Evaluating the Effects of Watershed Land Use Distribution and BMP Data on HSPF Water Quality Predictions

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Keywords: *Best Management Practices, BMP Reduction, TMDL, Target Goals, Water Quality*

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ABSTRACT

Preventing impairment of waterbodies requires control, reduction and interception of contaminant losses at the field and subwatershed level. Three specific research objectives were accomplished in this study: 1) compare the HSPF-predicted flow, sediment, total nitrogen (TN) and total phosphorus (TP) loads resulting from simulation of spatially distributed site-specific and county-level disaggregated land use data at subwatershed and watershed levels, 2) evaluate the effects of site-specific and county-level disaggregated BMP data on modeled BMP responses in HSPF-predicted flow, sediment, TN and TP loads at the watershed level, and 3) analyze the long-term effects of the two spatial BMP datasets on achieving the Chesapeake Bay Total Maximum Daily Load (TMDL) goals for sediment, TN and TP. Site-specific data are derived from the local watershed inventory while disaggregated data are based on county-level aggregated data that are distributed to portions of river segments that intersect each county. The study site was the Upper Opequon Watershed in northern Virginia. Results for each research objective are as follows: (1) HSPF-predicted flow, sediment, TN and TP were higher using disaggregated land use data in subwatersheds at monthly and annual time-steps. (2) Predicted load reductions were higher with site-specific BMP data than with disaggregated data for the study watershed. (3) Current levels of cost-shared BMP implementation in the Upper Opequon Watershed using either site-specific or county-level disaggregated BMP datasets do not meet the Chesapeake Bay TMDL goals. Increasing BMP implementation level to 100% of the available land also failed to meet TMDL target goals. Generally, use of disaggregated land use data does not accurately represent the existing watershed conditions. Further, for the study watershed, use of disaggregated county-level BMP data poorly represented actual watershed conditions, which resulted in higher pollutant yields and higher levels of BMPs needed to meet water quality goals. The study suggests that site-specific land use and BMP data must be used during TMDL implementation planning to maintain credibility with local stakeholders and improve the accuracy of the developed implementation plans.

Keywords: *Best Management Practices, BMP Reduction, TMDL, Target Goals, Water Quality*

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List of Abbreviations

AGCHEM	AGCHEM is the HSPF module that allows users to model nutrients as part of the processes that take place in pervious segments of watersheds
AGNPS	Agricultural Non-Point Source Pollution Model is a system of computer models developed to predict nonpoint source pollutant loadings within agricultural watersheds
ANOVA	Analysis of variance is a general statistical method that can be used to test the hypothesis that the means of two or more groups are equal, under the assumption that the sampled populations are normally distributed
ANSWERS	Areal Nonpoint Source Watershed Environment Response Simulation is a model used to assess the impacts of alternative management schemes on agricultural land
APEX	Agricultural Policy/Environmental eXtender Model, a field-scale water quality model
BMPs	Best Management Practices which refer to reasonable and cost-effective means to reduce the likelihood of pollutants entering a water body
BASINS	Better Assessment Science Integrating Point and Nonpoint Sources, an environmental modeling package that integrates a geographical information system (GIS) and nation-wide watershed data, used for environmental assessment and modeling
CBA	Chesapeake Bay Agreement of 2000
CBWM	Chesapeake Bay Watershed Model or simply Bay Model
CBP	Chesapeake Bay Program
CREAMS	Chemicals, Runoff and Erosion from Agricultural Management Systems Model
CN_2	Average curve number, an empirical parameter used in hydrology for

	predicting direct runoff or infiltration from rainfall excess
DEM	A Geographical Information System digital elevation model which represents physical features on the earth's surface
EPIC	Environmental Policy Integrated Climate Model, previously known as Erosion Productivity Impact Calculator
GLEAMS	Groundwater Loading Effects from Agricultural Management Systems Model
HSPF	Hydrologic Simulation Program-FORTRAN is a water quality model
IQUAL	HSPF modules that allow users to model the water quality processes occurring on impervious areas
JSER	Exponent in the matrix soil scour equation, which simulates gully equation
K1	Exponent parameters for the Freundlich curve used for adsorption
KAM	Coefficient of organic-N ammonification
KDNI	Coefficient of denitrification of NO_3 for lower soil layer
KIMP	Coefficient of P immobilization
KNI	Coefficient of first order nitrification
KSER	Coefficient in the detached sediment wash-off equation
MON-NITUPT	Fractions of the total annual N plant uptake target applied to each month
MUSLE	Modified Universal Soil Loss Equation used in erosion prediction
MS4	Municipal Separate Storm Sewer Systems
N1	Coefficient parameter for the Freundlich curve used for adsorption
N	Nitrogen, a chemical element
NCDC	U.S. National Climatic Data Center for weather data in the United Sates
NOAA	U.S. National Oceanic and Atmospheric Administration

NMP	Nutrient Management Plan, a documented farm plan
NRCS	Natural Resources Conservation Service
NPS	Non-Point Source, diffuse and unregulated pollution sources
NSE	Nash-Sutcliffe Efficiency, a statistical data analysis statistic
ORGP	Initial P storage in the surface, upper, lower or groundwater layer parameter in the HSPF model
P4AD	Coefficient of adsorbed phosphate in the HSPF model
P	Phosphorus, a chemical element
PBIAS	Percent bias is a statistical analysis metric for data analysis
PET	Potential evapotranspiration
PQUAL	The simpler empirical HSPF modules that allow users to model the water quality processes occurring in pervious areas
PUPTGT	Total annual target for plant uptake of P for all soil layers and all crops during the calendar year
RE	Relative Error, error approximation in some data representing a discrepancy between an exact value and some approximation to it
SERCC	Southeast Regional Climate Center
STAC	The Scientific and Technical Advisory Committee provides scientific and technical guidance to the Chesapeake Bay Program on measures to restore and protect the Chesapeake Bay
SWCD	Soil and Water Conservation Districts
TMDL	Total Maximum Daily Loads, is a program mandated by the Clean Water Act, and is a watershed management process that integrates watershed planning with water quality assessment and protection. It is the maximum amount of pollution that a waterbody can receive and still meet the

	applicable water quality standards
TN	Total N - sum of nitrate-nitrogen (NO_3-N), nitrite-nitrogen (NO_2-N), ammonia-nitrogen (NH_3-N) and organically bonded nitrogen
TP	Total P - includes the amount of P in solution (reactive) and in particulate form (adsorbed and organic)
UAL	Unit area load which is load per unit area resulting from pollutant loss from a given land use
USDA- NASS	United States Department of Agriculture – National Agricultural Statistics Service (Agricultural Census)
USEPA	United States Environmental Protection Agency
USGS	United States Geological Survey
USLE	Universal Soil Loss Equation, an erosion prediction tool
VADCR	Virginia Department of Conservation and Recreation
VADEQ	Virginia Department of Environmental Quality
WEPP	The Water Erosion Prediction Project (WEPP) Model is a physically based erosion simulation model

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1 Introduction

1.1 Background and Problem Statement

Section 319 of the 1987 amendments to the Clean Water Act (CWA) requires States to establish nonpoint source (NPS) control programs by identifying their NPS impaired or threatened water resources. The act also requires development and implementation of controls to improve or prevent water quality impacts to those specified waters (USEPA, 2002). Use of water quality models to predict the effectiveness of water pollution abatement strategies in watersheds is a standard practice. Monitoring of watershed response to alternative management measures is required to determine if water quality goals are being achieved, but the monitoring process itself is expensive, uncertain and slow for many real-time management decisions. Modeling provides a timely and cost-effective means of screening and evaluating alternative management measures before and after they are implemented. When a water quality model is used to predict watershed water quality response, effort must be made to reduce model errors in output associated with input data. This requires use of quality input data and an understanding of the expected errors in the input data and model output. Spatial input data includes digital elevation models (DEM), land use, soils and best management practices (BMPs). Parameterizing distributed-parameter water quality models is particularly challenging because of their significant data requirements, which vary both spatially and temporally.

When data such as land use and BMPs are lumped at a larger scale (for example, county scale), the data can be discretized to smaller sub-basins in order to provide model input data in the absence of site-specific data. However, impaired segments of a water body (such as a stream or river) can be better described from a locally-derived land use and other site-specific spatial data. Land use affects the watershed hydrologic response, which in turn drives the generation of NPS pollution. Accurate representation of watershed conditions in hydrologic and water quality models is important in designing watershed plans needed to achieve desired pollution reduction goals. For instance, the Chesapeake Bay Agreement (CBA) of 1983 called for a 40% reduction in manageable nutrient loads by all Chesapeake Bay jurisdictions by 2010 (CBA, 2000).

To achieve such a goal requires reasonably accurate watershed estimates of nutrient loadings. Inaccurate estimation of watershed conditions can result in uncertain modeled outputs. The

implication of having errors in model outputs can lead to non-attainment of target goals and lack of confidence by the public in the simulated results. There is also need to simulate nutrients and use physically-based models that are more responsive to implemented management measures and atmospheric deposition than the empirically-based models during the development of better watershed Total Maximum Daily Load (TMDL) plans. A TMDL is the maximum amount of pollution that a waterbody can receive and still meet applicable water quality standards. To meet water quality standards, all significant pollutant sources and processes within a watershed need to be adequately represented for the evaluation of alternative control measures. When spatial data inadequately capture important aspects of pollutant sources, it is likely that such data can contribute to model output error. When management decisions are based on uncertain model outputs, failure of implemented management strategies can occur (Schueler, 1996b). In ungauged watersheds, use of disaggregated data from large and/or regional scales may be the only practical source of spatial data. County-level aggregated spatial data are common in the US and can be disaggregated and distributed to watersheds within the county using their area-weight ratios. Research is needed to better understand the uncertainty introduced into model results by using spatially disaggregated data.

Aggregated (lumped) data at county and state scales are available from federal agencies such as United States Department of Agriculture – National Agricultural Statistics Service (USDA-NASS) /Agricultural Census data, and have been used by the Chesapeake Bay Program (CBP) and other modelers (CBP, 2010c; Yagow et al., 2012). Knowledge on how lumped data can affect predicted pollutant loads and estimates of BMP responses in local watersheds is important for continued use of these data in hydrologic and water quality modeling. Patil et al. (2011) observed that model disaggregation algorithms are based on specific data distributions, which in many cases are assumed to be normal. Distributed data computed by disaggregation algorithms may have errors resulting from the assumed and the actual distributions. The accuracy of spatial data depends upon the size of watershed and approach used in mapping. It is essential to understand the effect of spatial variability on watershed water quality model output since predictions are dependent upon the spatially variable model input data and how BMPs are represented spatially. Uncertainties resulting from spatial scale deserve more attention. Knowledge of variations in model outputs associated with use of aggregated and/or

disaggregated data should help inform which spatial extent is suitable and necessary to minimize model output errors for locally impaired stream segments (small stream segments). This is because data lumped at a larger scale and then discretized and used to simulate local impaired segments of small stream segments may not be representative of the site-specific conditions.

Comparison of the spatial effects of different watershed land use and BMP data on modeled responses can help generate knowledge about differences related to these data sources. Model outputs obtained from these spatial input data are important in watershed management, planning and decision-making processes. Inclusion of risk factors associated with errors in spatial data used in hydrologic and water quality modeling can be utilized in various ways (e.g. increasing margins of safety) to reduce chances of failing to meet management goals. The selection of pollution management strategies requires confidence in the assessment of pollutant contribution from different land uses and the nature of spatial data used. Accurate assessment of the pollutant load depends on the ability of the model to provide adequate estimates of load reductions for possible implementation plans.

Most studies cited in the literature review of chapter 2 focus on geographic information system (GIS) resolution related spatial data issues. It is important to generate more information on impacts of using different model input spatial data types on modeled outputs such as nutrient loads. This is particularly important for the Chesapeake Bay Watershed Model (CBWM), which uses county and state level to sub-county level subwatershed data. Studies that compare and report on the impacts of using the county-level aggregated versus site-specific spatial data are largely still missing. Water quality modeling is accomplished at the basin-wide scale for planning and modeling at this scale yields insufficient detail for establishing specific loads or for determining specific, needed management changes at the subwatershed scale (Yagow et al., 2012). For instance, serious concerns have been raised by state leaders, conservation groups, landowners and business communities about local, subwatershed reduction goals derived from the CBWM TMDL model (VADCR, 2012). The concerns relate to the manner in which the TMDL assumes a level of precision beyond its capability and without regard for the economic consequences to stakeholders. Thus, this research compares and evaluates the effects of using the different land use and BMP data types on the Hydrologic Simulation Program-Fortran – Agricultural Chemicals (HSPF – AGCHEM) model. The results are intended to inform the

decision-making process that provides for the development and implementation of finer-scale watershed implementation plans.

1.2 Research Goal and Objectives

The overall goal of this research was to evaluate the effects of land use and installed BMP distribution on predicted flow, sediment, and nutrients (N and P).

1.2.1 Specific Objectives

To achieve the goal, the following specific research objectives were investigated:

1. Compare HSPF-predicted flow, sediment, TN and TP loads resulting from simulation of spatially distributed site-specific and county-level aggregated land use datasets at watershed level and sub-basin levels.
2. Evaluate the differences in the use of cost-shared site-specific versus county-level spatially disaggregated BMP data on modeled BMP responses in HSPF-predicted flow, sediment, TN and TP loads at the watershed outlet.
3. Evaluate the long-term effects of the two spatially distributed cost-shared site-specific and county-level disaggregated BMP data, and their impacts on achieving the Bay TMDL target goals for local watersheds.

1.3 Research Questions

1. What level of differences in HSPF modeled responses are associated with the use of county-level aggregated land use data that are disaggregated to watershed and sub-basin levels as compared to site-specific land use?

Hypothesis: Differences in modeled loadings from site-specific and disaggregated land use on the study watershed are significant at monthly and annual scales at $\alpha = 0.05$.

2. What differences exist in the HSPF-modeled BMP responses between site-specific and county-scale disaggregated BMP data?

Hypothesis: BMP responses achieved with site-specific and county-lumped BMP datasets are significantly different at an annual time-scale at $\alpha = 0.05$.

3. (a) Do current levels of cost-shared BMP implementation in Upper Opequon Watershed meet the Chesapeake Bay TMDL goals using site-specific and county-level disaggregated BMP datasets simulated for the period 1988-2027?

(b) If current levels of cost-shared BMP implementation do not meet the Chesapeake Bay TMDL goals, what levels of BMP implementation are required to achieve the TMDL goals in Upper Opequon Watershed using the site-specific and county-level disaggregated BMP datasets?

1.4 Research Rationale and Contributions to New Information

The United States Environmental Protection Agency (USEPA) completed the Chesapeake Bay TMDL in 2010. The TMDL's goal is to ensure that all pollution control measures needed to fully restore the Bay and its tidal rivers are in place by 2025, with practices in place by 2017 to meet 60 percent of the necessary pollution reductions. The USEPA expects Bay states to develop and implement watershed implementation plans, using the TMDL approach (VADCR, 2012). All of the waterbodies in the Chesapeake Bay Watershed, including the Upper Opequon Watershed, are subject to the provisions of the Bay TMDL. Hence, the TMDL sets legally binding reduction goals for all 92 tidal and the upland non-tidal segments. Each Bay river-segment must have an implementation plan. The TMDL establishes Bay-wide target load reductions for nitrogen (N), phosphorus (P) and sediment. The load reductions are used to calculate local watershed target loads required to achieve the overall Bay-wide target goals. As a result, all TMDL target loads for the same pollutant in the same river basin from all localities must add up to the TMDL load. The TMDL has direct consequences on economic activities in the entire watershed as it limits sediment and nutrient loadings to the Bay estuary. In developing local target loads for the TMDL, the CBP used county-level aggregated data on land use and cost-shared BMPs rather than site-specific land use and BMP data that were available in many circumstances. This was done for cost reasons and because of congressional restrictions placed on the use of site-specific BMP data by federal agencies. Whether the modeled outputs from county-level spatial data are suitable for use at a finer geographical scale for locally impaired river segments is not clear for the development of local-scale management plans. Little information on studies that comprehensively compare modeled results based on site-specific and county-level aggregated spatial data is available in literature.

Through the Bay clean-up program, agencies such as Virginia Department of Conservation and Recreation (VADCR) provide local stakeholders with information on target TMDL loads, current watershed loads, land use, BMPs and other spatial and water quality data to help them determine the level of local effort required if TMDL target loads are not being met. The effort by the VADCR is also important with regard to transparency and accountability of the TMDL allocated loads. According to VADCR (2012), the subwatershed target TMDL loads are derived from the USEPA's Chesapeake Bay Watershed Model (CBWM) that uses county-level aggregated data, and VADCR questions whether the county-level datasets accurately represent local pollution control efforts that have occurred over the past 30 years.

Thus, this research focused on modeling the effects of variability in watershed spatial data, specifically land use and agricultural BMPs for control of pollutant losses to meet the Chesapeake Bay TMDL (2010) water quality target goals. The impact on agricultural and other business activities is evaluated via analysis of simulated loads and costs of required TMDL implementation strategies. The study findings are useful for local governments, modelers, planners and watershed managers in the Chesapeake Bay Watershed and other watersheds nation-wide.

This study uses local (site-specific) versus county-level lumped land use datasets, and site-specific versus county-level lumped cost-shared BMP datasets in evaluating the effects on modeled flow, sediment, and TN and TP loads at a local scale. Research findings in this study are useful in understanding the implications of using disaggregated county-level land use and BMP data in developing local watershed management strategies. The new information contributes to and facilitates actions by local stakeholders to control N, P and sediment and achieve target load allocations. Findings will help modelers, planners, managers and local authorities understand the possible differences in pollutant loads that can result from using local data disaggregated from larger scale spatial datasets. Further, the study advances existing knowledge in quantifying impacts of spatial scales of watershed data on individual landowners and stakeholders implementing water quality plans at a local scale. Informing about the possible variability in the loads obtained from different simulated watershed spatial-scale datasets is important in decision-making during implementation of finer geographical scale watershed strategies. In this view, the scope and understanding of scientific and economic implications of

watershed water quality management and decision making practices at the local scale is increased by this study.

Research results also provide science based information to environmental planners and policy analysts in targeting resources where they are needed most at finer geographical scales. An informed choice between site-specific and larger scale lumped spatial data is important in remediating water pollution to meet local and basin-scale water quality goals. This information is critical to environmental policy formulation, such as the design of voluntary and federal cost-shared BMP programs for water quality protection. In general, the research findings are useful to watershed and land use planners, and natural resource managers evaluating the potential consequences of using different spatial-scale datasets.

2 Literature Review

2.1 Watershed Planning and Management

A watershed is defined as the land area where water drains into a water body such as a lake or a point on a river. The watershed is the most appropriate geographic unit to protect water resources (Schueler, 1996a). Political boundaries usually do not coincide with the natural drainage boundaries of a watershed. Thus, the most effective watershed planning is developed in cooperation with other communities within the watershed. Planning ensures quality of water for drinking, and recreational use, enhanced water supply, wildlife habitat protection and improved natural resources, and controlled flooding by restoring riparian and wetland areas (NIRPC, 2012). Effective watershed planning requires involving and encouraging stakeholders to share their concerns and offer suggestions for possible solutions. By involving stakeholders in the initial stages of project development, long-term success is enhanced. The primary criterion for water quality is whether the waterbody meets designated uses. Designated uses are recognized uses of water established by state and federal water quality programs (Brown et al., 2000). For an impaired water body, identifying pollution sources and their causes helps in the design of the most successful control measures. Watershed protection programs generally require monitoring programs for evaluation of program effectiveness and modeling to assess alternative management scenarios before they are implemented.

2.2 Nonpoint Source Pollution

Nonpoint source pollution is broadly categorized according to its origin of agricultural, silvicultural or urban (Bouraoui and Dillaha, 1996). The NPS pollution is mainly attributed to anthropogenic activities and disturbance of existing ecosystems. The generated loadings such as sediments, pesticides, nutrients, and other pollutants play a key role in the impairment of water bodies. Industrial activities, urban growth and use of fertilizers on lawns and gardens, atmospheric deposition, and septic tanks, are major sources of NPS pollution in urban centers. The NPS pollutants may be transported in solution with runoff water, suspended in water, or adsorbed on eroded soil particles (Im et al., 2003) and via subsurface flow in the case of nitrates and other dissolved pollutants (Gburek, 2000).

The challenge facing water quality and environmental protection requires placing high priority on management practices and cost-effective strategies for the protection, improvement and management of waterbodies. Cost-effective management alternatives aim to improve the general water quality targeting certain water quality standards and limited resources. Preventing pollution of water resources involves controlling, reduction and interception in pollutant movement at the watershed level. For example, the Chesapeake Bay TMDL (2010) calls for a 25% reduction in N, 24% reduction in P and 20% reduction in sediment. Achievement of these goals is to be realized via development of management plans and their full implementation by 2025, with at least 60% of the plans to be in place by 2017 (USEPA, 2010). Thus, the selection of pollution management strategies and realization of the desired pollution reductions must entail increased confidence in the assessment of pollutant contribution from different land uses. Accurate assessment of the pollutant load depends on the ability of the water quality model to provide adequate estimates of load reductions for the selected implementation strategies.

2.3 Watershed Land Use

Accurate prediction of pollutant contributions from the different land uses within a watershed requires accurate estimation of land use areas for the water quality model to provide realistic modeled BMP responses (Hunsaker et al., 1995). According to Tong and Chen (2002), a significant relationship exists between land use and in-stream water quality, especially for NPS pollutant loads. Runoff from agricultural lands can be enriched with nutrients and sediment while runoff from developed areas can be enriched with heavy metals, industrial wastes, and salts from road deicers. Depending on the environmental pathway (surface runoff, vadose zone, macropores, atmospheric and baseflows), contaminants may undergo transformations as they move down-gradient that alter their concentrations and/or mass through dilution, reaction, or sink types of processes (Gburek, 2000). Processes such as evapotranspiration, interception, infiltration, and percolation can change the water balance and the surface water temperature (Tong and Chen, 2002). Land use and cover heavily impact the magnitude of these processes (Bhaduri et al., 2001; Hanratty and Stefan, 1998) and the surface water quality. Amount of surface runoff, streamflow and groundwater flow, as well as the physical, chemical and biological processes in the receiving water bodies, are thus affected by any changes in the hydrologic processes (Gburek, 2000).

Model predictions based on spatial input datasets that have errors may augment errors in the predicted water quality responses. The effect of varying GIS derived spatial input data on model output errors has been recognized (Cotter et al., 2003; Eckhardt et al., 2003; Patil eta l., 2011). When land use characteristics are used to derive model parameters, the resulting relative distribution and classification of land use within a watershed can affect prediction of flow and water quality response (Patil et al., 2011; Cotter et al., 2003). Cotter et al. (2003) have reported the effects caused by GIS resolution scale on the distribution of pasture, forest, and urban areas. Studies (Cotter et al., 2003; Hunsaker et al., 1995) show that a coarser DEM data resolution can affect watershed area, slope and slope length. Distribution of pasture, forest, and urban areas within the watershed are also be affected at coarser resolution of land use and can have significant uncertainty in predicted sediment, NO_3-N, and TP. Hunsaker et al. (1995) also found that the disaggregation of land use impacted the average curve number (CN_2) for a watershed, which changed predicted infiltration and surface runoff in the SWAT model. As a result, predicted flow, nutrient, and sediment transport from the watershed were affected. Decreased NO_3-N loads were predicted with decreases in flow and decreased TP loads with a decrease in sediment loads. Arabi et al. (2006) studied the role of watershed subdivision on the predicted BMP effectiveness using the SWAT Model. The results showed that the evaluation of the predicted impacts of BMPs on sediment and nutrient yields were very sensitive to the level of land use subdivision. This author found that sediment yield increased by 200 percent between the coarsest and finest subdivision as a result of upland and channel erosion processes.

2.4 Best Management Practices

Best Management Practices are systems of methods for controlling NPS pollution to levels compatible with water quality goals (Arabi et al., 2008) within urban, agricultural, forested and other types of watersheds. The practices are developed based on local watershed knowledge and implemented on the watershed. This is because BMP effectiveness is site-specific. That means BMPs working successfully in one watershed or field may not be necessarily suitable in another watershed or field. Agricultural BMP simulation requires information on crop planting and harvest dates, crop rotations as well as the fertilizer application (timing, application method and rate) and tillage operations timing (Folle et al., 2007). Additionally, for an impaired watershed there must be a clear identification of the pollutant of concern and its mechanism of transport.

Two approaches have been used to evaluate BMP effectiveness (Cho, 2007): monitoring and modeling. Mostaghimi et al. (1997) reported that the most suitable way of evaluating the impact of management practices on NPS control is via a comprehensive monitoring system. Monitoring systems allow data collection for analysis of BMP effectiveness. For most watersheds, however, it is not cost-effective to implement comprehensive monitoring systems that can detect changes in water quality over the short-term. An alternative approach to BMP assessment is to use NPS models in identifying critical source areas within a watershed for BMP implementation and then evaluating the likely outcomes of the alternative scenarios using modeling. Modeling of management alternatives has advantages of minimizing costs associated with developing, implementing, and monitoring water quality management plans. Unlike small scale monitoring studies on plots and fields, where results from specific alternative practices may be directly compared to treatments under controlled conditions, the effectiveness of BMPs at a watershed level is not easily measured directly (Santhi, 2001). Thus, estimation of BMP effectiveness requires a stepwise selection of suitable BMPs for a particular problem and site, assessing the benefits of the suitable BMPs, ranking alternative BMPs based on cost-effectiveness, and selecting a management system that meets the desired goals (Dillaha, 1990). In this research, three agricultural BMPs, nutrient management plans (NMPs), cover crops and livestock fencing with-off stream watering (SL-6 Grazing Land Protection), were simulated to achieve the research objectives.

