Observed and simulated mean discharges for the study period are 4.7 m^3/s and 4.1 m^3/s, respectively, corresponding to 498 mm and 434 mm of annual streamflow. The largest difference between observed and simulated flows is for the maximum discharge over the study period, 158.6 m^3/s on 9/17/1999, simulated at almost a third of that value; 57.0 m^3/s. The underpredictions of the largest daily flows in this watershed may be caused by a lack of accounting for snow accumulation and melting, underpredicting humidity and

the use of an “irrigation by need” management approach in the model which likely underestimates actual practices in the area.

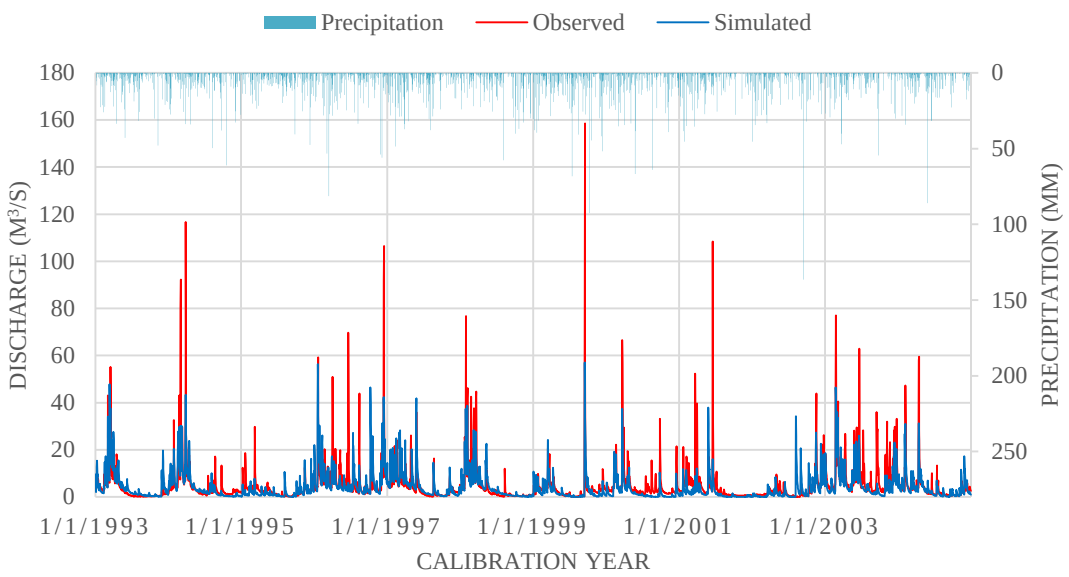


Figure 2: Discharge Calibration Hydrograph and Hyetograph

Calibration statistics are presented in table 5. Daily streamflow is relatively well predicted by the model with a correlation coefficient of 0.66 and an NSE of 0.42 indicating that the model explains 42% of observed daily flow variability. These statistics improve as the temporal scale is widened to monthly and annual bases where correlation with observed flows reaches 0.83 and the model explains up to 2/3 of observed flow variations. These statistics are comparable to those reported in other work using the SWAT model in Maryland watersheds (Chu et al., 2004; Sexton et al, 2010, 2011). Calibration of SWAT sediment and nutrient sub-components on yearly averaged measurements of suspended solids and nutrients results in better correlations (0.77 to 0.91) and Nash-Sutcliffe coefficients (0.47 to 0.79) than for flow indicating that the

overall calibration of the model is adequate for the purpose of simulating the relative response of the watershed to varying hydro-climatic conditions.

Table 5: Calibration Statistics

	Hydrology (SurQ)					
Statistic	**Daily**	**Monthly**	**Annual**	**Sediment (TSS, Annual)**	**Total Nitrogen (TN, Annual)**	**Total Phosphorus (TP, Annual)**
r	0.66	0.83	0.80	0.91	0.77	0.91
NS	0.42	0.66	0.53	0.57	0.47	0.79
Bias [%]	-12.18	-12.28	-9.14	50.12	-13.20	-5.83
MSE	35.52	6.28	1.72	$1.2x10^3$	$1.7x10^5$	$7.2x10^3$

Correlations between annual model predictions and observations of discharge, sediment, TN and TP are depicted graphically in figure 3. There is good agreement between observed and simulated discharges on an annual basis with a regression line slope of 0.9. Sediments are slightly over predicted with a slope of 1.2 especially for years with lower sediment loads. TN has a regression line slope of 0.7 indicating some level of under estimation. The trend line in this case is affected by the data point for 1996 in which nearly twice as much TN was observed as for the second highest nitrogen exporting year. There is good correlation between simulated and observed TP, with a trend line slope of 0.8. In prior studies on other Maryland watersheds, both Chu et al. (2004) and Sexton et al. (2011) noted that 1996 was an unusually wet year. As climate change may generate more years of this type, it is important that the watershed's response be simulated correctly for this case. Calibration results demonstrate that flow, sediments and TP are accurately predicted for this unusual year while TN is less accurate. The TN under-prediction for 1996 is believed to have resulted from additional nitrogen inputs into this and other Maryland watersheds, in the form of an ammonium-based road deicer, used

by county agents during the winter of 1996, which is not accounted for in the model (Sexton et al., 2011). Sexton et al. (2011) also observed that, in Maryland, 1999 contained some particularly wet months with high discharges. The corresponding year is simulated well by the calibrated model, except possibly for a mild under-prediction of TP.

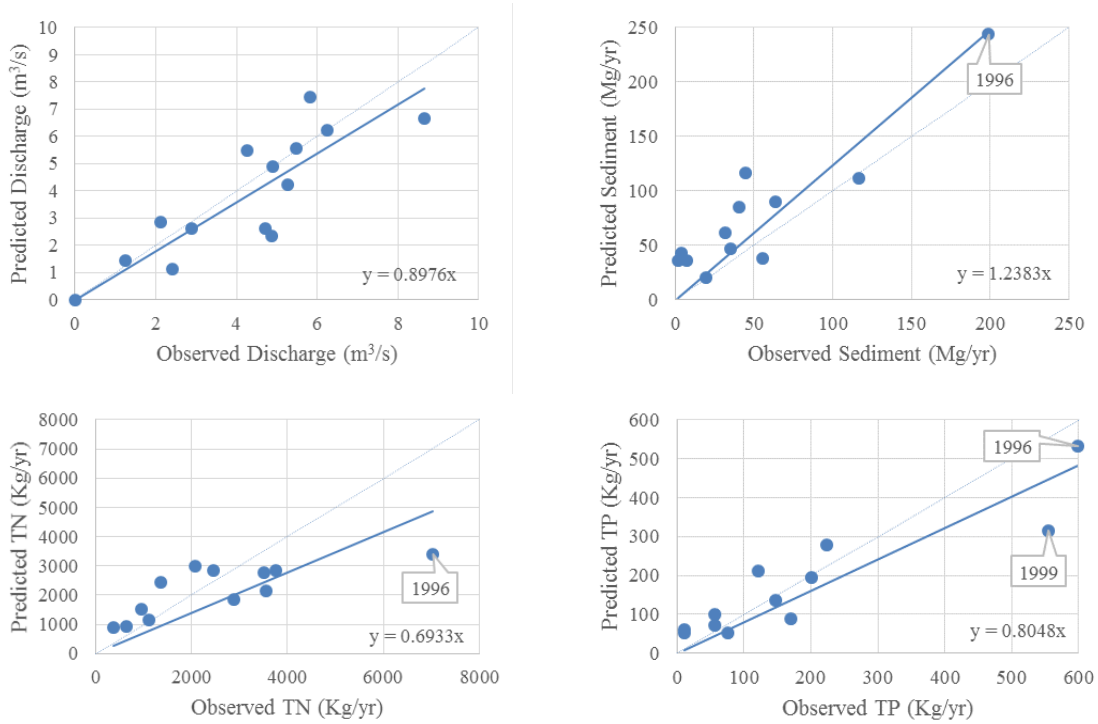


Figure 3: SWAT Annual Calibration for Greensboro Watershed with Trendline (y=Kx, solid) and 1:1 Line (dotted)

Baseline Critical Source Areas (CSAs)

The values of SurQ, TSS, TN and TP generation above which HRUs are considered to be CSAs at the 10% and 20% levels (break points) are presented in Table 6,

along with the percentage of watershed area that these HRUs represent and the percentage, by mass, of each constituent that is generated within them. With 7705 HRUs in the watershed, the 10% CSA level consists of the top 771 HRUs in terms of constituent generation and the 20% level consists of the top 1541 HRUs. With respect to surface runoff, the top 10% and 20% CSAs are those that produce more than 406 mm and 359 mm of runoff annually, respectively. The 10% and 20% runoff CSAs occupy 10% and 21% of the watershed area and generate 16% and 31% of the watershed's surface runoff, respectively. These results indicate that for the Greensboro watershed under current climate there is a 1.5:1 (or greater) advantage to focusing runoff reduction efforts on CSAs rather than placing related BMPs and control structures at non-CSA locations. A target reduction of 25% of surface runoff may be achieved, for example, by implementing BMPs that are 80% effective over 16% of the watershed area (the top 20% CSAs) whereas a minimum of 31% of the watershed area would need to receive such BMPs if they are placed at non-CSA locations. The smaller implementation area resulting from targeting CSAs is expected to lead to lower financial and social costs while producing the same level of environmental improvement.

Table 6: Critical Source Area Break Points for Baseline Conditions at Two Targeting Levels, with Corresponding CSA Area Fraction (A) and Export Contribution (E)

	SurQ			**TSS**		
Rank	**Break Pt (mm/yr)**	**A (%)**	**E (%)**	**Break Pt (kg/ha/yr)**	**A (%)**	**E (%)**
Top 10%	>406	10	16	>1030	8	27
Top 20%	>359	21	31	>730	18	46

	TN			**TP**		
Rank	**Break Pt (kg/ha/yr)**	**A (%)**	**E (%)**	**Break Pt (kg/ha/yr)**	**A (%)**	**E (%)**

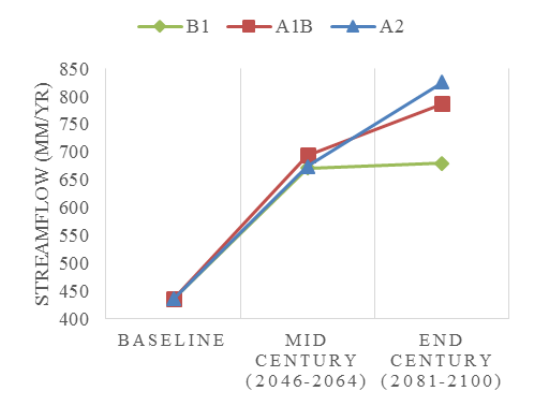
Top 10%	>24	3	11	>1.9	5	23
Top 20%	>16	11	31	>1.3	13	39

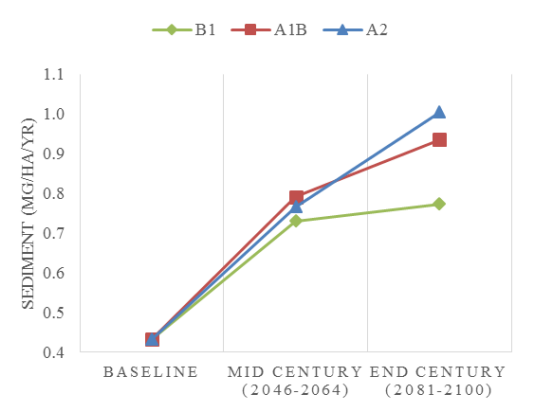
Results of CSA identification for sediments and nutrients under current climate are similar to those for surface runoff but with a larger advantage ratio. For sediments, nearly 30% of the generated mass comes from 8% of the watershed area (top 10% CSAs) and nearly 50% comes from 18% of the area (top 20% CSAs), which corresponds to advantages of 3.4:1 and 2.6:1, respectively, over non-targeted approaches to sediment control. Similarly, 11% of TN is generated over just 3% of the watershed area and 11% of the area contributes 31% of the generated total, leading to advantage ratios of 3.7:1 and 2.8:1 for the top 10% and 20% of CSAs, respectively. The advantage of targeting BMPs to CSAs is even larger for phosphorus with ratios of 4.6:1 and 3.0:1 when the top 10% and 20% CSAs are considered, respectively. Overall these results indicate that under current climate, small land areas within the Greensboro watershed (3% to 21%) contribute substantially to runoff, TSS, TN and TP generation (11% to 46%), such that focusing BMP implementation efforts on these hotspots should provide the best ratio of environmental benefits to resource utilization. CSAs obtained at the 20% level are mapped later in this article to compare them graphically to CSAs resulting from climate change.

Watershed Response to Climate Change

The predicted outlet response of the Greensboro watershed to climate change scenarios B1, A1B and A2, is compared to its behavior under the current climate baseline in Figure 4. At mid-century, there is a substantial increase in annual streamflow,

sediments, total nitrogen and total phosphorus exports for all three climate change scenarios as compared to current climate. At this time point, the predicted response the three scenarios are relatively similar to one another. From mid- to end-century, watershed exports nearly stabilize under scenario B1 but keep increasing under A1B and A2. At end-century, watershed exports are lowest under scenario B1, reaching 681 mm/yr of runoff, 0.77 Mg/ha/yr of sediments, 17 kg/ha/yr of total nitrogen and 1.2 kg/ha/yr of total phosphorus. These represent increases of 56%, 79%, 56% and 52% over the baseline values of 434 mm/yr of runoff, 0.43 Mg/ha/yr of sediments, 11 kg/ha/yr of TN and 0.78 kg/ha/yr of TP, respectively. The largest exports are reached under scenario A2 for runoff (826 mm/yr), sediments (1.0 Mg/ha/yr) and total phosphorus (1.4 kg/ha/yr) and represent increases of 90%, 132% and 80% over the baseline. The largest end-century export of total nitrogen occurs under scenario A1B where 20.5 kg/ha/yr of TN flows out of the watershed, which is an 88% increase over the current climate baseline.





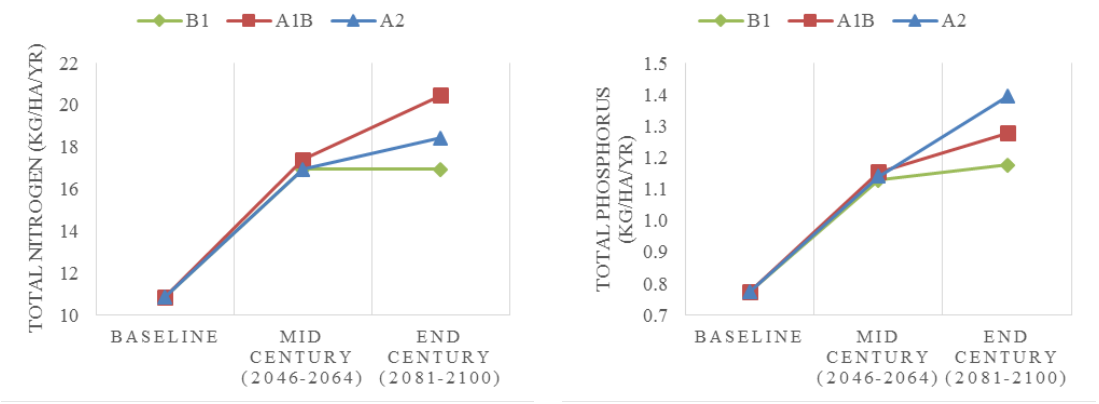


Figure 4. Hydrologic Response of the Greensboro Watershed (Outlet) to Climate Change Scenarios

The increases in exports predicted under climate change by the calibrated SWAT model for the Greensboro watershed are consistent with results presented by Woznicki et al. (2011) for an agricultural watershed at the Kansas-Nebraska border in the US. These authors found the B1, A1B and A2 scenarios to result in increases in streamflow, sediments, nitrogen and phosphorus at the outlet of their study watershed. They also found that increases were less significant under scenario B1 than under A1B and A2. For their study area, the climate models predicted increases in annual rainfall of 8% to 15%, which resulted in increases in streamflow, sediment, nitrogen and phosphorus export of the order of 20% to 50%. In the present study, climate models predict an increase in annual rainfall of 25% to 30% over the Greensboro watershed (Table 7); this generates increases of the order of 50% to 90% in predicted streamflow, nitrogen and phosphorus exports. In other words, with twice the predicted increase in annual rainfall due to climate change for eastern Maryland, compared to Kansas-Nebraska, the present modeling predicts approximately twice the increase in streamflow and constituent export for the Maryland watershed relative to the increases predicted by Woznicki et al. (2011) for their study watershed. The largest increase in yields predicted here is for sediments (132%)

and, while proportionally larger than for the watershed of Woznicki et al. (2011), it is lower than corresponding results in a Nebraska watershed presented by Van Liew et al. (2012) where a 7% increase in rainfall produced an increase in sediment yields of up to 150%.

Table 7: Percent Change in Precipitation for SRES B1, A1B and A2 End Century, Above Baseline

Daily Precipitation Event	**B1 End**	**A1B End**	**A2 End**
>80 mm	25%	50%	175%
60-80 mm	225%	325%	425%
40-60 mm	175%	100%	65%
20-40 mm	58%	63%	56%
10-20 mm	31%	21%	19%
5-10 mm	6%	-19%	-24%
0-5 mm	-1%	-33%	-32%
Change in Annual Precipitation:	25%	30%	29%

(Note: to compare with 15 year baseline, only first 15 years of each scenario's data were used)

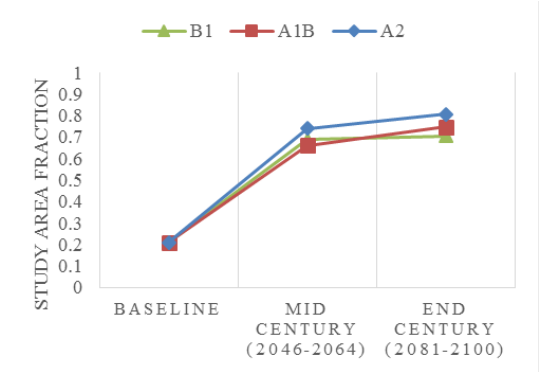
The differences in rainfall regimes predicted by climate models for the three climate change scenarios (Table 7) provide an explanation for predicted differences in constituent exports. The increase in annual rainfall (over baseline) is smallest for the B1 scenario (25%), which explains why it produces the lowest increases in streamflow and constituents relative to current climate. For the A2 scenario, there is a more substantial increase in large rainfall events (above 60 mm) relative to the baseline than in A1B and B1 which leads to more surface runoff, soil detachment and bound phosphorus transport and helps explain why this scenario produces the largest increases in exports of these constituents. The A1B scenario has the largest increase in annual rainfall (30%) but the increase is smaller for large events than in A2 and this leads to more infiltration and leaching of nitrogen than in A2, resulting in the higher TN export that is predicted for this scenario (Davis and Hunt, 2009).

The 25% to 30% increase in annual rainfall predicted by the GFDL AOGCM in this study is larger than found in several other studies (Jha et al., 2006; Woznicki et al., 2011; Van Liew et al., 2012; Bosch et al., 2014). One reason for the difference is that the Northeast climate region is expected to undergo a larger increase in rainfall than other US regions (Melillo et al., 2014). Another reason, as seen in Jha et al. (2006), is that the GFDL AOGCM predicts higher increases in rainfall under future climate than several other CMIP3 Global Climate Models (GCMs) and many studies use an average of these GCMs for their analysis. The multi-model approach has value given the uncertainty in future climate predictions, but, as stated earlier, the GFDL model was chosen for this study because of its higher accuracy, relative to others, in predicting past climate (Knutti et al., 2013). It is expected that this higher accuracy translates into higher accuracy in prediction of future climate as well. In the eventuality that a multi-model approach proves more accurate, the present results will remain valuable as a possible worst-case scenario for the study area.