2.4.1 Nutrient Management Plans

Nutrient management plans are developed by certified planners and involve BMPs that manage nutrient losses from the landscape. Basically, NMPs are farm plans that incorporate documented management strategies and farm records to provide recommendations on rates, timing, and application methods of nutrients based on soil-test results, manure/fertilizer nutrient analysis and expected crop yields (VADCR, 2005). The NMPs are widely used in the Chesapeake Bay Watershed for the control of N and P (Karigomba, 2009). The plans detail the type, use, timing, and placement of nutrients in manure or commercial fertilizer for each crop to minimize nutrient losses while maintaining crop yield. Plans should be revised every 2 to 3 years (CBP, 2010c)

According to CBP (2010c), enhanced nutrient management (Enhanced NM) matches nutrient availability (from all sources) to crop need according to the long-term average yield. The BMP

aims to balance nutrient uptake by crops with nutrient availability, resulting in zero residual nutrients. The CBWM Phase 5.3 classifies NMPs by creating a new land use category with properties more characteristic of land with nutrient management. The CBWM differentiates between enhanced NM and NMPs. In the CBWM, NMPs are simulated on cropped land uses and new land use categories such as high-till with manure nutrient management and low-till with manure nutrient management, which are used to limit the N application rate to 30% above the plant maximum uptake level. Enhanced NM is categorized as a BMP that limits the N application rate to 15% above the plant average uptake level and an incentive or crop insurance is used to cover the risk of yield loss. Nitrogen load reduction effectiveness of 7% is applied with this land use representation.

2.4.2 Cover Crops

Cover crops are small grain crops planted in the fall to sequester excess nutrients remaining in the field after harvesting row crops (Cestti et al., 2003; VADCR, 2005). The main nutrient targeted by cover crops is N. Nitrogen can remain in the soil after harvest of summer annual crops such as corn, soybeans, and vegetables. Nitrate is particularly subject to leaching toward groundwater if substantial N remains in the soil. During fall, NO_3-N levels in soils are more pronounced following years of reduced crop nutrient uptake because of drought conditions. Cereal cover crops trap N in their tissues as they grow, provided root growth is sufficient to reach the available soil N (CBP, 2010c)**.** Cover crops also help minimize P loss and bind soil particles together thereby minimizing soil erosion.

2.4.3 Livestock Fencing With Off-Stream Watering

Pasture area livestock fencing with off-stream watering involves the use of permanent or portable livestock water troughs placed away from the stream corridor. The practice consists of stream exclusion with remote livestock watering system or protected stream access, and it is applied to degraded stream riparian corridor land use (CBP, 2010c).Water is supplied to the grazing fields via pipelines, springs, water wells, and ponds. The BMP includes in-stream watering facilities such as stream crossings or access points and can be applied to pasture areas in association with or without improved pasture management systems (VADCR and VADEQ,

2006). The CBP applies the prescribed BMP which includes rotational grazing to upland pasture acres not associated with streams or with streams with livestock exclusion fencing (CBP, 2010 c).

2.5 Total Maximum Daily Loads

Excessive nutrients from agricultural activities and urban development have been identified as major causes of water quality impairment in the United States (USEPA, 2000b). Major pollutant constituents known to play a major role in NPS pollution include sediment and nutrients (N and P). Large amounts of sediment and nutrients in water bodies result in increased streambed embeddedness, accelerating growth of aquatic plants such as algae, increased turbidity and reduced dissolved oxygen in the water (USEPA, 2000a; 2002). Eventually, impairment of designated beneficial uses such as recreation, aesthetics, fishing, and water supply of the water body occurs.

The Federal Water Pollution Act, that was later amended to CWA in 1985, was originally enacted by Congress in 1972 with the aim "to restore and maintain the chemical, physical, and biological integrity of the Nation's waters" (USEPA, 2008). The USEPA TMDL Program derives its mandate from Section 303(d) of the 1985 federal CWA and USEPA's water quality planning and management regulations. The act require states to identify pollutants of concern and develop TMDLs for impaired water bodies that violate state water quality standards (USEPA, 1999, 2010). TMDLs are developed for particular water bodies listed as "impaired," for any pollutant that exceeds water quality standards in that water body. The TMDL is essentially a water pollution budget. It defines the amount of pollutant each source in the watershed can contribute to the water body while still allowing the water body to comply with applicable water quality standards. To achieve desired load reductions, a TMDL study determines the amount of each identified pollutant a water body can receive and still meet water quality standards, and the level of load reductions required from each source category. In general, a TMDL limits the amount of pollutant loads allowed into a water body to restore water quality (USEPA, 1999; VADCR and VADEQ, 2006; Yagow et al., 2012).

2.6 Nonpoint Source Pollution Models

A watershed model can be used to better understand the relationship between land use activities and water quality processes occurring within a watershed (Im et al., 2003; Novotny and Olem,

1994). Water quality models have been developed and used to continuously simulate stream flow, sediment, and nutrient loading from watersheds. Some commonly used models include AGNPS (Agricultural Nonpoint Source, Young et al., 1989), ANSWERS-2000 (Areal Nonpoint Source Watershed Environmental Response Simulation–2000, Bouraoui and Dillaha, 1996), APEX (Agricultural Policy and Environmental Extender Model, Williams et al., 2008), GWLF (Generalized Watershed Loading Function Model, Haith and Shoemaker, 1987), HSPF (Bicknell et al., 1996), and SWAT (Neitsch et al., 2005). These models are classified with respect to spatial scale (plot, field or watershed); physically (process)-based versus empirical; stochastic versus deterministic; and lumped versus distributed. Parameters of interest are simulated to predict hydrology, sediment, nutrients and/or pesticides (Thomas et al., 2004). The water quality models range from simple equations to complex lumped and distributed parameter models. Distributed parameter models can more accurately represent the effects of spatial variability of watershed features than the lumped models. Also, they can simulate pollutant sources and estimate pollutant losses at different locations within the watershed (Mostaghimi et al., 1997). However, the disadvantages of distributed parameter models include high data requirements, need for powerful computers to execute the complex programs, difficulty in identifying sensitive parameters during evaluation, and their use is time consuming in terms of data collection and execution times (Karigomba, 2009; Parsons et al., 2001). Tables 2-1 and 2-2 summarize the commonly used water quality models, their characteristics and simulated processes.

Table 2-1: Common Hydrologic Model Characteristics

Model	Time scale		Spatial scale		Time-step		Approach	Reference
	Event	Cont.	Field	Watershed	Hourly	Daily		
AGNPS	●			●		●	Empirical	(Migliaccio and Srivastava, 2007; Young et al., 1989)
ANSWERS-2000	●	●	●	●	●		Process-based	(Bouraoui and Dillaha, 1996; Hanratty, 1995; Parsons et al., 2001)
APEX		●	●	●	●	●	Process-based	(Parsons et al., 2001; Williams et al., 2008)
CREAMS		●	●			●	Process-based	(Hanratty, 1995; Parsons et al., 2001)
EPIC		●	●			●	Empirical	(Hanratty, 1995; Parsons et al., 2001)
GLEAMS		●	●			●	Process-based	(Shirmohammadi et al., 2001)
HSPF		●		●	●		Process-based	(Donigian, 2000)
SWAT		●		●		●	Process-based	(Arnold et al., 1998; Gassman et al., 2007)
WEPP	●	●	●				Empirical	(Ascough et al., 1997; Parsons et al., 2001)

Table 2-2: Modeled Hydrologic Processes

Model	Surface flow	Subsurface flow	Chem. Transport		Erosion	Precip	Reference
			Nutrient	Pesticides			
AGNPS	●		●		●		(Migliaccio and Srivastava, 2007; Young et al., 1989)
ANSWERS-2000	●		●		●	●	(Bouraoui and Dillaha, 1996)
APEX	●	●	●		●	●	(Williams et al., 2008)
CREAMS	●		●	●	●	●	(Hanratty, 1995)
EPIC	●	●	●	●	●	●	(Hanratty, 1995; Parsons et al., 2001; Williams et al., 1996)
GLEAMS	●	●	●	●	●	●	(Shirmohammadi et al., 2001)
HSPF	●	●	●	●	●		(Borah and Bera, 2004; Donigian, 2000)
SWAT	●	●	●	●	●	●	(Gassman et al., 2007; Neitsch et al., 2005)
WEPP					●	●	(Ascough et al., 1997; Parsons et al., 2001)

2.7 Description of HSPF Model

The HSPF model was selected for this research since using the HSPF model is consistent with the CBP, and is supported by USEPA and U.S. Geological Survey (USGS) for simulating point and NPS pollutants (USEPA, 2001). The model is a comprehensive watershed model and used for developing TMDL plans for impaired water bodies (USEPA, 2010); as such, HSPF is the core watershed model in the USEPA BASINS (Better Assessment Science for Integrating Point and Nonpoint Sources) (USEPA, 2010) modeling framework. The model characterizes the entire landscape of a watershed into pervious land (PERLND), impervious land (IMPLND), and receiving surface waters and impoundments (RCHRES). Its representation of land use is a feature that makes the model highly suitable for modeling streamflow and water quality for watersheds with mixed land uses. The HSPF model simulates streamflow as the sum of surface, interflow, and baseflow at user-defined temporal and spatial scales. It also simulates water quality constituents, including sediment, pathogens (fecal coliform, etc.), pesticide chemicals, nutrients (N and P), tracers (chloride, bromide, dyes, etc.), carbon dioxide, inorganic carbon, zooplankton, phytoplankton, benthic algae, organic carbon, biological oxygen demand (BOD), dissolved oxygen (DO), pH, and alkalinity at user-defined scales (Migliaccio and Srivastava, 2007; Mohamoud et al., 2010).

This model is a continuous, lumped parameter and conceptual model that can represent fate and transport of pollutants on both the land surface and in the stream. The model is based on the original Stanford Watershed Model IV as reported by Bicknell et al. (1996; 2005). Additionally, HSPF is a combination of the Agricultural Runoff Management (ARM) model, Nonpoint Source Runoff Model (NPS), Pesticide Runoff Transport (PTR) Model, and Hydrologic Simulation Program (HSP) (Bicknell et al., 2005; Im et al., 2003). The smallest hydrologic unit of spatial identity in HSPF is a zone (Bicknell et al., 2005; Migliaccio and Srivastava, 2007). A zone refers to the homogenously characterized hydrologic areas (PERLND and IMPLND). The HSPF model is extremely data intensive and requires a large quantity of watershed data for calibration to accurately simulate hydrology and water quality processes (Im et al., 2003).

The model simulates a complete land segment water budget on pervious (PWATER) and impervious (IWATER) lands. Flow from pervious lands mainly consists of surface runoff,

interflow, and groundwater (baseflow). Impervious lands (where little or no infiltration occurs) are characterized mainly by surface runoff. For each reach, a storage-volume relationship function table (FTABLE) is required to describe the relationship between water depths, surface area, volume, and discharge (Duda et al., 2001; VADCR and VADEQ, 2003b).

According to Bicknell et al. (2005), the Modified Universal Soil Loss Equation (MUSLE) is adjusted for sediment delivery to the stream with estimated sediment delivery ratios (SDRs). The MUSLE parameters that describe the overland sediment transport on pervious and impervious land are simulated using exponential relationships for soil detachment and wash-off based on Negev's equations. Erosion and sediment transport in the PERLND module is simulated as wash-off of detached sediment and scour of the soil matrix. Sediment yield from impervious surfaces in the IMPLND module is simulated using a build-up/wash-off relationship. Stream sediment movement, deposition and scour are simulated for sand, silt, and clay. These are characterized as non-cohesive (sand) and cohesive (silt and clay). The sand carrying capacity of the reach is predicted as a power function of the average flow velocity, while cohesive constituents are predicted based on the bed shear stress that is a function of slope and hydraulic radius of the reach (Bicknell et al., 1996; 2005).

Generally, the equations used to produce and remove sediment are based on the predecessor models ARM and NPS (Donigian and Crawford, 1976a, b). The algorithms representing land surface erosion in these models are derived from a sediment model developed by Negev (1967) and influenced by Meyer and Wischmeier (1969), and Onstad and Foster (1975). The supporting management practice factor, which has been added to the soil detachment by rainfall equation, is based on the "P'' factor in the Universal Soil Loss Equation (USLE) (Wischmeier and Smith, 1965). It was introduced in order to better evaluate agricultural conservation practices. The equation that represents scouring of the soil matrix (which was not included in ARM or NPS) is derived from Negev's method for simulating gully erosion (Bicknell et al., 2005; USEPA, 2001).

2.7.1 HSPF-AGCHEM Module

Simulation of chemical transport and fate in both the PERLND and IMPLND modules use various land-segment appropriate methods, for instance, first-order and Michaelis-Menten kinetics and isotherms. Cropland is simulated with a detailed NPS load simulation module

known as agricultural chemicals (AGCHEM) that includes application of fertilizer and manures, atmospheric deposition, crop uptake, soil binding, denitrification, and surface export (CBP, 2010c; Hunsaker et al., 1995).

The AGCHEM modules are process-based and consist of the PEST (pesticides) module, the NITR (N) module, and the PHOS (P) module. The AGCHEM modules are used in tracking nutrient cycling, mass balance, and runoff contributions from both pervious and impervious land segments. The modules provide detailed simulation of complex nutrient changes and transport in the soil profile (Bicknell et al., 2005; Im et al., 2003; Saleh and Du, 2004). Comprehensive nutrient balances are important in reflecting potential watershed areas for improvements as well as assessing the impact on water quality resulting from installed BMPs and land use changes (CBP, 2010c; Deliman et al., 2001). Extensive inputs and parameters are required during AGCHEM application to represent the complicated physical, chemical and biological processes in the soil profile (Liu, 2011).

Agricultural chemicals can also be simulated by the PQUAL module (empirically based), but in a simplified manner. In that case, neither full representation of the nutrient simulation processes nor nutrient balances are achieved. The PQUAL module simulates nutrient constituents using a simple regression relationship with flow and sediment yield. Also, PQUAL is used when sufficient data are not available for AGCHEM (USEPA, 2003b).

2.7.2 HSPF BMP Simulation

Two basic ways can be used to represent BMPs in HSPF (Zeckoski, 2012, personal communication). First, the HSPF built-in Utility Module Best Management Practices Editor (BMPRAC) was designed to specifically simulate BMPs. The utility module simulates the effects of BMPs by applying simple "removal" fractions to each constituent being modeled (Bicknell et al., 2005; USEPA, 2003b).

The BMPs can also be represented through the use of a multiplier in the MASS-LINK block (contains multiplication/potency factors for simulated parameters). Removal fractions are directly applied to the SCHEMATIC block (contains land use areas) of the user control input file (UCI). The SCHEMATIC block connects to the MASS-LINK block to route the pollutant

constituents. Two lines with the same land use are created via copying and pasting the line representing a particular land use area. The land use area in the original SCHEMATIC block is then adjusted so that it only represents the area not affected by the BMP. The land use area unaffected by the BMP retains the original PERLND/IMPLND and reach numbers. The MASS-LINK table number represented in the SCHEMATIC block referring to the constituents' potency factors (multiplication factors) through which the loadings are routed also remains unchanged for this unaffected land use. The BMP benefitted area is then represented in the second line. The new SCHEMATIC block line for the BMP benefitted area is then assigned to a new MASS-LINK table with a different value for routing constituents through the BMP. The BMP MASS-LINK table is created below the original constituency MASS-LINK table. For example, to reduce the sediment to a reach segment by the BMP, the constituent multiplication factor is multiplied by the BMP reduction efficiency in the BMP MASS-LINK table. Each BMP has its own entry in the SCHEMATIC block, and a corresponding BMP MASS-LINK number in the MASS-LINK table. If there are several subwatersheds where the same BMP is implemented, they can use the same MASS-LINK table (Zeckoski, 2012, personal communication). The MASS-LINK method is the simplest method to represent BMPs affecting overland transport, as it only requires modification of the UCI file first, and then adjusting a couple numbers for each simulation to be run.

Very complex detention scenarios may be best modeled explicitly by a web-based RCHRES BMP support tool (Mohamoud et al., 2010). A single instance of the BMPRAC module uses regression relationships to handle the transfer of all mass loads from any number of PERLNDs and IMPLNDs to a single RCHRES, as long as the same fractions are to be applied for each land use. If expected removal fractions vary by land use, then separate BMPRACs are required for each land segment to reach connection. The general equations for a removal are as follows:

$$REMOVE = FRAC \times INPUT \quad (2\text{-}1)$$

$$OUTPUT = INPUT - REMOVE \quad (2\text{-}2)$$

where *REMOVE* is mass removed (intercepted by BMP), *FRAC* is fraction to remove, *INPUT* is inflow mass, and *OUTPUT* is outflow mass (Bicknell et al., 2005).

The BMPs included in the module are changes in land use acreages due to land use planning/management, wet detention pond, dry detention pond, vegetated swales and filter strips (various widths), and stream buffers (7.62 m and 30.5 m). The module allows user-specified sediment and pollutant (N, P, BOD, fecal coliform, metals - copper, cadmium, and zinc) load reductions (USEPA, 2003b).

2.8 Model Sensitivity Analysis Techniques

Sensitivity analysis of watershed models is an essential component of planning for long-term, sustainable pollution control. The process of sensitivity analysis can lead to increased understanding and to more accurate estimated parameter values and, thus, reduced uncertainty in model output (Lenhart et al., 2002). Knowledge of sensitive input parameters is beneficial for model development and application. Sensitivity for a specific watershed is a function of the specific combination of parameter values that reflect weather and watershed characteristics that control the hydrologic response, along with the sediment and water temperature behavior (Donigian and Love, 2007). The sensitivity analysis process characterizes the impact of changes in model inputs on the model outputs (Tang et al., 2007). Thus, critical parameters and inputs, which indicate where most time and effort should be spent in the parameter estimation process, can be identified (Liu, 2011). The approach is used to apportion the sources of uncertainty to model output. Sensitivity is normally related to the conditions and characteristics of the specific watershed as well as the parameter itself.

Several techniques exist for conducting sensitivity analysis (Donigian and Love, 2007; Lenhart et al., 2002; Shoemaker and Benaman, 2004; Tang et al., 2007; van Griensven et al., 2006). These techniques are categorized as local and global methods. An example of a local method is "one-variable-at-a time" sensitivity analysis. Local methods can be used to analyze the effect of a model parameter on the model output based on its default or calibrated value (van Griensven et al., 2006). Local methods allow user control over the parameters adjusted and are easy to implement in terms of computational needs. White and Chaubey (2005) reported that these methods do not consider interaction between parameters and model non-linearity. They also do not consider the degree of uncertainty related to the given parameter. On the other hand, global methods include Morris method, generalized sensitivity analysis (GSA), analysis of variance

(ANOVA), Fourier amplitude sensitivity test (FAST), and Sobol's method. While global methods are more robust and provide reliable results, they are known to have high computational costs for complicated models (Liu, 2011). According to van Griensven et al., (2006), global sampling methods scan in a random or systematic way the entire range of possible parameter values and possible parameter sets. The sampled parameter sets can give the user a good idea of the importance of each parameter. These in turn can be used to quantify the global parameter sensitivity or the uncertainty of parameters and outputs.

Zheng and Keller (2006) reported that "one -variable-at-a time" is the most used sensitivity analysis method for conducting sensitivity analysis on complex watersheds. The method requires changing a single parameter with a corresponding response in change in the model output (Shoemaker and Benaman, 2004) and then ranking individual sensitivity indices to determine the most sensitive parameters for the different model output variables (Lenhart et al., 2002). Several nominal range approaches can be applied using parameter variations, ΔX (for example, at 10% and 25%) of the parameter mean value (Fontaine and Jacomino, 1997; Lenhart et al., 2002). Equation (2-3) can be used to calculate the relative sensitivity index (RSI) between the modeled output and input parameter as reported in White and Chaubey (2005).

$$RSI = (\delta y/y)/(\delta x/x) \quad \text{(2-3)}$$

where x is the parameter, y is the predicted output, and δx and δy correspond to ± percent change of the initial or calibrated parameter and corresponding output values, respectively.

2.9 Statistical Techniques in Watershed Modeling

Moriasi et al. (2007) reviewed model evaluation techniques (both statistical and graphical), and concluded that for a monthly time-step of outputs, model performance can be evaluated as "satisfactory" if Nash-Sutcliffe Efficiency (NSE) ≥ 0.50 and ratio of the root mean square error (RMSE) to the standard deviation of measured data (RSR) ≤ 0.70 (Table 2-3). For percent bias (PBIAS), the model simulation is satisfactory if PBIAS is ± 25% for streamflow, ± 55% for sediment, and ± 70% for N and P at monthly time-steps. Donigian (2000) recommended that PBIAS be considered satisfactory if ± 25% for streamflow, ± 45% for sediment and ± 35% for nutrients at monthly time-steps (Table 2-3).

Table 2-3: PBIAS Model Performance Criteria for Daily Hydrology and Monthly Load Outputs

Performance Rating	Hydrology	Sediment	N and P
Very Good	PBIAS < ±10	PBIAS < ±15	PBIAS < ±25
Good	±10 ≤ PBIAS < ±15	±15 ≤ PBIAS < ±30	±25 ≤ PBIAS < ±40
Satisfactory	±15 ≤ PBIAS < ±25	±30 ≤ PBIAS < ±55	±40 ≤ PBIAS < ±70
Unsatisfactory	PBIAS ≥ ±25	PBIAS ≥ ±55	PBIAS ≥ ±70
Source: (Moriasi et al., 2007; Singh et al., 2008)			
Very Good	PBIAS < ±10	PBIAS < ±20	PBIAS < ±15
Good	±10 ≤ PBIAS < ±15	±20 ≤ PBIAS < ±30	±15 ≤ PBIAS < ±25
Satisfactory	±15 ≤ PBIAS < ±25	±30 ≤ PBIAS < ±45	±25 ≤ PBIAS < ±35
Source: (Donigian, 2000)			

The PBIAS performance criteria presented in Table 2-3 are constituent specific. The PBIAS criteria reported by Donigian (2000) were specifically recommended for HSPF model performance. Santhi et al. (2001) and Singh et al. (2008) recommended satisfactory model performance at a monthly time-step when the coefficient of determination (R^2) is ≥ 0.6 for all simulated constituents, but a value of 0.5 is acceptable.

Cotter et al. (2003) evaluated the impact of varying spatial GIS resolutions of DEM, land use, and soil data on differences of SWAT predicted flow, sediment, and nutrient transport. The NSE was used as an indicator of how well model predictions matched measured stream data. Errors in the model output due to input data resolution were quantified as percent relative error (RE). Tang et al. (2007) employed the analysis of variance (ANOVA) F-test to evaluate the statistical significance of differences in the mean responses among the levels of each model parameter or parameter interaction. Arabi et al. (2008) used the mass difference similar to PBIAS approach to calculate BMP effectiveness for SWAT predicted loads. The results showed that the evaluation of the impacts of BMPs on sediment and nutrient yields was very sensitive to the level of land use subdivision.

Both non-parametric and parametric tests can be utilized for hypothesis and significance testing for data analysis (Hipel et al., 1988). Non-parametric statistical tests are used when the distribution of the test sample data is not known. The Kolmogorov-Smirnov (KS) test, the Signed

Rank Test, and the Rank Sum-Test are some non-parametric metrics used in watershed modeling assessment (Donigian, 2000). Hydrologic studies have reported use of KS-test to evaluate errors in model outputs (Ashkar, 1991; Haan and Skaggs, 2003; Patil et al., 2011; Rai et al., 2003; Zheng and Keller, 2006). Hamed and Ramachandra (1998) studied the variance of a modified Mann-Kendall trend test statistic on rainfall as well as streamflow data. The modified Mann-Kendall trend test statistic performed better in representing the effect of autocorrelation as compared to the original Mann-Kendall trend test. Meentemeyer et al. (2008) analyzed land-cover changes using differences of each land-cover type's total area, mean land-cover size, and number of land-covers between 1942 and 2000. The magnitude of changes were estimated using non-parametric two-tailed Wilcoxon signed-rank tests to evaluate the null hypothesis and found that there was no difference in area, mean land-cover size, and land-cover number over the years. Other studies (Carrubba, 2000; Davis et al., 2006; Dibike et al., 2008; Esterby et al., 1992; Hipel et al., 1988; Lameire, 2000; Lazaro, 1976; Melo and Froehlich, 2001; Rupert, 2008; ter Braak and Wiertz, 1994; Thompson et al., 2001) have also used the Wilcoxon signed rank test to study variability and hypotheses testing for different watersheds.

Associated with statistical techniques used in watershed hypothesis testing are the test significance levels. Different studies have tested hydrologic and water quality samples at varying levels of statistical significance depending on the goal of the study. Of the studies reviewed, most (Ashkar, 1991; Bhattarai and Baigent, 2009; Carrubba, 2000; Cosgrove and Taylor, 2007; Dibike et al., 2008; Esterby et al., 1992; Ficklin, 2010; Hamed and Ramachandra, 1998; Hinnell et al., 2010; Hipel et al., 1988; Khalidou et al., 2001; Lameire, 2000; Meentemeyer et al., 2008; Melo and Froehlich, 2001; ter Braak and Wiertz, 1994; Yang et al., 2010a) reported analyzing hydrologic and water quality data at 95% significance level. Some studies (Hipel et al., 1988; Lazaro, 1976; Rupert, 2008; Vogel and Fennessey, 1994) and (Davis et al., 2006; Maloszewski et al., 1992; Thompson et al., 2001) reported analyzing hydrologic and water quality data at 90% and 98 or 99% significance levels.

3 Case Study Area

Upper Opequon Watershed located in northern Virginia was selected as the study watershed for this research due to availability of historical data on flow, water quality, and land use. Additionally, this watershed is representative of watersheds with a majority of land in agriculture. The watershed is 14,941 ha in size and is south of the City of Winchester in Frederick County, Virginia. The City of Winchester is partly located in the watershed. The watershed is part of the Opequon Creek Watershed (Figure (3-1)). The Upper Opequon runs eastward into the Lower Opequon and then north into West Virginia. The watershed is part of the Potomac River basin, and is a tributary of the Potomac River, which empties into the Chesapeake Bay (Karigomba, 2009; VADCR and VADEQ, 2003a).

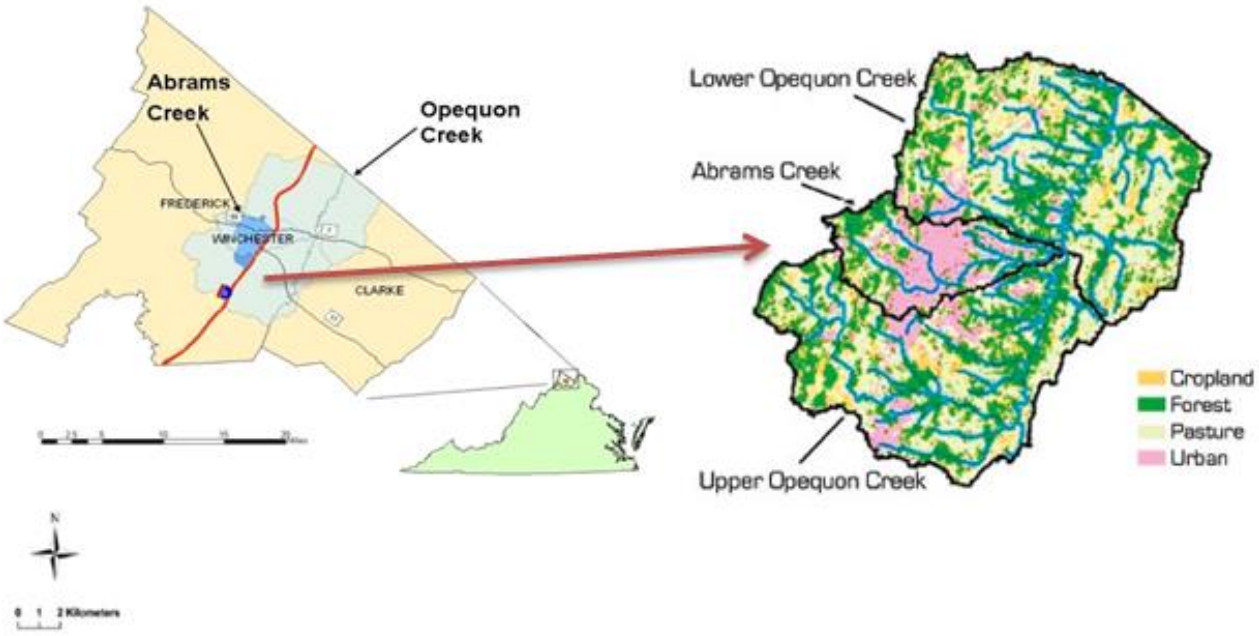


Figure 3-1: Study Area: Opequon Watershed in Virginia

According to VADCR and VADEQ (2003a), "the average annual precipitation for Opequon Watershed is 973 mm, most of which (56%) occurs during the crop-growing season (May-October). Average annual snowfall is 572 mm with the highest snowfall occurring during January. The average annual daily temperature of 12°C ranges from -0.06°C in January to 23.8°C in July. Soils in the Opequon Watershed are mainly in the Weikert-Berks-Blairton and Frederick-Poplimento-Oaklet series. The Weikert-Berks-Blairton (stony silt loam) soils are gently sloping to moderately steep, shallow and moderately deep, well drained soils with medium or fine textured subsoil, formed from weathered shale or sandstone. The Frederick-Poplimento-Oaklet (loam) soils are gently sloping to very steep well-drained soils with fine textured subsoil. These soils are formed from weathered limestone. The land use in the Upper Opequon is mainly agricultural (53%) and characterized by a gently sloping valley. Pasture covers 48% and cropland accounts for 5% of the total watershed area. The remainder of the watershed area is divided between forest (33%) and urban land uses (commercial, industrial, and transportation: 14%). The urban land uses are concentrated in and around the City of Winchester".

3.1 Subwatershed Delineation

The Upper Opequon river segment runs for approximately 40 km from its headwaters to the confluence with Abrams Creek. The watershed was previously delineated into 16 subwatersheds (Figure 3-2) during the development of bacteria and benthic TMDLs by Virginia Tech (VADCR and VADEQ, 2003a, b). The same delineation was used in this research. The stream network was delineated based on the blue line stream network from USGS topographic maps with each subwatershed having at least one stream segment. The subwatershed delineation by Virginia Tech was also influenced by uniformity of land use. The outlet of the watershed was designated subwatershed 1 with the uppermost subwatershed designated 16. The sub-watersheds 1, 2, and 4 were delineated to preserve the stream network of the watershed and result in much smaller sub-watersheds relative to the other sub-watersheds. The Upper Opequon is perennial and generally has a trapezoidal channel cross-section. According to VADCR and VADEQ (2003a), the daily measured discharge for the period of October 1987 through September 1997 at USGS gage 1615000 on Opequon Creek near Berryville, VA, ranged from 0.057 to 112.7 m^3/s with a mean

value of 1.5 m^3/s. Shallow aquifers in this watershed are overlain by limestone, and depth to the water table is in excess of 1.8 m.

Figure 3-2: Subwatershed Delineation in Upper Opequon Watershed

3.2 Previous Studies on Upper Opequon

Karigomba (2009) developed a methodology to estimate costs of implementing nutrient reduction strategies and improve water quality in the West Virginia Opequon Creek. A uniform reduction approach was used to evaluate each subwatershed to meet a reduction goal using site-specific land use contributions. The findings showed that nutrient reduction costs are much lower under site-specific land use contributions than using the Bay-wide averages. Wagner (2004) examined the effect of the reference watershed approach for TMDLs with benthic impairments using the GWLF and SWAT models and found that the Upper Opequon Watershed had considerably higher contribution of sediment from agriculture than from urban land. Echegaray (2009) applied the SWAT-karst model to simulate discharge and N loadings within the Opequon Creek karst-influenced watershed. It was found that SWAT-karst using a hydrologic response unit (HRU) to represent sinkholes better simulated streamflow than SWAT 2005 in the karst-influenced watershed. In 2003, the Biological Systems Engineering Department at Virginia Tech

developed five TMDLs for the Opequon Creek watershed: two to address benthic impairments (Abrams Creek and Lower Opequon Creek) and three to address bacteria impairments (Abrams Creek and Upper and Lower Opequon Creek). The TMDLs were approved by the USEPA in 2004. Corresponding TMDL implementation plans for the water were developed in 2006 (VADCR and VADEQ, 2006). The Upper Opequon Creek watershed was selected as the benthic TMDL reference for both Abrams Creek and the Lower Opequon Creek watersheds. The corresponding implementation plans called for 2,846 Mg/yr and 17,057 Mg/yr of target sediment load for Abrams and Lower Opequon Watersheds, respectively.

4 Model Development, Sensitivity Analysis, Calibration and Validation

4.1 Model Input Data

4.1.1 Weather Data

The HSPF model requires weather data to describe hydrology and water quality processes of the watershed. Weather data required by HSPF includes hourly precipitation, average daily temperatures (maximum, minimum, and dew point), average daily wind speed, and percent sun. An HSPF weather data input file was created for the period January 1980 through December 2010 using the weather data management utility support tool (WDMUtil). For the period of 1980 – 2002, the weather data were obtained from the bacteria TMDL Weather Data Management (WDM) file (VADCR and VADEQ, 2003a). These data were then extended to 2010 using data from the NCDC (National Climatic Data Center) (NCDC, 2012). Hourly weather data needed to conduct the model simulations were taken from the Star Tannery weather station for the extended period. The Star Tannery weather station is the closest weather station to the watershed that has collected hourly rainfall during the calibration and validation periods. Gaps due to missing data were filled-in using data from other nearby NCDC weather stations as listed in Table 4-1. Processing of raw weather data was required prior to input into the WDMUtil or extrapolated within the WDMUtil to obtain the following hourly values: precipitation (PREC), air temperature (ATEM), dew point temperature (DEWP), solar radiation (SOLR), wind speed (WIND), potential evapotranspiration (PEVT), potential evaporation (EVAP), and cloud cover (CLOU).

Table 4-1: Model Input Weather Data Stations

Type of Data	Location	Source	Frequency of Recording	Period of Record	Latitude Longitude
Percentage of Possible Sun, Dew Point, Wind Speed	Washington Reagan National Airport	NCDC (USW00013743)	Daily	1945 – present	35°52’ N 77°02’ W
Hourly Rainfall	Star Tannery	NCDC (USC00448046)	Hourly	1982 - present	39°4′ N 78°25′ W
Daily Rainfall, Min and Max Air Temp	Winchester	NCDC (USC00449181)	Daily	1982 – present	39°11’ N 78°07’W

4.1.2 Nutrient Data

The number of septic systems and the manure loads estimated for the 2003 bacteria TMDL were also used as input to model nutrients on cropland, pasture and directly to stream. Initial fertilizer application rates and amounts were obtained from the Mid-Atlantic Water Program's Nutrient Budgets for the Mid-Atlantic States (MAWP) (CBP, 2010a; MAWP, 2006) and USDA's Agricultural Census data (USDA, 2007). Manure from beef cattle that are confined in January and February and poultry litter from outside the watershed are applied to cropland and pasture. The poultry litter application rate was based on discussions held with farmers and local extension staff (Booher, 2012, personal communication; Marshall, 2012, personal communication; Rau, 2012, personal communication). Manure application rates are discussed in detail in section 4.2.4. Nutrient inputs from point sources were estimated from the HydroQual, Inc. "Opequon Creek Capacity Study" and Water Quality Data, available courtesy of Center for Watershed Studies at Virginia Tech (Kline, 2012, personal communication). Atmospheric deposition inputs were obtained for the study watershed from the CBP online database (2010c).

4.1.3 Land Use and Topography

The site-specific land use and soils data input were obtained from the bacteria TMDL (VADCR and VADEQ, 2003a). Land use used in the TMDL was developed using the 1995-1997 VADCR aerial photographs. The DEM used for stream network delineation was accessed from the USGS (USGS, 2012).

4.1.4 Flow and Water Quality Data

The observed daily flow data for Upper Opequon Watershed used were those for the period 1980 to1997 from the Center for Watershed Studies at Virginia Tech (2012) for the USGS gage 01615000 near the city of Berryville, VA, at a location close to the outlet of the watershed (Figure 4-1).

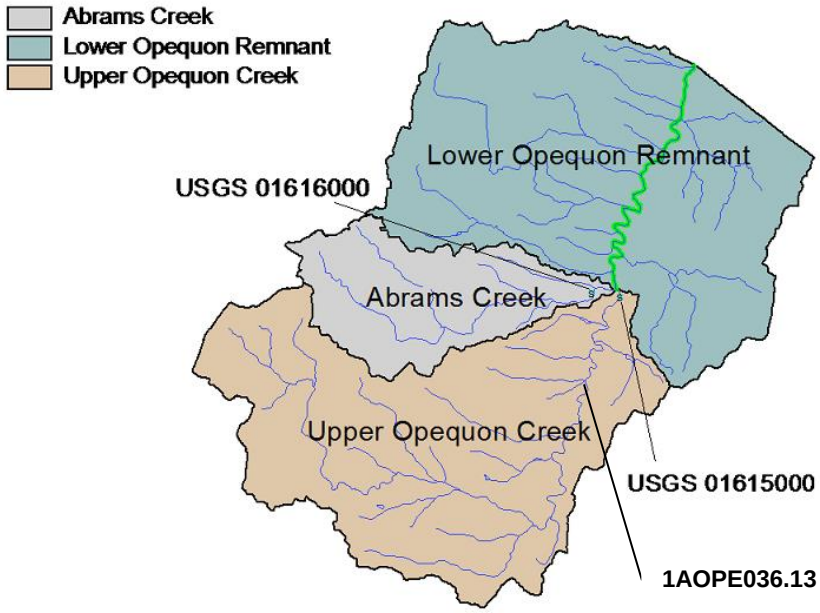


Figure 4-1: Flow and Water Quality Monitoring Stations (Center for Watershed Studies at Virginia Tech, 2012)

Monitored nutrient data from the VADEQ ambient water quality monitoring station 1AOPE036.13 (Figure 4-1) were used to calibrate and validate the water quality constituents (sediment, N and P). Figure 4-1 was available via courtesy of Center for Watershed studies at Virginia Tech (Kline, 2012, personal communication). Data availability periods are shown in Table 4-2. The monthly monitored data (grab samples) available included sediment (TSS), NO_3-N, NH_3-N+NH_4-N, TP, and PO_4-P concentrations.

Table 4-2: Flow and Water Quality Observed Data Available for Upper Opequon

Data type	Source	Time-step	Data availability
Flow	USGS	Daily	Jan. 1980 - present
Sediment	VADEQ	Monthly (grab samples)	Aug. 1991 - Apr. 2007
NO_3-N, NH_3-N+NH_4-N	VADEQ	Monthly (grab samples)	Aug. 1991- Dec. 2007
TP, and PO_4-P	VADEQ	Monthly (grab samples)	Aug.1991- Dec. 2007

Courtesy of VADEQ (Sieber, 2011, personal communication)

4.2 HSPF Model Simulation

The HSPF model was selected to simulate the fate and transport of sediment and nutrients (N and P). This facilitated use of site-specific land use and county-level aggregated land use and BMP data from the CBP database that was developed for use with HSPF (discussed in chapter 5). The HSPF hydrology parameters calibrated and validated for use in the 2003 bacteria TMDL study for the Virginia reach of Opequon Creek were used in this study. These hydrology parameters were revalidated with observed flow data from 1988 to 1997.

Sediment production and removal from pervious land surfaces was simulated using the SEDMNT module. The HSPF-AGCHEM modules were used to simulate N and P behavior on cropland, pasture, forest, and residential/urban pervious land. The IQUAL module was used to model the buildup and wash-off of N and P for impervious urban land. Modules HTRCH, SEDTRN, OXRX, NUTRX, and PLANK of RCHRES were used to simulate sediment and nutrients in the stream. The HSPF sub-modules SEDMNT, AGCHEM, and IQUAL were used to simulate sediment and nutrients.

4.2.1 Representation of Nutrients in HSPF Model

4.2.1.1 Land Application of Manure

Crop rotation in the watershed is a three-year cycle consisting of a corn-soybean rotation and four years of hay (Rau, 2012, personal communication; VADCR and VADEQ, 2003a). Winter cover crops are normally rye, oat, and barley (Rau, 2012, personal communication). During model simulation, the crops grown in the watershed were assumed that 90% of the corn/soybean acreage on which manure was applied. The decision was based on discussions with the Lord Fairfax Soil and Water Conservation District (LFSWCD) extension specialist (Rau, 2012, personal communication). Solid manures accumulated during confinement were applied to cropland January through May (prior to planting) and October through November after harvest. There are no dairies in the watershed. Since there was no information on the manure application rates on cropland, application rates were estimated using TMDL reports developed for Owl Run watershed in Fauquier County, VA, and those being developed for the Muddy Creek and Dry Run watersheds in Rockingham County and Augusta County, VA (Kline, 2012, personal communication). The watersheds have similar ecological characteristics to those of Upper

Opequon Watershed. During spring, manure (cattle and poultry) application to cropland was applied on the soil surface to hay and no-till corn, and was incorporated into the soil for corn in conventional tillage. Fall manure application was incorporated into the soil for cropland under rye/oats/barley, and surface-applied to cropland under rotational hay.

According to VADCR and VADEQ (2003a), the average beef cattle on pasture in the Upper Opequon Watershed were estimated at 1,060 pairs (cow/calf) on a daily basis. The actual number of beef cattle varied throughout the year due to the presence and absence of calves. The distribution of beef animal population among the subwatersheds based on the location of the operations is as follows: subwatersheds 6, 9, 10, 15 and 16 with each having 20, 100, 100, 446 and 394 beef cattle pairs (cow/calf), respectively. These figures are for 2003 and coincide with the 2003 land use used in the study.

Manure loading on pasture was estimated by multiplying the total number of cow/calf pairs on pasture by the amount of manure produced, 81 kg/ha-day (72 lb/ac-day) (MWPS, 1993). The confinement schedule of the cattle changes with season (Table 4-3), thus manure loading changes with season.

Table 4-3: Beef Cattle Confinement Schedule in Upper Opequon

Month	Time spent in confinement (%)	Time spent in the stream (hours/day)[a]
J	40	0.50
F	40	0.50
M	0	0.75
A	0	1.00
M	0	1.50
J	0	3.50
J	0	3.50
A	0	3.50
S	0	1.50
O	0	1.00
N	0	0.75
D	40	0.50

[a]*Time spent in and around the stream by cows that have stream access*
Source: VADCR and VADEQ, 2003a

Based on the 1060 cow/calf pairs in the Upper Opequon Watershed, Virginia Tech (VADCR and VADEQ, 2003a) determined the distribution of cattle between different land use types. The monthly distribution of cow/calf pairs in each land use type as well as in streams in the watershed is given in Table 4-4.

Table 4-4: Distribution of the Cow/Calf Pairs in Upper Opequon Watershed

Months	Confined	Pasture	Stream[a]	Loafing
J	491.0	721.2	1.5	13.8
F	558.5	819.9	1.7	16.2
M	0.0	1405.2	4.3	27.8
A	0.0	1312.8	5.4	28.6
M	0.0	1248.2	7.7	29.4
J	0.0	1266.3	18.3	30.2
J	0.0	1294.6	18.7	31.0
A	0.0	1322.5	19.1	31.8
S	0.0	1167.3	7.1	32.6
O	0.0	1035.8	4.3	20.0
N	0.0	1088.6	3.3	21.0
D	468.2	687.7	1.4	13.2

[a]*Number of equivalent beef cattle defecating in stream full time.*
Source: VADCR and VADEQ, 2003a

Pasture stocking rate depended on pasture type which determined the number of cattle grazing on a given pasture in the watershed, and its level of active grazing. These differences resulted in varying loadings in each subwatershed as shown in Table 4-5. During confinement, solid manure produced by beef cattle was collected for land application. Manure produced in each subwatershed was estimated based on the populations of beef cattle in the subwatershed and their confinement schedules (Table 4-3), and land applied to both cropland and pasture, with priority given to cropland. The manure application rates on cropland and pasture are given in Table 4-5.

Table 4-5: Estimated Monthly Manure N and P Inputs to Cropland and Pasture

Month	Cropland				Pasture*			
	NH_4-N *(kg/ha)*	Org-N *(kg/ha)*	PO_4-P *(kg/ha)*	Org-P *(kg/ha)*	NH_4-N *(kg/ha)*	Org-N *(kg/ha)*	PO_4-P *(kg/ha)*	Org-P *(kg/ha)*
J					0.85-5.02	1.17-6.81	0.03-1.63	0.03-1.63
F	18.46	24.43	5.83	5.83	0.76-4.53	1.08-6.19	0.05-2.51	0.05-2.51
M	36.92	48.87	14.55	14.55	0.11-0.61	0.58-3.41	0.03-1.52	0.03-1.52
A	36.92	48.87	14.55	14.55	0.11-0.61	0.13-0.82	0.01-0.51	0.01-0.51
M	14.77	19.55	11.63	11.63	0.11-0.62	0.15-0.84	0.01-0.51	0.01-0.51
J	3.70	4.89	2.91	2.91	0.11-0.58	0.13-0.80	0.02-0.76	0.02-0.76
J					0.43-2.40	0.58-3.30	0.01-0.51	0.01-0.51
A					0.43-2.40	0.58-3.30	0.02-1.01	0.02-1.01
S					0.43-2.40	0.56-3.27	0.00-0.13	0.00-0.13
O	5.62	7.44	8.85	8.85	0.21-1.24	0.29-1.69	0.01-0.51	0.01-0.51
N	5.62	7.44	8.85	8.85	0.21-1.21	0.28-1.65	0.08-4.04	0.08-4.04
D					0.21-1.26	0.29-1.70	0.03-1.63	0.03-1.63

**Rate varies with number of cattle in each subwatershed.*

4.2.2 Representation of Crops in HSPF

Planting, harvesting, and fertilizer and manure applications were scheduled, and plant uptake of nutrients and erosion-related cover developed for AGCHEM application in the UCI file. A number of input parameters required in HSPF for daily and monthly plant uptake simulation on crop lands were also developed. The HSPF model requires numerous input plant uptake parameters. Table 4-6 provides the estimated HSPF inputs for soil layer fractions of monthly N and P uptake for cropland used in this research. The monthly nutrient uptake fractions for corn and soybean were developed from nutrient uptake developed for the phase 4.3 CBWM for segment 740 (middle Potomac River basin) (CBP, 1997).

Table 4-6: Estimated Soil Zone Fractions of Monthly N and P Uptake for Cropland

Month	SZ		UZ		LZ		GWZ	
	N*	P**	N	P	N	P	N	P
J	0.01	0.05	0.56	0.80	0.43	0.15	0.00	0.00
F	0.01	0.05	0.56	0.80	0.43	0.15	0.00	0.00
M	0.01	0.05	0.65	0.80	0.34	0.15	0.00	0.00
A	0.01	0.05	0.65	0.80	0.34	0.15	0.00	0.00
M	0.01	0.05	0.65	0.80	0.34	0.15	0.00	0.00
J	0.01	0.05	0.65	0.80	0.34	0.15	0.00	0.00
J	0.01	0.05	0.60	0.80	0.39	0.15	0.00	0.00
A	0.01	0.05	0.55	0.80	0.44	0.15	0.00	0.00
S	0.01	0.05	0.50	0.80	0.49	0.15	0.00	0.00
O	0.01	0.05	0.45	0.80	0.54	0.15	0.00	0.00
N	0.01	0.05	0.56	0.80	0.43	0.15	0.00	0.00
D	0.01	0.05	0.56	0.80	0.43	0.15	0.00	0.00

SZ = surface zone, UZ = upper zone, LZ = lower zone and GWZ = ground water zone
**Nitrogen*
***Phosphorus*
Estimates based on CBP (1997) with some modifications on UZ N

4.2.3 Commercial Fertilizer Model Inputs

Since the Upper Opequon Watershed was predominantly a beef producing watershed, it was assumed that no commercial fertilizer was applied on pasture (Rau, 2012, personal communication). Fertilizer was only applied to field crops (corn, winter cover crops and rotational hay) using application rates from the MAWP (2006) and USDA's Agricultural Census data (1992-2007) for Frederick County, VA, and Clarke County, WV. For cropland, N and P were only applied April and October. Applied N was assumed to be converted to 25% NO_3-N and 75% NH_4-N. For P, 100% was assumed to transform to PO_4-P (Donigian et al., 1994; Liu, 2011). Further, nutrient inputs were either applied to the surface or the upper soil zone, depending on the nutrient application technique. Generally, in surface broadcasting fertilizer is applied to the surface zone, while with the soil incorporation, 10% of the fertilizer is applied to the surface zone and the remaining 90% is incorporated into the upper zone. This is based on the assumption that incorporation would produce an approximately uniform distribution of nutrient

in the top two soil layers (Donigian et al., 1994; Liu, 2011). Urban and residential lawn fertilizer application rates were obtained from the Phase 4.3 CBWM (CBP, 1997). Table 4-7 shows the commercial fertilizer applications. Atmospheric deposition data inputs were supplied to the model via the HSPF-WDMUtil over the simulation period. Both the dry and wet deposition time series data for Frederick County, VA were available from the CBWM (CBP, 2010c) for the period 1984 -2005 and these were extrapolated for the simulation period 1988-2009 using the BASINS WDM utility tool.

Table 4-7: Estimated Fertilizer Applications in the Upper Opequon

Month	Cropland			Lawns (urban/residential)
	NH_4-N *(kg/ha)*	**NO_3-N** *(kg/ha)*	**PO_4-P** *(kg/ha)*	**NO_3-N** *(kg/ha)*
J				
F				
M				
A	11.64	3.87	35.51	16.81
M				8.41
J	27.16	9.04		14.01
J				5.60
A				5.60
S				5.60
O	6.36	2.12	10.78	5.60
N				5.60
D				

4.2.4 Hydrology Simulation

Hydrology calibration in HSPF can be performed with the aid of the Hydrological Simulation Program-FORTRAN Expert system (HSPEXP) (Lumb et al., 1994a), which provides guidance for adjusting hydrologic parameters by comparing observed and simulated stream flows at a watershed or subwatershed outlet. However, in this research the previously calibrated hydrology parameters in the 2003 TMDL were revalidated for agreement with the observed data using time-series plots, PBIAS and R^2 statistical metrics.

4.2.5 Sediment Simulation

Generally, upland sediment erosion and transport on pervious and impervious lands are simulated using the modified soil loss equation (MUSLE) for soil detachment and wash-off. Within streams, sediment module equations based on Negev's equations are used for sediment transport, and deposition and scour are simulated for three classes: sand, silt, and clay. Non-cohesive (sand) sediment transport is simulated based on a sand-carrying capacity of the reach as a power function of the average flow velocity. Cohesive (silt, clay) sediment transport is simulated based on a bed shear stress as a function of the slope and hydraulic radius of the reach (Bicknell et al., 2005; Bicknell et al., 1996; Donigian and Love, 2003).

4.2.6 Nutrient Simulation

The nutrient sub-modules include AGCHEM, PQUAL, and IQUAL. The AGCHEM module was the major nutrient module used in this research because the main land uses in the Upper Opequon Watershed are forest (33%) and agriculture (53%). The AGCHEM module was developed for use on agricultural lands, and can also be applied on other pervious areas where plant nutrients are likely to be land applied, such as forests, golf courses, orchards, nursery land, parks, and lawns (Bicknell et al., 2005). The module consists of three sub-modules: MSTLAY, NITR and PHOS and is discussed further in chapter 5.

4.2.7 Sensitivity Analysis

Before calibrating the model, "one-variable-at-a-time" sensitivity analysis was used to characterize the sensitivity of model outputs with respect to nutrient inputs and parameters related to sediment and nutrient transport and interactions. The choice of "one-variable-at-time" sensitivity analysis was based on its wide use in watershed studies previously discussed in section 2.8. Sensitivity analysis was used to identify key parameters that disproportionally influence model output and that should thus be the focus during calibration. The primary outputs involved in the sensitivity analysis were TSS, nitrate (NO_3-N), and dissolved reactive P (PO_4-P) loadings. Each of the outputs was evaluated based on total monthly loads covering both the calibration (1991- 1997) and validation period (1998 – 2002).