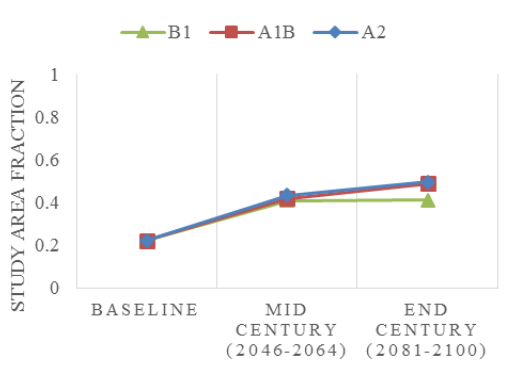
Effects of Climate Change on Critical Source Areas (CSAs)

The effects of climate change on the fraction of watershed area occupied by CSAs are presented graphically in Figure 5 for the three future climate scenarios. These CSAs correspond to HRUs that produce target constituents at levels that exceed the 20% break point values listed in table 6 established from baseline conditions. For all three climate scenarios, the land area occupied by CSAs is observed to increase markedly from baseline to mid-century with slightly higher changes in runoff and TN CSA areas under A2 than B1 and A1B. The increase in CSA area mostly continues from mid- to end-

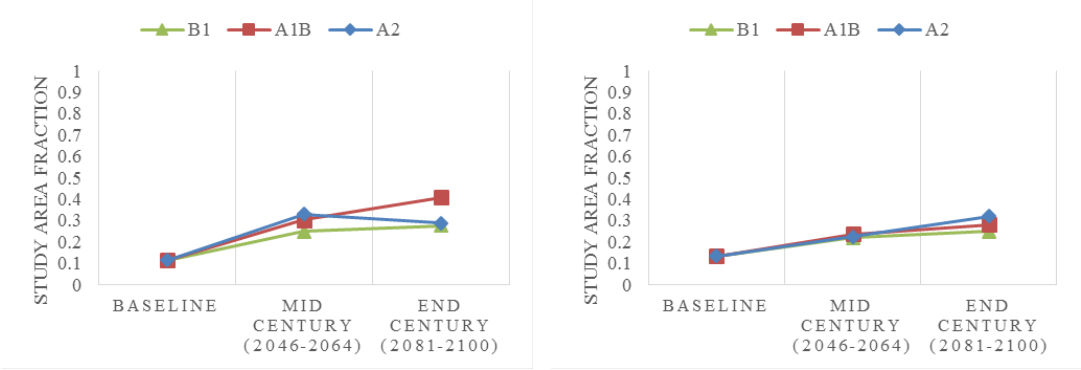
century in A1B and A2, but at a slower rate, and with the exception of the TN CSA in A2, which undergoes a decrease in area. For the B1 scenario, the area occupied by CSAs appears relatively constant between mid- and end-century time points. As expected, these trends in the fraction of watershed area occupied by hotspots follow the increases in streamflow and constituents predicted for the watershed outlet. With increased annual rainfall predicted under climate change, a larger number of HRUs generate runoff and constituents at levels that exceed the breakpoints established under baseline conditions. The relative magnitude by which CSA areas increase is, however, larger than that of constituents at the outlet, as will be seen below, leading to a decrease in the advantage gained by targeting BMP implementation to CSAs. Surface runoff is most notable in this respect with end-century CSAs (HRUs generating more than 359 mm/yr) that cover 70% to 80% of the watershed area.



A) SurQ



B) TSS



C) TN *D)* TP

Figure 5: Change in Watershed Area Fraction of CSAs Under SRES B1, A1B and A2 Climate Scenarios

Figure 6 presents the annual yields of surface runoff, sediments, nitrogen and phosphorus produced by the CSA HRUs at mid- and end-century for the three climate change scenarios. These curves follow trends similar to those for constituent export at the watershed outlet and for changes in CSA areas. The magnitude by which these quantities increase under future climate is amplified by both the predicted increase in rainfall and the increase in CSA area. For example, under the A2 scenario, the annual amount of sediments generated by CSAs at end-century is predicted to be nearly 5 times the amount generated under baseline conditions, because increased rainfall quantity and intensity are producing more sediments on each HRU and, jointly, CSA areas have increased by 2.5 times. Similarly, under A1B at end-century, total nitrogen export is predicted to be more than 4 times larger than under current climate because of increases in lower intensity precipitation (relative to A2) and a greater than 3 times increase in CSA area.

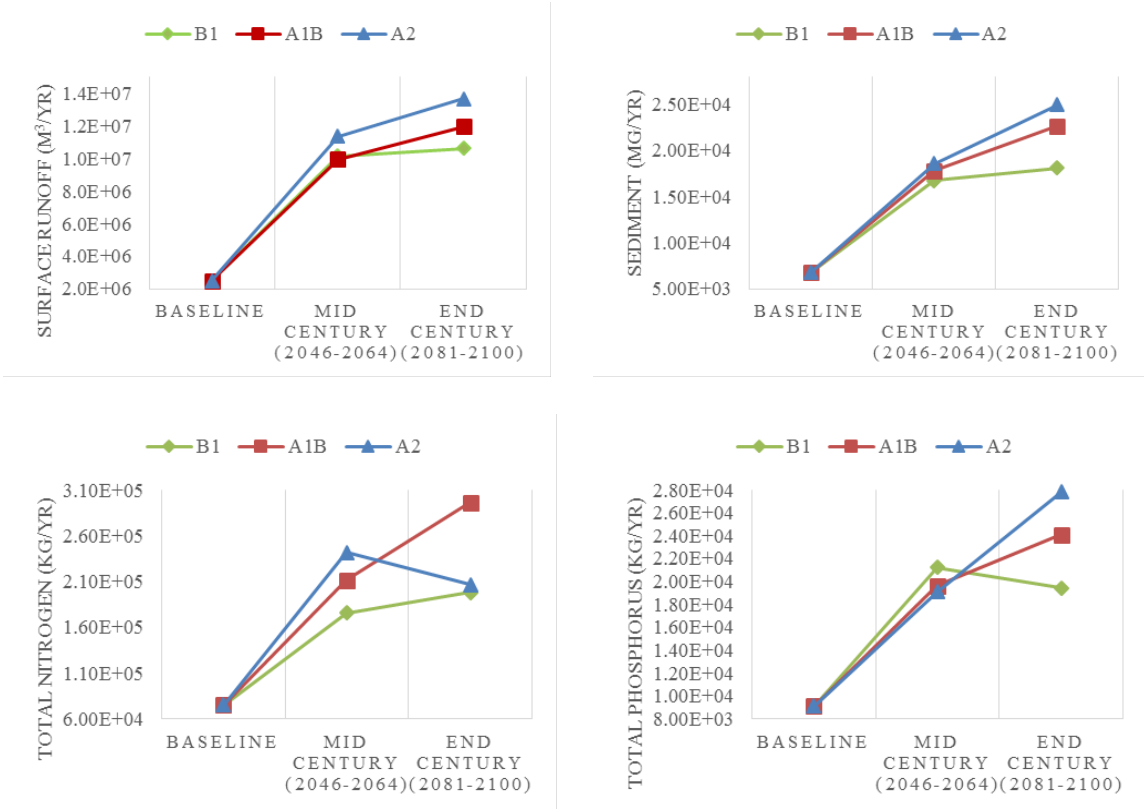


Figure 6. Constituent Export from CSAs under SRES B1, A1B and A2 Scenarios

The percentage of watershed area occupied by CSAs and their export contribution relative to the amount of constituents generated by all HRUs in the study watershed are presented in Table 8 for the three climate change scenarios (end-century) and the current climate baseline. For surface runoff, CSAs cover 21% of the watershed under current climate and 70% (B1) to 81% (A2) of the area under climate change. These CSAs contribute 31% of the total surface runoff produced within the watershed in current conditions and 82% (B1) to 89% (A2) with changed climate. The advantage ratio obtained by targeting runoff control BMPs to CSAs drops from 1.5:1 under current climate to between 1.1:1 (A2) and 1.2:1 (B1) with climate change. In this case, the low advantage ratio and large targeted area suggest that, under climate change, a CSA-based

approach to surface runoff control will no longer be valuable. Indeed, the present results suggest that surface runoff control measures will be required on all agricultural and urban lands within the study watershed to achieve the same level of reduction attainable under current climate with runoff BMPs covering just 21% of the land.

Table 8: Hotspot Area Fraction (A), Export Contribution (E), and Advantage Ratios E:A at Baseline and at End of Century

Constituent	Baseline			B1			A1B			A2		
	%		E:A	%		E:A	%		E:A	%		E:A
	E	A		E	A		E	A		E	A	
SurQ	31	21	1.5:1	82	70	1.2:1	86	75	1.1:1	89	81	1.1:1
TSS	46	18	2.6:1	75	37	2.0:1	78	45	1.7:1	81	45	1.8:1
TN	31	11	2.8:1	56	28	2.0:1	72	41	1.8:1	57	29	2.0:1
TP	39	13	3.0:1	60	25	2.4:1	63	28	2.3:1	66	32	2.1:1

For sediments, the area of CSAs is predicted to more than double as a result of climate change, from 18% of the watershed area in current climate to between 37% (B1) and 45% (A1B, A2). In current climate the CSAs generate 46% of sediments produced in the basin and this increases to between 75% (B1) and 81% (A2) under climate change. The advantage of implementing sediment control BMPs on CSAs drops from 2.6:1 in current conditions to between 1.8:1 (A1B) and 2.0:1 (B1) with climate change. These advantage ratios suggest that targeting sediment control BMPs to CSAs will remain a valuable strategy with changing climate in this watershed. It must be noted however that the 45% of land covered by CSAs in A1B and A2 represents more than 80% of the agricultural and urban land in the basin, and therefore from a practical standpoint (and assuming no sediment production in forests and wetlands), nearly all watershed

stakeholders may need to be involved in sediment BMP implementation and maintenance if those more severe climate change scenarios are realized.

The area fraction of CSAs for nitrogen is predicted to increase from 11% in current conditions to between 28% (B1) and 41% (A1B) with changed climate and their relative export contributions approximately double from 31% currently to between 56% (B1) and 72% (A1B). The corresponding advantage ratios decrease from 2.8:1 currently to between 1.8:1 (A1B) and 2.0:1 (B1) suggesting that CSA-based BMP targeting will remain valuable, especially if the B1 or A2 scenarios are realized. For phosphorus, the predicted increase in CSA area fraction is from 13% currently to between 25% (B1) and 32% (A2) with CSA contributions that increase from 39% of the watershed total presently, to between 60% (B1) and 66% (A2). For this constituent, CSA-based targeting of BMPs remains valuable despite a decrease of advantage ratios from 3.0:1 under current climate to between 2.1:1 (A2) and 2.4:1 (B1) with changing climate.

It is interesting to compare the reductions of advantage ratios predicted above to the results obtained under current climate by Wang (2015) for a suburban and an urban watershed in Maryland's Piedmont and Atlantic Coastal Plain physiographic regions. The advantage ratios for the suburban watershed were similar to those obtained for the Greensboro watershed under current climate (approximately 1.5:1, 2.7:1, 2.5:1 and 2.2:1 for SurQ, TSS, TN and TP, respectively) while those for the urban watershed were similar to those obtained in the present study under climate change (approximately 1.3:1, 1.7:1, 1.6:1 and 2.3:1, respectively). Accordingly, one might consider, at first analysis, that the impact of climate change on the study watershed is to render its pervious areas less effective at buffering the increased amounts of runoff caused by changing rainfall

patterns, making it behave in a manner similar to an urban environment where infiltration capacity is frequently overwhelmed by rainfall (and stormwater sewer systems carry this excess rainfall out of the watershed). With respect to water quality, the present results suggest that, with climate change, a broader segment of the residents of agricultural watersheds will need to participate in BMP implementation, in a manner similar to what is currently needed in urban environments under today's climate. As a consequence, community-oriented approaches to watershed sustainability, targeted at rural audiences, are expected to become increasingly relevant in the Northeast US (Leisnham et al., 2013; Chanse et al., 2014).

Maps of CSAs for surface runoff, sediments and nutrient generation are presented in Figure 7 for current climate and for the climate change scenarios that produce the largest increase in CSA area for each constituent (A2 for runoff, TSS and TP, A1B for TN). The red areas in these maps depict HRUs that fall above the 10% CSA break point values in Table 6 and the combination of orange and red areas represents CSAs obtained at the 20% break point level. These maps clearly illustrate the substantial increase in CSA area caused by climate change. In the case of runoff, the current climate CSAs are found on a few areas with soils of Hydrologic Soil Groups (HSGs) C and D, in the eastern part of the watershed and near streambeds. Climate change, under scenario A2, causes these CSAs to expand to cover most of the watershed, including areas with HSGs A and B. For sediments, the CSAs under current conditions are concentrated on a few high slope areas, in the western half of the watershed; climate change (scenario A2) expands those areas to cover the western half almost entirely, and produces several new CSAs near streams in the eastern subbasin. In the case of nitrogen, the current climate CSAs consist of

numerous small areas with agricultural or urban land use on infiltrable soils (HSGs A and B), mostly in the western half of the watershed; climate change (A1B) causes these areas to grow to include agricultural zones on less infiltrable HSG C soils and a larger proportion of both the western and eastern halves of the basin. For phosphorus, the CSAs under current climate also consist of several small export areas with agricultural land use, but contrary to nitrogen, these areas are mostly in the eastern half of the watershed, on HSG C and D soils that promote surface runoff production. Climate change scenario A2 expands these CSAs to nearly all watershed areas with poorly infiltrable soil.

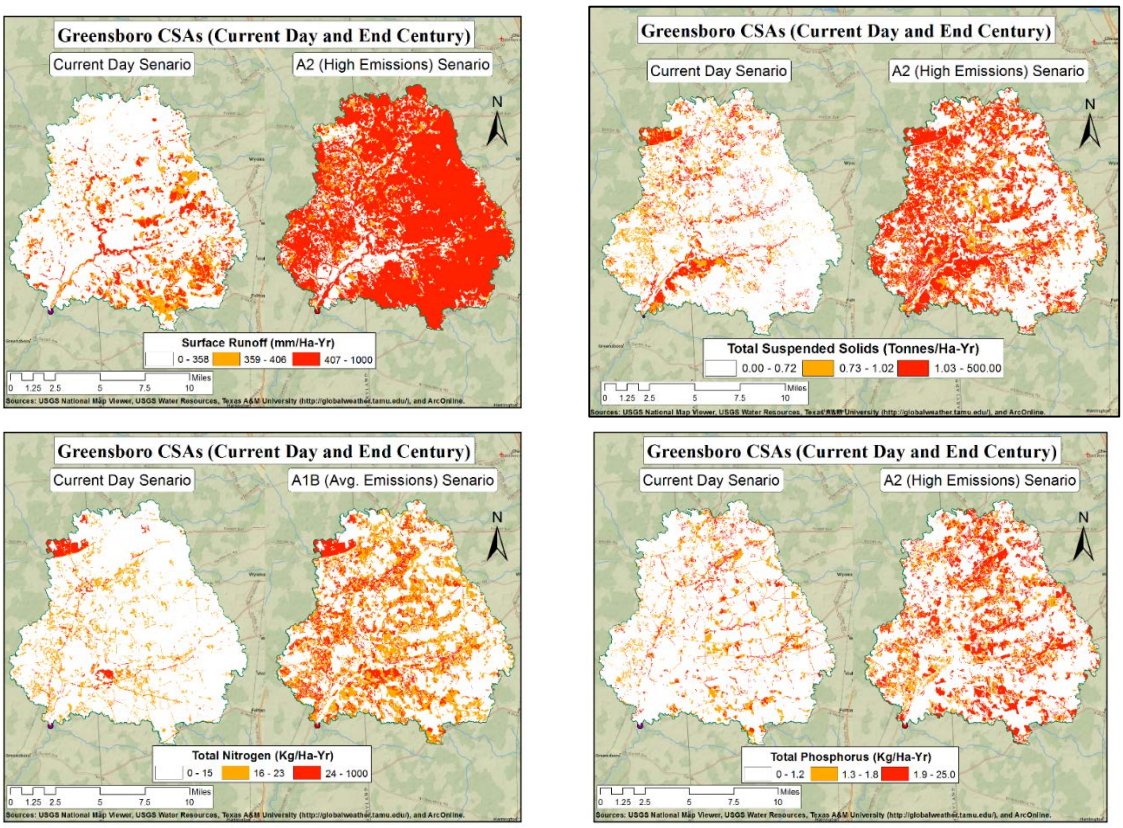


Figure 7: Changes in Critical Source Export Area by Target Pollutant and Climate Scenarios

The results presented here are to be interpreted in the context of the approach used in this work to define CSAs which applies a fixed set of thresholds, derived from baseline conditions, to define HRU hotspots under future climate. A consequence of this choice is that the increased annual rainfall predicted to occur under the three simulated scenarios (relative to the baseline) necessarily produced a concomitant increase in the area occupied by hotspots. This increase was not followed with a proportional increase in relative export contributions and therefore led to reduced advantage ratios. An alternative approach would have been to re-rank HRUs (by constituent) at the end of the simulations for each scenario and to consider the top 20% of them as CSAs. The fixed threshold approach was selected for this study so that the impacts of climate change on water quality could be evaluated in relation to today's water quality objectives rather than relative to a baseline that shifts upwards as climate change manifests along the selected scenarios. To illustrate the difference between the two approaches, one may consider phosphorus as an example. If the baseline CSAs at the 20% level (HRU breakpoint of 1.3 kg/ha/yr from Table 6) are targeted today to obtain a 40% decrease in TP export at the watershed outlet from 0.78 kg/ha/yr to 0.47 kg/ha/yr, then this reduction can be achieved, essentially, by placing 100% efficient BMPs on the baseline CSAs (neglecting additional attenuation from in-stream processes). Using a relative targeting approach, at the end-century mark, under the mildest climate change scenario (B1), the objective of reducing TP export by 40% at that time would correspond to a reduction from the 1.2 kg/ha/yr predicted at end-century to 0.72 kg/ha/yr. This target is 1.5 times greater than the target established based on today's hydro-climatic conditions and may not meet the desired water quality standards or the NPS component of a TMDL (i.e Load Allocation, LA;

Sexton et al., 2011). With the fixed break point approach of the present study, applying 100% efficient BMPs on the TP CSAs identified at end-century for the B1 scenario would lead to the same export level of 0.47 kg/ha/yr as is obtained with current climate (again, neglecting in-stream processes). Although the equality in this example is fortuitous, it is readily verified that the expected TP exports, with CSAs defined using fixed thresholds and 100% efficient BMPs, under A1B and A2, at end-century, are 0.51 kg/ha/yr and 0.44 kg/ha/yr, respectively, both of which are significantly closer to the present day target of 0.47 kg/ha/yr of this example than would be obtained with a relative threshold. Similar results are obtained for sediments and nitrogen provided that BMPs are 90% to 100% efficient, and for surface runoff provided that BMPs reduce runoff by 2/3 on the CSAs. The relative threshold approach to CSA identification may become more useful when specific concentrations are used as targets of watershed analysis or if TMDLs are updated to account for changes in streamflow resulting from climate change, which are to be investigated in future work.

3.6 SUMMARY AND CONCLUSIONS

This study evaluated the potential effects of climate change on the distribution of runoff, sediment, nitrogen and phosphorus CSAs in an agricultural watershed that flows into the Chesapeake Bay. The Bay's location in the US Northeast climate region is expected to cause it to receive the largest increases in annual rainfall and storm intensity of the conterminous US. Spatial data representing watershed soils, topography, land use and hydrography were obtained from federal databases. Discharge and concentrations of sediments, nitrogen and phosphorus in streamflow, at the watershed outlet, were obtained

from the USGS and weather data were obtained from NOAA for the 15-year period from 1990 to 2004. The spatial and weather data were used to develop input files for the SWAT hydrologic model which was then calibrated against the outlet data using the SUFI-2 method. The correlation coefficients between calibrated model and observed values ranged from 0.8 to 0.9 on an annual basis, Nash-Sutcliffe coefficients ranged from 0.5 to 0.8 and regression lines between predicted and observed values had slopes of 0.7 to 1.2. These calibration results are comparable to values from the literature that were considered to range from satisfactory to very good.

Critical Source Areas of runoff, sediments, TN and TP were identified from the output of the calibrated model, representing baseline conditions (current climate). CSAs were determined separately for each constituent, at two threshold levels corresponding to the 10% and 20% of top generating HRUs in the watershed, and their areas and export contributions were computed. The efficiency advantage resulting from targeting BMP to CSAs (ratio of export contribution to area, E:A) were calculated for all constituents and threshold levels. At the 10% threshold, baseline CSAs occupied 3% to 10% of the watershed area and contributed 11% to 27% of constituents. At the 20% level they occupied 11% to 21% of the area and contributed 31% to 45% of constituents. The advantage ratios under current climate were approximately 1.5:1 for runoff and 3:1 for other constituents (slightly higher at the 10% level and lower at the 20% level, as expected), indicating, for example, that phosphorus exports may be reduced by nearly 40% by placing BMPs on 13% of the watershed area.

The response of the study watershed to climate change was evaluated by simulation, using the calibrated SWAT model, with weather time series downscaled from

predictions of the NOAA GFDL CM2.1 AOGCM for mid-century (2046-2064) and end-century (2081-2100) time frames, under SRES scenarios B1 (low emissions), A1B (medium emissions) and A2 (high emissions). The increase in annual precipitation predicted by the AOGCM at end-century ranged from 25% (B1) to 30% (A1B and A2) over current climate. In response, streamflow at the watershed outlet was predicted to increase by 56% (B1) to 90% (A2) over current conditions. Sediment yield was predicted to increase by 79% (B1) to 132% (A2), TN by 56% (B1) to 88% (A1B) and TP by 52% (B1) to 80% (A2) over current conditions, in response to climate change. Stated differently, a low emissions future (B1) is predicted to produce increases of 50% to 80% in watershed yields over current conditions (a factor of 1.5 to 1.8 times the current yields), while medium or high emissions futures (A1B or A2) produce increases over a higher bracket at 80% to 132% (factors of 1.8 to 2.3 times current yields) in the study area.

CSAs were identified from outputs of calibrated SWAT model simulations of the study watershed's response to climate change using the 20% threshold level of the baseline analysis. For surface runoff, climate change was predicted to cause the area of CSAs to more than triple relative to baseline conditions, going from 21% under current climate to between 70% (B1) and 81% (A2) of watershed area. The contribution of these CSAs to total runoff generation more than doubled but advantage ratios dropped from 1.5:1 under current climate to approximately 1.1:1 with climate change, suggesting that targeting runoff control BMPs to CSAs will no longer be valuable under future climates. The areas occupied by CSAs for other constituents were predicted to increase by factors of mostly 2 to 3 under climate change and their export contribution were predicted to

increase by factors near 2, resulting in advantage ratios that decreased from 3:1 in the baseline to approximately 2:1 with climate change. Accordingly, CSA-targeting of BMPs, for sediment, nitrogen and phosphorus control, is expected to remain valuable with climate change. However, the large predicted increase in watershed area covered by CSAs suggests that a larger number of stakeholders may need to be involved in BMP implementation with climate change (2 to 3 times more than under current condition). Consequently, community-oriented participatory approaches related to water quality education and to BMP adoption, implementation and maintenance, are expected to become more important in helping to meet the Chesapeake Bay TMDLs, even in rural environments, as climate changes.

Acknowledgements

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3.7 REFERENCES

Abbaspour, K.C. 2013. SWAT-CUP 2012. Retrieved from http://www.neprashtechnology.ca/Downloads/ SwatCup/Manual/Usermanual_Swat_Cup_2012.pdf

Abbaspour, K. C., Johnson, C. A., and M.Th. Van Genuchten. 2004. Estimating uncertain flow and transport parameters using a sequential uncertainty fitting procedure. Vadose Zone Journal, 3(4), 1340–1352.

Arnold, J. G., and P. Allen. 1999. Automated methods for estimating baseflow and groundwater recharge from streamflow records. J. Americam Water Resources Assoc., 35(2):411–424.

Arnold, J. G., Allen, P. M., and G. Bernhardt. 1993. A comprehensive surface-groundwater flow model. J. Hydrol., 142(1–4):47–69. http://doi.org/10.1016/0022-1694(93)90004-S

Arnold, J. G., Allen, P., Muttiah, R., and G. Bernhardt. 1995. Automated base flow separation and recession analysis techniques. Ground Water, 33(6):1010–1018.

Arnold, J. G., Moriasi, D. N., Gassman, P. W., Abbaspour, K. C., White, M. J., Srinivasan, R., C. Santhi, R. D. Harmel, A. van Griensven, M. W. Van Liew, N. Kannan and M. K. Jha. 2012. SWAT: Model use, calibration, and validation. Trans. ASABE, 55(4):1491–1508.

Bosch, N.S., M.A. Evans, D. Scavia and J.D. Allan. 2014. Interacting Effects of Climate Change and Agricultural BMPs on Nutrient Runoff Entering Lake Erie. J. Great Lakes Research, 40(2014):581-589.

Chanse, V., P.T. Leisnham, A. Rockler, J. McCoy, L. Cain, S. Wilson, H. Montas, A. Shirmohammadi, A. Mohamed. 2014. A community-based participatory research approach for stormwater management: Implications of differing BMP approaches in two urban watersheds. EDRA45, The Environmental Design Research Association Conference (New Orleans, LA: May 31st, 2014).

Chen, L., Zhong, Y., Wei, G., Cai, Y., and Z. Shen. 2014. Development of an integrated modeling approach for identifying multilevel non-point-source priority management areas at the watershed scale. Water Resources Research, 50(5), 4095–4109. http://doi.org/10.1002/2013WR015041

Chesapeake Bay Program. 2012. Discover the Chesapeake. Published Online, Retrieved September 21, 2015, from http://www.chesapeakebay.net/discover/bay101/facts

Chu, T. W., Shirmohammadi, A., Montas, H., and A. Sadeghi. 2004. Evaluation of the SWAT model's sediment and nutrient components in the Piedmont physiographic region of Maryland. Trans. ASAE, 47(5):1523–1538.

Climate Change Data for SWAT (CMIP3). (n.d.). Retrieved December 2, 2015, from http://globalweather.tamu.edu/cmip

Davis, A., and W. Hunt. 2009. Bioretention Technology: Overview of Current Practice and Future Needs. J. Environmental Engineering, 135(3), 109–117. http://doi.org/10.1061/(ASCE)0733-9372(2009)135:3(109)

Executive Order 13508, 3 C.F.R. (2009). Retrieved June 29, 2015, from https://www.whitehouse.gov/the-press-office/executive-order-chesapeake-bay-protection-and-restoration

Garvin, S.M. and J.A. Enck. 2010. Chesapeake Bay Total Maximum Daily Load for Nitrogen, Phosphorus and Sediment. U.S. Environmental Protection Agency, Washington D.C., available online at: http://www2.epa.gov/chesapeake-bay-tmdl/chesapeake-bay-tmdl-document

Gassman, P., Reyes, M., Green, C., and J. Arnold. 2007. The Soil and Water Assessment Tool: Historical Development, Applications, and Future Research Directions. Trans. ASABE, 50(4):1211–1250.

Global Weather Data for SWAT. (n.d.). Retrieved December 2, 2015, from http://globalweather.tamu.edu/

Harmel R.D., Smith P.K., Migliaccio K.W., Chaubey I., Douglas-Mankin K.R., Benham B., S. Shukla, R. Muñoz-Carpena and B.J. Robson. 2014. Evaluating, interpreting, and communicating performance of hydrologic/water quality models considering intended use: A review and recommendations. Environ. Modelling and Software, 57:40–51.

Huaifeng, G., Zuhao, Z., Dayong, Q., Jiguo, Y., and C. Qiang. 2010. Analysis of Critical Source Areas about Multi-source Nutrient Loadings Based on SWAT Model in Jiyun River Basin. HKIE Trans., 17(2):14–19. http://doi.org/10.1080/1023697X.2010.10668191

Huang, J. J., Lin, X., Wang, J., and H. Wang. 2015. The precipitation driven correlation based mapping method (PCM) for identifying the critical source areas of non-point source pollution. J. Hydrol. 524:100–110. http://doi.org/10.1016/j.jhydrol.2015.02.011

Jha, M.K., J.G. Arnold, P.W. Gassman, F. Giorgi and R.R. Gu. 2006. Climate Change Sensitivity Assessment on Upper Mississippi River Basin Streamflows using SWAT. J. American Water Resources Assoc. 42(4):997-1016.

Joos, F., I. C. Prentice, S. Sitch, R. Meyer, G. Hooss, G.-K. Plattner, S. Gerber and K. Hasselmann. 2001. Global warming feedbacks on terrestrial carbon uptake under the Intergovernmental Panel on Climate Change (IPCC) emission scenarios. Global Biogeochemical Cycles, 15(4):891-907

Kheshgi, H.S., and A.K. Jain. 2003. Projecting future climate change: Implications of carbon cycle model intercomparision, Global Biogeochemical Cycles, 17(2):1047, doi:10.1029/2001GB001842.

Knutti, R., D. Masson and A. Gettelman. 2013. Climate Model Genealogy: Generation CMIP5 and How We Got There. Geophysical Review Letters, 40:1194-1199.

Leisnham, P., H. Montas, A. Shirmohammadi, V. Chanse, D. Lansing, A. Rockler, T. Hutson, J. McCoy, L. Cain, S. Wilson, D. Lipton, K. Brubaker and Y. Wang. 2013. Watershed Diagnostics for Improved Adoption of Management Practices: Integrating Biophysical and Social Factors Across Urban and Agricultural Landscapes. In 2013 ASABE Annual International Meeting Paper. Paper number 131668614, 2013 Kansas City, Missouri, July 21 - July 24, 2013. (doi: http://dx.doi.org/10.13031/aim.20131668614)

Lim, K.J., B.A. Engel, Z. Tang, J. Choi, K.-S. Kim, S. Muthukrishnan and D. Tripathy. 2005. Automated Web GIS Based Hydrograph Analysis Tool, WHAT. J. American Water Resources Assoc., 41(6):1407–1416. http://doi.org/10.1111

Maryland Geological Survey. 2015. Maryland Geology. Online Publication. Retrieved September 28, 2015, from http://www.mgs.md.gov/geology/

Maurer, E. P., Brekke, L., Pruitt, T., Thrasher, B., Long, J., Duffy, P., M. Dettinger, D. Cayan and J. Arnold. 2014. An Enhanced Archive Facilitating Climate Impacts and Adaptation Analysis. Bulletin of the American Meteorological Society, 95(7), 1011–1019. http://doi.org/10.1175/BAMS-D-13-00126.1

Meehl, G. A., Covey, C., Delworth, T., Latif, M., McAvaney, B., Mitchell, J. F. B., R. J. Stouffer and K.E. Taylor. 2007. THE WCRP CMIP3 MULTIMODEL

DATASET: A New Era in Climate Change Research. Bulletin of the American Meteorological Society, 88(9):1383–1394. http://doi.org/10.1175/BAMS-88-9-1383

Melillo, J.M., T.C. Richmond and G.W. Yohe (eds). 2014. Climate Change Impacts in the United States: The Third National Climate Assessment. U.S. Global Change Research Program, 841pp. U.S. Government Printing Office, Washington, DC. doi:10.7930/J0Z31WJ2.

Moriasi, D. N., Arnold, J. G., Van Liew, M. W., Bingner, R. L., Harmel, R. D. and T.L. Veith. 2007. Model evaluation guidelines for systematic quantification of accuracy in watershed simulations. Trans. Asabe, 50(3):885–900.

Mueller, D. and D. Helsel. 2013. Nutrients in the Nation's Waters--Too Much of a Good Thing? [Government]. Retrieved September 21, 2015, from http://pubs.usgs.gov/circ/circ1136/circ1136.html#FOREWORD

Nakicenovic, N., and R. Swart, eds. 2000. Emissions scenarios: A Special Report of Working Group III of the Intergovernmental Panel on Climate Change. Intergovernmental Panel on Climate Change. Cambridge University Press. New York, NY.

Nash, J.E. and J.V. Sutcliffe. 1970. River Flow Forecasting Through Conceptual Models, Part I - A Discussion of Principles. J. Hydrol., 10(1970):282-290.

Niraula, R., L. Kalin, P. Srivastava and C.J. Anderson, 2013. Identifying Critical Source Areas of Nonpoint Source Pollution with SWAT and GWLF. Ecological Modelling, 268(2013):123-133.

Ritter, W.F. and A. Shirmohammadi.(Eds). 2001. Agricultural Nonpoint Source Pollution-Watershed Management and Hydrology. Lewis Pubrs, Washington, D.C., 342p.

Sexton, A. M., Sadeghi, A. M., Zhang, X., Srinivasan, R., and A. Shirmohammadi. 2010. Using NEXRAD and rain gauge precipitation data for hydrologic calibration of SWAT in a northeastern watershed. Trans. ASABE, 53(5):1501–1510.

Sexton, A. M., Shirmohammadi, A., Sadeghi, A. M., and H.J. Montas. 2011. A stochastic method to characterize model uncertainty for a nutrient TMDL. Trans. ASABE, 54(6):2197–2207.

Shang, X., Wang, X., Zhang, D., Chen, W., Chen, X., and H. Kong. 2012. An improved SWAT-based computational framework for identifying critical source areas for agricultural pollution at the lake basin scale. Ecological Modelling, 226, 1–10. http://doi.org/10.1016/j.ecolmodel.2011.11.030

Van Liew, M.W., S. Feng and T.B. Pathak. 2012. Climate Change Impacts on Streamflow, Water Quality, and Best Management Practices for the Shell and Logan Creek Watersheds in Nebraska, USA. Int. J. Agric. & Biol. Eng., 5(1):13-34.

White, M. J., Storm, D. E., Busteed, P. R., Stoodley, S. H., and S.J. Phillips. 2009. Evaluating Nonpoint Source Critical Source Area Contributions at the Watershed Scale. Journal of Environmental Quality, 38(4), 1654–63.

Winchell, M. F., Folle, S., Meals, D., Moore, J., Srinivasan, R., and E.A. Howe. 2014. Using SWAT for sub-field identification of phosphorus critical source areas in a saturation excess runoff region. Hydrological Sciences Journal, 60(5), 844–862. http://doi.org/10.1080/02626667.2014.980262

Woznicki, S.A., A.P. Nejadhashemi and C.M. Smith. 2011. Assessing Best Management Practice Implementation Strategies under Climate Change Scenarios. Trans. ASABE, 54(1):171-190.

Wang, Y., 2015. A Diagnostic Decision Support System for Selecting Best Management Practices in Urban/Suburban Watersheds. Ph.D. Thesis, Department of Civil and Environmental Engineering, University of Maryland at College Park.

Yang, J., Reichert, P., Abbaspour, K. C., Xia, J., and H. Yang. 2008. Comparing uncertainty analysis techniques for a SWAT application to the Chaohe Basin in China. J. Hydrol., 358(1-2):1–23. http://doi.org/10.1016/j.jhydrol.2008.05.012

CHAPTER 4: EFFECTIVENESS OF BEST MANAGEMENT PRACTICES WITH CHANGING CLIMATE IN A MARYLAND WATERSHED – OBJECTIVE 2

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Abstract.

The potential impacts of climate change on BMP effectiveness were investigated using SWAT simulations for an agricultural watershed that drains into the Chesapeake Bay, in the US Northeast climate region. Critical Source Areas (CSAs) for sediments, nitrogen and phosphorus, identified for current and future climate (IPCC SRES A1B and A2), were classified by density to support BMP prioritization. BMPs were designed for these CSAs and tested under current and future climate using SWAT simulations, to evaluate their robustness. A second set of BMPs was designed by optimization for all agricultural and urban lands in the study watershed, and was tested similarly for robustness. In both cases, the design goal was for the watershed's water quality response

to meet the Bay TMDLs once BMPs were implemented. Results indicate that CSA Density values of 2 and 3 (hotspots exporting excess amounts of 2 or 3 constituents) may be good prioritization targets, but reaching the Bay TMDLs would still require targeting all CSAs. BMPs designed for CSAs under current climate were effective to reach Bay TMDLs under current climate but not under SRES A1B and A2. BMPs designed for CSAs under future scenario A2 were effective to reach the Bay TMDLs under all climate scenarios, except for nitrogen under A2. Similarly, BMPs optimized for agricultural and urban lands, when designed for current climate, were effective in meeting the TMDLs for current climate only. Optimizing these BMPs for future climate produced a design that met TMDLs under both current and future climate, except for nitrogen with future climate. However, in this case, the nitrogen TMDL was exceeded by a smaller amount than in the CSA design. Results indicate that, in the US Northeast, BMPs designed to remediate water quality problems under current climate will be insufficient to maintain water quality with climate change. Increased annual rainfall and storm intensity will increase the proportion of watershed area needing BMPs and current hotspots will generate excess amounts of new constituents that will require re-design of existing BMPs. Community-based participatory strategies will likely be required to foster BMP adoption and sustain water quality gains in the Chesapeake Bay region.

Keywords.

Climate change, Best Management Practices, BMPs, NPS pollution, SWAT model, water quality, watershed hydrology

4.1 INTRODUCTION

Non-point source pollution (NPS) from urban and agricultural areas has been identified as a major contributing factor to water quality degradation of the Chesapeake Bay (Garvin and Enck, 2010). To help improve Bay water quality, the federal government's Environmental Protection Agency (EPA) issued a set of Bay wide Total Maximum Daily Loads (TMDLs) for Total Suspended Sediments (TSS), Total Nitrogen (TN), and Total Phosphorus (TP). These TMDLs define yield limits that Chesapeake Bay sub-watersheds should meet to produce sustainable improvements in Bay water quality. Jurisdictional governments were then tasked with developing Watershed Implementation Plans (WIPs) describing the strategies that watersheds in their jurisdictions would use to meet the Bay TMDLs. Upon completion of the WIPs, resources could be secured from federal programs to assist with the implementation of the identified remediation measures.

The identification of Critical Source Areas (CSAs), as applied to NPS pollutants in agricultural and mixed land-use watersheds, has been the subject of substantial research (Chen et al., 2014; Chu et al., 2004; Huaifeng et al., 2010; Huang et al., 2015; Sexton et al., 2010; Shang et al., 2012; White et al., 2009; Winchell et al., 2014). The preferred method is to use a calibrated, spatially distributed, and physically-based hydrologic and water quality model, such as the Soil and Water Assessment Tool (SWAT) (Jeffrey G. Arnold et al., 1993). Models of this type adapt well to varying soils, topographies, land uses, management practices and weather conditions, and are commonly considered to represent the state of the art in the field. This flexibility enables them to also be used in the second step of WIP development: the design of Best

Management Practices (BMPs) for remediation of the water quality problems caused by each CSA. In this step, the models are used to simulate the expected water quality impacts of BMP implementation on CSAs before their actual biophysical realization in a target watershed (Arabi et al., 2006, 2008; Chiang et al., 2012; Giri et al., 2014). The models make it possible to evaluate the effectiveness of a range of potential BMP designs, and to select that which is most appropriate for the target watershed, before the more costly step of BMP implementation is undertaken.

In the US Northeast climate region, where the Chesapeake Bay watershed is located, climate change is expected to produce the largest increases in annual rainfall and storm intensity of the country (Melillo et al., 2014). The potential impacts of this climatic non-stationarity on the effectiveness of WIPs developed to meet the Bay TMDLs under current climate conditions is largely unknown. In the central Great Plains climatic region, two studies have reported that, with moderate increases in annual rainfall, BMPs would remain essentially as effective under climate change as they are today (Woznicki et al., 2011; Van Liew et al., 2012). In the Midwest, Bosch et al. (2014) predicted a slightly larger annual increase in rainfall under climate change would decrease the effectiveness of BMPs designed for current climate. In Ontario (Canada), Parker et al. (2008) suggested that, with climate change, it would be necessary to take some agricultural land out of production from an agricultural watershed, as BMPs would become insufficient to meet water quality standards. Meanwhile, in South Korea, Park et al. (2014) found that the effectiveness of specific BMPs would either increase or decrease with climate change, due to changes in rainfall distribution throughout the year, with no net increase in annual rainfall. From these studies, it is clear that the increases in annual

rainfall and storm intensity predicted to occur in the U.S. Northeast under climate change could have a variety of impacts on the effectiveness of BMPs, targeted in WIPs, to meet the Bay TMDLs. Improving understanding of how these BMPs will fare under climate change will help allocate resources for their design and implementation, in a way that remains effective in the long term.