A relative sensitivity index reported by White and Chaubey (2005) was used to calculate and compare the results. The normalized form of the sensitivity index (RSI) was calculated as

$$RSI = (\frac{y_2 - y_1}{y})/(\frac{x_2 - x_1}{x}) \quad \text{(4-1)}$$

where x is the base/calibrated value of parameter, y is the base value of output, and x_2 and x_1 indicate a ±10%, 25% and 50% change of the base parameter value, respectively. Correspondingly, y_2 and y_1 are output responses to x_2 and x_1. The sensitivity index can be positive, zero or negative indicating positive correlation, no correlation, and negative correlation. The greater the absolute value, the more sensitive a model output is to a particular parameter (Liu, 2011; Storm et al., 1986; White and Chaubey, 2005) as shown in Table 4-8. The input parameters were ranked according to the magnitude (significance) of their indices.

Table 4-8: Parameter Relative Sensitivities (Storm et al., 1986)

Description	Sensitivity index
Insensitive	$Sr < \|0.01\|$
Slightly sensitive	$\|0.01\| \leq Sr < \|0.10\|$
Moderately sensitive	$\|0.10\| \leq Sr < \|1.00\|$
Sensitive	$\|1.00\| \leq Sr < \|2.00\|$
Extremely sensitive	$Sr \geq \|2.00\|$

4.3 Statistical Methods

Following the literature review and based on wider applications of the Wilcoxon signed rank test among the non-parametric tests considered in watershed studies, the Wilcoxon signed rank test was selected for hypothesis testing conducted at 95% significance level in this research. The Wilcoxon signed-rank test is used when comparing two related samples, matched samples, or repeated measurements on a single sample to assess whether their population mean ranks differ (i.e. it's a paired difference test). It can be used as an alternative to the paired Student's t-test, when the population cannot be assumed to be normally distributed (Richard, 2011). This test can be performed on small samples and large samples, based on six steps that should be used as follows: 1) null and research hypotheses are stated (that is, H_o: median or mean difference between the pairs is zero and H_1: median or mean difference is not zero), 2) the level of significance associated with the null hypothesis is determined, 3) the test statistic is then computed, 4) the value needed for rejection of the null hypothesis using the appropriate table of

critical values or p-values are established, 5) Then the test statistic value obtained or its p-value is compared to the critical value or level of significance, and 6) results are interpreted and reported.

Visual inspection of the time-series plots and literature reviewed model evaluation criteria (Donigian, 2000; Moriasi et al., 2007; Santhi et al., 2001; Singh et al., 2008) were used to evaluate model performance. The model performance criteria values are presented in section 4.6. The agreement between predicted and observed constituent loadings was evaluated by visual and statistical comparisons on daily (for flow only) and monthly time-steps based on available observed data (Table 4-2). The statistical comparisons are presented using PBIAS and R^2 as follows:

$$PBIAS = \frac{\sum_{i}^{n}(O_i - P_i)}{\sum_{i}^{n}(O)} * 100 \quad \text{..... (4-2)}$$

where,

O_i = observed daily or monthly values for the i^{th} day or month,

P_i = simulated monthly values for the i^{th} day or month, and

n = total number of days or months.

Source: Moriasi et al., (2007).

$$R^2 = \frac{\sum_{i=1}^{n}(O_i - \overline{O})(P_i - \overline{P})}{\left[\sum_{i=1}^{n}(O_i - \overline{O})^2\right]^{1/2}\left[\sum_{i=1}^{n}(P_i - \overline{P})^2\right]^{1/2}} \quad \text{..... (4-3)}$$

where,

Oi = observed value for the ith day or month,

$\overline{O}$ = mean of the observed daily or monthly value,

Pi = simulated value for the ith day or month,

$\overline{P}$ = mean of the simulated daily or monthly value, and

n = total number of days or months.

Source: Ramanarayanan et al. (1996).

4.4 Model Calibration and Validation

The HSPF hydrology parameters were calibrated and validated for use in the 2003 bacteria TMDL based on the site-specific land use data for the Upper Opequon Watershed (VADCR and VADEQ, 2003a) using the HSPEXP expert system (Lumb et al., 1994b). The same land use was used for calibration and validation of all simulated constituents in this study. Recalibration was not necessary and the existing 2003 TMDL calibrated hydrology parameter values were judged adequate based on validation period results. The model was run for one year to provide a one year start-up time period to allow the initial values for the HSPF hydrology storage parameters (UZS, LZS, AGWS, GWVS) to stabilize since their values can impact the simulation for a period of months to a few years (USEPA, 2000). Initial water quality parameters were based on Phase IV CBWM parameters for the Mid-Potomac River (segment 740) (CBP, 1997). The calibration period was 1991 to 1997 and the validation period was from 1998 to 2002 to coincide with the land use data developed in the bacteria TMDL. Sediment was calibrated (1991-1997) and validated (1998-2002) following guidelines discussed in BASINS Technical Note 8 (USEPA, 2006). The modeled output loads were then compared to the observed data. For sediment, the VADEQ determines the minimum monitoring detection limit at 3 mg/L (Kline, 2012, personal communication; Sieber, 2011, personal communication). The available monitored data from VADEQ ambient monitoring station 1AOPE0036.13 for the period 1991 to 2002 were used to calibrate the nutrient parameters. Monitored nutrient data available for the calibration period included NO_3-N, NH_3+NH_4-N, PO_4-P, and TP concentrations. A majority of observed NH_3+NH_4-N values were below the minimum detection limit, so only NO_3-N, PO_4-P and TP were used to calibrate and validate the model. Sediment and AGCHEM parameters were adjusted to obtain a satisfactory agreement between predicted and observed sediment, NO_3-N, PO_4-P and TP.

4.5 Results for Sensitivity Analysis

The normalized RSI was calculated and reported on sensitive parameters using Equation (4-1). The sensitive parameters were then classified and ranked according to the criteria in Table 4-8. Sensitivity results for sensitive sediment parameters are presented in Table 4-9. Selected parameters for sensitivity analysis were based on literature review (Donigian and Love, 2007; Im

et al., 2003; Liu, 2011) and recommendations through HSPF modeling experiences at the Center for Watershed Studies at Virginia Tech (Kline and Zeckoski, 2012, personal communication).

Table 4-9: Summary Results of Relative Sensitivity Indices

Parameter	Description	Sensivity index (RSI)						Sensitivity level	Rank
		TSS		*NO_3-N*		*PO_4-P*			
	Sediment	***Max***	***Min***	***Max***	***Min***	***Max***	***Min***		
JSER	Exponent in the matrix soil scour equation, which simulates gully erosion	-0.31	-1.36					Sensitive	1
TAUCS	Reach critical shear stress for scour	-0.13	-0.42					Moderately sensitive	2
KSER	Coefficient in the detached sediment wash-off equation	0.40	0.28					Moderately sensitive	3
TAUCD	Reach critical shear stress for deposition	0.00	-0.06					Slightly sensitive	4
	Nitrogen								
KDNI	Coefficient of denitrification of NO_3 for lower soil layer			9.1	-8.7			Extremely sensitive	1
MON-NITUPT	Fractions of the total annual N plant uptake target applied to each month			1.7	-1.7			Sensitive	2
KNI	Coefficient of first order nitrification (surface layer)			0.4	-0.1			Moderately sensitive	3
KAM	Coefficient of organic-N ammonification (all soil layers)			0.2	0.2			Moderately sensitive	
	Phosphorus								
OrgP	Initial P storage in the surface, upper, lower or groundwater layer					7.52	-7.52	Extremely sensitive	1
KIMP	Coefficient of P immobilization (surface and upper soil layer)					1.00	-1.00	Sensitive	2
K1	Exponent parameters for the Freundlich curve used for adsorption (surface and upper layers)					0.63	-0.63	Moderately sensitive	3
N1	Coefficient parameter for the Freundlich curve used for adsorption (surface and upper layers)					0.05	0.02	Slightly sensitive	4
P4AD	Coefficient of adsorbed phosphate (both upper and lower layers)					0.04	-0.04	Slightly sensitive	5
PUPTGT	Total annual target for plant uptake of P for all soil layers and all crops during the calendar year					0.01	-0.03	Slightly sensitive	6

Of the model parameters that were analyzed, 14 parameters were found to be sensitive according to the criteria set forth in Table 4-8. Determining the RSI for each of the parameters involved six model runs through changing the parameter from the base value by ±10%, 25%, and 50%.

Generally, the most sensitive sediment parameter was the exponent in the matrix soil scour equation (JSER), which simulates gully erosion with a minimum RSI = -1.36 observed when the base value was reduced by 50%. This value however changed to-0.31 when the base value was increased by 50%. The reach critical shear stress for deposition (TAUCD) was the least sensitive with a minimum RSI = 0.0 when the base was reduced by 50% and a maximum value of -0.06 at 50% increase in base value.

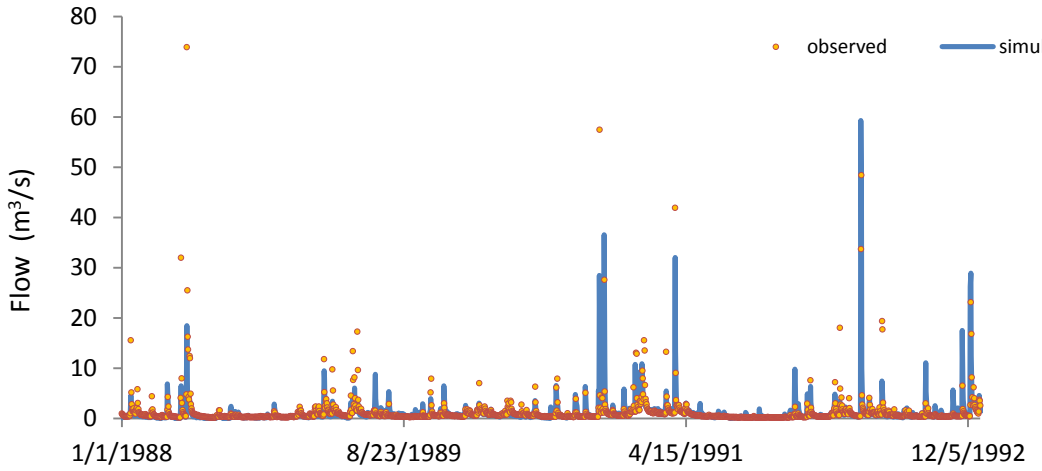
The HSPF-AGCHEM nutrient parameters: KNI, KDNI, NITUPT, KAM, KIMP and ORGP were found to be at least moderately sensitive and subjected to calibration from 1991 – 1997 and validation using observed data from 1998-2002 at station 1AOPE036.13. The coefficient of de-nitrification for NO_3-N in the lower soil layer (KDNI) was the most sensitive parameter. The parameter KDNI had the highest RSI = 9.1 when the base value was increased by 10% and the lowest RSI = -8.7 when reduced by 10%. Initial organic-phosphorus (ORGP) storage in the surface, upper, lower soil zones and groundwater was the second most sensitive parameter after KDNI. The parameter ORGP had a maximum RSI = 7.52 and minimum RSI = - 7.52 when the base value was changed by ±25%, respectively.

4.6 Results for HSPF Calibration and Validation

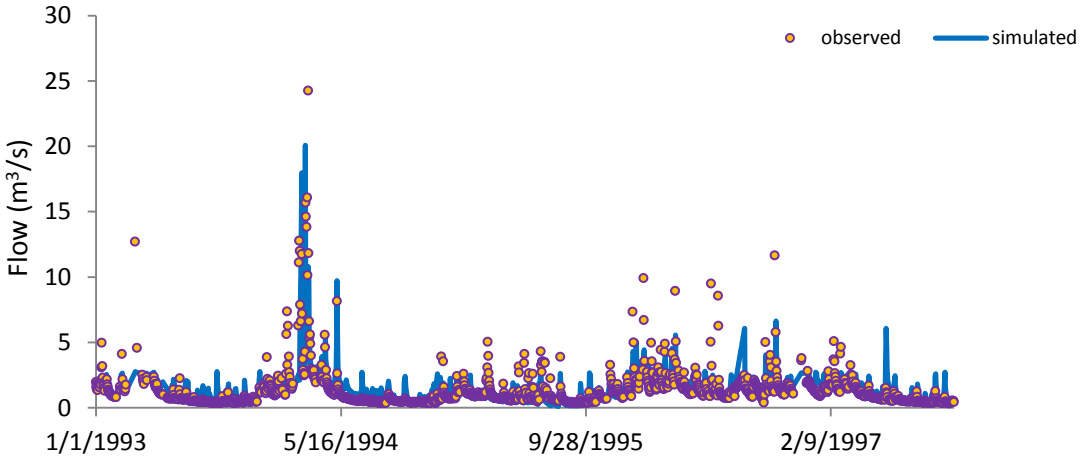
The simulated hydrology, TSS, NO_3-N, PO_4-P and TP were compared with their observed values at daily (for hydrology) and monthly time-steps during calibration and validation periods. Model performance statistics and criteria were found in the literature (Donigian, 2000; Moriasi et al., 2007; Ramanarayanan et al., 1996; Santhi et al., 2001; Singh et al., 2008). Table 2-3 discussed in section 2.9 summarized PBIAS model performance criteria used when assessing model performance.

4.6.1 Hydrology Calibration and Validation

The starting HSPF flow parameters were satisfactory. There was overall good visual agreement between the simulated and the observed flows as shown in Figure 4-2.



a) Flow Validation Plot 1



b) Flow Validation Plot 2

Figure 4-2: Time-Series Results for Flow Validation

Positive values of PBIAS indicate model under-prediction while negative values represent model over-prediction of the parameter of concern (Moriasi et al., 2007). The PBIAS statistic (Table 4-10) showed that the model under-estimated daily flow by 8.17% while R^2 was estimated at 0.52.

Table 4-10: Statistical Model Performance Results for Daily Flow

	Validation	Criteria	Remarks
PBIAS (%)	-8.17	PBIAS < ±10	Very good
R^2	0.52*	≥ 0.60	Acceptable

**a value of 0.5 is acceptable (Santhi et al., 2001)*

4.6.2 Sediment Calibration and Validation

The four sediment sensitive parameters (JSER, KSER, TAUCS and TAUCD) identified in Table 4-9 were subjected to calibration. Some parameters that were not identified during sensitivity analysis were also modified during calibration. These included reach parameters KSAND and EXPSND. The latter two parameters were not sensitive according to the criteria in Table 4-8, however, they were observed to have some impact on in-stream sediment particles (sand, silt and clay) distribution during calibration. The initial sediment overland flow erosion-related parameters were first adjusted, followed by in-stream sediment transport parameters. Parameters KSAND and EXPSND were adjusted to generate the appropriate sand, silt, and clay fractions balance in the stream.

Predicted and observed monthly TSS concentrations were compared using equations (4-2) and (4-3). The criteria provided in Table 2-3 and R^2 value criterion in section 2.9 were used as a guide in estimating satisfactory model performance. The calibrated sediment-related parameter values along with allowable parameter ranges provided in the HSPF user's manual are shown in Table 4-11. All calibrated parameters were within the HSPF allowable range.

Table 4-11: Initial and Final Calibrated Sediment Parameters, and HSPF Allowable Parameter Ranges

			HSPF Allowable Ranges[c]
Sediment Parameter	***Initial***	***Final***	*Bicknell et al. (2005)*
KSER	1.22 - 3.29[b]	1.19 – 2.31[b]	0 – infinity
JSER	2.00	2.00	0 – infinity
KSAND	0.50	0.50	0 – infinity
EXPSND	1.50	1.45	0 – infinity
TAUCD	0.01 - 0.12[a]	0.01 – 0.14[a]	-1.0E-10 – infinity
TAUCS	0.05 - 0.71[a]	0.05 – 0.82[a]	-1.0E-10 – infinity

[a] *Silt and clay, respectively with range varying by reach*
[b] *Range varying by land use.*
[c] *HSPF allowable range as suggested in the HSPF User's Manual (Bicknell et. al., 2005).*

Table 4-12 is a summary of sediment statistical model performance values at a monthly time-step. The PBIAS and R^2 were estimated within acceptable range of 19% and 0.63, respectively. The PBIAS metric shows that the model was under-predicting by 19% when compared to the

observed data. Calibration results for TSS were above this minimum threshold value, which is acceptable.

Table 4-12: Monthly Sediment Statistical Model Performance Results

	Calibration	Validation	Criteria	Remarks
PBIAS (%)	19	-18	±15 ≤ PBIAS < ±30	Good
R^2	0.63	0.60	≥ 0.60	Acceptable

A calibration model output time-series plot for the sediment parameters is provided in Figure 4-3. There was general agreement between the predicted and observed values as shown in the calibration time-series plot (Figure 4-3).

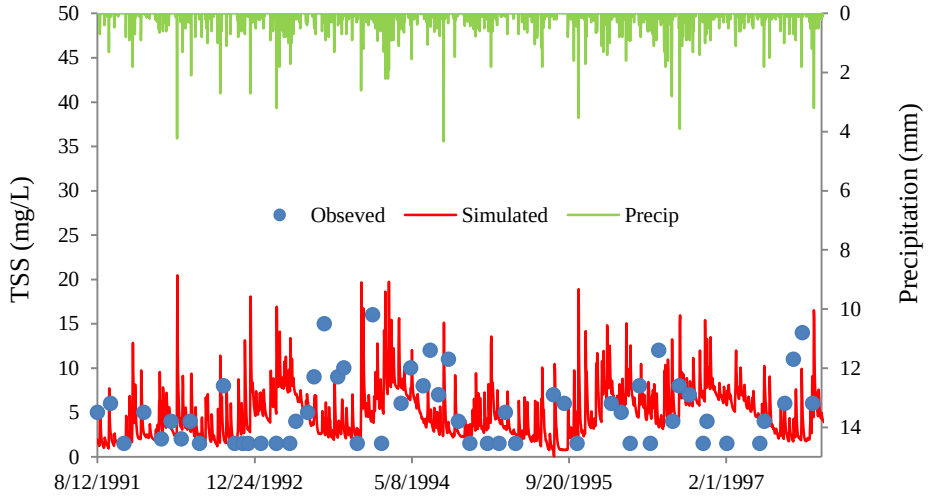


Figure 4-3: Time-Series Results for Sediment Calibration

Five discrepancies were observed in monitored data points where high TSS concentration values had been recorded and reported even on dates where no or very little precipitation occurred with no subsequent flow generated. These data points were assumed to have resulted from some upstream disturbance of the stream during sampling, such as livestock in the stream. The data points were treated as outliers and removed from the time-series used for calibration (Table 4-13).

Table 4-13: Sediment Observed Outliers' Data

	8/2/1993	1/3/1994	8/6/1998	7/20/1999	7/13/2000
TSS observed (mg/L)	15	16	20.7	26.5	22.5
Precipitation (mm)	0	0	0	0	0
Precipitation previous day (mm)	0	0	0	0	0

The observed data used in the validation had more sample points below the minimum detection limit. Figure 4-4 is the validation time-series plot for the TSS.

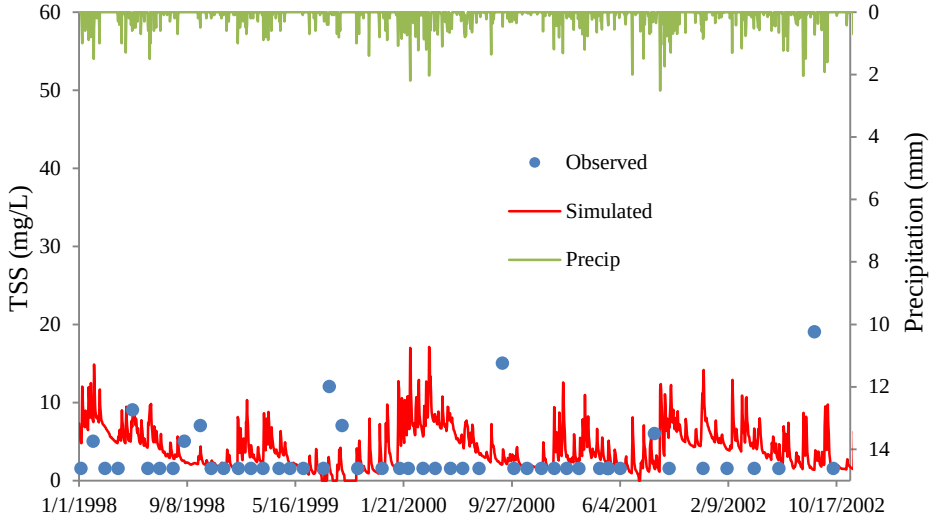


Figure 4-4: Time-Series Results for Sediment Validation

Figure 4-4 shows there is good agreement between the predicted and observed data points. Sediment observed data points at detection limit of 3 mg/L were reduced to 1.5 mg/L following discussions with Kline (2012, personal communication). The criteria for satisfactory model performance were met; the model was over-predicting by 18% and yield good R^2 value of 0.60 (Table 4-12).

4.6.3 Nutrient Calibration and Validation

The HSPF-AGCHEM sensitive nutrient parameters are described in Table 4-9. The parameters were then calibrated from 1991 to 1997, and validated from 1998 to 2002 using observed data from station 1AOPE036.13 (Figure 4-1).The calibrated parameters values and their HSPF allowed range are provided in Table 4-14.

Table 4-14: Calibrated Values of Nutrient Parameters

			HSPF Allowable Ranges[c]
Nutrient Parameter	***Initial***	***Final***	*Bicknell et al. (2005)*
KDNI	0.00 - 0.00[b]	0.00 - 0.90[b]	0.0 – infinity
MON-NITUPT	1.00 – 20.00[b]	0.10 – 0.30[b]	0.0 – infinity
KNI	1.00 – 20.00	0.100 – 0.300	0.0 – infinity
KAM	0.00 – 0.0035[b]	0.00- 0.003[b]	0.0 – infinity
KIMP	0.00 – 15.00[a]	0.00 – 14.00[a]	0.0 – infinity
OrgP	50	45[c]	0.0 – infinity

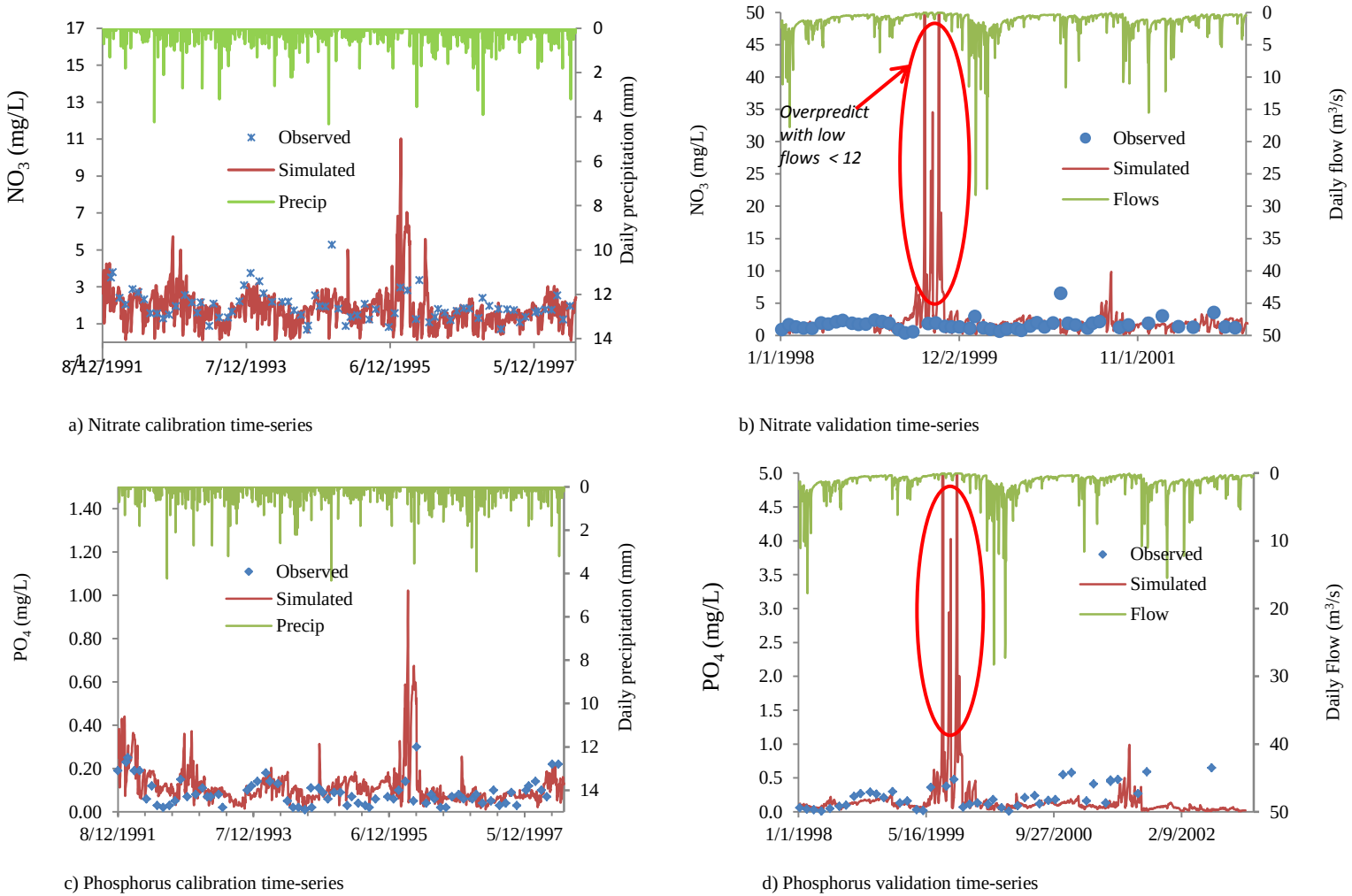
[a] Range varying by soil profile, [b] Ranges varying by landuse, [c] only for surface soil layer

The statistical values for the nutrient outputs at monthly time-steps that were obtained during evaluation of the model performance are summarized in Table 4-15.

Table 4-15: Monthly PBIAS and R^2 Values of Evaluated Model Output on Nutrients

	Calibration		**Validation**	
Constituent	***Monthly PBIAS***	***Monthly R^2***	***Monthly PBIAS***	***Monthly R^2***
NO_3-N	*6*	0.49	-4	0.40
Criteria	*PBIAS < ±25*	*0.60*	*PBIAS < ±25*	*0.60*
Remarks	*Very good*	*Acceptable*	*Very good*	*Not acceptable*
PO_4-P	*-37*	0.89	46	0.86
Criteria	*±25 ≤ PBIAS < ±40*	*0.60*	*±40 ≤ PBIAS < ±70*	*0.6*
Remarks	*Good*	*Acceptable*	*Satisfactory*	*Acceptable*

The six-year calibration period showed the model was under-predicting the average monthly NO_3-N concentration by 6%. It over-predicted the NO_3-N concentration by 4% over the five-year validation period. The R^2 values for calibration and validation periods were 0.49 and 0.40, respectively. These values show that the model was performing below the recommended satisfactory R^2 value of 0.6. The calibration and validation of NO_3-N concentrations for PBIAS were considered good and these results are shown in Figure 4-5.



a) Nitrate calibration time-series

b) Nitrate validation time-series

c) Phosphorus calibration time-series

d) Phosphorus validation time-series

Figure 4-5: Time-Series Results for Nutrient Calibration and Validation

Comparatively, the monthly statistical results for PO_4-P were weaker than PBIAS values recommended by Donigian (2000), but within the accepted range of Moriasi et al. (2007) and Singh et al. (2008). The PBIAS value shows the model over-predicted by 37% during the calibration period, while it under-predicted PO_4-P by 46% during the validation period. In contrast, calibration and validation values for R^2 were quite good at 0.89 and 0.86, respectively (Table 4.15). The graphical representation between the simulated and observed PO_4-P data points was also adequate (Figure 4-5). The summer of 1999 experienced low flow conditions seen in Figure 4-5 b) and d). Over this low flow period, HSPF was observed to seriously over-predict nutrient losses. The cause for this model behavior is discussed in section 4.6.4.

4.6.4 Discussions and Conclusions on Model Calibration and Validation

The summer of 1999 was characterized by dry weather conditions with most flow that was either equal to or less than 12 mm (Figure 4-5 (b) and (d)). Unrealistic model predictions of nutrient (N and P) output concentrations were observed. In Upper Opequon Watershed, several point sources exist including the general and VPDES permitted point sources such as Parkins Mills sewage treatment plant, Fredrick County Landfill, Stonebrook Swim and Racquet Club, and Franciscan Missionary Center. A review of the time-series in the model input showed all nutrient discharge from point sources were within the allowed permit restrictions, and therefore no violations of the permits were revealed in the input time-series.

Literature (Hall, 2007; Hall et al., 2008; Zeckoski, 2011) reported similar model behavior in bacteria HSPF simulations under low-flow conditions. This occurs during dry weather when flows in low stream-order, upland streams decrease and approach zero. In HSPF simulations for bacteria, this condition is corrected by introducing a "cut-off stage". The model "cut-off stage" simply stops the model from simulating bacteria loads mainly from direct deposit sources below a certain flow rate (Hall, 2007; Hall et al., 2008). This study concluded that there is a limitation in HSPF that requires further research. However, this model limitation did not affect the expected modeled total nutrient loads. This is because mass is a product of concentration and discharge (volume) at a given point in time, and therefore the high concentration at low flow conditions did not affect the pollutant load prediction.

5 Effects of Spatial Land Use and BMP Data on Modal Results

This chapter presents procedures to accomplish research objectives 1 and 2 involving the effects of spatial variability in land use distribution and installed BMP data on HSPF-predicted flow, sediment, and nutrient. The chapter also covers the procedure used to accomplish the research objective 3 on the level of BMPs required to achieve the Bay TMDL target goals.

5.1 Effects of Watershed Land Use Data on HSPF-AGCHEM Flow and Sediment and Nutrient Loadings Predictions

5.1.1 Site-Specific and Disaggregated Land Use Data Inventories

The land use map for the Upper Opequon consisting of 24 land uses developed by VADCR aerial photographs of 1995-1997and which were verified by Virginia Tech in 2003 (VADCR and VADEQ, 2003a, b) were used in this study. The 24 land uses were consolidated into 6 categories (Appendix 1) for modeling purposes following the approach used in the bacteria TMDL (VADCR and VADEQ, 2003a). These data provided the site-specific land use dataset for the Upper Opequon Watershed. The Upper Opequon Watershed county-level aggregated land use data developed in 2002 were used as a second source of land use input data. The CBP model data are available for stakeholders' use in water quality modeling for the Bay region watersheds. The county-level aggregated data can be downloaded at: ftp://ftp.chesapeakebay.net/Modeling/phase5/Phase532/land_use/ (accessed April 15, 2011). The county aggregated data was then disaggregated to subwatersheds using the local subwatershed to total watershed area weighted- ratios, and spatially distributed on the entire watershed. The procedure entails computing the ratio of subwatershed area to the amount of watershed area and multiplying that ratio by the watershed county-level aggregated land use area. The distribution of site-specific and disaggregated land use areas on the study watershed are presented in Table 5-1. The distribution to the watershed was necessary because the scale of CBWM output limits the development of targeted management actions at a finer spatial scale (Yagow et al., 2012). The county-wide aggregated land uses in the CBP watershed modeling activities are classified into 25 classes. The CBWM combines GIS spatial data and Classification and Regression Tree (CART) analysis to generate the Bay-wide land use data. The data sources used are NLCD imagery, USDA-Agricultural Census data by county, NOAA Coastal Change Analysis Program (CCAP) 2001, and Landsat Raster Reflectance 2001 (CBP, 2010b). Many of the CBWM agricultural

categories are not strictly land uses. Some land uses also reflect BMPs, and these do not strictly equate to spatially-derived land use categories. The CBWM BMPs that are simulated as land use categories include NMPs and conservation tillage. The 25 CBWM land uses were reclassified and consolidated into 6 broader agricultural and urban/residential land use categories to match the site-specific land uses (Appendix 2).

Table 5-1: Distribution of Land Use Areas in Hectares (ha) of Upper Opequon Watershed

Subwatershed	Cropland (ha)		Pasture (ha)		Loafing lot (ha)		Forest (ha)		Residential (ha)		Urban (ha)		Subwatershed Total (ha)	
	site-spec	disaggregated	site-spec	disaggregated	site-spec	disaggregated	site-spec	disaggregated	site-spec	disaggregated	site-spec	disaggregated	site-spec	disaggregated
1	0.00	1.54	9.96	8.26	0.00	0.02	3.85	5.91	0.00	1.78	4.33	0.61	**18.14**	**18.12**
2	9.39	20.53	144.09	110.93	0.00	0.26	81.86	79.47	1.70	23.64	6.60	8.10	**243.64**	**242.94**
3	9.80	31.17	113.93	168.50	0.00	0.40	155.14	120.69	87.25	35.95	4.01	12.31	**370.12**	**369.02**
4	0.00	5.75	31.90	31.09	0.00	0.07	34.82	22.27	1.54	6.64	0.00	2.27	**68.26**	**68.09**
5	19.39	53.16	450.00	287.29	0.00	0.68	148.99	205.79	9.23	61.30	3.40	20.97	**631.01**	**629.19**
6	1.82	42.02	237.09	227.21	0.00	0.54	206.32	162.75	50.28	48.46	3.56	16.60	**499.07**	**497.58**
7	0.04	79.47	292.63	429.72	0.00	1.02	371.62	307.81	175.59	91.66	103.97	31.38	**943.85**	**941.06**
8	30.97	60.40	380.97	326.64	0.00	0.78	271.38	233.97	4.86	69.68	29.23	23.85	**717.41**	**715.31**
9	88.58	117.61	440.81	635.87	0.00	1.51	464.45	455.43	246.07	135.67	156.68	46.44	**1,396.60**	**1,392.52**
10	140.93	107.13	731.01	579.07	1.09	1.40	355.06	414.82	29.55	123.56	14.33	42.31	**1,271.98**	**1,268.28**
11	9.07	54.57	413.81	294.98	0.00	0.70	201.42	211.30	13.72	62.91	9.88	21.54	**647.89**	**646.00**
12	51.21	140.49	900.12	759.47	0.00	1.81	435.51	543.97	252.02	162.02	29.23	55.47	**1,668.10**	**1,663.22**
13	133.81	154.62	804.66	835.87	0.00	1.99	556.03	598.70	168.14	178.34	173.32	61.05	**1,835.95**	**1,830.57**
14	0.00	56.32	190.65	304.33	0.00	0.72	216.88	218.02	230.93	64.94	30.00	22.23	**668.46**	**666.55**
15	211.62	159.39	906.28	861.66	0.00	2.05	651.98	617.21	111.74	183.85	10.93	62.91	**1,892.55**	**1,887.07**
16	98.02	174.17	1082.11	941.58	0.00	2.24	744.74	674.45	111.90	200.93	31.38	68.74	**2,068.14**	**2,062.12**
Total Area	**805**	**1,258**	**7,130**	**6,802**	**1.09**	**16.19**	**4,900**	**4,873**	**1,495**	**1,451**	**611**	**497**	**14,941**	**14,898**

County-level land use data disaggregated based on the CBP land use data for Upper Opequon in 2002 to match the 1995-1997 site-specific land use verified by Virginia Tech in 2003

Source: CBP, 201b; VADCR and VADEQ, 2003a.

5.1.2 Statistical Analysis

The HSPF model was run for the each land use data type and the resultant modeled responses (flow, sediment, TN and TP) compared at subwatershed and watershed levels. The simulation period was 22 years from 1988 to 2009, with each model run performed first with site-specific and a second time with disaggregated land use data input. Site-specific land use provided the modeled baseline outputs. The differences in the resulting flow, sediment, TN, and TP predictions were calculated and quantified via comparing the outputs from the different spatial distribution of land use. The differences were quantified as percentage relative errors (%RE) using the following equation:

$$\%RE = \frac{LU_d - LU_{ss}}{LU_{ss}} x100 \quad \text{..... (5-1)}$$

where LU_d = modeled output from disaggregated land use and LU_{ss} = the baseline output from site-specific land use, respectively for monthly and annual flow and loadings. The resulting calculated relative errors are presented in tables and figures discussed in chapter 6. The Wilcoxon signed-rank test was used to test the null hypothesis based on its wide application in watershed studies (Carrubba, 2000; Dibike et al., 2008; Lameire, 2000; Meentemeyer et al., 2008; Rupert, 2008; Thompson et al., 2001), with a 95% significance level, which is widely used in testing significance differences in hydrologic and water quality studies (Cosgrove and Taylor, 2007; Dibike et al., 2008; Meentemeyer et al., 2008; Yang et al., 2010b). It was hypothesized that differences in modeled loadings from site-specific and disaggregated land use to watershed are significantly different at monthly and annual scales. The Wilcoxon signed-rank test was conducted using the SAS® Wilcoxon signed-rank test (SAS, 2008).

5.2 Evaluating the Effects of Disaggregating BMPs on Modeled BMP Responses

5.2.1 Pre-BMP (Baseline) Scenario Development

Using the Upper Opequon Watershed site-specific land use, the site-specific and disaggregated county-level BMP data sources were simulated for the period 1988-2009. The study watershed is dominantly a beef producing watershed, thus no commercial fertilizer was considered for application on pasture due to continuous manure droppings. Fertilizer was applied to field crops using recommended fertilizer application rates and amounts from the MAWP (2006), and

USDA's Agricultural Census data (1992-2007) for Frederick County, VA, and Clarke County, WV. The monthly fertilizer application rates are provided in Tables 4-5 and 4-7. The pre-BMP/baseline scenario included a fertilizer application period of 22 years (1988-2009). The simulated baseline loadings were monthly and annual HSPF-predicted flow, sediment, TN and TP loads.

5.2.2 Distribution of Best Management Practices

A spatially referenced (site-specific) cost-shared GIS BMP data layer for the Upper Opequon Watershed was obtained from the VADCR and LFSWCD (McRae, 2011, personal communication) (Appendix 3).The BMP data were processed using ArcGIS software (ESRI, 2010) and their corresponding BMP benefited areas on the watershed determined. There are undoubtedly additional unreported BMPs within the study area but they are voluntary and, therefore, not included in the databases. Three agricultural BMPs (NMPs, cover crops and streamside fencing) were selected for study because they were the dominant agricultural BMPs reported in both the site-specific and county-level disaggregated databases.

The BMPs derived from county-level disaggregated database had more BMP units (benefited area) than the site-specific state data, which are presumably more representative of actual watershed conditions. The Upper Opequon Watershed county-level disaggregated BMP benefitted areas (Appendix 4) were obtained from the CBWM BMP database. These data were obtained prior to the May 2011 revisions. The BMP data can be downloaded at: ftp://ftp.chesapeakebay.net/Modeling/phase5/Phase532/bmpacres/ (accessed April 15, 2011). Following CBWM output variations that resulted from the 2011 model input data revisions, the state of Virginia requested USEPA to use the CBWM outputs that were used in the development of watershed implementation plans phase I (WIPs I) to develop WIPs II targeting localities. The WIPs I were developed before the revisions (VADCR, 2012). Due to these circumstances, it was necessary to run the model using the BMP data used during the WIPs I. The disaggregated BMP areas required spatial referencing to suitable BMP-land use locations on the watershed. In total, there were 98 different disaggregated BMP data points for the watershed. Spatially distributing these BMPs involved down-scaling to the subwatershed level and assigning each of the BMPs of interest to its appropriate land use using the following sequence of 6 steps:

1. Using the disaggregated BMP datasheet with their corresponding upland filtered areas for the entire watershed, each BMP was itemized starting at number 1 to 98 following their order on list.
2. An equivalent number of 98 point features representing the BMP data points were randomly generated within the watershed boundary map using ArcGIS random point feature tool (ESRI, 2010). Each point feature on the map represented a certain BMP in the spreadsheet, which had a unique benefitted area associated with it.
3. The stream network delineation and land use maps were then overlaid onto the randomly generated point features. This helped identify the spatial location of the point feature within the boundary of the catchment and its sub-basins, and the land use where it was located.
4. The ArcGIS information identifier tool and the Layer Attribute Table were then used to identify the random numbering on the point feature. The random number was matched with the corresponding itemized BMP in the spreadsheet list.
5. Based on the appropriateness of the land use on which the point feature representing a certain BMP was spatially located, the three desired agricultural BMPs that fell on pasture and cropland were isolated from the rest of the BMP cluster in the subwatersheds.
6. BMP data points that fell on appropriate land uses (that is, streamside fencing BMP on pasture, and NMPs and cover crops on cropland) were then removed from the excel listing. The randomization procedure was repeated for the remaining BMP data points until all the desired BMPs were randomly located on the appropriate land use. Figure 5-1 shows the final point features distribution representing the three agricultural BMPs on the watershed.

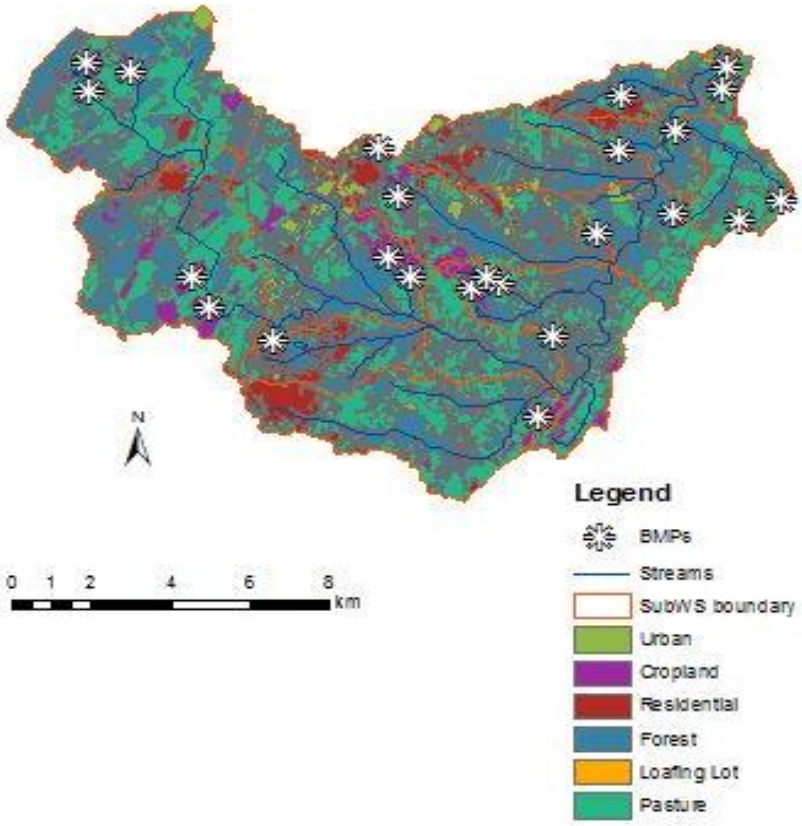


Figure 5-1: Random Distribution of Disaggregated BMPs in Upper Opequon Watershed

According to Keeling (2012, personal communication), the VADCR uses the Agricultural Cost Share tracking program average buffer width of 10 m (35 ft) and multiplies it by the linear length of fencing to estimate the area of the riparian buffer created between the fence and stream bank. This is then subtracted from the total area benefited to estimate the upland grazing management portion of that BMP. The BMP area benefited is upland of that fencing and is related to rotational grazing or prescribed grazing on the pasture area. The CBP uses factors of 4 and 2 multiplied by the riparian buffer area to estimate the total benefited area for the control of TN and TP/sediment losses, respectively. Using either of the two factors to calculate areas benefitted for N or P should provide the same answer and both represent the same stream fencing length. Stream fencing length is then calculated as the buffer area (ha) times 10,000 square meters/ha and divided by the average buffer width (10 m). Stream fencing accompanies both grass and forest buffers placed on the "trp" land use, which stands for trampled riparian pasture land and can benefit either regular pasture land (pas) or pasture with nutrient management (npa) (Yagow, 2013, personal communication). The streamside fencing for the county-level disaggregated areas benefitted by the buffers are provided in

Appendix 4. In the CBWM, livestock exclusion BMP is a land use change and does not directly appear in Appendix 4. The buffers benefitted areas in this table are the upland areas which receive credit for a filtering benefit. The buffers benefitted areas used were only those for P and sediment control on degraded pasture corridor (Grass/ForestBuffersTrpPS). In Appendix 4, these buffers are shown by line numbers 70, 72, 87 and 89 of the table. These areas should be exactly half that of the "TrpN" areas. Table 5-2 provides the final benefitted area calculation (streamside fencing) and distribution of BMP data and their benefitted areas on the watershed.

Table 5-2: Distribution of BMPs in the Upper Opequon Watershed

BMP Name	BMP Type			
	site-specific		disaggregated	
	subwatershed	area benefitted (ha)	subwatershed	area benefitted (ha)
NMPs	12	51.21	5	14.36
	13	12.76	8	30.97
	16	55.89	10	96.51
			12	51.23
			13	133.81
			15	93.18
			16	4.30
	Total	**119.86**	**Total**	**424.36**
Cover Crop	8	16.60	2	5.44
	9	31.98	5	5.90
	10	23.48	6	1.78
	11	26.32	8	3.26
	12	10.12	10	31.35
	13	82.59	11	56.43
	15	18.22	13	39.96
			15	53.16
	Total	**209.31**	**Total**	**197.28**

Streamside Fencing

site-specific					disaggregated	
Practice	**subwatershed**	**linear length (m)**	**buffer area (ha)***	**"TrpPS" buffer type**	**subwatershed**	**area benefitted (ha)**
SL-6	9	609.6	0.6096	Grass	10	0.135
SL-6	10	444.4	0.4444	Grass	10	0.530
SL-6	16	914.4	0.9144	Forest	16	0.085
WP-2	10	381.0	0.3810	Forest	16	0.345
Total		**2,349.4**	**2.35**			**0.5475**
Upland area filtered for P/S			**4.70**			**1.095**

**linear length multiplied by buffer width of 10 m.*

Table 5-2 shows streamside fencing buffer protection length of 2,349.4 m and 547.5 m for site-specific and disaggregated BMP data, respectively.

The CBWM new BMP-categories of disaggregated cover crops were consolidated into one group consisting of cover crop early drilled wheat (CoverCropEDW), cover crop standard drilled wheat (CoverCropSDW) and commercial cover crop early drilled wheat (ComCoverCropEDW). For NMPs, this study simulated disaggregated NMPs provided in Appendix 4 as Enhanced NM. Enhanced NMs were discussed in section 2.4.1. County-level lumped BMP areas that were more than available land use on which they fell were redistributed on the neighboring subwatersheds.

5.2.3 Characterization of NMPs as Applied in Upper Opequon Watershed

The NMPs were simulated by adjusting the nutrient applications rates to the benefited areas. In the HSPF UCI file, this was achieved by creating a new land use, for example, a new cropland land use for the benefited area and assigning it a unique PERLND number for the given subwatershed. The model then routed pollutants from this PERLND via the same MASS-LINK block as for the original cropland land use. The original land use area was reduced by an amount equal to the NMP benefited area for the subwatershed. The procedure was discussed in detail in section 2.7. Information on characteristics of NMPs in the Upper Opequon Watershed was obtained via discussions with nutrient management specialists working in Frederick County (Booher, 2012, personal communication; Marshall, 2012, personal communication), and by interviewing farmers within the watershed.

The NMP practices in the Upper Opequon Watershed mainly consist of poultry litter imported from neighboring areas such as Page County, VA, and the State of Pennsylvania. Rarely do farmers apply dairy manure as beef cattle are the dominant livestock in the watershed, and beef animals spend almost all their time on pasture in this watershed. Information on NMP practice and nutrient application rates discussed in the subsequent sections were obtained from farmers in the watershed and field experts (Booher, 2012, personal communication; Marshall, 2012, personal communication; Rau, 2012, personal communication). Poultry litter laboratory tests show that poultry litter used in Upper Opequon contains on average 5.71 kg- NH_4/Mg (11.42 lbs-NH_4.N/ton) and 29.125 kg-TN/Mg (58.25 lbs-TN/ton). Litter application rates are mainly N-based NMPs (Booher and Rau, 2012, personal communication), and depend on the manure nutrient levels, soil test-P and the manure application history. The average amount of litter applied per acre is 3.36 Mg/ha, but the rate ranges from 0 - 4.48 Mg/ha. Rate of litter application translates to 19.23 kg-NH_4-N/ha and 65.40 kg-Org-N/ha. According to the laboratory tests, the

average litter test-P was estimated at 62.93 kg-P_2O_5/ha (56.05 lbs-P_2O_5/ac). The average poultry litter test-P shows that P is applied 39 kg-P_2O_5/ha (160%) beyond the corn-P needs. Most of this excess P is retained and accumulate in the soil while some P is lost via run-off to the Opequon Creek.

The average corn expected yield for Frederick County is 6.8 Mg/ha (108 bushels/acre) and soybean yield of 1.45 Mg/ha (23 bushels/acre) (USDA, 2007). The soils in the Upper Opequon were found to belong to the soil hydrologic group IVB. Soybeans do not require N applications during the growing season as most of its N is derived via leguminous atmospheric N-fixation. The corn N needs were 123.5 kg-N/ha (110 lbs-N/ac) and 24.25 kg-P_2O_5/ha (21.6 lbs-P_2O_5/ac) with respect to the soil hydrologic group IVB. The corn P-needs were determined from the soil test-P data results obtained from the nutrient specialists in the watershed (Booher, 2012, personal communication; Marshall, 2012, personal communication) for the period 2008-2010. The monthly distribution of poultry litter is shown in Table 5-3.

Table 5-3: Estimated Poultry Litter and Commercial Fertilizer Application Rates with NMPs

Month	Pre-BMP N rate (kg/ha)		NMPs N rate (kg/ha)		Pre-BMP fertilizer (kg/ha)		NMPs fertilizer (kg/ha)		Pre-BMP P rate (kg/ha)		NMPs P rate (kg/ha)	
	NH_4	Org-N	NH_4	Org-N	NH_4	NO_3	NH_4	NO_3	NH_4	Org-N	NH_4	Org-N
	Corn/Hay*		Corn/Hay**		Corn/Hay		Corn	Corn	Corn/Hay		Corn/Hay	
J												
F	18.46	24.43	3.03/2.7	12.28/10.80					5.83	5.83	2.83	2.83
M	36.92	48.87	6.05/5.32	24.58/21.73					14.55	14.55	6.81	6.81
A	36.92	48.87	6.05/5.32	24.58/21.73					14.55	14.55	6.81	6.81
M	14.77	19.55	2.43/2.14	9.82/8.64					11.63	11.63	5.45	5.45
J	3.70	4.89	0.61/0.54	2.46/2.16					2.91	2.91	1.36	1.36
J***					38.8	12.91	7.22	2.41				
A												
S												
O	5.62	7.44	1.01/0.89	2.58/2.27	6.70	2.33			8.85	8.85	4.14	4.14
N	5.62	7.44	1.01/0.89	2.58/2.27					8.85	8.85	4.14	4.14
D												

Note: No commercial fertilizer applied on hay under NMPs because all its N-needs are sufficiently met by poultry litter application.
**Value same for corn and hay*
***First and second values refer to corn and hay respectively*
****Commercial fertilizers applied as side-dress six weeks after planting*

For modeling purposes, it was assumed that 55% of organic N from the poultry litter was available to plants over the growing season when applied in spring or early fall (Mullins, 2000). Further, of the residual organic N, 20% was assumed available for crops in the subsequent growing season for cropland continuously receiving manure (4 out of 5 years) (VADCR, 2005). For ammonium, 90% was assumed plant available while 10% loss would occur through volatilization (Booher, 2012, personal communication). The remaining balance of required N was estimated using Virginia's Nutrient Management Standards and Criteria (2005) and soil productivity, plus residual from previous manure and legume history. The balance (deficit) was applied as a side-dress application of either dry urea, or UAN (urea ammonium nitrate) solution. Phosphorus from manure was assumed to be 50% organic-P, and 50% available PO_4-P (Liu, 2011).