The goal of this study is to quantify the impact of climate change on BMP effectiveness for Chesapeake Bay watersheds within the Atlantic Coastal Plain physiographic region and US Northeast climate region. The objectives are to assess the robustness, against climate change, of BMPs designed to meet TMDL requirements under current climate, and to evaluate the potential benefits of designing BMPs directly for future climate conditions. The analysis is performed for a representative watershed in the study region and applies two different techniques. The first technique is a forward design approach, in which CSAs in the calibrated model are targeted with BMPs and the efficiencies required to meet TMDL goals via these targeted installations are determined. In the second technique, an inverse approach, non-CSA areas are included; a synthetic time series that meets the TMDL goals is generated and used as the model calibration target, with BMP efficiencies as the tuned parameters. The next three sections of this article describe the study watershed and target TMDL, the materials and methods used for the investigation, and the results obtained.

4.2 STUDY AREA AND TMDLS

The study area is the Greensboro watershed (Figure 1), an agricultural sub-watershed of the Choptank River (USGS HUC 0206005) on the Eastern Shore of

Maryland, extending over part of Caroline County, MD, and Kent County, DE. The Greensboro watershed has an area of 298 km^2 and a flat topography with most slopes below 1%. Its land use consists of 49% agricultural, 34% natural and 6% urban areas and its soils are predominantly of Hydrologic Soil Group C (50%), B (26%) and D (20%). The area's annual average rainfall is 1070 mm.

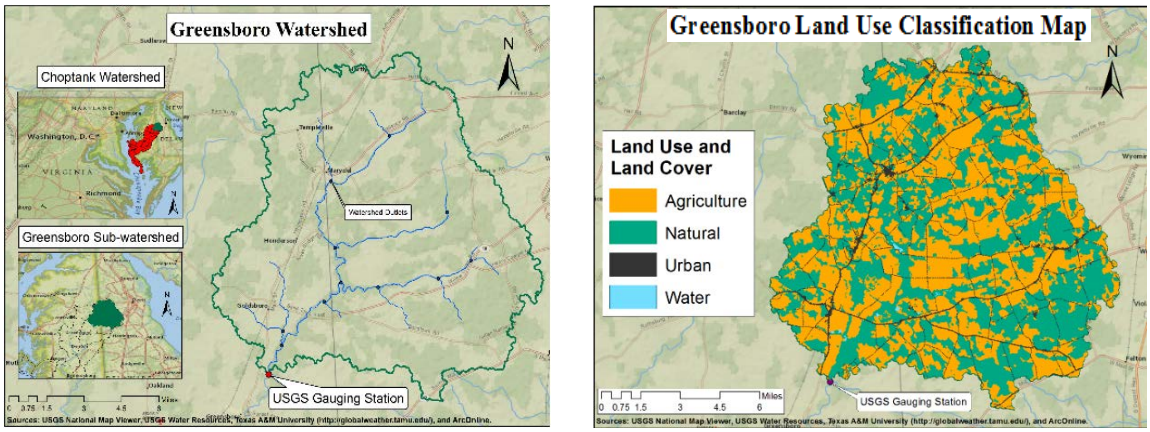

Figure 1. Location and Land Use Map for the Study Watershed

The hydrologic and water quality responses of the Greensboro watershed to current climate and IPCC SRES future climate scenarios B1, A1B and A2 (IPCC Working Group III, 2000) were simulated by Renkenberger et al. (2015) using the SWAT model (Arnold et al., 1993). The time period for the current conditions baseline was selected as the 15 years between 1990 and 2004 based on data availability from USGS gage 01491000 at the watershed outlet. Climate change predictions were targeted at the mid-century horizon (2046-2064) and end-century time frame (2081-2100). Table 1 summarizes the results for the baseline and end-century in terms of predicted annual rainfall, streamflow (SurQ), sediment yield (TSS), nitrogen yield (TN) and phosphorus

yield (TP) at the watershed outlet. Annual rainfall is expected to increase by 25% to 30% under climate change and, due to the nonlinearity of hydrologic and water quality processes, this produces larger increases in streamflow and constituent yields. Climate change scenario A2 is predicted to produce the largest amounts of streamflow, sediments and phosphorus, while A1B produces the largest nitrogen yield due to differences in rainfall intensity patterns between the two future scenarios. Additional details on model calibration and simulation results are in Renkenberger et al. (2015).

Table 1. Hydrologic and Water Quality Response of the Greensboro Watershed under Current and Changing Climates, in Relation to Target TMDL (adapted from Renkenberger et al. (2015))

			Constituent					
			TSS		TN		TP	
Scenario	Rainfall (mm/yr)	SurQ (mm/yr)	Yield (kg/ha/yr)	Reduction Needed	Yield (kg/ha/yr)	Reduction Needed	Yield (kg/ha/yr)	Reduction Needed
Baseline	1070	434	432	33%	10.9	45%	0.78	23%
B1	1340	681	773	63%	17.0	64%	1.18	49%
A1B	1390	789	936	69%	20.5	70%	1.28	53%
A2	1380	826	1004	71%	18.4	67%	1.39	57%
Water Quality TMDL (Target):			289		6.04		0.60	

The EPA developed TMDLs for the Chesapeake Bay and its sub-watersheds, for sediment, nitrogen and phosphorus (Garvin and Enck, 2010). The Chesapeake Bay Program (CBP) provides these TMDLs via an interactive interface on dedicated websites through its Chesapeake Bay TMDL Tracking and Accounting System (BayTAS) ("Chesapeake Bay Program"; "Chesapeake Bay TMDL Tracking and Accounting System (BayTAS)"). BayTAS offers simulated loadings in pounds per year for historical, present

day and the future 2025 TMDL target. The year 2025 is, ideally, when Bay jurisdictions will have met the Bay's TMDL for TSS, TN and TP.

This study derived TMDL targets for the Greensboro watershed from EPA TMDL data for the Upper Choptank River sub-watershed (CHOTF), which contains the study watershed, and is 1061 km^2 in area, with 60% agricultural, 34% natural and 6% urban land uses. A two-step process was used: first, relative reductions in TSS, TN and TP needed to attain the reported 2025 TMDL based on the 1985 baseline were computed; then, these relative reductions were applied to the baseline yields calculated for the Greensboro watershed by Renkenberger et al. (2015). The resulting Greensboro TMDLs are presented in the bottom row of Table 1: 289 kg/ha/yr for sediments, 6.04 kg/ha/yr for nitrogen and 0.60 kg/ha/yr for phosphorus. The table also lists the reductions in watershed yields that are needed to attain the TMDLs under current climate and future climate scenarios. The required reductions range from 23% to 71% and are uniformly lower with current climate than with climate change scenarios, owing to the predicted increase in yields with future climate in this study.

The Critical Source Areas (CSAs) on which BMPs should be placed to meet TMDL requirements in the Greensboro watershed, were identified, on a per-constituent basis, by Renkenberger et al. (2015) and are presented in Table 2. The values presented here were obtained at the 20% targeting level and correspond to those Hydrologic Response Units (HRUs) in the SWAT model that generate over 730 kg/ha/yr of sediments, 16 kg/ha/yr of nitrogen and 1.3 kg/ha/yr of phosphorus. Under current climate (baseline) each of these groups contains 1541 HRUs, accounting for 20% of the total number of HRUs in the Greensboro watershed SWAT model. The size of the groups, and

their area and export contributions, increase with climate change due to the predicted increase in watershed yields. Overall, the CSAs occupy between 11% and 45% of the watershed area and contribute between 31% and 81% of the constituents it generates. A comparison with Table 1 shows that in nearly all cases these CSAs generate more constituents than the reduction needed to meet the TMDL and therefore targeting highly efficient BMPs to these locations should be sufficient to achieve the related water quality goals. The two exceptions are for total nitrogen under current climate and under scenario B1 where the required reductions of 45% and 64% exceed the respective 31% and 56% contributions of CSAs. In these two cases, in-stream attenuation processes will be accounted for and used to further reduce nitrogen yield, and if insufficient, then a larger set of CSAs would need to be targeted.

Table 2. Critical Source Area (CSA) Characteristics in the Greenboro Watershed (adapted from Renkenberger et al. (2015))

	CSA Contribution (%)					
	TSS		TN		TP	
Scenario	**Area**	**Export**	**Area**	**Export**	**Area**	**Export**
Baseline	18	46	11	31	13	39
B1	37	75	28	56	25	60
A1B	45	78	41	72	28	63
A2	45	81	29	57	32	66
CSA Threshold (Kg/ha/yr)	730		16		1.3	

4.3 MATERIALS AND METHODS

The principal material used in this study was the hydrologic and water quality SWAT model of the Greenboro watershed developed and calibrated by Renkenberger et al. (2015). The ArcGIS (ESRI Inc.) Geographic Information System (GIS) software,

ArcSWAT interface software and the SWAT-CUP optimization program (Abbaspour, 2013) were also used in various parts of the study. Weather time series for current conditions and for climate change scenarios were obtained from the SWAT data web servers at Texas A&M University (("Global Weather Data for SWAT"; "Climate Change Data for SWAT (CMIP3)"). The investigation was separated into three major steps: 1) identification of CSA Density or Critically Dense Areas (CDAs) for BMP implementation; 2) evaluation of climate change effects on CSA-targeted BMPs, and; 3) assessment of climate change impacts on non-CSA targeted BMPs. To identify a CDA a system of measurement was developed to assess the criticality of an HRU. This system measures the number of hotspots for which each HRU is a CSA. These measured values are termed Critical Density Values (CDVs). Analysis was simplified by applying a single generic BMP to all hotspots and to assess the extent to which CSAs were remediated by this BMP, with climate change. Both CSA-targeted and non-CSA targeted approaches to BMP implementation were used to assess the potential advantages of each approach in terms of robustness against climate change. In both cases, BMP efficiencies needed under current climate to meet TMDLs were applied to future climate to evaluate their long-term effectiveness and BMP efficiencies needed to meet TMDLs under future climate conditions were applied to current conditions to assess their present-day effects. The analyses were performed for the current climate baseline and for the SRES climate change scenarios A1B and A2, which were predicted to produce the largest change in watershed behavior (in the previous study).

Identification of Critically Dense Areas (CDAs)

CDAs were identified by processing the per-constituent CSAs obtained by Renkenberger et al. (2015) at the 10% and 20% threshold levels. Logic functions available in common spreadsheet software were used to count and register the number of constituents (TSS, N and P) for which each CSA was a hotspot, at each threshold level, for current climate and for the A1B and A2 scenarios. The logic processing formulas used for this purpose are illustrated by equations 1 and 2.

$$CSA\ Density\ at\ 10\%\ Break \begin{array}{l} = IF(TSS > "CBV\_TSS\_10", 1,0) \\ + IF(TN > "CBV\_TN\_10", 1,0) \\ + IF(TP > "CBV\_TP\_10", 1,0) \end{array} \quad (1)$$

$$CSA\ Density\ at\ 20\%\ Break \begin{array}{l} = IF(TSS > \text{CBV\_TSS\_20}, 1,0) \\ + IF(TN > \text{CBV\_TN\_20}, 1,0) \\ + IF(TP > "CBV\_TP\_20", 1,0) \end{array} \quad (2)$$

Where:
TSS = Total Suspended Sediment
TN = Total Nitrogen
TP = Total Phosphorus
CBV_CC_LV = Critical Break Value for Constituent CC at CSA level LV

Note: As set up in MS Excel, if a logic statement is true then the value of that statement is 1. If false then the value of an individual statement is 0. This method ensures that each hotspot area is assigned one and only one density value.

With three constituents considered in this analysis, a CSA can be assigned a value from 1 to 3 or Critical Density Value (CDV). The resulting Critically Dense Area (CDA) classification represents HRUs that are hotspots for all three constituents (CDA3) for 2 constituents (CDA2) or for a single constituent (CDA1). A BMP prioritization scheme may consider CDA3s as having the highest priority for implementation as they contribute excessive amounts of TSS, TN and TP. The contributions of these critical hotspots to constituent generation within the watershed were calculated to determine whether

targeting them would be sufficient to reach the established TMDLs. These calculations were repeated with hotspots of both CDVs 2 and 3 (i.e. CDA2+CDA3 hotspots) and for CDVs 1+2+3 (all hotspots) to identify the level of density required to attain the target TMDLs under the three investigated climate scenarios. Hotspot density was mapped using ArcGIS to visually appraise hotspot criticality in the study watershed, as a function of climate.

BMP Implementation on CDAs

A generic BMP was targeted to CDAs at the level (3, 2+3, or 1+2+3) needed to attain the target TMDLs. The BMP was designed to remove a fixed fraction of the HRU export of each constituent, calculated as the ratio of the reduction required to meet the TMDL (listed in Table 1) to the export contribution of CDAs (relative to the total contribution of watershed HRUs). This removal fraction, expressed as a percentage, corresponds to the efficiency of a BMP targeted to the CDA required to meet the TMDL for a particular constituent:

$$BMP_{TSS}^{\%ef} = 100 \ \ TSS^{R\%} \Big/ \sum_{D=d}^{3} TSS_{D}^{TEx\%} \tag{3}$$

$$BMP_{TN}^{\%ef} = 100 \ \ TN^{R\%} \Big/ \sum_{D=d}^{3} TN_{D}^{TEx\%} \tag{4}$$

$$BMP_{TP}^{\%ef} = 100 \ \ TP^{R\%} \Big/ \sum_{D=d}^{3} TP_{D}^{TEx\%} \tag{5}$$

Where
$BMP_{XX}^{\%ef}$ = BMP removal efficiency for TSS, TN, or TP
$XX^{R\%}$ = TSS, TN or TP removal percentage per TMDL (table 1)
$XX_{D}^{TEx\%}$ = TSS, TN or TP percentage of total export by CSAs at density rating d
d = bottom of the target CDV range (1, 2 or 3)

As an example of these calculations, consider the TSS component of a BMP designed for current climate, where a 33% reduction in sediments is needed to meet the TMDL (Table 1). If CDAs contribute 46% of the total amount of sediments generated by watershed HRUs (i.e. 0.72 = 33% / 46%), this BMP would need to be designed with a sediment reduction efficiency of 72%. In other words, in this example, if sediment yield over the watershed, without BMPs, is denoted Y, then the amount of sediments that the BMP must remove is 33% Y = 0.72 x 46% Y, or 72% of the sediments contributed by CSAs. This approach is expected to result in a slight over-design of BMPs as it does not account for potential in-stream attenuation processes that occur between HRUs and the watershed outlet. BMP efficiencies were calculated similarly for other constituents (TN and TP). These calculations were performed to produce three BMP designs for TMDL attainment: a design based on current climate conditions (baseline), and an additional design for each of SRES scenarios A1B and A2. The CDAs used in these designs were at the same levels (either 3, 2+3 or 1+2+3) to ease comparisons.

The SWAT model of the Greensboro watershed was used to simulate the study area's hydrologic and water quality response with the designed generic BMPs placed on target CDAs (BMP option 10 in SWAT) (Neitsch et al., 2011). The designed reductions for nitrogen were applied to both organic and soluble nitrogen in those BMPs while those for phosphorus were applied to both particulate and soluble phosphorus. Two sets of three simulations were performed. In the first set, the BMPs designed for current climate were implemented on the CDAs identified for the current climate and the watershed's response was simulated with each of the three climate scenarios (current, A1B and A2). This was done to evaluate the robustness against climate change of BMPs designed only

to address current water quality challenges. In the second set, three simulations were also performed (one for each climate scenario) but this time, the BMPs designed to reach the TMDL under scenario A2 were implemented on the CDAs identified for the A2 scenario. This was done to determine whether a design based on future conditions would be effective under current climate and whether a design based on scenario A2 is also effective under climate predicted for the A1B scenario.

Simulation results were processed to locate those CSAs that remain after BMPs are implemented. The CSA thresholds used for this step were the same ones used previously (table 2) and these CSAs were classified into the density groups defined earlier. These residual post-BMP CDAs were mapped to appraise visually the effectiveness of each design, with climate change, and their areas were computed and tabulated. Averages of the annual yields of TSS, TN and TP, predicted at the watershed outlet, were also computed from simulation outputs and compared to the target TMDLs using the relative error formula:

$$ERROR_{XX} = 100 \frac{Y_{XX}^{annual} - TMDL_{XX}}{TMDL_{XX}} \quad (6)$$

Where:
$ERROR_{XX}$ = Relative TMDL attainment error for constituent XX (TSS, TN, TP)
Y_{XX}^{annual} = Average of simulated annual yields, with BMPs, for constituent XX
$TMDL_{XX}$ = TMDL for constituent XX

BMP Parameterization on Non-CSA Targets

Implementation of BMPs on non-CSA targets may be required for watersheds where an appropriate hydrologic and water quality model is unavailable or where uncalibrated model predictions are in doubt and the lack of gaging data precludes

calibration. The present study simulated such a situation by targeting all agricultural and urban land, in the Greensboro watershed, for BMP implementation. Similar to the CSA-targeted approach described earlier, generalized BMPs were designed for implementation over non-CSA targets. However, in contrast to that approach, a pair of BMPs were designed in each study scenario: one for agricultural land and another for urban land. In addition, instead of the forward approach used for BMP design in the previous analysis, an inverse approach (optimization) was applied for the non-CSA designs. For this purpose, synthetic time series, representing the desired levels of TSS, TN and TP at the watershed outlet, were derived from the results of prior watershed response simulations with no BMPs. These synthetic series were constructed by subtracting the required TMDL reduction levels from (table 1) from annual predictions obtained from simulations without BMPs. In short, simulated observations from the calibrated model, modified to meet TMDL targets, became the new observations that BMPs would be calibrated against. Generalized BMPs were then positioned over all agricultural and urban lands in the SWAT model of the Greensboro watershed, and the SWAT-CUP software was used to calibrate these generalized BMPs, separately for agricultural and urban land, such that their combined addition to the model would reproduce the synthetic outlet time series. This calibration was performed to produce three pairs of BMP designs, one pair each for current climate, SRES A1B and SRES A2. The SUFI-2 optimization algorithm (Abbaspour et al., 2004) was selected for this purpose as it is the most widely used in conjunction with SWAT-CUP. The parameter set for optimization was defined to include all TMDL related parameters for the generalized BMPs: sediment reduction, organic nitrogen reduction, soluble nitrogen reduction, particulate phosphorus reduction and

soluble phosphorus reduction. The selected SWAT land use codes over which to perform the optimization were HAY and AGRR for agricultural land and URLD, URMD, URHD and UIDU for urban land. The range of allowed parameter values for calibration was set as 0% to 100% for all nutrient related reduction-level parameters in the generic SWAT BMP. The results of this optimization-oriented approach to BMP design were evaluated using diagnostic statistics commonly used for model calibration: Pearson's correlation coefficient (r) and the Nash-Sutcliffe Efficiency (NSE; referred to as coefficient of determination, R^2, in statistics, cf. equation 3 in Nash and Sutcliffe (1970)):

$$r = \frac{\sum_{i=1}^{n}\left(Y_i^{obs} - \bar{Y}^{obs}\right)\left(Y_i^{sim} - \bar{Y}^{sim}\right)}{\sqrt{\sum_{i=1}^{n}\left(Y_i^{obs} - \bar{Y}^{obs}\right)^2 \sum_{i=1}^{n}\left(Y_i^{sim} - \bar{Y}^{sim}\right)^2}} \quad (7)$$

$$NSE = 1 - \frac{\sum_{i=1}^{n}\left(Y_i^{obs} - Y_i^{sim}\right)^2}{\sum_{i=1}^{n}\left(Y_i^{obs} - \bar{Y}^{obs}\right)^2} \quad (8)$$

Where for all equations:
Y_i^{obs} = Observed values at given time step
Y_i^{sim} = Simulated values at given time step
$\bar{Y}^{obs}$ = Observed mean
$\bar{Y}^{sim}$ = Simulated mean

The BMPs designed for non-CSA targets were further evaluated in the same way as those designed earlier for CDAs. They were implemented in SWAT models of the Greensboro watershed and subjected to baseline and SRES A2 scenarios to evaluate their robustness over current and changed climate. Residual CDAs that remained after BMP implementation were identified and mapped. The TMDL attainment error produced by each design (equation 6) was computed and compared across designs and climate scenarios.