A mix of hay (that is, rotational hay that follows the corn-soybean-hay 7-year rotation) and pasture grass is grown in the watershed, and the common species are the tall fescue/orchard grass and timothy/clover mix. Accordingly, the soil test-P levels in the watershed showed that hay production nutrient needs under NMPs were 90 kg-N/ha (80 lbs-N/ac) and 9.09 kg-P_2O_5/ha (8.1 lbs-P_2O_5/ha). To meet hay nutrient N-needs, poultry litter was applied at the rate of 2.9 Mg/ha (1.3 tons/ac). In the Upper Opequon Watershed over 90% of crops are grown under no-till drilling with a few isolated cases of conventional tillage (Rau, 2012, personal communication). To account for the impacts of no-till on cropland the following BMP effectiveness factors were used in the model TN: 8%, TP: 22%, TSS: 30% as recommended by the MAWP reported in the CBP (2010c).

Commercial fertilizer applications were estimated and simulated with 25% of N application assumed to be converted into NO_3-N, 75% of N application was assumed to be converted into NH_4-N. No P_2O_5 application was required from commercial fertilizer since all P-needs of the crops were supplied in excess from the poultry manure applications based on the current N-based NMPs practice.

In the case of cover crop and livestock exclusion BMPs, the BMP effectiveness values which represent the efficiency with which a BMP acts in reducing loads were obtained from the CBP Scenario Builder (CBP, 2010c). The BMP effectiveness values were multiplied with the constituent multiplication factors found in the MASS-LINK block of the HSPF model. The

estimated BMP response (E%) values that were used are shown in Table 5-4 for Valley and Ridge Non-Tidal region.

Table 5-4: Cover Crops and Livestock Exclusion BMP Effectiveness Values

BMP	TSS (E%)	TN (E%)	TP (E%)
Cover Crop (normal drilling)	20	29	15
Streamside fencing	40	25	30

E% indicates BMP effectiveness

Source: CBP (2010c)

5.2.4 Statistical Analysis

The effects of using site-specific and disaggregated county-level BMP datasets were evaluated by comparing pre-BMP/baseline model simulations with simulations with BMPs. The three BMPs were lumped together and simulated. Percentage BMP load reduction (E%) was then computed using the equation:

$$E\% = \frac{x_2 - x_1}{x_1} x100 \quad \ldots\ldots\ldots\

installations of livestock fencing. The average annual modeled BMP and hypothetical scenario outputs for the period 1988-2027 were then compared with CBP Bay TMDL target goals.

The average annual edge-of-stream loads (in tons per year) corresponding to each land use category from the CBP TMDL (CBP, 2010d) were obtained and used to calculate the area-weighted unit area loads (UALs) for the Upper Opequon Watershed. The UALs are land use specific load losses per unit area. The applications of UALs in this study are presented in section 6.3 of chapter 6, and their derivation is provided in the subsequent discussions.

Comparing the CBP reported county aggregated land use in 2002 (Table 5-1) for the Upper Opequon Watershed and the 2011 revised land use categories (Table 5-5), in the Bay TMDL CBWM outputs for the Virginia segment (14,898 ha versus 12,898 ha) provide a difference of 2,000 ha (13.4%). The CBWM phase 5.3.2 input data revisions were conducted in May 2011 which resulted in the above difference as compared to the 2002 CBWM land use data presented in Table 5-1. The changes in the model's inputs and outputs revealed deficiencies in the model's simulation of agricultural nutrient management as well as high variability in loads when evaluated at the local scale (VADCR, 2012). The Virginia Bay TMDL 2011 revised land use area (Table 5-5) in the TMDL outputs compared to the site-specific land use (Table 5-1) gives a difference of 2,043 ha (13.7%). For consistency with the land use category target loads, areas of land use categories used in the CBWM outputs for the Virginia Bay TMDL were used to calculate the UALs for the study watershed. The UALs were obtained by dividing the average annual loads by the corresponding acreage for each land use category (Table 5-5) following the disaggregate method of Yagow et al. (2012). The resulting UALs are in Table 5-5.

Table 5-5: Calculated Average Unit Area Target Loads for Each Land Use According to EPA TMDL Allocation for Upper Opequon

CBP Land Use Code	CBP Land Use Category	Land Use Group	CBP Area ha	Distribution (%)	Unit Area Loads (UAL)		
					Sediment Mg/ha/yr	TN kg/ha/yr	TP kg/ha/yr
hom	high-till without manure	Cropland	682.2	5.48	1.26	14.86	2.61
hwm	high-till with manure		214.6	1.73	1.10	14.16	1.41
lwm	low-till with manure		146.7	1.18	0.34	12.45	0.81
nhi	high-till with manure nutrient management		8.9	0.07	0.87	12.89	1.26
nho	high-till without manure nutrient management		10.2	0.08	1.28	14.16	2.65
nlo	low-till with manure nutrient management		6.1	0.05	0.61	12.16	1.04
urs	nursery		0.3	0.00	2.35	100.25	72.03
alf	alfalfa	Pasture	189.5	1.52	0.31	3.92	0.72
nhy	hay with nutrients nutrient management		155.6	1.25	0.31	3.92	0.15
hyw	hay with nutrients		1217.6	9.79	0.31	4.20	0.04
npa	pasture nutrient management		9.6	0.08	0.49	2.88	0.95
hyo	hay without nutrients		271.0	2.18	0.31	2.03	0.02
pas	pasture (no nutrient management)		2587.0	20.80	0.43	2.72	0.94
trp	pasture corridor		132.5	1.06	5.09	23.62	10.70
afo	animal feeding operations	Loafing lot	16.3	0.13	2.11	388.64	39.30
for	forest	Forest	4795.0	38.55	0.09	1.35	0.11
hvf	harvested forest		48.4	0.39	0.54	6.33	0.46
pul	low-intensity pervious urban	Residential	1224.3	9.84	0.20	3.30	0.47
puh	high-intensity pervious urban		190.3	1.53	0.20	3.33	0.48
bar	bare-construction	Urban	36.8	0.30	11.92	13.35	7.79
imh	high-intensity impervious urban		253.0	2.03	1.26	3.89	1.63
iml	low-intensity impervious urban		217.8	1.75	1.26	3.89	1.63
ext	extractive		26.0	0.21	2.11	6.69	3.96
Total			**12,898***	**100**			

**Revised Bay model data as reported by VADCR (2012). CBP = Chesapeake Bay Program*

The UALs in Table 5-5 were then area-weighted to provide group UALs for each of the consolidated land use groups in Table 6-10 of chapter 6. The grouped UALs were then multiplied by the corresponding site-specific land use area for each of the six land use groups to obtain the local watershed annual target pollutant loads. To make comparisons with target loads, the long-term average annual sediment and nutrient loads were calculated for this watershed using the HSPF model loads output. Long-term average annual loadings were used because TMDLs are written as long-term average annual target loads (Mandel et al., 2008; MDDEQ, 2012; VADCR and VADEQ, 2003b; Yagow, 2004; Yagow et al., 2012; Younos et al., 2007), and not for a specific year. The results were then compared to the expected Bay TMDL annual target goals.

6 Results and Discussion

In the US, aggregated land use, agricultural production, and livestock population data at county and state scales are available from federal agencies such as USDA/Agricultural Census data, and are extensively used in the CBWM. Model input data lumped at a larger scale and disaggregated for use in simulating locally impaired watersheds may not be representative of site-specific conditions. In this study, modeled loadings based on county-level aggregated data were compared with site-specific data (land use and BMPs) for the Upper Opequon Watershed.

6.1 Effects of Watershed Land Use Data on HSPF-AGCHEM Predictions of Flow and Sediment and Nutrient Loadings

The research question addressed in this section was, are the differences arising from the use of county-level aggregated versus site-specific land use data in HSPF-predicted flow, sediment, TN and TP loads using different land use spatial data at subwatershed and watershed levels significant? It was hypothesized that differences in modeled loadings from site-specific and disaggregated land use are significant at monthly and annual time-scales at $\alpha = 0.05$.

6.1.1 Comparison of Land Use Areas

Preliminary analysis of the land use spatial data (Table 5-1) established both significant and minor differences in land use areas. Shown in Table 6-1, these differences vary across the subwatersheds. The aggregated land use data were obtained from the 2002 CBP data (CBP, 2010b) and disaggregated across the subwatersheds via area-weighted-ratios using the site-specific subwatershed to watershed area. This approach is similar to that used in the CBWM.

Table 6-1: Differences in Site-Specific and Disaggregated Land Use Areas at Subwatershed Level

Subwatershed	Cropland (ha)	Pasture (ha)	Loafing lot (ha)	Forest (ha)	Residential (ha)	Urban (ha)
1	1.54	-1.70	0.02	2.06	1.78	-3.72
2	11.13	-33.16	0.26	-2.39	21.94	1.50
3	21.38	54.57	0.40	-34.45	-51.30	8.30
4	5.75	-0.81	0.07	-12.55	5.10	5.60
5	33.77	-162.71	0.68	56.80	52.06	17.57
6	40.20	-9.88	0.54	-43.56	-1.82	13.04
7	79.43	137.09	1.02	-63.81	-83.93	-72.59
8	29.43	-54.33	0.78	-37.41	64.82	-5.38
9	29.03	195.06	1.51	-9.03	-110.40	-110.24
10	33.81	-151.94	0.30	59.76	94.01	27.98
11	45.51	-118.83	0.70	9.88	49.19	11.66
12	89.27	-140.65	1.81	108.46	-90.00	26.23
13	20.81	31.21	1.99	42.67	10.20	-112.27
14	56.32	113.68	0.72	1.13	-165.99	-7.77
15	-52.23	-44.62	2.05	-34.78	72.11	51.98
16	76.15	-140.53	2.24	-70.28	89.03	37.37
Area difference	***453.68***	***-327.55***	***15.10***	***-27.49***	***-43.20***	***-114.09***
%RE	***56.38***	***-4.59***	***1,381.11***	***-0.56***	***-2.89***	***-18.68***

Note: Positive values indicate that disaggregated land use area is higher than site-specific land use area. Negative values indicate that site-specific land use area is higher than disaggregated land use area.

The differences in land use area at the watershed-level are minor except for cropland (56%) and loafing lots (1,381%). Land use area differences can result in significant variations in modeled loadings particularly for cropland and loafing lots, which are major sources of nutrient per unit area. For this watershed, the overall difference in total land use area is 43.5 ha, which represents about 0.29% of the total watershed area. This variation is generally negligible when compared to the total watershed area of 14,941 ha and it arises from the different approaches used in developing the land use categories which were discussed in sub-section 5.1.1. Table 6-7 discussed later in section 6.1.5 directly compares predicted flow and loadings from each land use group based on the two land use assessments.

6.1.2 Results of Modeled Monthly Loadings at the Watershed Outlet

The HSPF model was run using site-specific and county-level disaggregated land use for the period 1988-2009. Average monthly watershed modeled results from the two land use distributions for flow and mass losses of sediment, TN and TP are shown in Table 6-2.

Table 6-2: Effects of Site-Specific and Disaggregated Land Use on Average Monthly Flow, Sediment, TN and TP Losses at Watershed Outlet

Month	Flow			Sediment			Total N			Total P		
	site-spec (mm)	disagg (mm)	%RE	site-spec (Mg)	disagg (Mg)	%RE	site-spec (kg-N)	disagg (kg-N)	%RE	site-spec (kg-P)	disagg (kg-P)	%RE
J	40.39	40.21	-0.45	835	891	6.71	9,334	9,584	2.68	978	968	-1.02
F	40.23	40.08	-0.37	1,192	1,275	6.96	11,478	1,1846	3.21	1,098	1,149	4.64
M	48.00	47.84	-0.33	781	837	7.17	9,844	1,0310	4.73	906	967	6.73
A	36.75	36.83	0.22	800	1,001	25.13	10,221	1,1586	13.35	830	1,011	21.81
M	33.67	33.75	0.24	508	652	28.35	7,267	8,192	12.73	620	789	27.26
J	30.23	30.16	-0.23	861	938	8.94	9,891	1,0582	6.99	1,003	1,128	12.46
J	18.79	18.65	-0.75	79	91	15.19	4,011	4,186	4.36	253	331	30.83
A	17.26	17.36	0.58	299	400	33.78	5,118	5,963	16.51	548	717	30.84
S	22.79	22.70	-0.39	717	778	8.51	10,094	1,0862	7.61	955	1,048	9.74
O	27.48	27.57	0.33	1,367	1,491	9.07	1,0634	12,005	12.89	1,182	1,321	11.76
N	29.28	29.39	0.38	919	1,027	11.75	8,480	9,375	10.55	1,987	2,048	3.07
D	38.73	38.58	-0.39	989	1,031	4.25	8,765	8,744	-0.24	1,186	1,150	-3.04
Average	***31.97***	***31.93***	***-0.10***	***779***	***868***	***13.82***	***8,761***	***9,436***	***7.95***	***962***	***1,052***	***12.92***
p-value		**0.3730**			**0.1970**			**0.0005**			**0.0005**	

*disaggregated

Average monthly modeled outputs show slightly higher predicted flow from site-specific land use than disaggregated land use. The flow differences over the months are generally small with %RE less than 1%. Flow is not significantly different with $p = 0.373$ at $\alpha = 0.05$. Flow variations in most months are only fractions of 1 mm depths. Average annual predicted sediment load is higher for disaggregated land use data than site-specific land use data. The %RE over the months varies between 4 to 34% with an average of 14%. The Wilcoxon signed-rank test at $\alpha = 0.05$ has $p = 0.197$, thus sediment loads are not significantly different at the watershed outlet. For TN %RE varies between -0.2 to 17% with disaggregated land use data having higher TN losses than site-specific land use data. The TN losses are statistically significantly different with $p = 0.0005$ at $\alpha = 0.05$. Similarly, TP losses are higher for disaggregated than site-specific land uses and %RE varies from -1 to 31% with an average of 4.8%. The Wilcoxon test statistic at $\alpha = 0.05$

shows TP loads are significantly different with p = 0.0005. Negative %RE means flow and loads from site-specific land use are more than that from disaggregated land use.

6.1.3 Results of Modeled Monthly Loadings at Subwatershed Outlets

Table 6-3 shows modeled results at the subwatershed level.

Table 6-3: Effects of Site- Specific and Disaggregated Land Use on Average Monthly Flow, Sediment, TN and TP Loadings at Subwatershed Outlet

Subws	Flow (mm)			Sediment (Mg)			TN (kg)			TP (kg)		
	site-spec	disagg	p-value	site-spec	disagg	p-value	site-spec	disagg	p-value	site-spec	disagg	p-value
1[a]	40.4	40.2	0.3730*	835	891	0.1970*	9334	9584	0.0005	978	968	0.0005
2	31.9	32.1	1.000*	779	868	0.0040	8812	9491	0.0005	967	1057	0.0005
3	0.84	0.79	0.0005	19	24	0.0049	290	303	0.1680*	29	33	0.0110
4	30.6	30.7	0.0015	757	769	0.9873*	8525	9172	0.0005	942	1028	0.0005
5	1.2	1.3	0.0005	81	89	0.0005	602	658	0.0005	84	92	0.0005
6	29.3	29.2	0.5693*	785	792	0.0640*	8238	8695	0.0005	735	741	0.2334*
7	2.1	2.9	0.0005	86	114	0.0005	838	957	0.0005	110	131	0.0005
8	26.1	26.2	0.0005	666	717	0.2661*	7613	8016	0.0005	826	881	0.0024
9	3.11	3.8	0.0005	147	167	0.0005	1606	1620	0.0640*	203	216	0.9097*
10	21.5	21.8	0.0005	565	606	0.0005	6105	6459	0.0005	584	606	0.0005
11	15.6	15.8	0.0005	396	429	0.0005	7678	5665	0.0005	473	515	0.0005
12	3.4	3.8	0.0005	186	212	0.0010	1659	1653	0.0005	220	225	0.0005
13	11.3	11.6	0.0923*	341	357	0.0005	5015	5679	0.0005	473	475	0.2661*
14	1.5	1.9	0.0005	59	81	0.0005	518	788	0.0005	103	106	0.0005
15	7.5	7.9	0.0005	244	252	0.0005	3654	3941	0.0005	341	315	0.0005
16	3.90	4.1	0.0005	249	285	0.0005	2252	2672	0.0005	287	348	0.0005

[a]*Subwatershed 1is also the watershed outlet, disagg indicates disaggregated and *Indicates insignificant difference at $\alpha = 0.05$*

Variations in average monthly flow and loadings at the subwatersheds outlets are presented in Table 6-3. The monthly flow is significantly different in all subwatersheds except in subwatersheds 1 (p = 0.373), 2 (p = 1.000), 6 (p = 0.5693) and 13 (p = 0.0923). Sediment is significantly different except in subwatershed 1 (p = 0.197), subwatershed 4 (p = 0.9873), subwatershed 6 (p = 0.064) and subwatershed 8 (p = 0.2661). Total N is significantly different in all subwatersheds except subwatersheds 3 (p = 0.168) and 9 (p = 0.064). Total P is not significantly different in three subwatersheds namely, 6, 9, and 13 with corresponding p-values of 0.2334, 0.9097 and 0.2661, respectively. Thus, in a majority of subwatersheds predicted flow

and loadings were statistically significantly different. Predicted flow and pollution loads from individual land use groups are discussed in section 6.1.5.

6.1.4 Relative Errors in Average Monthly Loadings at Subwatershed Level

Table 6-4 presents a summary of %RE for average monthly modeled outputs for each individual subwatershed.

Table 6-4: Relative Errors to Site-Specific Land Use for Average Monthly Flow and Loadings at Subwatershed Level

Subwatershed	Flow %RE	Sediment %RE	TN %RE	TP %RE
1	-0.50	6.71	2.68	-1.02
2	0.63	11.42	7.71	9.31
3	-5.95	26.32	4.48	13.79
4	0.33	1.59	7.59	9.13
5	8.33	9.88	9.30	9.52
6	-0.34	0.89	5.55	0.82
7	38.10	32.56	14.20	19.09
8	0.38	7.66	5.29	6.66
9	22.19	13.61	0.87	6.40
10	1.40	7.26	5.80	3.77
11	1.28	8.33	-6.22	8.88
12	11.76	13.98	-0.36	2.27
13	2.65	4.69	13.24	0.42
14	26.67	37.29	52.12	2.91
15	5.33	3.28	7.85	-7.62
16	5.13	14.46	18.65	21.25

Flow has the highest and lowest %RE in subwatersheds 7 (38%) and 4 (0.33%), respectively. There are considerable %RE for sediment in subwatersheds 3 (26%), 7 (33%), 9 (14%), 12 (14%), 14 (37%) and 16 (14%). Similarly, large %REs corresponding to TP are in the same subwatersheds except subwatershed 12. This would be expected because the model simulated P loss largely as a function of sediment loss. Large %RE for TN loads are found in subwatersheds 7 (14%), 14 (52%) and 16 (19%). In Table 5-1, these subwatersheds have higher cropland area resulting from disaggregated land use data. For example, there is 79 ha, 56 ha and 76 ha additional cropland acreage in subwatersheds 7, 14 and 16, respectively. Differences in modeled

outputs are below the zero line mark in subwatersheds 1, 3 and 6 for flow, subwatersheds 11 and 12 for TN, and subwatersheds 1 and 15 for TP, respectively (Table 6-4). The site-specific land use outputs are higher than the disaggregated land use data in those subwatersheds. How these differences affect the modeled outputs for individual land uses is discussed in Table 6-7, section 6.1.5. Overall, at the watershed outlet (subwatershed 1) flow, sediment, TN and TP have differences of -0.5%, 7%, 3% and -1%, respectively.

The general distribution of %RE can be visualized in Figure 6-1. The %RE spikes for flow, sediment and TP are notable in subwatersheds 7 and 14. Except for site-specific residential land use, the rest of the land uses in subwatershed 14 were much more for disaggregated land use data than site-specific land use data. Thus, sharp %RE spikes in some subwatersheds are due to large differences between site-specific and disaggregated land use, which provide additional surface area for flow and load generation. The %RE values for average monthly TN generally decrease moving downstream towards the watershed outlet in subwatershed 1 (Figure 6-1).

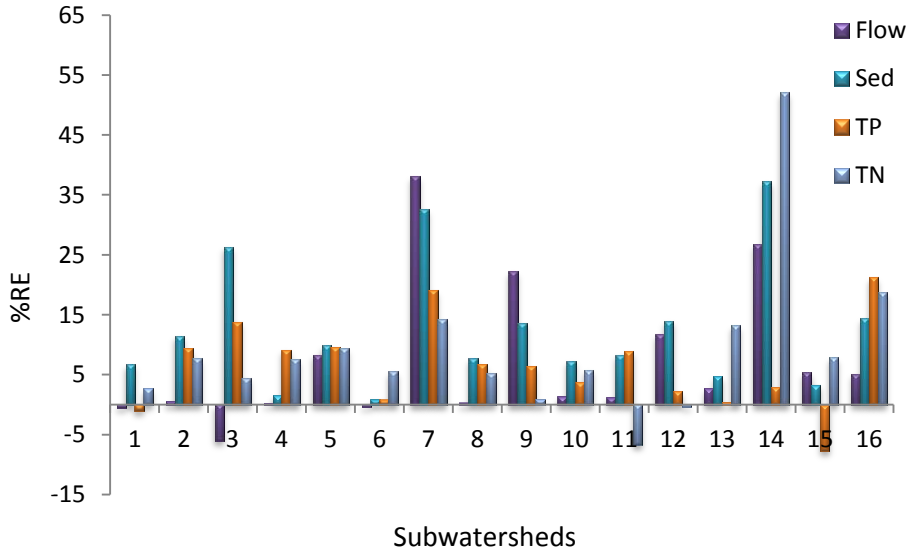


Figure 6-1: Bar Chart for Monthly Relative Errors of Modeled Outputs to Site-specific Land Use

6.1.5 Annual Predicted Loadings at the Watershed Outlet

Table 6-5 compares annual predicted loads for the two land use assessments for the Upper Opequon Watershed.

Table 6-5: Effects of Site-Specific and Disaggregated Land Use on Annual Predicted Flow, Sediment, TN and TP Loadings at the Watershed Outlet

Year	Flow (mm)		Sediment (Mg)		Total N (kg)		Total P (kg)	
	site-spec	disaggregated	site-spec	disaggregated	site-spec	disaggregated	site-spec	disaggregated
1988	124.3	123.9	3,820	5,304	42,551	46,993	5,502	6,190
1989	195.5	196.7	4,502	6,034	66,145	70,040	8,568	9,907
1990	181.5	181.7	4,502	5,146	64,685	66,181	9,182	9,633
1991	372.9	374.3	23,878	31,162	145,964	158,794	18,418	20,295
1992	274.2	273.8	21,196	30,056	153,143	179,343	21,332	24,950
1993	465.4	466.2	20,008	26,788	142,928	153,731	22,855	24,677
1994	610.5	613.6	46,916	64,418	266,364	291,534	43,570	48,032
1995	203.8	202.7	7,424	9,322	71,065	73,370	11,653	11,662
1996	590.4	592.3	39,268	50,966	268,526	284,155	39,082	41,782
1997	426.8	425.1	9,134	12,136	110,078	115,425	14,130	15,033
1998	416.6	417.9	13,012	17,360	123,703	130,200	21,195	22,408
1999	135.8	135.9	1,886	2,728	48,833	51,619	5,268	5,998
2000	472.7	473	20,500	26,576	149,866	154,984	18,250	19,595
2001	233	233.3	11,732	15,922	89,460	94,611	13,078	14,163
2002	340	339.3	12,078	15,208	93,019	92,903	10,187	10,882
2003	528.6	529.6	31,578	40,798	178,025	186,065	25,065	26,948
2004	490.9	491.5	12,640	19,888	115,725	129,279	14,077	17,500
2005	427.2	428.5	21,674	27,250	113,859	117,975	20,323	20,327
2006	508.6	510.3	38,916	50,900	238,734	259,854	35,735	39,003
2007	401.4	402.3	15,940	21,684	106,585	116,005	13,902	15,387
2008	525.4	527.1	30,384	43,572	171,271	203,744	23,472	28,725
2009	338.8	339.3	10,648	14,050	82,737	86,655	11,463	12,083
Total	***8,264***	***8,278***	***401,636***	***537,268***	***2,843,264***	***3,063,458***	***406,307***	***445,180***
Average	***3756***	***376***	***18,256***	***24,421***	***129,239***	***139,248***	***18,468***	***20,235***
%RE	***0.2***		***33.8***		***7.7***		***9.6***	
p-value (at α = 0.05)	***0.012***		***<0.0001***		***<0.0001***		***<0.0001***	

Similar to average monthly flow, differences in average annual flow are minor (Table 6-5). The average %RE of flow is 0.2% and statistically significant with $p = 0.012$. Average annual sediment loads differ by 34% at the watershed exit. Discrepancies in land use areas as sediment moves from the upstream subwatersheds may have resulted in this large error. Sediment loads are statistically significant with $p < 0.0001$. Average annual TN loads are significant with $p < 0.0001$ and the difference is 8% (10,009 kg-TN/yr). Predicted TP loads differ by 1,767 kg-TP/yr which is approximately 10% in relative error to the site-specific TP load. Total P loads are statistically significantly different with $p < 0.0001$. Simulated flow and loadings resulting in more than 10% variation can pose a threat during decision-making process because most TMDLs are commonly associated with a conservative margin of safety of 10%.

6.1.6 Relative Errors in Average Annual Predicted Loadings at Subwatershed Level

Table 6-6 is a summary of the %RE results and their corresponding tests of significance differences.