4.4 RESULTS AND DISCUSSION

Identification of CDAs

Constituent maps of Critically Dense Areas (CDAs) in the Greensboro watershed are presented in Figure 2 for the 10% and 20% CSA threshold levels, under current and future climate. At the 10% threshold, CSAs correspond to HRUs that generate more than 1030 kg/ha/yr of sediments, 24 kg/ha/yr of nitrogen or 1.9 kg/ha/yr of phosphorus. These CSAs are mostly single-constituent hotspots (CDA1) and, as discussed in Renkenberger et al. (2015) the proportion of the watershed that they occupy increases substantially under future climate. The predominance of CDA1 at the 10% level indicates that the most sensitive areas of the watershed are each quite specific in the type of potential pollutant that they generate. If targeting these areas was sufficient to reach the desired TMDLs, then implementing constituent-specific BMPs there would likely be the most economical option. In the baseline case (current climate) the combined CDA 1, 2 and 3 at the 10% level occupy 13.6% of total watershed area, but, unfortunately contribute only 31% to TSS, 30% to TN and 30% to TP, which is insufficient to reach the TSS and TN TMDLs listed in table 1. Accordingly, as far as baseline conditions are concerned (at least) BMP implementation should target the broader set of CSAs identified at the 20% level.

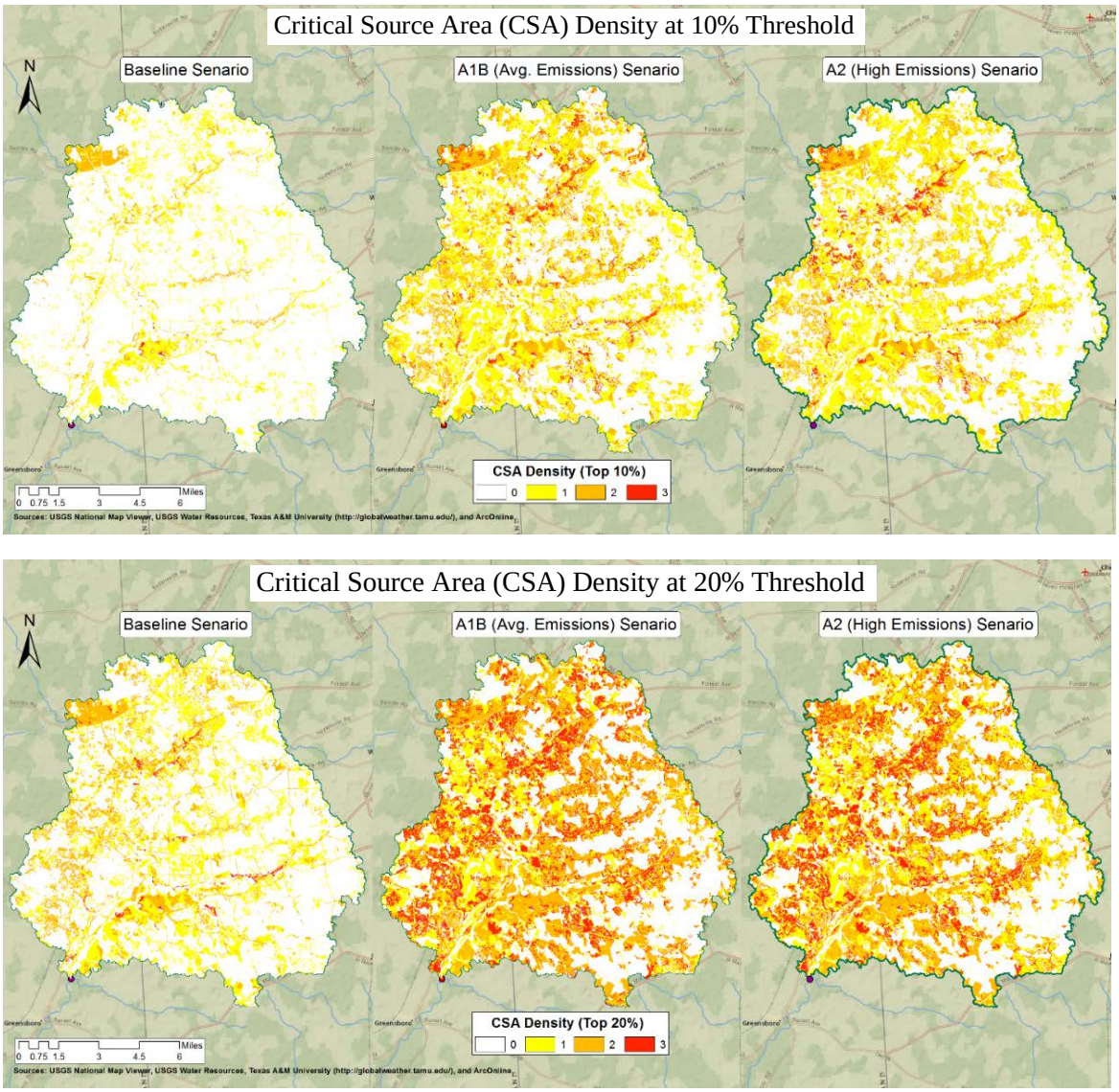

Figure 2: CSA Density Maps at Thresholds of 10% (Top) and 20% (Bottom) for the Baseline and Scenarios A1B and A2

At the 20% threshold level, CSAs consist of those HRUs that generate constituents in excess of the levels listed in table 2 (bottom row) and, as for the 10% CSAs, the fraction of the watershed that they occupy increases substantially with climate change. In contrast to the 10% CSAs, the 20% CSAs are mostly of CDA1 only under current climate (64% of CSA area), and CDA2 that dominate under A1B (46% of CSA

area) and A2 (38% of CSA area) scenarios (Table 3). The manner in which CDAs expand, from the 10% to the 20% level, differs between the baseline and the two future scenarios. Under current climate, CSA expansion occurs primarily via the addition of new areas and secondarily by conversion of single-constituent CSAs to multi-constituent CSAs (density increase). Conversely, under future climate, density increases dominate CSA expansion and the total area occupied by CSAs remains nearly constant between the 10% and 20% level. Furthermore, the CDAs are quite similar between the A1B and A2 scenario, covering essentially all agricultural and urban land in the watershed, in addition to some non-forested natural areas. As discussed by Renkenberger et al. (2015) this suggests that the increased annual rainfall predicted under future climate scenarios, will be sufficient to overwhelm the buffering capacity of agricultural lands, turning them mostly into hotspots. It further suggests that, whether the future occurs along scenario A1B or A2, nearly all agricultural and urban lands may require some form of BMP to meet established TMDLs.

Table 3. Contribution of CDAs (20% level) to Watershed Area and Constituent Generation

		CDA Contribution (%)			
	CDV		Export		
Scenario		Area	TSS	TN	TP
Baseline	3	1	4	2	3
	2+3	11	24	28	25
	1+2+3	31	54	57	53
A1B	3	14	36	26	28
	2+3	41	69	70	69
	1+2+3	58	85	87	78
A2	3	13	34	26	25
	2+3	35	66	61	62

	1+2+3	58	86	86	79

Under the baseline scenario, hotspots for 2 and 3 constituents (CDA2+3) generate almost half of the total pollution produced by all CSAs, while occupying just 1/3 of the total hotspot area. With climate change scenarios A1B and A2, the CDAs2+3 generate most of the constituents produced. Taken together, these results suggest that for both current and future conditions, prioritizing BMP implementation on multi-constituent hotspots (CDA2 and CDA3) may be a useful strategy to obtain significant water quality improvements at a lower cost than if all CSAs are targeted. For the Greensboro watershed, a comparison of results in table 3 with TMDL requirements in table 2 shows that, for scenario A1B, the TMDLs may indeed be reached by targeting only CDAs 2 and 3 . Unfortunately, this does not hold for either current conditions or for scenario A2, where the CDA1salso need to be targeted. For this reason, the total of all CSAs (CDA1+2+3) will be used as BMP targets in the remainder of this study. In a policy context, however, where BMP implementation may be effected over a sequence of years or decades, targeting the higher density hotspots first would remain the preferred approach based on the above results. This approach may simultaneously provide an initial improvement in water quality and the time to develop and implement the social programs needed to enhance BMP adoption by the remaining watershed stakeholders, prolonging water quality improvements into a sustainable future.

BMP Implementation on CDAs

Table 4 presents results of BMP efficiency calculations and implementation area for designs based on current climate and on scenarios A1B and A2 (future climate

designs) when BMPs are aimed at density 1+2+3 CSAs. With today's climate, the BMPs need to achieve reductions from 43% to 79% in constituent generation and be sited over 31% of the watershed area to meet the Chesapeake Bay TMDLs. When designed to meet the TMDLs with future climate, the BMPs need to effect reductions in potential pollutants ranging from 68% to 82% and be implemented over 58% of the study watershed. In other words, designing BMPs that will remain effective for sediment and phosphorus under the selected climate change scenarios will require them to be from 33% to 67% more efficient at preventing the loss of these constituents than today, and they will need to be placed over nearly twice as much of the watershed's surface. For nitrogen, approximately the same BMP efficiency of nearly 80% will be needed in all scenarios, but, again, they will need to be implemented on twice as much area in the future compared to today.

Table 4: BMP Removal Efficiencies and Area Fractions to Meet Relative TMDL Reductions at the Land Surface by Climate Scenario

Design Scenario	**BMP-Targeted Area**	**Required BMP Efficiency**		
		TSS	TN	TP
Baseline	31%	61%	79%	43%
A1B	58%	81%	78%	68%
A2	58%	82%	74%	72%

The effects of BMPs designed for current climate conditions on the watershed's response, under both current and future climates, are presented graphically in Figure 3. These effects are displayed in terms of the residual CDAs (20% level) that are predicted to remain after BMP implementation, as identified from SWAT simulations with BMPs in place. As expected, the BMPs are found to be effective in reducing the amount of CSAs under current weather, resulting in just 5% of the watershed area that can still be

classified as hotspots. Eighty percent of these are phosphorus CSAs, owing most probably to the relatively low BMP efficiency designed for CSA control in this case (43%). Despite these residual CSAs, the watershed is predicted to meet the TMDLs for both sediment and phosphorus, with an error of the order of just 1% (table 5). The case of nitrogen is slightly different however as, after BMP implementation, less than 0.5% of the watershed area is occupied by residual CSAs for nitrogen under current climate, yet the nitrogen TMDL is predicted to be exceeded by 24%. The reduction of nitrogen yield produced by BMPs (32%) is substantial, but comes short of the 45% needed to reach the TMDL (table 1). Since the BMP efficiencies were designed specifically to reach the TMDLs, there must be a nitrogen contribution at the watershed outlet that is not controlled by SWAT's generic BMP (for example baseflow); its contribution can be estimated as 29% of the total nitrogen yield of the watershed (before BMP implementation).

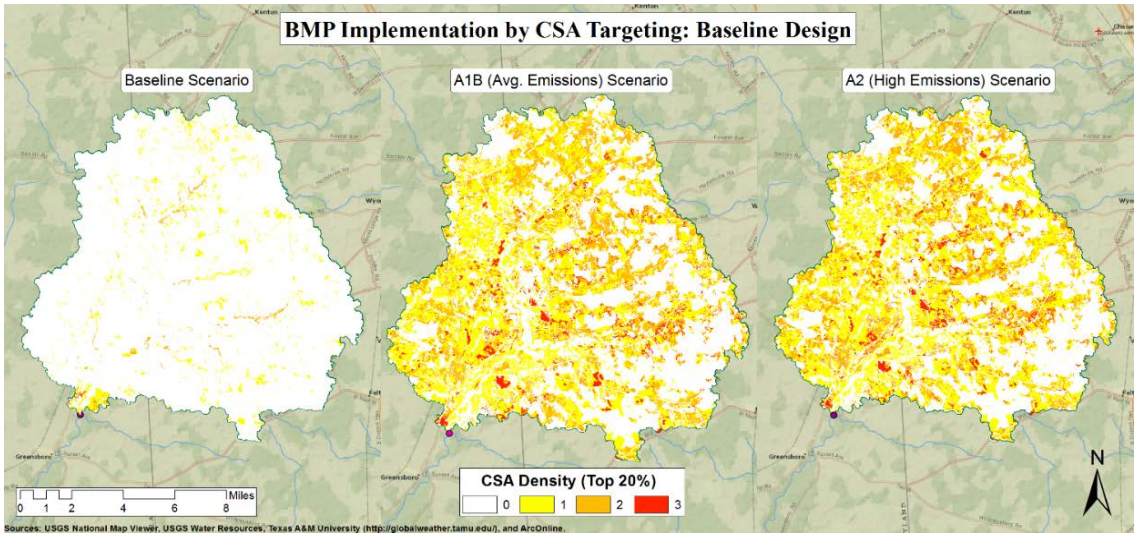

Figure 3: Residual CDAs with Baseline BMP Design Subjected to Current, A1B and A2 Climate Conditions

BMPs designed for the current climate are not effective at controlling constituent exports under climate change in the Greensboro watershed. The residual CSAs that remain after such BMPs are subjected to the A1B scenario occupy 49% of the watershed area, and they grow to 51% of the area under scenario A2 (figure 3). Approximately 80% of these residual hotspots produce excessive amounts of sediments while 40% or fewer generate excessive nutrients. Accordingly, all TMDLs are exceeded by this design; is not robust against climate change. The watershed's yield of sediment and phosphorus are more than twice their respective TMDLs and phosphorus yield is of the order of 70% above the TMDL for both A1B and A2 scenarios (table 5). In this watershed, climate change effectively negates the investments in BMP implementation performed to meet TMDLs under current climate. The lack of future effectiveness of BMPs designed based on today's conditions results from the expansion of hotspot areas under climate change and the larger amount of constituents generated by HRUs with future climate, both of which are consequences of increased annual rainfall and increase frequency of severe storms, as discussed by Renkenberger et al. (2015). Bosch et al. (2014) found a similar decrease in BMP effectiveness for watersheds in the Lake Erie region while Woznicki et al. (2011) and Van Liew et al. (2012) found no change for watersheds in Nebraska. This trend is as expected given that, of the three US climatic regions in these studies (including the present study) the Northeast is expected to see the largest changes in annual rainfall and precipitation intensity under climate change, followed by the Midwest and the central part of the Great Plains regions, respectively (Melillo et al., 2014).

Table 5: BMP Removal Efficiency Performance (Targeting CDAs)

	Evaluation Scenario TMDL Attainment Error (%)

Design Scenario	Baseline			A1B			A2		
	TSS	TN	TP	TSS	TN	TP	TSS	TN	TP
Baseline	1.4	23.6	0.5	114.3	141.0	63.6	126.4	143.4	79.1
A2	-51.9	0.8	-35.4	-2.3	96.0	-7.9	1.2	100.8	0.2

Figure 4 presents the effects of BMPs designed for climate scenario A2, on the watershed's response to current and future climates. In this case, where climate change is considered in the design, the residual CSAs remaining after BMP implementation occupy 5% or less of the watershed area, for all climate scenarios. The majority of these residual CSAs (60% to 75%) generate only excessive phosphorus, because of the lower efficiency of the design BMPs for this constituent. This climate-change-based BMP design effectively meets the Chesapeake Bay TMDLs for the 3 constituents under today's conditions and also meets TMDLs for both sediment and phosphorus under both future climate scenarios (table 5). The only shortcoming of the design is nitrogen control in future scenarios, where the TMDL is exceeded by 100%. Here again, as BMPs were designed to attain the TMDL, it appears that a fraction of the watershed's nitrogen yield (of the order of 42%) is not reachable by SWAT's generic BMP (possibly a baseflow contribution).

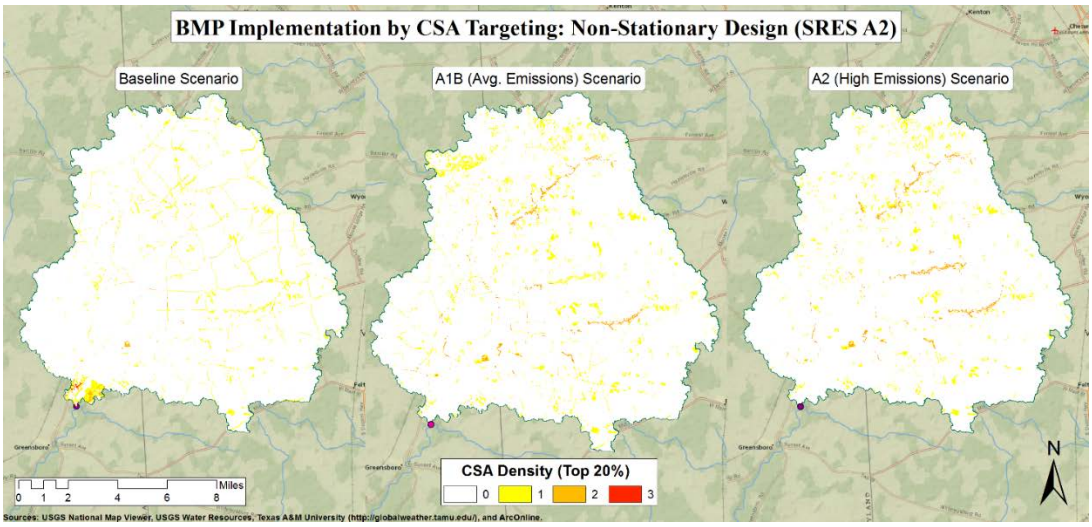

Figure 4: Residual CDA with A2 BMP Design Subjected to Current, A1B and A2 Climate Conditions.

The present results suggest that, for long-term effectiveness, BMPs should be designed by considering future climate and implemented on the corresponding CSAs. Such BMPs will be effective today and will not need to be redesigned or reimplemented, which can often be more costly than building them initially. Design and implementation using the A2 climate scenario (20% fixed threshold) will require targeting 58% of the land area with BMP efficiencies of 82%, 74% and 72% for TSS, TN and TP respectively. The large target area suggests a time-stepped approach for implementation which, as proposed earlier, may focus first on density 2 and 3 CSAs, and would be accompanied with social programs aimed at increasing BMP adoption over time by the majority of watershed stakeholders. Such an approach would be expected to provide sustainable improvements in water quality with minimal waste of invested resources.

BMP Parameterization on Non-CSA Targets

BMP designs for the alternative targeting scenario where, rather than CSAs, BMPs are to be implemented on all agricultural and urban land, are presented in table 6. For the design based on current climate conditions, the optimization of BMP efficiencies (inverse approach) was successful for all constituents, with diagnostic statistics very near 1.0 (table 7). In this case, to meet the Chesapeake Bay TMDLs, the designed BMPs require efficiency from 30% to 60% in urban areas and from 30% to 90% in agricultural areas. BMP design was also successful under the assumption of climate change, except for total nitrogen. BMP designs for the A1B and A2 scenarios resulted in negative Nash-Sutcliffe coefficients for TN, indicating that the target levels of nitrogen yield (adjusted to meet the TMDL) could not be reached (Table 7). As a result, the BMP efficiencies for nitrogen removal reached their upper limit of 100%. BMP efficiencies for other constituents ranged from 55% to 90% on urban land and 60% to 95% on agricultural land. In similarity with BMPs targeted to CDAs, those targeted directly to urban and agricultural land require higher efficiencies when designed for future climate than for current climate. However, those designed here, under current climate, occupy more of the watershed area (55%) than in the CSA approach (31%); thus, their required efficiencies are lower than in the CSA-based design.

Table 6: BMP Parameterization to meet 2025 TMDL Targets (% Removal)

Design Scenario	Land Use	Sediment	OrgN	SolN	OrgP	SolP
Baseline	Urban	55%	40%	35%	60%	30%
	Agricultural	50%	60%	90%	50%	30%
A1B	Urban	85%	>100%	>100%	75%	55%

	Agricultural	95%	>100%	>100%	85%	60%
A2	Urban	90%	>100%	>100%	75%	55%
	Agricultural	95%	>100%	>100%	85%	60%

Where:
X = Nitrogen or Phosphorus species
OrgX = Organically bound Nitrogen or Phosphorus
SolX = Soluble Nitrogen or Phosphorus

Table 7: BMP Calibration Diagnostic Statistics by Design Scenario

	Baseline			**A1B**			**A2**		
Statistic	TSS	TN	TP	TSS	TN	TP	TSS	TN	TP
r	1.00	0.96	1.00	0.91	0.82	0.99	0.88	0.90	0.98
NSE	0.99	0.94	0.97	0.87	-3.17	0.93	0.87	-4.17	0.98

The effects of BMPs designed for agricultural and urban land, under current climate, on the watershed's response for current and future climates, are mapped in figure 5. The design is quite effective when exposed to current climate, with residual CDA occupying only 8% of the watershed area after BMP implementation. Some of the residual CDAs are non-forested natural land that was not targeted for BMP implementation in this strategy, and hence continues to generate sediments above the CSA thresholds. The design is found to meet the Chesapeake Bay TMDLs to within 1%, at worst, for all constituents (table 8). This design is, however, not robust against climate change scenarios A1B and A2, similar to what was observed in targeted CDAs. Here, post-implementation residual CDAs occupy from 36% (A1B) to 39% (A2) of the watershed surface, and are mostly of CDA1 (single constituent). The TMDLs are exceeded under future climate by approximately 50% for TP and 100% for TSS and TN (table 8), with relatively minor differences between scenarios A1B and A2.

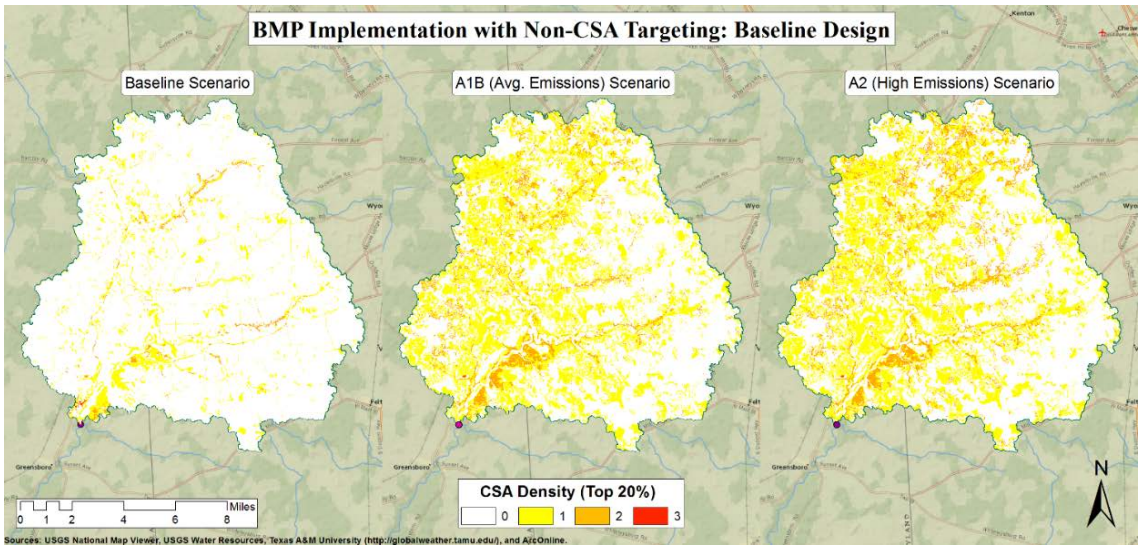

Figure 5: Residual CSA Density with Baseline BMP Design for Agricultural and Urban Land, Subjected to Current, A1B and A2 Climate Conditions.

The predominance of CDA1 residuals under climate change (figure 5) is interesting given that CDA2s were the most frequent in the watershed before BMP implementation (figure 2). This indicates that the BMP design performed under current climate for agricultural and urban lands will remain effective at controlling at least one potential pollutant in the future. Climate change will, however, cause one other potential pollutant to be produced at excessive levels on each of the locations where BMPs were implemented, generating a need for redesign of the BMPs. The constituents that are newly generated vary by HRU, for example excessive phosphorus may be produced in an area where nitrogen remains under control, and excessive sediments may be generated in another area where phosphorus remains controlled. A false sense of security may have resulted from implementing BMPs on all agricultural and urban lands in the watershed (an over-design relative to a CSA-targeted approach), and stakeholder frustrations may emerge as water quality remains unimproved, or worsens, with the changing climate.

Table 8: BMP Removal Efficiency Performance (Non-CSA Targeting)

Design Scenario	Evaluation Scenario TMDL Attainment Error (%)								
	Baseline			A1B			A2		
	TSS	TN	TP	TSS	TN	TP	TSS	TN	TP
Baseline	-3.3	1.0	-5.5	114.3	106.1	59.7	102.8	96.5	47.7
A2	-49.2	-27.7	-35.0	-1.9	57.4	0.2	-2.3	48.8	-6.4

The response of the Greensboro watershed to current and future climate when implemented BMPs designed to meet the Chesapeake Bay TMDLs under scenario A2 are presented in Figure 6. The resulting BMPs, designed considering future climate, are clearly more robust against climate change than when designed for current conditions. The residual CDAs occupy 12% of the watershed area under scenarios A1B and A2, and just 5% under current climate. TMDLs for all constituents are met under current condition (Table 8) and those for sediment and phosphorus are also attained under climate change. The only non-attainment is for nitrogen under scenarios A1B and A2, where the TMDL is exceeded by approximately 50%. This level of exceedance is half of that obtained earlier for BMP designs targeted at CDAs (forward design) and results from the higher BMP design efficiencies obtained with the optimization approach (inverse method) used here. The inverse approach tacitly incorporates the effects of nitrogen sources that may not be controllable by SWAT's generic BMPs, as it automatically updates the BMP efficiencies needed (up to 100%) to attain the TMDLs at the watershed outlet. The approach is substantially more computationally demanding than setting BMP design efficiencies from the required TMDL reductions and export contributions of CSAs (forward design) but has the demonstrated advantage that it will adjust design efficiencies to minimize TMDL attainment errors, even in the presence of extraneous sources of a

constituent that may not be directly controllable by BMPs (eg. a possible contribution from baseflow). Ideally, such extraneous contributions would be controlled at their sources, but they may be located in distant watersheds, and have travelled over decades to reach the study area's outlet, such that the results of their treatment (while important and needed) would be expected to undergo a similar lag before actual effects are observed near the Bay.

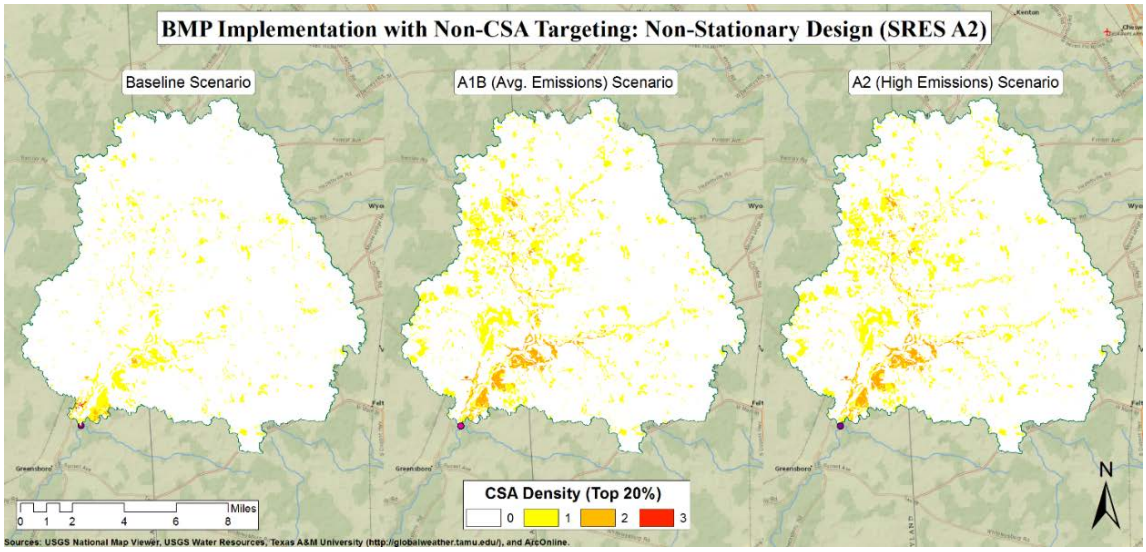

Figure 6: Residual CDAs with A2 BMP Design for Agricultural and Urban Land, Subjected to Current, A1B and A2 Climate Conditions.

4.5 SUMMARY AND CONCLUSIONS

This study investigated the potential impacts of climate change on BMP effectiveness in an agricultural watershed located within the Chesapeake Bay basin, in the U.S. Northeast climate region, Atlantic Coastal Plains physiographic region. As a result of climate change, the region is expected to undergo the largest increases in annual rainfall and storm intensity in the nation. Prior results of Renkenberger et al. (2015),

based on SWAT simulations, were used to identify Critical Source Areas (CSAs) of sediment, nitrogen and phosphorus in the watershed, at two threshold levels (10% and 20%), under current climate and SRES scenarios A1B and A2. The threshold levels correspond to the proportion of HRUs, ranked from highest to lowest generators of constituents that are considered hotspots under current climate. A set of target TMDLs for sediments, nitrogen and phosphorus were established based on EPA Chesapeake Bay TMDLs for the Choptank River and on the predicted response of the watershed.

This study proposed and analyzed a method for prioritizing CSAs for BMP implementation. The method classifies CSAs based on the number of potential pollutants that are generated in excess by each hotspot, Critical Density Value (CDV). A Critically Dense Area or CDA2, for example, is one that generates excessive amounts of 2 constituents under a given climate scenario. Results indicated that targeting BMPs to CSAs identified at the 10% level would be insufficient to attain the TMDLs under current climate and future climate scenarios A1B and A2. At the 20% level, CDA2 and CDA3s were found to generate most potential pollutants under climate change, and almost half of the total (while occupying 1/3 of the watershed area) under current climate. This suggested that a prioritization scheme for BMP implementation may favorably focus first on the higher CDAs in this watershed. However, it was also found that CSAs of all densities eventually need to be targeted to attain the Bay TMDLs and therefore, while a density-based prioritization may be effective to optimize resource use during the initial phase of implementation, it will need to be expanded to the remaining CSAs in the longer term. Climate change scenarios A1B and A2 caused a substantial increase in the BMP target area required to meet Bay TMDLs, from 31% of the watershed surface under

current climate, to 58% with climate change, which includes all agricultural and urban lands, plus some non-forested natural areas. This result suggested that achieving sustainable water quality improvements in the watershed will require the involvement of most of its stakeholders, and consequently, that social programs aimed at increasing BMP adoption will be key to reaching water quality goals in the study area, with a changing climate.

BMPs were designed for the watershed's CSAs by solving for and specifying the efficiencies needed to attain the target TMDLs under current climate and under climate change. These BMPs were then tested against all climate scenarios, using SWAT, to evaluate their robustness. BMPs with removal efficiencies of 61% for TSS, 79% for TN and 43% for TP were effective in reaching the sediment and phosphorus TMDLs under current climate (target area of 31% of the watershed surface), and slightly less effective for nitrogen due to extraneous sources (23% exceedance of TMDL). These BMPs were, however, not effective under climate change scenarios A1B and A2, and led to exceedance of TMDLs by 64% to 141%. BMPs designed for future climate (scenario A2; target area of 58% of the watershed surface) with removal efficiencies of 82% for TSS, 74% for TN and 72% for TP were effective at reaching all three TMDLs under current climate and effective at reaching sediment and phosphorus TMDLs under future climate. These BMPs could not reach the target nitrogen TMDL due to extraneous sources that are not controlled by BMPs (e.g., baseflow contribution).

As an alternative approach to designing and placing BMPs, an optimization technique was developed and used to design BMPs for all agricultural and urban lands in the watershed (55% of the watershed surface area), as an alternative to CSA-based

targeting. The robustness of these design approaches was assessed by testing them against all climate scenarios using SWAT simulations. Under current climate, BMPs with removal efficiencies of 30% to 90% (on a per-constituent basis) were able to meet the Bay TMDLs. However, when subjected to climate change, these BMPs lost their effectiveness, and the watershed exceeded the TMDLs by 48% to 114%. Optimizing BMP efficiencies to meet the Bay TMDLs under climate change scenario A2 was successful for sediments and phosphorus, with BMP efficiencies of 55% to 95%, but not for nitrogen where design efficiencies were set to their theoretical maximum at 100%. With these BMPs, the watershed attained all current climate TMDLs, as well as TMDLs for sediment and phosphorus under the A1B and A2 scenarios. As with prior cases, non-attainment of the nitrogen TMDLs under climate change was attributed to extraneous sources that are not controlled by BMPs. The attainment shortfall was, however, less than for CSA-targeted BMPs where design efficiencies were computed using a forward CSA-targeted (rather than the land-use-based optimization) approach.

Results of this study indicate that, in agricultural areas of the US Northeast climate region, where the Chesapeake Bay watershed is located, BMPs designed to reach the Bay TMDLs under current climate conditions will become insufficient with climate change. In the study watershed, for example, the increase in annual precipitation and storm intensity resulting from climate change was predicted to cause CSAs to nearly double in area, to a point where they cover the majority of agricultural and urban lands, and even some non-forested natural zones. Accordingly, it is anticipated that new BMPs will need to be implemented in large portions of agricultural watersheds in the U.S. Northeast that are not currently identified as hotspots, just to maintain the water quality

improvements resulting from current BMPs. In addition, the present results indicated that while current climate CSAs may have been hotspots for a single constituent, climate change is predicted to cause them to produce excessive amounts of multiple constituents. Accordingly, if existing BMPs were designed to address single-constituent problems, they will need to be re-designed or retrofitted to mitigate their expanded production of potential pollutants caused by the changing climate. Addressing these impacts of climate change on sustainable water quality improvements and BMP adoption in the region is likely to be both expensive and frustrating. Wherever possible, in the U.S. Northeast, BMP design and implementation plans should focus on expected conditions resulting from climate change, rather than current conditions, to reduce the need for costly future redesigns of BMPs. In addition, as the surface area occupied by hotspots is expected to expand to, essentially, all zones productively used by humans, the participation of all community stakeholders will become crucial to achieving sustainable water quality. The development of effective strategies for enhancing such participation is therefore likely to become as important as technical skill in this region to ensure a healthy and productive future that is robust against climate change (Chanse et al., 2014; Leisnham et al., 2013).

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4.6 REFERENCES

Abbaspour, K.C. 2013. SWAT-CUP 2012. Retrieved from http://www.neprashtechnology.ca/Downloads/ SwatCup/Manual/Usermanual_Swat_Cup_2012.pdf

Abbaspour, K. C., Johnson, C. A., and M.TH. Van Genuchten. 2004. Estimating uncertain flow and transport parameters using a sequential uncertainty fitting procedure. Vadose Zone Journal, 3(4), 1340–1352.

Arabi, M., Frankenberger, J. R., Engel, B. A., and J.G. Arnold. 2008. Representation of agricultural conservation practices with SWAT. Hydrological Processes, 22(16), 3042–3055. http://doi.org/10.1002/hyp.6890

Arabi, M., Govindaraju, R. S., Hantush, M. M., and B.A. Engel. 2006. Role of Watershed Subdivision on Modeling the Effectiveness of Best Management Practices with Swat1. JAWRA Journal of the American Water Resources Association, 42(2), 513–528. http://doi.org/10.1111/j.1752-1688.2006.tb03854.x

Arnold, J. G., Allen, P. M., and G. Bernhardt. 1993. A comprehensive surface-groundwater flow model. Journal of Hydrology, 142(1–4), 47–69. http://doi.org/10.1016/0022-1694(93)90004-S

Bosch, N.S., M.A. Evans, D. Scavia and J.D. Allan. 2014. Interacting Effects of Climate Change and Agricultural BMPs on Nutrient Runoff Entering Lake Erie. J. Great Lakes Research, 40(2014):581-589.

Chanse, V., P.T. Leisnham, A. Rockler, J. McCoy, L. Cain, S. Wilson, H. Montas, A. Shirmohammadi, A. Mohamed. 2014. A community-based participatory research approach for stormwater management: Implications of differing BMP approaches in two urban watersheds. EDRA45, The Environmental Design Research Association Conference (New Orleans, LA: May 31st, 2014).

Chen, L., Zhong, Y., Wei, G., Cai, Y., and Z. Shen. 2014. Development of an integrated modeling approach for identifying multilevel non-point-source priority management areas at the watershed scale. Water Resources Research, 50(5), 4095–4109. http://doi.org/10.1002/2013WR015041

Chesapeake Bay Program. (n.d.). Retrieved December 2, 2015, from http://www.chesapeakebay.net

Chesapeake Bay TMDL Tracking and Accounting System (BayTAS). (n.d.). Retrieved December 2, 2015, from https://stat.chesapeakebay.net/?q=node/130&quicktabs_10=1

Chiang, L.-C., Chaubey, I., Hong, N.-M., Lin, Y.-P., and T. Huang. 2012. Implementation of BMP Strategies for Adaptation to Climate Change and Land Use Change in a Pasture-Dominated Watershed. International Journal of Environmental Research and Public Health, 9(10), 3654–84.

Chu, T. W., Shirmohammadi, A., Montas, H., and A. Sadeghi. 2004. Evaluation of the SWAT model's sediment and nutrient components in the Piedmont physiographic region of Maryland. Transactions of the ASAE, 47(5), 1523–1538.

Davis, A., and W. Hunt. 2009. Bioretention Technology: Overview of Current Practice and Future Needs. Journal of Environmental Engineering, 135(3), 109–117. http://doi.org/10.1061/(ASCE)0733-9372(2009)135:3(109)

Garvin, S.M. and J.A. Enck. 2010. Chesapeake Bay Total Maximum Daily Load for Nitrogen, Phosphorus and Sediment. U.S. Environmental Protection Agency, Washington D.C., available online at: http://www2.epa.gov/chesapeake-bay-tmdl/chesapeake-bay-tmdl-document

Giri, S., A.P. Nejadhashemi, S. Woznicki and Z. Zhang. 2014. Analysis of best management practice effectiveness and spatiotemporal variability based on different targeting strategies. Hydrological Processes, 28(3), 431–445. http://doi.org/10.1002/hyp.9577

Huaifeng, G., Zuhao, Z., Dayong, Q., Jiguo, Y., and C. Qiang. 2010. Analysis of Critical Source Areas about Multi-source Nutrient Loadings Based on SWAT Model in Jiyun River Basin. HKIE Transactions, 17(2), 14–19. http://doi.org/10.1080/1023697X.2010.10668191

Huang, J. J., Lin, X., Wang, J., and H. Wang. 2015. The precipitation driven correlation based mapping method (PCM) for identifying the critical source areas of non-

point source pollution. Journal of Hydrology, 524, 100–110. http://doi.org/10.1016/j.jhydrol.2015.02.011

Jayakody, P., Parajuli, P. B., and T.P. Cathcart. 2014. Impacts of climate variability on water quality with best management practices in sub-tropical climate of USA. Hydrological Processes, 28(23), 5776–5790. http://doi.org/10.1002/hyp.10088

Leisnham, P., H. Montas, A. Shirmohammadi, V. Chanse, D. Lansing, A. Rockler, T. Hutson, J. McCoy, L. Cain, S. Wilson, D. Lipton, K. Brubaker and Y. Wang. 2013. Watershed Diagnostics for Improved Adoption of Management Practices: Integrating Biophysical and Social Factors Across Urban and Agricultural Landscapes. In 2013 ASABE Annual International Meeting Paper. Paper number 131668614, 2013 Kansas City, Missouri, July 21 - July 24, 2013. (doi: http://dx.doi.org/10.13031/aim.20131668614)

Melillo, J.M., T.C. Richmond and G.W. Yohe (eds). 2014. Climate Change Impacts in the United States: The Third National Climate Assessment. U.S. Global Change Research Program, 841pp. U.S. Government Printing Office, Washington, DC. doi:10.7930/J0Z31WJ2.