Table 6-6: Effects of Site-specific and Disaggregated Land Use on Flow, Sediment TN and TP at Subwatershed level

Subwatershed	Flow			Sediment			Total N			Total P		
	difference (mm)	%RE	p-value	difference (Mg-sed)	%RE	p-value	difference (kg-TN)	%RE	p-value	difference (kg-TP)	%RE	p-value
1[a]	0.7	0.2	0.007	6,165	33.8	<0.0001	10,009	7.7	<0.0001	1,767	9.6	<0.0001
2	0.6	0.2	0.007	2,090	11.4	<0.0001	10,077	7.8	<0.0001	1,777	9.6	<0.0001
3	0.3	3.3	<0.0001	112	19.9	<0.0001	202	4.5	<0.0001	65	10.3	<0.0001
4	0.5	0.2	<0.0001	1,953	11.0	<0.0001	9,589	7.6	<0.0001	1,685	9.3	<0.0001
5	1.0	7.3	<0.0001	115	12.3	<0.0001	659	9.3	<0.0001	93	9.4	<0.0001
6	-0.7	-0.2	0.095*	1,835	0.5	0.0040	8,792	7.2	<0.0001	1,571	9.1	<0.0001
7	-2.2	-8.8	<0.0001	432	2.2	<0.0001	1,422	14.2	<0.0001	256	19.8	<0.0001
8	1.0	0.3	<0.0001	1,212	0.4	0.6640*	5,972	5.3	<0.0001	1,107	6.8	0.0001
9	-3.4	-9.2	<0.0001	241	0.6	0.2340*	655	3.5	0.001	148	2.1	0.485*
10	3.5	1.4	<0.0001	866	0.3	0.0010	4,210	4.6	<0.0001	774	5.7	<0.0001
11	2.3	1.2	<0.0001	781	0.4	0.0010	3,761	5.9	<0.0001	835	8.9	<0.0001
12	-0.5	-1.3	<0.0001	311	0.6	0.0001	-63	-0.3	0.0001	878	9.4	0.0001
13	3.3	2.5	<0.0001	366	0.2	0.0131	4,860	6.6	<0.0001	2.6	7. 6	<0.0001
14	-2.1	-11.5	<0.0001	263	1.7	<0.0001	-303	-3.2	<0.0001	25	2.0	1.000*
15	5.3	6.0	<0.0001	193	0.2	<0.0001	4,278	7.9	<0.0001	731	10.9	<0.0001
16	2.9	6.2	<0.0001	432	0.7	<0.0001	4,869	18.7	<0.0001	726	21.5	<0.0001

*[a]subwatershed 1indicates differences at the watershed outlet, *indicates output significantly different at α = 0.05, and %RE- = percentage relative error (Equation (5-1))*

For flow, most subwatersheds had differences that were less than 10%. The maximum %RE is -12% in subwatershed 14, while the minimum %RE is 0.2% in subwatersheds 1, 2 and 6. Flow is significantly different in all subwatersheds except subwatershed 6 ($p = 0.095$) at $\alpha = 0.05$ (Table 6-6). County-level disaggregated land use data produced more loads than site-specific land use data. Sediment has maximum and minimum differences of 34% in subwatershed 1(watershed outlet) and 0.2% in subwatershed 15, respectively. The Wilcoxon signed-rank test had sediment not significantly different in subwatershed 8 ($p = 0.6640$) and subwatershed 9 ($p = 0.2340$) at $\alpha = 0.05$ (Table 6-6). Total N has its highest difference of 19% in subwatershed 16 and minimum %RE of -0.3% in subwatersheds 12, and the load differences are significantly different in all subwatersheds ($p < 0.0001$). Total P has its maximum and minimum differences of 22% and 2% in subwatersheds 16 and 14, respectively. The %RE for sediment and TP are all above the zero line of the bar chart. Total P loads are significantly different except subwatershed 9 ($p = 0.485$) and subwatershed 14 ($p = 1.000$) (Table 6-6). In subwatersheds 12 and 14, modeled TN from site-specific land use data exceeds the disaggregated land use output by -0.3 and -3.2, respectively. It is expected that a predicted difference exceeding 10% in annual loads would pose a risk in decision-making. The visualization of subwatershed %RE on predicted average annual flow and total mass losses of sediment, TN and TP are shown in Figure 6-2.

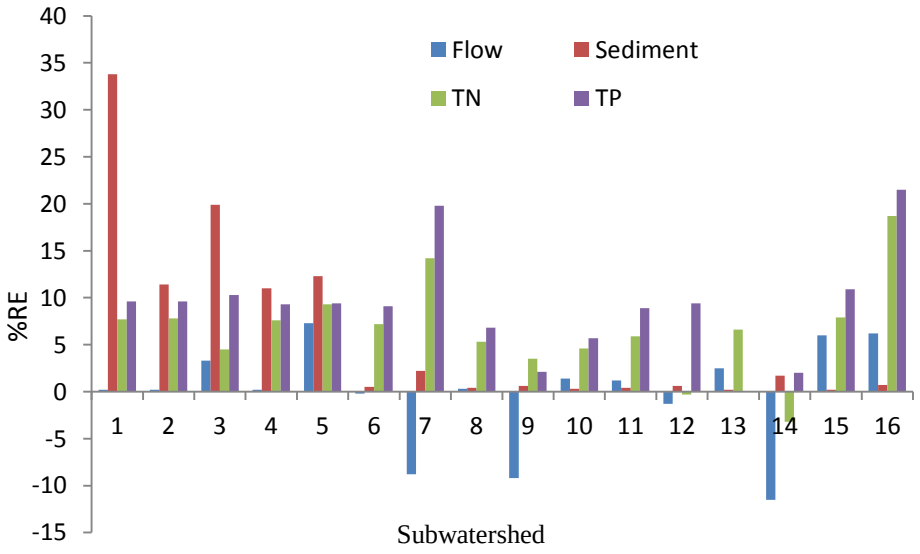


Figure 6-2: Bar Chart for Annual Relative Errors of Modeled Outputs to Site-Specific Land Use

An interesting observation in Figure 6-2 is that the error spikes found in monthly predicted flow and loads are not seen in annual model predictions (Figure 6-1). Instead, there is a large %RE in sediment at the exit of the watershed. With large area differences in cropland and loafing lots, it was expected that this would cause large variations in predicted flow and loadings. However, it is not clear why there is such change in predicted behavior of flow and loadings between the monthly and annual model predictions.

The effects of land use on average annual predicted flow and loadings between the two land use assessments are compared in Table 6-7. The comparison between the two methods helps explain why there are differences between the two approaches yet their predicted flow and loadings are so similar.

Table 6-7: Effects of Land Use on Average Annual Predicted Flow, Sediment, TN and TP Loadings

Land Use	Flow (mm)			Sediment (Mg/yr)			TN (kg/yr)			TP (kg/yr)		
	Site-spec	disagg	%RE	Site-spec	disagg	%RE	Site-spec	disagg	%RE	Site-spec	disagg	%RE
Cropland	88	93	5.68	2,387	4,072	70.59	81,608	87,734	7.51	9,375	10,724	14.39
Pasture	202	200	-0.99	6,756	6,628	-1.89	97,878	95,642	-2.28	13,013	12,900	-0.87
Loafing Lot	70	71	1.43	23	36	56.52	77,694	79,820	2.74	11,277	12,100	7.30
Forest	164	184	12.20	3,502	4,365	24.64	78,166	92,732	18.63	10,795	12,877	19.29
Urban	80	76	-5.00	148	115	-22.30	78,054	80,279	2.85	10,630	10,583	-0.44
Residential	186	104	-44.09	929	729	-21.53	81,041	80,291	-0.93	10,065	9,798	-2.65

disagg indicates disaggregated

The variation in predicted flow and loadings follow a similar pattern as their variations in land use areas. The variation in sediment loss from cropland has the highest %RE of 71% (Table 6-7). This would be expected following the large difference in cropland area (Table 6-1). The same observation is found with the loafing lot sediment load. The difference in forest area was 0.56% with the site-specific land use data being slightly more than disaggregated data. However, it is not clear why the predicted constituents from the disaggregated forest land use are more than those of site-specific data. The rest of the land use groups show the site-specific predictions being more than the disaggregated land use data. Overall, the magnitude of differences in cropland and loafing lot are large and explain why at the outlet of the watershed loads balance out to provide the close similarities observed in Table 6-5. It is obvious from Table 6-7 that

cropland and loafing lots are important pollutant generating land uses. Such land uses become significant contributors of pollutants, which impact the quality of water bodies (Bhaduri et al., 2001; Bouraoui et al., 1998; Hanratty and Stefan, 1998; Tong and Chen, 2002; Tong et al., 2009).

6.1.7 Discussions and Implications of Load Differences on TMDL Implementation Strategies

Implementation of TMDL strategies occurs at the field and subwatershed levels, particularly for NPS pollution. At the watershed outlet, Table 6-5 shows that the differences in the annual simulated flow and loadings are statistically significant. According to Yagow (2012, personal communication) differences greater than 10% can pose a risk to TMDL implementation plans for point and NPS pollutants. In general, TMDL plans are selected and implemented based on the long-term average annual loadings. Studies show TMDLs are developed with a 10% margin of safety (MDDEQ, 2012; VADCR and VADEQ, 2003a; Walker, 2001; Yagow, 2004; Yagow et al., 2003) and a difference of approximately 34% in sediment loads is substantial and can affect the planning process

Additionally, the higher loads with disaggregated land use when compared to site-specific land use have direct implications on watershed pollution control management cost estimates for the study watershed. The costs emanate from the number of additional BMP units required to meet target loads. For instance, there are extra units in NMPs and cover crops BMP and linear length of riparian buffer fencing, in which runoff would need to be treated to achieve the target loadings. There are also extra unit cost estimates for design and installation, and hiring personnel for educational outreach. The cost estimates would be less in the present study with site-specific land use data, which resulted in lower loadings and BMP needs.

To illustrate this point, NMPs are used in this study to show the additional probable cost estimates that might be incurred when the watershed management strategies are developed on the basis of disaggregated land use outputs. The average annual loads for TN were calculated under each land use distribution and are 129,239 and 139,248 kg-TN/yr for site-specific and disaggregated land use, respectively. The corresponding TP loads are 18,468 and 20,235 kg-TP/yr for site-specific and disaggregated land use, respectively. Estimated costs for implementing NMPs on cropland correspond to the cost of equipment and labor for soil testing and possibly manure storage, hiring a consultant to design the plan, and the costs of applying

nutrients in a different manner. There is also the possibility that NMPs will reduce farming costs due to reduced nutrient application costs but analysis focuses on the additional costs associated with cost-shared NMPs. Assuming a 3-year useful life for a plan once it is developed, and including the costs of soil testing, implementation and in some cases cost savings and yield increases, net cost estimates range from -$74.10/ha-yr (that is, a net cost savings due to cost savings from manure transportation out of the farm) to $34.58/ha-yr in 2001 dollars (USEPA, 2003a).

In this study, a cost estimate of $34.58/ha-yr is used. This cost estimate does not specifically refer to the practice in the study watershed, and thus is only used for comparison purposes. Assuming that NMPs are implemented on 25% of total cropland would require 314 ha of disaggregated cropland versus 201 ha of site-specific cropland. Thus, the total comparative estimated costs of implementing NMPs on the watershed when disaggregated land use data are used would be $10,858 versus $6,951 for site-specific land use data. The difference would amount to $11,721 in additional costs in 3 years for this study watershed. Cost estimate per unit area of cropland load can be calculated if the total loading from cropland is known. The cost estimates calculated for NMPs show that using disaggregated land use data for this watershed would require 56% more money than site-specific land use data. Similar results were found by Karigomba (2009), in which nutrient reduction costs were lower under site-specific land use contributions than using the Bay-wide averages by 290%. The study by Karigomba (2009) found that the cost of implementing BMPs in three subwatersheds of Opequon Creek in West Virginia using the Chesapeake Bay averaged land use values was approximately $1.1 million compared to $282,000 using site-specific land use values.

Thus, errors in assessing the correct land use distribution in a watershed can affect cost estimates during planning and can have other implications in terms of modeled loadings. The CBP is using county-level aggregated land use data in modeling local watersheds. The choice of using county-level aggregated land use data should be determined by comparing the costs associated with acquiring and utilizing site-specific land use data, which will provide more accurate NPS pollution control assessment and targeting of limited pollution control resources with the potentially inflated control costs with disaggregated land use data.

In conclusion, this assessment implies that using disaggregated data results in more uncertainty during TMDL development that then must be addressed during the development of the implementation plan. Saving costs during TMDL development may result in less confidence in required TMDL loads. This would result in more effort (higher implementation plan development costs) during implementation planning to better characterize the uncertainty and develop an attainable implementation plan.

6.2 Effects of Disaggregating BMPs on Modeled BMP Responses Using HSPF Model

The effects of locally-derived site-specific and county-level spatially disaggregated BMP datasets on HSPF-predicted flow, sediment, TN and TP loads at subwatershed and watershed levels are evaluated and compared in this section. The question of what differences exist in the HSPF modeled BMP responses between site-specific and county-level disaggregated BMP data is discussed. It was hypothesized that BMP responses attained by site-specific and disaggregated county-lumped BMP datasets are significantly different at an annual temporal scale at $\alpha = 0.05$.

6.2.1 Best Management Practices Benefited Areas

The response of a BMP is an estimate of how well the BMP reduces the NPS delivery to the receiving water body. Site-specific BMP simulation would theoretically be expected to represent the effects of BMPs in upland areas better than county-level disaggregated BMP data that are distributed to subwatersheds. This is because site-specific BMPs better represent the actual spatial location in the watershed while disaggregated county-level data places BMPs solely based on the land use areas. The NMPs from the disaggregated BMP data were based on the enhanced NM for crops (Appendix 4). The summary of Upper Opequon Watershed BMPs benefitted areas derived from Table 5-2 is presented in Table 6-8.

Table 6-8: Estimated Area of BMPs for Site-specific versus Disaggregated BMP Datasets

BMP type	site-specific (ha)	disaggregated (ha)	difference (ha)
NMPs	119.86	424.36	304.50
Cover crops	209.31	197.28	-12.03
Streamside fencing (buffer area)	2.35	0.5475	-1.80

The NMPs benefited area for NMPs for the disaggregated BMP data is greater than that for the site-specific by 304.5 ha. Cover crops benefited area from the site-specific category have more area than the disaggregated BMP area by 12 ha (6%). For streamside fencing, the site-specific data are 76% (1.8 ha) more than the disaggregated BMP data. The implications are that if individual BMPs from site-specific and disaggregated BMP datasets are simulated and compared, then differences in modeled load reductions are likely to be quite large.

6.2.2 Annual Loads and Load Reductions due to BMPs

Watershed management plans are derived based on the long-term average annual modeled responses. In this study, average annual loads and their resulting BMP responses were simulated and compared over a period of 22 years (1988-2009). The modeled outputs of interest were flow and mass losses of sediment, TN and TP. Except for NMPs, site-specific BMP data have more cover crops and streamside fencing benefitted areas than disaggregated BMP data (Table 5-2). The simulated results are summarized in Table 6-9.

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Table 6-9: Annual Simulated Flow and Loads at the Watershed Outlet for Site-Specific and Disaggregated BMPs

Year	Flow (mm)			Sediment (Mg)			Total N (kg)			Total P (kg)		
	pre-BMP	site-spec	disaggregated	pre-BMP	site-spec	disaggregated	pre-BMP	site-spec	disaggregated	pre-BMP	site-spec	disaggregated
1988	124.3	123.6	123.2	3,820	3,622	3,710	42,551	36,570	40,383	5,502	4,912	5,018
1989	195.5	194.3	193.7	4,502	2,864	2,894	66,140	47,986	59,426	8,568	6,305	6,547
1990	181.5	180.4	179.9	4,502	2,614	2,676	64,685	44,319	58,695	9,182	7,268	7,385
1991	372.9	370.1	369	23,878	21,032	21,820	145,964	112,864	135,715	18,418	16,318	17,315
1992	274.2	272.5	271.6	21,196	15,802	16,720	153,143	109,861	125,870	21,332	16,377	17,143
1993	465.4	462	460.6	20,008	17,218	17,686	142,928	109,844	130,780	22,855	20,172	21,422
1994	610.5	606	604.2	46,916	39,426	40,704	266,364	213,718	236,678	43,570	37,393	38,898
1995	203.8	202.4	201.8	7,424	6,950	7,258	71,065	57,873	70,493	11,653	11,090	11,558
1996	590.4	586.4	584.7	39,268	36,338	37,270	268,526	226,475	206,421	21,082	19,045	20,720
1997	426.8	423.7	422.4	9,134	7,396	7,682	110,078	78,374	102,203	14,130	12,965	13,657
1998	416.6	413.6	412.4	13,012	11,116	11,280	123,703	94,029	115,529	21,195	18,965	20,088
1999	135.8	134.8	134.4	1,886	968	998	48,833	37,715	44,620	52,68	4,267	4,397
2000	472.7	469.3	467.9	20,500	19,176	19,530	149,866	128,015	144,249	18,250	15,667	16,958
2001	233	231.6	230.9	11,732	7,842	8,136	89,460	59,315	68,576	13,078	10,112	10,540
2002	340	337.5	336.5	12,078	10,510	10,944	93,019	69,636	90,136	10,187	10,080	10,093
2003	528.6	524.8	523.2	31,578	28,290	29,048	178,025	142,046	166,058	25,065	21,002	22,573
2004	490.9	487.4	485.9	12,640	10,146	10,510	115,725	78,903	106,539	14,077	13,822	14,040
2005	427.2	423.9	422.7	21,674	19,772	20,334	113,859	86,133	109,011	20,323	17,563	18,740
2006	508.6	505.1	503.5	38,916	33,966	35,362	238,734	190,744	218,576	35,735	32,475	34,102
2007	401.4	398.2	397.1	15,940	12,302	12,814	106,585	68,571	93,906	13,902	13,647	13,788
2008	525.4	521.7	520.1	30,384	23,762	24,968	171,271	111,188	14,0104	23,472	16,948	18,688
2009	338.8	336.4	335.4	10,648	6,518	6,582	82,738	51,406	70,728	11,463	7,915	8,452
Total	**8,264**	**8,181**	**8,206**	**401,636**	**337,630**	**348,926**	**2,783,733**	**2,155,583**	**2,585,694**	**406,307**	**351,307**	**371,523**
Average	**376**	**372**	**373**	**18,256**	**15,347**	**15,860**	**126,533**	**97,981**	**117,532**	**18,468**	**15,968**	**16,887**
Average Reduction		**3.8**	**2.7**		**2,909**	**2,396**		**28,552**	**9,002**		**2,500**	**1,581**
% reduction		**1.0**	**0.7**		**15.9**	**13.1**		**22.5**	**7.1**		**13.5**	**10.2**
p-value		**<0.0001**			**<0.0001**			**<0.0001**			**<0.0001**	

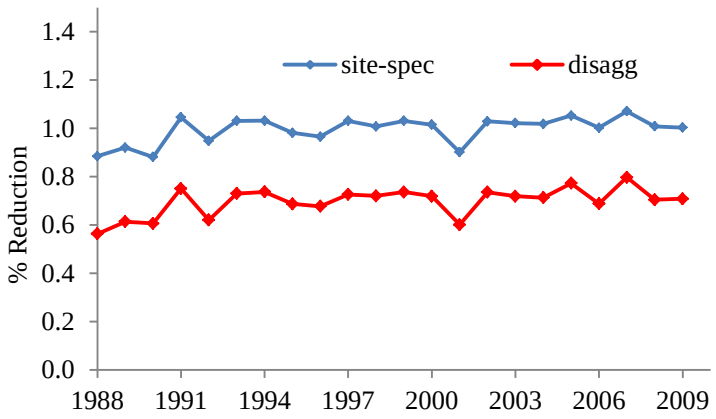
Differences in the modeled annual flow (Table 6-9) from the two BMP datasets is significantly different ($p < 0.0001$) at $\alpha = 0.05$. Though flow is statistically different, the variations over the simulation period are minor. There is an average reduction difference of 1.1 mm which represents 0.3% difference. For simulated loadings, site-specific BMP data resulted in lower pollutant yields than the disaggregated BMP data because of higher benefitted areas in cover crops and streamside fencing BMPs. Average annual load reduction difference in sediment is 513 Mg-sediment/yr or 2.8% difference between the two BMP data sources. The Wilcoxon signed-rank test finds differences in the sediment loads significantly different with $p < 0.0001$ at $\alpha = 0.05$ (Table 6-9). Load variation in average annual TN reduction is 19,550 kg-TN/yr or 15.4%. This variation is significant with $p < 0.0001$ at $\alpha = 0.05$ (Table 6-9). Average annual TP load reduction variation between the two BMP datasets is 919 kg-TP/yr or 3.3%. The test of significance showed that differences in TP loads are significant with $p < 0.0001$ at $\alpha = 0.05$ (Table 6-9).

In addition to the simulated BMP impacts, pollutant losses were also impacted by the no-till BMP. According to Rau (2012, personal communication) over 90% of the watershed is under no-till. The practice was simulated as a "pre-BMP" prior to implementing the three BMPs that were simulated in this study. The impacts of no-till reduced the amount of load reduced by the simulated two BMP data types. The BMP model input effectiveness values are discussed in section 5.2.3. Results of load reductions in each year due to BMP responses and the corresponding time-series changes are shown in Table 6-10 and Figure 6-3, respectively.

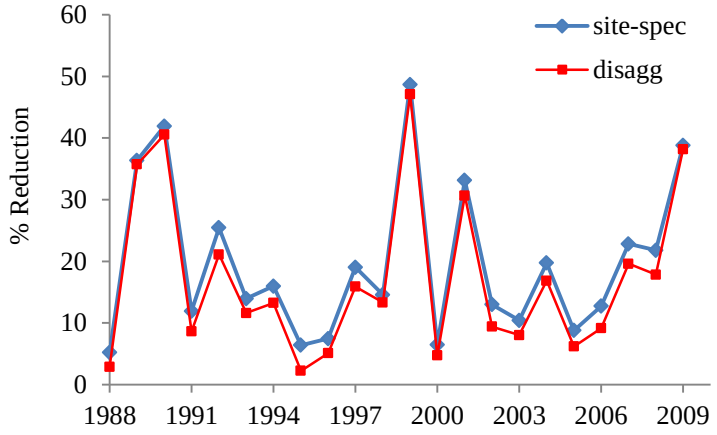
Table 6-10: Modeled Site-Specific and Disaggregated BMPs Annual Flow, Sediment, TN and TP Reductions

Year	*Flow (E%)*		*Sediment (E%)*		*Total N (E%)*		*Total P (E%)*	
	site-spec	*disaggregated*	*site-spec*	*disaggregated*	*site-spec*	*disaggregated*	*site-spec*	*disaggregated*
1988	0.88	0.56	5.18	2.88	14.06	5.10	10.72	8.80
1989	0.92	0.61	36.38	35.72	27.45	10.15	26.41	23.59
1990	0.88	0.61	41.94	40.56	31.48	9.26	20.85	19.57
1991	1.05	0.75	11.92	8.62	22.68	7.02	11.40	5.99
1992	0.95	0.62	25.45	21.12	28.26	17.81	23.23	19.64
1993	1.03	0.73	13.94	11.61	23.15	8.50	11.74	6.27
1994	1.03	0.74	15.96	13.24	19.76	11.14	14.18	10.72
1995	0.98	0.69	6.38	2.24	18.56	0.80	4.83	0.82
1996	0.97	0.68	7.46	5.09	15.66	23.13	9.66	1.72
1997	1.03	0.73	19.03	15.90	28.80	7.15	8.24	3.35
1998	1.01	0.72	14.57	13.31	23.99	6.61	10.52	5.22
1999	1.03	0.74	48.67	47.08	22.77	8.63	19.00	16.53
2000	1.02	0.72	6.46	4.73	14.58	3.75	14.15	7.08
2001	0.90	0.60	33.16	30.65	33.70	23.34	22.68	19.41
2002	1.03	0.74	12.98	9.39	25.14	3.10	1.05	0.92
2003	1.02	0.72	10.41	8.01	20.21	6.72	16.21	9.94
2004	1.02	0.71	19.73	16.85	31.82	7.94	1.81	0.26
2005	1.05	0.77	8.78	6.18	24.35	4.26	13.58	7.79
2006	1.00	0.69	12.72	9.13	20.10	8.44	9.12	4.57
2007	1.07	0.80	22.82	19.61	35.67	11.90	1.83	0.82
2008	1.01	0.70	21.79	17.83	35.08	18.20	27.79	20.38
2009	1.00	0.71	38.79	38.19	37.87	14.52	30.95	26.27
Min	***0.88***	***0.56***	***5.18***	***2.24***	***14.06***	***0.80***	***1.05***	***0.26***
Max	***1.07***	***0.80***	***48.67***	***47.08***	***37.87***	***23.34***	***30.95***	***26.27***
Mean	***0.99***	***0.70***	***19.75***	***17.18***	***25.23***	***9.88***	***14.09***	***9.98***
Stdev	***0.06***	***0.06***	***12.63***	***13.17***	***6.98***	***6.33***	***8.95***	***8.50***

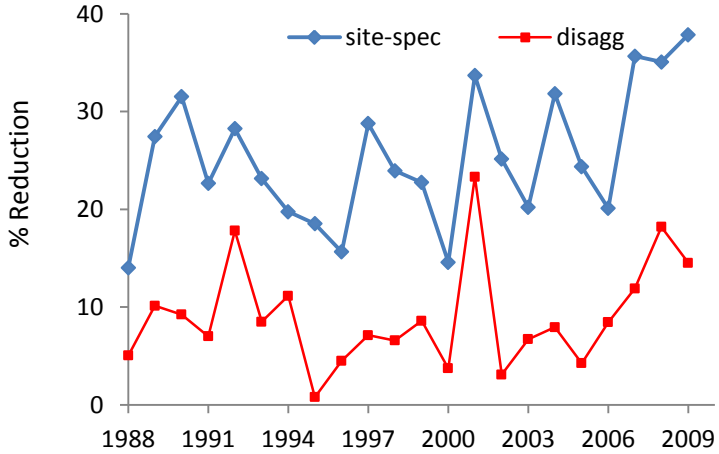
E% indicates percent flow and load reductions



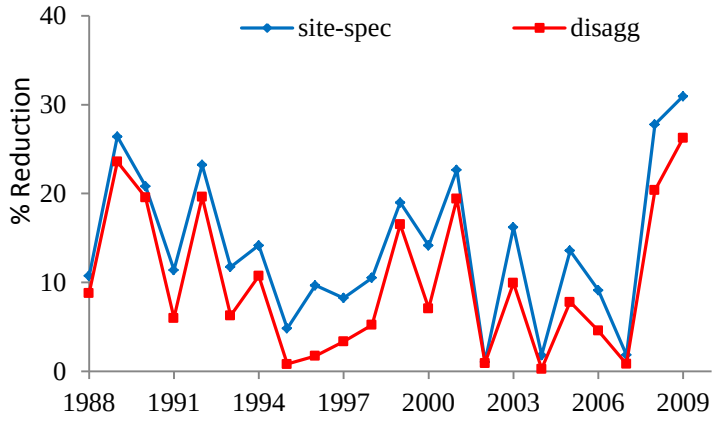
a) Average Annual Flow Reduction



b) Average Annual Sediment Reduction



c) Average Annual Total N Reduction



d) Average Annual Total P Reduction

Figure 6-3: Modeled Differences in BMP Effectiveness (% Reductions) Using Site-Specific versus Disaggregated BMP Data Sources for Flow, Sediment, TN, and TP

Flow reduction by site-specific BMPs ranges from 0.88 to 1.07 % with an average of 0.99% per annum while that for disaggregated BMPs ranges between 0.56 to 0.80% with an average annual of 0.70% (Table 6-10). Figure 6-3 a) shows a slightly higher flow reduction by site-specific BMP data than disaggregated BMP data with both fluctuating minimally along the time-series over the simulation time. The minimal flow reductions are because of evapotranspiration by the cover crops during the growing season. The implemented BMPs are generally not designed for flow reduction.