Nakicenovic, N., and R. Swart, eds. 2000. Emissions scenarios: A Special Report of Working Group III of the Intergovernmental Panel on Climate Change. Intergovernmental Panel on Climate Change. Cambridge University Press. New York, NY.

Nash, J.E. and J.V. Sutcliffe. 1970. River Flow Forecasting Through Conceptual Models, Part I - A Discussion of Principles. J. Hydrol., 10(1970):282-290.

Park, J.-Y., Yu, Y.-S., Hwang, S.-J., Kim, C., and S.-J. Kim. 2014. SWAT modeling of best management practices for Chungju dam watershed in South Korea under future climate change scenarios. Paddy and Water Environment, 12(1):65–75. http://doi.org/10.1007/s10333-014-0424-4

Parker, G.T., R.L. Droste and K.J. Kennedy. 2008. Modelling the effect of Agricultural Best Management Practices on Water Quality Under Various Climatic Scenarios. J. Environ. Eng. Sci., 7(2008):9-19.

Renkenberger, J., H. Montas, P. Leisnham, V. Chanse, A. Shirmohammadi, A. Sadeghi, K. Brubaker, A. Rockler, T. Hutson and D. Lansing. 2015. Climate Change Impact on Critical Source Area Identification in a Maryland Watershed. Transactions of the ASABE, in review. ASABE, St-Joseph, MI.

Sexton, A. M., Sadeghi, A. M., Zhang, X., Srinivasan, R., and A. Shirmohammadi. 2010. Using NEXRAD and rain gauge precipitation data for hydrologic calibration of SWAT in a northeastern watershed. Transactions of the ASABE, 53(5), 1501–1510.

Shang, X., Wang, X., Zhang, D., Chen, W., Chen, X., and H. Kong. 2012. An improved SWAT-based computational framework for identifying critical source areas for agricultural pollution at the lake basin scale. Ecological Modelling, 226, 1–10. http://doi.org/10.1016/j.ecolmodel.2011.11.030

Van Liew, M.W., S. Feng and T.B. Pathak. 2012. Climate Change Impacts on Streamflow, Water Quality, and Best Management Practices for the Shell and Logan Creek Watersheds in Nebraska, USA. Int. J. Agric. & Biol. Eng., 5(1):13-34.

Wang, Y., 2015. A Diagnostic Decision Support System for Selecting Best Management Practices in Urban/Suburban Watersheds. Ph.D. Thesis, Department of Civil and Environmental Engineering, University of Maryland at College Park.

White, M. J., Storm, D. E., Busteed, P. R., Stoodley, S. H., and S.J. Phillips. 2009. Evaluating Nonpoint Source Critical Source Area Contributions at the Watershed Scale. Journal of Environmental Quality, 38(4), 1654–63.

Winchell, M., Folle, S., Meals, D., Moore, J., Srinivasan, R., and E.A. Howe. 2014. Using SWAT for sub-field identification of phosphorus critical source areas in a saturation excess runoff region. Hydrological Sciences Journal, 60(5), 844–862. http://doi.org/10.1080/02626667.2014.980262

Woznicki, S.A., A.P. Nejadhashemi and C.M. Smith. 2011. Assessing Best Management Practice Implementation Strategies under Climate Change Scenarios. Trans. ASABE, 54(1):171-190.

Woznicki, S. A., and A.P. Nejadhashemi. 2014. Assessing uncertainty in best management practice effectiveness under future climate scenarios. Hydrological Processes, 28(4), 2550–2566. http://doi.org/10.1002/hyp.9804

CHAPTER 5: FINAL CONCLUSIONS AND FUTURE WORK

5.1 SUMMARY

This study addressed two major objectives: 1) to quantify the expected impacts of climate change on CSAs for a watershed within the Chesapeake Bay's Atlantic Coastal Plain physiographic region, and 2) to quantify the impact of climate change on BMP effectiveness for the same study area. To quantify climate change impacts on CSAs, a baseline hydrologic water quality model (SWAT) was built and calibrated to current climatic conditions. With an established baseline, climate variables, based on IPCC SRESs, were then introduced into the model to simulate future climate conditions. The study area's CSA changes in response to IPCC SRESs were tracked, analyzed and mapped. The second objective quantified BMP resilience to climate change. Two methods were developed for BMP targeting and implementation under baseline and future climatic conditions. Each method evaluated resilience by comparing design and implementation philosophies from traditional stationarity to non-stationarity. Together, these investigations aim to provide policy makers with the tools to establish WIPs that will be resilient against climate change and ensure TMDLs milestones are met now and continue to be met in the future.

Results from the first objective show that the selected climate change IPCC SRESs, analyzed by a Fixed Threshold Quantile Method (FTQM), would mean a substantial increase in total hotspot area and total hotspot export for all constituents (i.e., TSS, TN and TP). In terms of HRU area, study results suggest that we can expect at least a doubling of total hotspot area for TSS, TN and TP from baseline scenario to the more

extreme IPCC SRES A2 end century scenario. Similar to trends exhibited by hotspot area, total hotspot mass export increases for all constituents. While total mass export by hotspot areas do not exhibit the same dramatic increase as changes in hotspot area, total mass exports for all constituents start at near 70% above the baseline. These projections, if realized, will make management much more difficult and costly

Results from the second objective show that designing BMPs without climate change in mind would eventually entail significant retrofitting and or a continuing failure to meet water quality standards set by the Bay TMDL. Two BMP implementation methods, CSA Density and non-CSA targeting, were developed and employed to explore and confirm the aforementioned conclusion. The first method targeted “dense” hotspots (those contributing to multiple pollutant loads) and applied BMPs based on baseline conditions. Unfortunately, by the end of the century for SRES A2, TMDL attainment error ranged from nearly 80% to over 140% above TMDL water quality targets. The second method, non-CSA targeting, showed similar results with an error range between 50% and 100% above TMDL targets. The second method exhibited less error but largely as a result of higher BMP efficiency. Lastly, both methods failed to control TN within the boundary conditions attributed to each method. Unfortunately, both methods suggest that TMDL attainment will require treating a large surface area, to include most all urban and agricultural land, with high efficiency BMPs. As a result, we highly recommend that a prioritization scheme, targeting denser CSAs for BMP implementation, be developed as it may be the best way to focus efforts over time.

The study objectives and results show policy makers and watershed managers how critical it is to consider climate variability for WIP development and

implementation; i.e. identification of CSAs and implementation of BMPs. The methods developed and utilized for each objective provide valuable tools for ensuring long-term sustainability of agricultural watersheds in the Chesapeake Bay. One subtle method, that warrants further attention here, involves the use of SWAT's "generic" BMP feature for each targeting method described in Chapter 4. One reason for implementing generic BMPs in our research is due to the previously mentioned social dimension of BMP implementation. For nonpublic land, wide implementation is only successful when socioeconomic forces on stakeholders are considered. Baumgart-Getz et al., (2012) identified significant and insignificant socioeconomic forces (reviewed in section 1.3.3). A generic BMP, simply a land based reduction target for TSS, TN and TP, allows farmers and other landowners the power to choose how they might meet TMDL targets. The reverse would, in a sense, require policy makers and environmental managers to impose land use changes on stakeholders. It is easy to imagine that the latter approach could cause tension and alienate the two groups. Preventing this is important as these relationships are very significant to successful BMP implementation (Baumgart-Getz et al., 2012). Fortunately, the flexible methods presented in this research provide a mechanism to avoid this problem. Additionally, generic methods also have to power to be adapted to other land uses such as urban and suburban watersheds. All of these considerations are important to successfully manage the Bay's ~165,000 km^2 of urban, suburban and agricultural land uses now and into the distant future.

5.2 FUTURE WORK

Cursory explorations of the data and identified assumptions lead to very important and interesting future work. Examples of future work include: improving the design of generic BMPs in SWAT, examining other methods for identifying critical break values, examining other methods for establishing CSA Density and integrating BMP implementation strategies into a larger model that includes social research and outreach — a diagnostic decision support system (DDSS).

Using the generic BMP model in SWAT for objective 2 was useful for focusing on TSS, TN and TP mass load reductions. However, the BMP itself did not simulate reductions in surface and subsurface discharge as well as possible increases in evapotranspiration. There were essentially no changes made to the hydrologic processes that would normally occur within most BMPs. This is problematic as literature has suggested that BMP performance is dependent on input concentrations and thus a function of total flow (Li & Davis, 2009). Adding a hydrologic component to SWAT's generic BMP would offer additional insight to what kinds of BMPs should be implemented for specific areas.

Critical Break Values (CBVs) were defined and established in the exploration of objective 1. Our study used a Fixed Threshold Quantile Method (FTQM) to identify top exporting (top 10% and 20%) HRUs for climate variability analysis and then BMP implementation. This analysis was done primarily within ESRI's ArcMap software but is not the only method for establishing CSAs. While reviewed literature was often vague or did not specify, other data classification schemes offered by the ArcMap software include: Jenk's Optimization Method, Equal Interval, Geometric interval, standard

deviation, manual classification and defined interval schemes. An exploration of various techniques, combinations of techniques and finer categorization, e.g. 95th or 71st percentile, by pollutant constituent may be valuable as land managers begin to examine prioritization schemes and their cost-benefit ratios.

Further considering classification schemes for CSA definition, we can also further optimize BMP prioritization schemes by adjusting and or using mixed thresholds to define CBVs. Exploring the effects on CSA Density would better address the fact that each constituent, TSS, TN, and TP, has different cumulative distributions. In a cost benefit analysis, using different or mixed thresholds can adjust density scores so that TMDLs are met solely by implementing BMPs on land areas with a density value of 3 (most dense). As an example of these calculations, consider TSS, TN and TP set to the 45th percentile threshold, using the FTQM, to be 320 kg/ha/yr, 7.21 kg/ha/yr, and 0.39 kg/ha/yr for each constituent respectively. This might result in a CSA density change where Density 3 CSAs make up 47% of the watershed area and would require BMP efficiencies for TSS, TN and TP of 96%, 90%, and 85% respectively, to meet TMDL targets (Example derived from data in Renkenberger et al., 2015b). Optimizing by density for smallest area might significantly reduce area for this implementation method, at the cost of requiring highly efficient BMPs. In this example we use the results shown in Renkenberger et al., 2015b Table 4 and find that we can achieve an 11% reduction in total BMP-Targeted area with TSS, TN and TP BMP efficiency increases of 14%, 16% and 13% for each constituent respectively.

Additional future work involves model integration. In the opening of this paper, watershed components and watershed modeling are discussed, including the fact that

watershed models often lack social and biological components. Developing larger coupled models will provide Bay jurisdictions additional decision power and increase WIP efficiency. Wang, Y., (2015), Chanse et al. (2014) and Leisnham et al. (2013) have explored advances in social and biological coupling, but these approaches have yet to be adopted on a wide scale.

Lastly, future work in all the previously mentioned areas should also consider the fundamental reason for achieving and maintaining sustainability. This study examines the impact of climate change on the Chesapeake Bay and our ability to be resilient against those changes. Interestingly, some results indicated that natural areas can become CSAs under extreme climate scenarios. This highlights another line of future inquiry. Can and should we adapt to a new and different Bay ecosystem? If so, when? We need to also consider ecosystem non-stationarity. They too will not inherently always be the same, despite our best efforts, and thus not always provide the same ecosystem services and resources. If at some point climate change forces us to use BMPs to prevent a changing ecosystem rather than restore it, what will and what should we do? Adapting to permanent environmental change is a big question for the scientific community to consider. The threshold between restoration and permanent change may be important to identify to prevent environmental damage and or ensure our survival as a species.

APPENDIX 1: FINAL PARAMETERIZATION

Each of the sections below list the model parameters used in calibration, their definitions as defined by SWAT's Theoretical Documentation Version 2009 (Neitsch et al., 2011), the type of change made to SWAT input files by SWAT-CUP and the final fitted parameter range.

HYDROLOGIC PARAMETERS

Model Input Parameter	**Definition**	**Type of Change**	**Fitted Range (All Groupings)**
CN2.mgt	Runoff Curve Number (Moisture Condition 2)	Relative	-20% to 13%
OV_N.hru	Manning's "n" value for overland flow	Relative	-30% to 44%
CANMX.hru	Maximum canopy storage	Absolute	1.5 to 17.5 mm
DDRAIN.mgt	Depth to subsurface drain	Absolute	875 to 1025 mm
TDRAIN.mgt	Time to drain soil to field capacity	Absolute	13.6 to 28.8 hrs
GDRAIN.mgt	Drain tile lag time	Absolute	3.7 to 11.2 hrs
ESCO.hru	Soil evaporation compensation coefficient	Absolute	-0.22 to 0.05
EPCO.hru	Plant uptake compensation coefficient	Absolute	-0.46 to 0.04
SURLAG.bsn	Surface runoff lag time coefficient	Absolute	-3.8 to -2
SLSUBBSN.hru	Subbasin average slope length	Relative	-2% to 35%
HRU_SLP.hru	Subbasin average slope steepness	Relative	-7% to 20%
CH_N2.rte	Manning's "n" value for the main channel	Relative	-12% to 9%
SOL_AWC(..).sol	Available water capacity of the soil layer	Relative	-11% to 10%
ALPHA_BF.gw*	Baseflow alpha factor	Replace	0.0308 days
REVAPMN.gw	Threshold depth of water in the shallow aquifer for "revap" to occur	Absolute	-242 to19 mm
GW_REVAP.gw	Groundwater "revap" coefficient	Relative	-0.07 to 0.06
Model Input Parameter	Definition	Type of Change	Fitted Range (All Groupings)

GW_DELAY.gw	Groundwater delay aquifer recharge	Absolute	-5.7 to 12.8 days
RCHRG_DP.gw	Deep aquifer percolation coefficient	Absolute	-0.006 to 0.032
DEP_IMP.hru	Depth to impervious layer for modeling perched water tables	Absolute	-3249 to -2083 mm
GWQMN.gw	Threshold depth of water in the shallow aquifer required for return flow to occur	Absolute	-387 to 839 mm
Note: ALPHA_BF.gw was fit to a single value using the SWAT BFlow software discussed in section 1.6.3.			

TOTAL SUSPENDED SEDIMENT (TSS) PARAMETERS

Model Input Parameter	Definition	Type of Change	Fitted Range (All Groupings)
PRF.bsn	Peak rate adjustment factor for sediment routing in the main channel	Absolute	-0.03 to 0.02
SPEXP.bsn	Exponent parameter for calculating sediment reentrained in channel sediment routing	Absolute	0.30 to 0.40
SPCON.bsn	Linear parameter for calculating the maximum amount of sediment that can be reentrained during channel sediment routing	Absolute	0.0060 to 0.0065
CH_COV1.rte	Channel erodibility factor	Absolute	0.05 to 0.11
CH_COV2.rte	Channel cover factor	Absolute	1.1 to 1.2
USLE_P.mgt	USLE equation support practice	Absolute	-1.18 to -1.10
USLE_K().sol	USLE equation soil erodibility (K) factor	Relative	-0.50 to 0.03
LAT_SED.hru	Sediment concentration in lateral flow and groundwater flow	Absolute	152 to 310 mg/l

TOTAL NITROGEN (TN) PARAMETERS

Model Input Parameter	Definition	Type of Change	Fitted Range (All Groupings)
ERORGN.hru	Organic N enrichment ratio	Replace	-4.7 to 4.4
NPERCO.bsn	Nitrogen percolation	Replace	0.2 to 0.3

	coefficient		
RCN.bsn	Concentration of nitrogen in rainfall	Replace	-3.3 to -1.4 mg/l
CMN.bsn	Rate factor for humus mineralization of active organic nitrogen	Replace	4.3E-4 to 6.4E-4
CDN.bsn	Denitrification exponential rate coefficient	Replace	2.4 to 2.7
N_UPDIS.bsn	Nitrogen uptake distribution parameter	Replace	55 to 64
HLIFE_NGW_BSN.bsn	Half-life of nitrogen in groundwater	Replace	120 to 152 days
CH_ONCO_BSN.bsn	Channel organic nitrogen concentration in basin	Replace	2.7 to 7.2 ppm
BC1_BSN.bsn	Rate constant for biological oxidation of NH3	Replace	0.58 to 0.64 1/day
BC2_BSN.bsn	Rate constant for biological oxidation NO2 to NO3	Replace	0.80 to 1.04 1/day
BC3_BSN.bsn	Rate constant for hydrolosis of organic nitrogen to ammonia	Replace	0.22 to 0.26 1/day
SOL_ORGN().chm	[mg/kg] Initial organic N concentration in the soil layer	Replace	0 to 62 mg/kg
SOL_NO3().chm	[mg/kg] Initial NO3 concentration in the soil layer	Replace	0 to 34 mg/kg
SHALLST_N.gw	Concentration of nitrate in groundwater contribution to streamflow from subbasin	Replace	831 to 895 mg/l
LAT_ORGN.gw	Organic N in baseflow	Replace	230 to 279 mg/l

TOTAL PHOSPHORUS (TP) PARAMETERS

Model Input Parameter	**Definition**	**Type of Change**	**Fitted Range (All Groupings)**
ERORGP.hru	Organic P enrichment ratio	Replace	1.9 to 3.5
PPERCO.bsn	Phosphorus percolation coefficient	Replace	10.3 to 11.2
PSP.bsn	Phosphorus sorption coefficient	Replace	0.38 to 0.42
PHOSKD.bsn	Phosphorus soil partitioning	Replace	96.3 to 120.0

	coefficient		
P_UPDIS.bsn	Phosphorus percolation coefficient	Replace	67.2 to 77.5
RSDCO.bsn	Residue decomposition coefficient	Replace	0.049 to 0.051
CH_OPCO_BSN.bsn	Channel organic phosphorus concentration in basin	Replace	84.3 to 93.5 ppm
BC4_BSN.bsn	Rate constant for decay of organic phosphorus to dissolved phosphorus	Replace	1.02 to 1.12 1/day
SOL_ORGP().chm	Initial organic P concentration in surface soil layer	Replace	44.4 to 48.4 mg/kg
GWSOLP.gw	Concentration of soluble phosphorus in groundwater contribution to streamflow from subbasin	Replace	-897.1 to -827.5 mg/l
LAT_ORGP.gw	Organic P in baseflow	Replace	-61.0 to -39.2 mg/l

CLIMATE CHANGE PARAMETERS

Model Input Parameter	IPCC Scenario and Period	Definition	Type of Change	Assigned Value
CO2.sub	Baseline (1990-2010)	Carbon dioxide concentration	Replace	370 ppmv
CO2.sub	SRES B1 Mid Century (2046-2064)	Carbon dioxide concentration	Replace	484 ppmv
CO2.sub	SRES B1 End Century (2081-2100)	Carbon dioxide concentration	Replace	540 ppmv
CO2.sub	SRES A1B	Carbon dioxide	Replace	527 ppmv

	Mid Century (2046-2064)	concentration		
CO2.sub	SRES A1B End Century (2081-2100)	Carbon dioxide concentration	Replace	678 ppmv
CO2.sub	SRES A2 Mid Century (2046-2064)	Carbon dioxide concentration	Replace	529 ppmv
CO2.sub	SRES A2 End Century (2081-2100)	Carbon dioxide concentration	Replace	766 ppmv

APPENDIX 2: EXTENDED CALIBRATION AND VALIDATION STATISTICS

Summarized below are additional statistics for model calibration and validation. Values in parenthesis are statistics from the default uncalibrated model while the values that come before are the statistics from the final parametrized model.

HYDROLOGY

Calibration Period

Statistic	Daily	Monthly	Annual
r	0.66 (0.05)	0.83 (0.19)	0.80 (-0.05)
NS	0.42 (-2.25)	0.66 (-0.41)	0.51 (-1.37)
Bias [%]	-12.18 (-5.86)	-12.28 (-5.94)	-10.17 (-5.09)
MSE	35.52 (199.74)	6.28 (26.43)	1.78 (8.62)

Validation Period

Statistic	Daily	Monthly	Annual
r	0.67 (0.08)	~ 1.00 (0.35)	0.99 (-0.03)
NS	0.43 (-2.37)	0.95 (-0.38)	0.64 (-4.02)
Bias [%]	-20.77 (23.08)	-20.63 (22.92)	-23.99 (47.64)
MSE	35.76 (212.43)	41.25 (70.91)	1.02 (14.06)

TOTAL SUSPENDED SEDIMENT (TSS)

Calibration Period

Statistic	Daily	Monthly	Annual
r	0.55 (0.11)	0.60 (0.05)	0.91 (0.42)
NS	0.23 (-466.54)	-0.01 (-2137.73)	0.57 (-247.07)
Bias [%]	49.53 (1275.18)	96.08 (2235.36)	50.12 (1303.09)
MSE	8.96E+03 (5.42E+06)	2.84E+03 (6.03E+06)	1.23E+03 (7.18E+05)

Validation Period

Statistic	Daily	Monthly	Annual
r	0.41 (0.18)	0.50 (0.50)	0.57 (-0.13)
NS	-0.19 (-414.16)	-0.32 (-0.32)	-1.14 (-550.90)
Bias [%]	77.26 (1347.60)	99.67 (99.67)	78.98 (1382.12)
MSE	5.65E+03 (1.97E+06)	3.02E+03 (3.02E+03)	1.73E+03 (4.46E+05)

TOTAL NITROGEN (TN)

Calibration Period

Statistic	Daily	Monthly	Annual
r	0.56 (0.10)	0.77 (0.09)	0.77 (0.32)
NS	0.21 (-1.64)	0.57 (-5.38)	0.47 (-0.74)
Bias [%]	-14.42 (-60.88)	-2.98 (-36.73)	-13.20 (-60.89)
MSE	6.21E+06 (2.08E+07)	1.65E+06 (2.43E+07)	1.70E+06 (5.56E+06)

Validation Period

Statistic	Daily	Monthly	Annual
r	0.59 (0.13)	0.69 (0.16)	0.86 (0.30)
NS	-0.15 (-3.02)	-0.19 (-6.76)	0.55 (-3.92)
Bias [%]	-3.43 (-43.12)	10.09 (-22.58)	-3.99 (-43.39)
MSE	4.00E+06 (1.40E+07)	2.48E+06 (1.62E+07)	1.45E+05 (1.58E+06)

TOTAL PHOSPHORUS (TP)

Calibration Period

Statistic	Daily	Monthly	Annual
r	0.49 (0.10)	0.51 (0.02)	0.91 (0.12)
NS	0.24 (-14.78)	0.13 (-105.52)	0.79 (-6.84)
Bias [%]	-6.06 (187.30)	17.41 (416.83)	-5.83 (188.71)
MSE	1.10E+05 (2.26E+06)	2.02E+04 (2.49E+06)	7.23E+03 (2.75E+05)

Validation Period

Statistic	Daily	Monthly	Annual
r	0.62 (0.19)	0.67 (0.14)	0.86 (-0.15)
NS	0.26 (-13.93)	0.32 (-11.02)	-0.58 (-14.41)
Bias [%]	-50.27 (152.93)	-45.75 (159.65)	-50.28 (157.88)
MSE	6.53E+04 (1.32E+06)	3.00E+04 (5.27E+05)	2.16E+04 (2.11E+05)

CITED REFERENCES

Abbaspour, K. (2015). SWAT-CUP. Swiss Federal Institute of Aquatic Science and Technology. Retrieved from http://www.neprashtechnology.ca/Downloads/SwatCup/Manual/Usermanual_Swat_Cup_2012.pdf

Abbaspour, K., Johnson, C., & Van Genuchten, M. (2004). Estimating uncertain flow and transport parameters using a sequential uncertainty fitting procedure. Vadose Zone Journal, 3(4), 1340–1352.

Abbaspour, K., Rouholahnejad, E., Vaghefi, S., Srinivasan, R., Yang, H., & Kløve, B. (2015). A continental-scale hydrology and water quality model for Europe: Calibration and uncertainty of a high-resolution large-scale SWAT model. Journal of Hydrology, 524, 733–752. http://doi.org/10.1016/j.jhydrol.2015.03.027

Arabi, M., Frankenberger, J. R., Engel, B. A., & Arnold, J. G. (2008). Representation of agricultural conservation practices with SWAT. Hydrological Processes, 22(16), 3042–3055. http://doi.org/10.1002/hyp.6890

Arabi, M., Govindaraju, R. S., Hantush, M. M., & Engel, B. A. (2006). Role of Watershed Subdivision on Modeling the Effectiveness of Best Management Practices with Swat1. JAWRA Journal of the American Water Resources Association, 42(2), 513–528. http://doi.org/10.1111/j.1752-1688.2006.tb03854.x

Arnold, J., & Allen, P. (1999). Automated methods for estimating baseflow and groundwater recharge from streamflow records. Journal of the Americam Water Resources Association, 35(2), 411–424.

Arnold, J. G., Allen, P. M., & Bernhardt, G. (1993). A comprehensive surface-groundwater flow model. Journal of Hydrology, 142(1–4), 47–69. http://doi.org/10.1016/0022-1694(93)90004-S

Arnold, J. G., Allen, P., Muttiah, R., & Bernhardt, G. (n.d.). Automated base flow separation and recession analysis techniques. Ground Water, 33(6), 1010–1018.

Arnold, J. G., Moriasi, D. N., Gassman, P. W., Abbaspour, K. C., White, M. J., Srinivasan, R., … others. (2012). SWAT: Model use, calibration, and validation. Transactions of the ASABE, 55(4), 1491–1508.

Arocena, R. (2007). Effects of Submerged Aquatic Vegetation on Macrozoobenthos in a Coastal Lagoon of the Southwestern Atlantic. International Review of Hydrobiology, 92(1), 33–47. http://doi.org/10.1002/iroh.200610881

Art, H. (Ed.). (1993). The Dictionary of Ecology and Environmental Science (1st ed). New York: H. Holt.

Baumgart-Getz, A., Prokopy, L. S., & Floress, K. (2012). Why farmers adopt best management practice in the United States: a meta-analysis of the adoption literature. Journal of Environmental Management, 96(1), 17–25. http://doi.org/10.1016/j.jenvman.2011.10.006

Carbon Dioxide: Projected emissions and concentrations. (n.d.). Retrieved December 2, 2015, from http://www.ipcc-data.org/observ/ddc_co2.html

Chanse, V., P.T. Leisnham, A. Rockler, J. McCoy, L. Cain, S. Wilson, H. Montas, A. Shirmohammadi, A. Mohamed. 2014. A community-based participatory research approach for stormwater management: Implications of differing BMP approaches in two urban watersheds. EDRA45, The Environmental Design Research Association Conference (New Orleans, LA: May 31st, 2014).

Chen, L., Zhong, Y., Wei, G., Cai, Y., & Shen, Z. (2014). Development of an integrated modeling approach for identifying multilevel non-point-source priority management areas at the watershed scale. Water Resources Research, 50(5), 4095–4109. http://doi.org/10.1002/2013WR015041

Chesapeake Bay Program. (n.d.). Retrieved December 2, 2015, from http://www.chesapeakebay.net

Chesapeake Bay TMDL Tracking and Accounting System (BayTAS). (n.d.). Retrieved December 2, 2015, from https://stat.chesapeakebay.net/?q=node/130&quicktabs_10=1

Chiang, L.-C., Chaubey, I., Hong, N.-M., Lin, Y.-P., & Huang, T. (2012). Implementation of BMP Strategies for Adaptation to Climate Change and Land Use Change in a Pasture-Dominated Watershed. International Journal of Environmental Research and Public Health, 9(10), 3654–84.

Chu, T. W., Shirmohammadi, A., Montas, H., & Sadeghi, A. (2004). Evaluation of the SWAT model's sediment and nutrient components in the Piedmont physiographic region of Maryland. Transactions of the ASAE, 47(5), 1523–1538.Davis, A., & William Hunt. (2009). Bioretention Technology: Overview of Current Practice and Future Needs. Journal of Environmental Engineering, 135(3), 109–117. http://doi.org/10.1061/(ASCE)0733-9372(2009)135:3(109)

Climate Change Data for SWAT (CMIP3). (n.d.). Retrieved December 2, 2015, from http://globalweather.tamu.edu/cmip

Discover the Chesapeake. (n.d.). [NGO]. Retrieved September 21, 2015, from http://www.chesapeakebay.net/discover/bay101/facts

Dressing, S. (2003, July). National Management Measures to Control Nonpoint Source Pollution from Agriculture. EPA Office of Water (4503T). Retrieved from http://water.epa.gov/polwaste/nps/agriculture/agmm_index.cfm

Duriancik, L. F., Bucks, D., Dobrowolski, J. P., Drewes, T., Eckles, S. D., Jolley, L., … Weltz, M. A. (2008). The First Five Years of the Conservation Effects Assessment Project. Journal of Soil and Water Conservation, 63(6), 185A–197A. http://doi.org/10.2489/jswc.63.6.185A

EPA. (2010). Bay TMDL Executive Summary FINAL. Retrieved from http://www.epa.gov/reg3wapd/pdf/pdf_chesbay/FinalBayTMDL/BayTMDLExecutiveSummaryFINAL122910_final.pdf

Eutrophication: Causes, Consequences, Correctives; Proceedings of a Symposium. (1969). Washington: National Academy of Sciences.

Executive Order 13508, 3 C.F.R. (2009). Retrieved June 29, 2015, from https://www.whitehouse.gov/the-press-office/executive-order-chesapeake-bay-protection-and-restoration

Gaiser, E. E., Childers, D. L., Jones, R. D., Richards, J. H., Scinto, L. J., & Trexler, J. C. (2006). Periphyton Responses to Eutrophication in the Florida Everglades: Cross-System Patterns of Structural and Compositional Change. Limnology and Oceanography, 51(1), 617–630.

Gassman, P., Reyes, M., Green, C., & Arnold, J. (2007). The Soil and Water Assessment Tool: Historical Development, Applications, and Future Research Directions. Transactions of the ASABE, 50(4), 1211–1250.

Giri, S., Nejadhashemi, A. P., Woznicki, S., & Zhang, Z. (2014). Analysis of best management practice effectiveness and spatiotemporal variability based on different targeting strategies. Hydrological Processes, 28(3), 431–445. http://doi.org/10.1002/hyp.9577

Global Weather Data for SWAT. (n.d.). Retrieved December 2, 2015, from http://globalweather.tamu.edu/

Google Groups - SWAT-CUP. (n.d.). Retrieved February 2, 2015, from https://groups.google.com/forum/#!forum/swat-cup

Gregory, K. J. (2011). Wolman MG (1967) A cycle of sedimentation and erosion in urban river channels. Geografiska Annaler 49A: 385-395. Progress in Physical Geography, 35(6), 831–841. http://doi.org/10.1177/0309133311414527

Huaifeng, G., Zuhao, Z., Dayong, Q., Jiguo, Y., & Qiang, C. (2010). Analysis of Critical Source Areas about Multi-source Nutrient Loadings Based on SWAT Model in Jiyun River Basin. HKIE Transactions, 17(2), 14–19. http://doi.org/10.1080/1023697X.2010.10668191

Huang, J. J., Lin, X., Wang, J., & Wang, H. (2015). The precipitation driven correlation based mapping method (PCM) for identifying the critical source areas of non-point source pollution. Journal of Hydrology, 524, 100–110. http://doi.org/10.1016/j.jhydrol.2015.02.011

Iman, R. L., Davenport, J. M., Zeigler, D. K., United States. Department of Energy., Sandia Laboratories., Sandia Laboratories. Statistics and Computing Division 1223., & Texas Tech University. Department of Mathematics. (1980). Latin hypercube sampling (program user's guide). Albuquerque, N.M. : Dept. of Energy, Sandia Laboratories,.

IPCC Working Group III. (2000). Emissions Scenarios: A Special Report of IPCC Working Group III. [Geneva]: Intergovernmental Panel on Climate Change.

Kyoung Jae Lim, Bernard A. Engel, Zhenxu Tang, Joongdae Choi, Ki-Sung Kim, Suresh Muthukrishnan, & Dibyajyoti Tripathy. (2005). Automated Web GIS Based Hydrograph

Analysis Tool, WHAT. Journal of the American Water Resources Association, 41(6), 1407–1416. http://doi.org/10.1111

Leisnham, P., H. Montas, A. Shirmohammadi, V. Chanse, D. Lansing, A. Rockler, T. Hutson, J. McCoy, L. Cain, S. Wilson, D. Lipton, K. Brubaker and Y. Wang. 2013. Watershed Diagnostics for Improved Adoption of Management Practices: Integrating Biophysical and Social Factors Across Urban and Agricultural Landscapes. In 2013 ASABE Annual International Meeting Paper. Paper number 131668614, 2013 Kansas City, Missouri, July 21 - July 24, 2013. (doi: http://dx.doi.org/10.13031/aim.20131668614)

Legates, D. R., & McCabe, G. J. (1999). Evaluating the use of "goodness-of-fit" Measures in hydrologic and hydroclimatic model validation. Water Resources Research, 35(1), 233–241. http://doi.org/10.1029/1998WR900018

Li, H., & Davis, A. P. (2009). Water Quality Improvement through Reductions of Pollutant Loads Using Bioretention. Journal of Environmental Engineering, 135(8), 567–576. http://doi.org/10.1061/(ASCE)EE.1943-7870.0000026

Maryland Geology. (n.d.). [Government]. Retrieved September 28, 2015, from http://www.mgs.md.gov/geology/

Maurer, E. P., Brekke, L., Pruitt, T., Thrasher, B., Long, J., Duffy, P., … Arnold, J. (2014). An Enhanced Archive Facilitating Climate Impacts and Adaptation Analysis. Bulletin of the American Meteorological Society, 95(7), 1011–1019. http://doi.org/10.1175/BAMS-D-13-00126.1

McKay, M., Beckman, R. J., & Conover, W. J. (1979). A Comparison of Three Methods for Selecting Values of Input Variables in the Analysis of Output from a Computer Code. Technometrics, 21(2), 239–245. http://doi.org/10.2307/1268522

Meehl, G. A., Covey, C., Delworth, T., Latif, M., McAvaney, B., Mitchell, J. F. B., … Taylor, K. E. (2007). THE WCRP CMIP3 MULTIMODEL DATASET: A New Era in Climate Change Research. Bulletin of the American Meteorological Society, 88(9), 1383–1394. http://doi.org/10.1175/BAMS-88-9-1383

Moriasi, D. N., Wilson, B. N., Douglas-Mankin, K. R., Arnold, J. G., & Gowda, P. H. (2012). Hydrologic and water quality models: use, calibration, and validation. Transactions of the ASABE, 55(4), 1241–1247.

Morris, J. T. (1991). Effects of Nitrogen Loading on Wetland Ecosystems with Particular Reference to Atmospheric Deposition. Annual Review of Ecology and Systematics, 22, 257–279.

Mueller, D., & Helsel, D. (2013, January 11). Nutrients in the Nation's Waters -Too Much of a Good Thing? [Government]. Retrieved September 21, 2015, from http://pubs.usgs.gov/circ/circ1136/circ1136.html#FOREWORD

Muñoz−Carpena, R., Vellidis, G., Shirmohammadi, A., Wallender, W. (2006). EVALUATION OF MODELING TOOLS FOR TMDL DEVELOPMENT AND IMPLEMENTATION. Transactions of the ASABE, 49(4), 961–965.

National Centers for Environmental Information (NCEI). (n.d.). Retrieved December 2, 2015, from http://www.ncdc.noaa.gov/

Neitsch, S. L., Arnold, J. G., Kiniry, J. R., & Williams, J. R. (2011, September). Soil and Water Assessment Tool Theoretical Documentation. Texas Water Resources Institute. Retrieved from http://swat.tamu.edu/media/99192/swat2009-theory.pdf

Pachauri, R. K., Mayer, L., & IPCC (Eds.). (2015). Climate Change 2014: Synthesis Report. Geneva, Switzerland: Intergovernmental Panel on Climate Change.

Powledge, F. (2006). The Millennium Assessment. BioScience, 56(11), 880–886. http://doi.org/10.1641/0006-3568(2006)56[880:TMA]2.0.CO;2

Rabalais, N., Diaz, R., Goolsby, D., & Brezonik, P. (2000, May). An Integrated Assessment in the Northern Gulf of Mexico. National Science and Technology Council Committee on Environment and Natural Resources. Retrieved from http://oceanservice.noaa.gov/products/hypox_final.pdf

Renkenberger, J., Montas, H., Leisnham, P., Chanse, V., Shirmohammadi, A., Ali Sadeghi, … David Lansing. (2015a, October). CLIMATE CHANGE IMPACT ON CRITICAL SOURCE AREA IDENTIFICATION IN A MARYLAND WATERSHED.

Renkenberger, J., Montas, H., Leisnham, P., Chanse, V., Shirmohammadi, A., Ali Sadeghi, … David Lansing. (2015b, October). EFFECTIVENESS OF BEST MANAGEMENT PRACTICES WITH CHANGING CLIMATE IN A MARYLAND WATERSHED.

Sexton, A. M., Sadeghi, A. M., Zhang, X., Srinivasan, R., & Shirmohammadi, A. (2010). Using NEXRAD and rain gauge precipitation data for hydrologic calibration of SWAT in a northeastern watershed. Transactions of the ASABE, 53(5), 1501–1510.

Shang, X., Wang, X., Zhang, D., Chen, W., Chen, X., & Kong, H. (2012). An improved SWAT-based computational framework for identifying critical source areas for agricultural pollution at the lake basin scale. Ecological Modelling, 226, 1–10. http://doi.org/10.1016/j.ecolmodel.2011.11.030

Shirmohammadi, A., Montas, H., & Bergstrom, L. (n.d.). Water Quality Models. In Chapter 9 Water Quality Models.

Skrobialowski, S. (2014, August 12). Filtered vs Unfiltered. Retrieved from h2oteam@usgs.gov

SWAT Calibration Techniques. (n.d.). Retrieved from http://swat.tamu.edu/media/90112/swat-calibration-techniques_slides.pdf

SWAT: Soil and Water Assessment Tool. (n.d.). Retrieved December 2, 2015, from http://swat.tamu.edu/

USGS 01491000 CHOPTANK RIVER. (2015). Retrieved December 2, 2015, from http://waterdata.usgs.gov/usa/nwis/uv?01491000

Wang, Y., 2015. A Diagnostic Decision Support System for Selecting Best Management Practices in Urban/Suburban Watersheds. Ph.D. Thesis, Department of Civil and Environmental Engineering, University of Maryland at College Park.

White, M. J., Storm, D. E., Busteed, P. R., Stoodley, S. H., & Phillips, S. J. (2009). Evaluating Nonpoint Source Critical Source Area Contributions at the Watershed Scale. Journal of Environmental Quality, 38(4), 1654–63.

Winchell, M., Folle, S., Meals, D., Moore, J., Srinivasan, R., & Howe, E. A. (2014). Using SWAT for sub-field identification of phosphorus critical source areas in a saturation excess runoff region. Hydrological Sciences Journal, 60(5), 844–862. http://doi.org/10.1080/02626667.2014.980262

Winchell, M., Srinivasan, R., DiLuzio, M., & Arnold, J. G. (2007, February). ArcSWAT Interface For SWAT 2005: User's Guide. Retrieved from http://swat.tamu.edu/software/arcswat/

Yang, J., Reichert, P., Abbaspour, K. C., Xia, J., & Yang, H. (2008). Comparing uncertainty analysis techniques for a SWAT application to the Chaohe Basin in China. Journal of Hydrology, 358(1-2), 1–23. http://doi.org/10.1016/j.jhydrol.2008.05.012