Sediment reduction by site-specific BMPs ranges from 5.18 to 48.67% with an average of 19.75% per annum. Percent sediment reduction due to the effects of disaggregated BMPs ranges between 2.24 to 47.08% with an average of 17.18% (Table 6-10). There is 2.57% average annual reduction difference by the two BMP datasets. Figure 6-3 b) shows higher sediment reduction by the site-specific than the disaggregated BMP data. Reduction by both BMPs fluctuates substantially over the simulation period.

Total N load reduction by site-specific BMPs ranges between 14.06 to 37.87 % with a corresponding a yearly average of 25.23%. Total N load reduction by disaggregated BMPs ranges from 0.80 to 23.34%, with an average annual reduction of 9.88% (Table 6-10). The average annual TN load reduction difference is 15.35%. Figure 6-4 c) is the reduction time-series of the site-specific and disaggregated BMPs on TN. Fluctuation in TN reduction is erratic down the time-series with site-specific BMP data having higher reductions than disaggregated BMP data.

Results of the TP load reduction by site-specific BMPs ranges from 1.05 to 30.95%. Average annual reduction is 14.09%. Disaggregated BMPs have TP load reduction ranges from 0.26 to 26.27% and an average annual reduction of 9.98% (Table 6-10). The difference in the average annual reduction by both datasets is 16.29%. Similar to the sediment load reduction, there is substantial fluctuation in the load reduction along the time-series over the simulation period (Figure 6-4 d).

Statistically, the reduction differences in sediment, TN and TP suggest that loads from the two BMP datasets are likely to differ by more than 10% when compared to the pre-BMP loads. Considering that cropland is only 5% of the entire watershed, there remains a large area that is

unprotected with BMPs. Additionally; pasture area benefitting from streamside fencing by both datasets is insignificant when compared to the total pasture area.

6.2.3 Discussion and Implication of Load Reduction Differences on TMDL Implementation Plans

Findings in this section show that county-level disaggregated BMP data provide higher yield reductions from NPS pollution than site-specific BMP data. This is because distribution of county-level disaggregated BMP data provided much higher BMP benefited areas for NMPs and livestock fencing than site-specific data, which better reflected actual watershed conditions. Implications of this are that if the benefits of BMPs are overestimated it suggests that larger reductions will need to be achieved from point sources and this could limit development/require possibly unnecessary and expensive point source pollution controls in portions of the City of Winchester, which is partly within the Upper Opequon Watershed.

For comparison between site-specific and disaggregated BMP data, cost estimates of implementation associated with the three simulated agricultural BMPs are explored in this section to understand the possible impact of differences on benefited areas. The USEPA (2003a) reported that the costs of implementing cover crops range from $9.88 to $98.8/ha-yr ($4 to $40/ac-yr) in 2001 dollars depending on the crop being planted. In 2006, the VADCR estimated the average cost based on VADCR BMP database for Frederick and Clarke Counties for implementing cover crops BMP at $98.8/ha-yr (VADCR and VADEQ, 2006), a value that is used in this study. Estimated costs for implementing NMPs on cropland are discussed in subsection 6.1.6. This study uses the $34.58/ha-yr ($14/ac-yr), which is the estimated cost of implementing NMPs in 2001 dollars. The VADEQ and VADCR (2006) reported the average cost of implementing livestock fencing with off-stream watering (SL-6 Grazing Land Protection) based on the VADCR BMP database for Frederick and Clarke Counties at $55.77/m ($17/ft). However, for clarity neither does the Livestock Exclusion (WP-2T) fencing represent the SL-6 practice in VADCR database nor the Precision Rotation Grazing practice as used in the CBWM. The SL-6 can contain both WP-2T and Rotation Grazing (Yagow, 2013, personal communication). The VADCR and VADEQ (2006) estimated the cost of WP-2T practice at $13.12/m ($4.00/ft) including annual maintenance.

Planning cost estimates for implementation of the county-level disaggregated NMPs (424.36 ha) for this watershed would be approximately $14,674 compared to $4,144 for site-specific NMPs (119.84 ha). Use of disaggregated NMP data would increase NMP costs by approximately $10,530 (254%)

more than the site-specific NMP data sources, and in 3-years the cumulative difference would be approximately $31,590. The estimated costs of implementing disaggregated county-level cover crops (197.28 ha) would be $19,491 compared to $20,680 for 209.31 ha of site-specific cover crops. Disaggregated cover crops implementation would cost approximately $1,189 (5.7%) less than site-specific BMPs because of their lower estimated area of cover crops. In Table 5-2, the buffer length for the site-specific SL-6 BMP streamside fencing was 2,013 m and would cost $112,287 approximately. The buffer length for the site-specific WP-2 practice was 381 m (Table 5-2) and its installation and maintenance each year would cost $4,999. The disaggregated WP-2 fencing would be expected to cost approximately $7,183. This suggests that the disaggregated streamside fencing would underestimate the costs of establishing the stream buffer fencing by $110,103 (94%).

In practice, BMPs are applied at the local-scale and if landowners are to implement BMPs to reduce pollution of local streams, there is need to ensure that model predictions are sufficiently accurate to justify the expenses incurred by implementing agencies (implementation planning and execution), individual landowners and other stakeholders. Based on this research and the foregoing discussion, at a local scale, it appears that the use of disaggregated county-level BMP data would increase uncertainty in TMDL development and required loadings to meet water quality goals. This uncertainty must be addressed during implementation planning phase and requires that the development of the local TMDL be based on site-specific data. To achieve water quality goals and reduce TMDL development and implementation costs, it makes sense to use site-specific data in the development of both the initial TMDL and follow-up implementation plans to reduce data collection costs. Disaggregated BMP data are less accurate at the local scale and result in poorer estimates of loads and required implementation than site-specific data. This has to be corrected during the development of local TMDLs and implementation plans to insure that water quality goals are achieved and that individual landowners are not required/encouraged to implement BMPs that will not achieve the desired water quality goals.

6.3 Long-Term Effects of BMP Spatial Representation on Water Quality Goals

This section provides an analysis of the long-term impacts of the two BMP data sources on achieving the Bay TMDL target goals for local watersheds. The analysis includes assessing the impacts of site-specific and county-level disaggregated BMP datasets, and the level of BMP implementation required to achieve the Bay TMDL pollutant reduction goals. Agricultural BMPs consisting of NMPs, cover crops and livestock fencing with off-stream watering were simulated

for the period 1988-2027. Average annual loads for sediment, TN and TP were compared to the Bay TMDL target goals for the Upper Opequon Watershed. The long-term average annual loads were hypothesized to meet the Upper Opequon Bay TMDL target loads by 2025. Additionally, hypothetical scenarios were developed to estimate additional BMP implementation level required to meet the Bay TMDL goals for the target watershed. The study used land use-specific UALs that were calculated from the output of the existing Bay TMDL model of land-based nutrient pollutants to calculate average annual target loads.

6.3.1 Calculating the Long-Term TMDL Average Annual Target Loads

The average annual edge-of-stream loads that relate to each land use category from the CBP Virginia portion of the Bay TMDL (2010) were obtained and used to calculate the UALs for the Upper Opequon Watershed (Table 5-5 of chapter 5). The UALs were then used to estimate average annual Bay TMDL target loads for each of the 6-consolidated land uses as shown in Table 6-11.

Table 6-11: Annual TMDL Target Loads for Upper Opequon Watershed Using Site-Specific Land Use

Consolidated Land Use	Site-spec Area (ha)	Area-weighted annual target load					
		Sediment		TN		TP	
		UAL (Mg/ha/yr)	Load (Mg/yr)	UAL (kg/ha/yr)	Load (kg/yr)	UAL (kg/ha/yr)	Load (kg/yr)
Cropland	804.7	1.1	878	14.4	11567	2.1	1708
Pasture	7130.1	0.5	3682	3.8	26914	0.9	6379
Loafing Lot	1.1	2.1	2	388.6	425	39.3	43
Forest	4900.1	0.1	461	1.4	6835	0.1	566
Residential	1494.5	0.2	302	3.3	4932	0.5	706
Urban	610.9	2.0	1242	4.7	2858	2.2	1322
Total	**14,941**		**6,567**		**53,531**		**10,724**
			6,910[a]		**73,975[b]**		**11,720[c]**

[a,b,c] *target loads calculated using disaggregated land use area.*

The long-term average annual TMDL target loads are calculated using site-specific land use inventory for the study watershed. From Table 6-11 the average annual target loads from all the land use categories are 6,567 Mg-sediment/yr; 53,531 kg-TN/yr and 10,724 kg-TP/yr. For comparison purposes, the average annual target loads obtained using county-level aggregated

land use areas differ by 5, 38% and 9% for sediment, TN and TP, respectively (Table 6-11). These are notable and significant differences in the target loads. The Wilcoxon signed-rank test on modeled responses for all constituents had $p < 0.0001$.

Wagner (2004) reported that most of the sediment loss from the Opequon Watershed (Abrams, Upper and Lower Opequon subwatersheds) comes from agriculture compared to urban land. Percent pollutant contributions by the individual land uses are given in Table 6-12. Pasture is the major contributor to total pollutant losses (Table 6-12).

Table 6-12: Percentage of Pollutant Yield at Watershed Outlet for Individual Land Uses Using Site-Specific Land Use

Land use	% Sediment	%TN	%TP
Cropland	13.4	21.6	15.9
Pasture	56.1	50.3	59.5
Loafing Lot	0.04	0.79	0.4
Forest	6.9	12.8	5.3
Residential	4.6	9.2	6.6
Urban	18.9	5.3	12.3

As indicated in Table 6-12, pasture provides higher pollutant losses even though it has lower UALs because there is 9 times more pasture than cropland, which has higher UALs due to seasonal tillage and nutrient applications.

Referring to Table 6-11, results suggest that calculated average annual target loads based on UALs from county-level aggregated land use categories can contribute to errors. When county-level aggregated land use is used to provide the target loads, it may overestimate or underestimate the target loads depending on how area-weighting of the disaggregated land uses apportions the key pollutant generating land uses on the watershed. For the Upper Opequon Watershed, disaggregated land use apportioned more cropland and loafing lot area to the watershed than the actual conditions that are represented by the site-specific land use. Pollution losses depend on land use areas, and the estimated UALs vary depending on the accuracy of the land use areas. Thus, use of county-level aggregated land uses to provide local watershed TMDL allocated loads can underestimate or overestimate UALs compared to site-specific land use and

this can cause significant differences in the calculated average annual target loads. Cropland will generally generate higher UALs due to tillage and seasonal nutrient applications, and given its overestimation by over 56% can cause major differences in the final simulated average annual loads (Table 6-7). The county-level spatial distribution of land uses provide lower areas compared to site-specific land use for the rest of the land use categories as follows: pasture area by 4.6%, residential area by 2.9% and urban area by 18.7% (Table 6-1). Except for urban area where site-specific land use is 18.7% higher than disaggregated land use, the variations in the remaining land use areas (pasture, forest and residential) are less than 5%, and reasonable. According to Rau (2012, personal communication) over 90% (724 ha) of the cropland area in the Upper Opequon Watershed is under no-till practice with 84 ha under conventional tillage. However, of the 1,258 ha county-level disaggregated cropland; the CBWM database shows 1,081 ha are in conventional tillage under its associated high-till land use categories. Only approximately 177 ha are classified as low-till land. Consequently, the disaggregated land use data seriously misrepresents actual agricultural land use in the watershed.

6.3.2 Estimating Average Annual Simulated Loads for the Upper Opequon Watershed

Table 6-13 compares the average annual loads with CBP TMDL target loads for the Upper Opequon Watershed. In general, the results indicate that at the present BMP implementation level, the watershed does not meet the CBP TMDL 2025 target loads for sediment, TN and TP and additional reductions are required.

Table 6-13: Chesapeake Bay TMDL Target and HSPF Simulated Average Annual Loads

Scenario	Sediment Load		Total N Load		Total P Load	
	Mg-sed/yr	% of TMDL Target	TN-kg/yr	% of TMDL Target	TP-kg/yr	% of TMDL Target
TMDL Target	6,657		53,531		10,724	
Pre-BMP	19,581	294	129,649	242	19,580	182
Site-specific BMPs	17,316	260	116,054	216	18,356	171
Disaggregated BMPs	17,632	264	122,055	228	18,589	173

The average annual pre-BMP loads for sediment, TN and TP are higher than the target load by 194%, 142% and 82%, respectively and BMPs and other measures are required to reduce the

loads. The average annual loadings due to impacts of site-specific BMPs are 160%, 116% and 71% more than the 2025 target goals for sediment, TN and TP, respectively. The loadings due to the effects of county-level disaggregated BMPs are 164%, 128% and 73% higher than the target loads for sediment, TN and TP, respectively. This indicates that additional management measures are required to reduce the loadings to the TMDL target loads. However, the study watershed has other cost-shared agricultural, forest and urban stormwater management, voluntary BMPs that were not simulated in this study and therefore the actual loadings from the watershed may be lower than predicted here.

6.3.3 Hypothetical Scenarios for Best Management Practices

The present implementation level of BMPs failed to meet the Bay TMDL target goals for sediment, TN and TP using either the site-specific or disaggregated BMP datasets. Three hypothetical future BMP implementation scenarios were developed to determine how much additional BMP implementation would be needed to meet the TMDL target loads. The scenarios used three simulated BMPs discussed earlier, and it was assumed that the status quo in land use is maintained and the prevailing weather conditions continue. The hypothetical scenarios were developed based on only site-specific BMP data. In subwatersheds where site-specific BMPs existed, the BMP benefitted area was increased by 25, 50 and 100% of the available land use areas on which each BMP could be applied. The subwatersheds with no existing site-specific BMPs, BMPs were progressively increased to 25, 50 and 100% of the available land use on which the BMPs could be applied. For streamside fencing, the hypothetical scenarios were applied to eligible riparian pasture segments next to the stream in subwatersheds 6, 9, 10, 15 and 16 that had existing cattle operations. Streamside fencing BMP benefitted area was expressed in equivalent hectares as required for HSPF input. The corresponding hypothetical BMP benefitted areas are shown in Table 6-14 and results of average annual scenarios reductions are shown in Table 6-15.

Table 6-14: BMP Hypothetical Implementation Scenarios and Benefitted Area Distribution

Sub-watershed	Cropland									Pasture				
	Total Cropland Area (ha)	Existing NMPs (ha)	Hypothetical Scenario (ha)			Existing cover crops (ha)	Hypothetical Scenario (ha)			Total Pasture Area (ha)	Existing Buffer Fencing (ha)	Hypothetical Buffer Areas (ha)		
			25%	50%	100%		25%	50%	100%			25%	50%	100%
1	0.00									9.96				
2	9.39		2.35	4.70	9.39		2.35	4.70	9.39	144.09				
3	9.80		2.45	4.90	9.80		2.45	4.90	9.80	113.93				
4	0.00									31.90				
5	19.39		4.85	9.70	19.39		4.85	9.70	19.39	450.00				
6	1.82		0.46	0.91	1.82		0.46	0.91	1.82	237.09		2.78	5.57	11.13
7	0.04		0.01	0.02	0.04		0.01	0.02	0.04	292.63				
8	30.97		7.74	15.49	30.97	16.60	24.34	32.09	30.97	380.97				
9	88.58		22.15	44.29	88.58	31.98	54.13	76.27	88.58	440.81	SL-6: 0.61	1.14	1.67	2.72
10	140.93		35.23	70.47	140.93	23.48	58.71	93.95	140.93	731.01	SL-6: 0.44 WP-2: 0.38	5.53	10.24	19.65
11	9.07		2.27	4.54	9.07	9.07				413.81				
12	51.21	51.21				27.32	33.29	39.27	51.21	900.12				
13	133.81	12.76	46.21	66.91	133.81	82.59	95.40	108.20	133.81	804.66				
14	0.00									190.65				
15	211.62		52.91	105.81	211.62	18.22	66.57	114.92	211.62	906.28		3.36	6.72	13.43
16	98.02	55.89	66.42	76.96	98.02		24.51	49.01	98.02	1082.11	SL-6: 0.91	6.32	11.73	22.55

Buffer area multiplied by 2 or 4 provides equivalent upland area benefitted for P/sediment and for N, respectively.

Table 6-15: Hypothetical Average Annual Simulated Load Reductions

Scenario	Sediment			TN			TP		
	Average Load (Mg-sed)	Reduction (Mg-sed)	%TMDL Target	Average Load (kg-TN)	Reduction (kg-TN)	%TMDL Target	Average Load (kg-TP)	Reduction (kg-TP)	%TMDL Target
Target	6,657			53,531			10,724		
Pre-BMP	19,581			129,649			19,580		
25%	16,265	3,316	244	113,507	16,142	212	17,670	1,910	164
50%	14,844	4,737	222	107,178	22,471	200	16,580	3,000	154
100%	10,603	8,978	142	97,435	32,214	182	11,435	8,145	106

%E indicates BMP reduction

By 2025, the 25% BMP implementation scenario has average annual loads which are 144, 112 and 64% higher than the target loads for sediment, TN and TP, respectively. The BMPs implemented at the 50% scenario results in 122, 100 and 54% higher average annual loads for sediment, TN and TP, respectively. The 100% BMP implementation scenario yields average annual sediment, TN and TP loads which are 42, 82 and 6% higher than the target goals, respectively. These results show that pollution losses are not effectively controlled to CBP TMDL target goals even by the 100% BMP implementation scenario. Thus, the three simulated agricultural BMPs alone cannot achieve reductions required by the TMDL. These results suggest that additional agricultural and other BMPs would need to be installed on the appropriate land uses to meet the CBP TMDL target goals. In reality, the study watershed has other cost-shared agricultural, forest and stormwater management, and voluntary BMPs that were not simulated in this study and the actual loadings from the watershed would be lower than predicted here.

7 Summary and Recommendations

The overall goal of this research was to evaluate the effects of spatial variability in land use distribution and watershed installed BMPs on HSPF-predicted flow, sediment, and nutrient (N and P). To achieve the goal, three specific research objectives were accomplished.

First, a comparison was made between the HSPF-predicted flow, sediment, TN and TP loads at the subwatershed and watershed levels resulting from different land uses consisting of site-specific and disaggregated county-level aggregated land use datasets. The first research question was what level of differences are associated with the use of county-level spatially aggregated land use data that are disaggregated to subwatershed level as compared to site-specific land use in HSPF modeled responses? Second, the effects of site-specific and county-scale spatial disaggregated BMP distributions on modeled BMP responses in HSPF-predicted flow, sediment, TN and TP loads at the watershed level were evaluated and quantified. The corresponding research question was what differences exist in the HSPF modeled BMP responses between site-specific and county-scale disaggregated BMP data? Thirdly, the study evaluated the required BMP implementation level to meet the Bay TMDL 2025 target goals for sediment, TN and TP assuming that only NMPs, streamside fencing and cover crops BMPs were available for implementation. The third research question had two components: (a) Do current levels of cost-shared BMP implementation in Upper Opequon Watershed meet the Chesapeake Bay TMDL goals using site-specific and county-level disaggregated BMP datasets simulated for the period 1988-2027? (b) If current levels of cost-shared BMP implementation do not meet the Chesapeake Bay TMDL goals, what levels of BMP implementation are required to achieve the TMDL goals in Upper Opequon Watershed using the site-specific and county-level disaggregated BMP datasets?

To answer the first and second questions, the spatial land use and BMP data for the study watershed were simulated using HSPF-AGCHEM from 1988 to 2009. For the third set of questions the simulation was performed for the period 1988 to 2027. The Upper Opequon Watershed in northwest Virginia with a majority of the land under agriculture was selected as a study watershed to investigate these research questions.

7.1 Summary of Results

Modeled outputs using the two land use datasets showed that flow and water quality loads were significantly different at both monthly and annual temporal scales in a majority (13 of 16) of the subwatersheds at $\alpha = 0.05$. The spatially disaggregated land use obtained from county-level data generally resulted in higher loadings in subwatersheds for both monthly and annual time-steps as compared to the site-specific land use data for the study watershed. This might not be the case for other watersheds. The higher pollutant loadings with county-level disaggregated spatial data resulted from overestimation of cropland area for the study watershed. The county-level disaggregated cropland was 56% more than the site-specific cropland. The increased cropland area from the disaggregated land use data resulted in higher nutrient losses than the site-specific land use data because of higher unit area loads from cropland due to tillage and seasonal nutrient applications. The overestimation of cropland would increase pollutant loads and would require more BMP implementation to offset the increased loads leading to increased implementation estimated costs that are burdensome to planners, funding agencies, landowners and agricultural producers. For the Upper Opequon Watershed, the findings suggest that 56% more (area wise) NMPs would be needed using disaggregated land use compared to site-specific land use data. The use of site-specific land use data would better represent the actual watershed, lead to more watershed-specific pollutant load predictions for which watershed-specific BMP implementation plans could be developed. Implementation planning costs would be lower because of the more accurate initial land use estimates that would not have to be changed as much during implementation planning.

To answer the second research question, three agricultural BMPs were simulated using the HSPF model. Model predictions with site-specific BMP data generally resulted in lower pollutant yields than the disaggregated BMP dataset. At an annual temporal scale flow, sediment, TN and TP yields for site-specific and county-level disaggregated BMP data were significantly different at $\alpha = 0.05$. For the Upper Opequon Watershed, the differences due to the source of BMP data were overall more than 10% in-terms of pollutant loadings. These variations are likely to impact implementation planning process costs a substantive impact on targeted reductions and BMP implementation costs that must be addressed through more detailed implementation planning efforts.

Answering the final set of research questions involved using land use-specific unit area loads obtained from the CBWM results, which were used to establish TMDL target loads for the Upper Opequon Watershed. The HSPF model was then run using site-specific land use with BMPs from site-specific and disaggregated BMP datasets. Neither BMP dataset nor developed hypothetical scenarios met the target loads for simulated sediment, TN and TP.

7.2 Implications for TMDLs and Other Watershed Management Planning

Implementation of TMDL strategies occurs at the finer geographical scale (field) or subwatershed level. The TMDL implementation plans are based on the long-term average annual load reductions. In this study, most of the simulated differences in pollutant loads using site-specific and disaggregated county-level land use and BMP data were more than 10%. The differences had substantive implications for planners, funding agencies, landowners and other stakeholders. All of the waterbodies in the Chesapeake Bay Watershed, including the Upper Opequon Watershed, became subject to the provisions of the Chesapeake Bay TMDL following its completion in 2010. The TMDL established Bay-wide load reductions and in plans for its implementation, target loads have been proposed for all river basins in the Bay region. As a consequence, the Bay TMDL has the potential to affect economic activities including agriculture and industrial production throughout the entire watershed. The CBP is not using the best available site-specific data which would more accurately characterize watershed land use and actual BMP implementation and provide more accurate estimates of expected watershed and subwatershed pollutant losses. Such data would allow implementers to better target resources to areas producing disproportional loadings – which are more accurate than using disaggregated data. The random manner in which the county-level disaggregated BMP data were distributed in the study watershed suggests that their use in TMDL planning can result in unnecessary BMP effort in the subwatersheds. This is because randomly distributing county-level BMP data can inaccurately represent the actual BMP placement. Use of county-level disaggregated data may result in overestimation of BMPs and land use in some subwatersheds and underestimation in others. These initial errors will need to be identified and accounted for during the implementation plan development and will increase the cost of implementation plan development due to the increased work required in identifying the errors and correcting them.

In practice, BMPs are applied at the local scale and if water quality control is to be assured via BMP implementation, there is need to ensure that model predictions are sufficiently accurate to justify the expenses incurred by states, individual landowners and other stakeholders. Estimated costs calculated in this study were meant only for comparison purposes and do not imply the actual costs for implementing TMDL strategies on Upper Opequon Watershed. This is because other cost-shared agricultural, forest and urban stormwater management, voluntary BMPs were not simulated in this study and, therefore, the actual loadings from the watershed will undoubtedly be lower than predicted here.

To improve the efficacy of TMDL implementation plans in subwatersheds of the Chesapeake Bay Watershed the following recommendations are made:

1. Target loads for TMDL implementation activities at the local or subwatershed level should be established using local site-specific spatial data that reflect local land use and BMP implementation levels if possible. This will improve the accuracy of initial TMDLs and help target resources where they are most needed. Winning the confidence of local stakeholders can result in more voluntary effort than if they see unrealistic estimates of current land use and BMP implementation efforts.
2. Where county-level aggregated data are the only data available, care must be taken in their use to avoid overestimating or underestimating the existing land use and BMP effort.

   A combination of satellite land use imagery used together with aggregated data may be a useful approach to more accurately estimate watershed conditions. Local committees such as planning district commissions as used in Virginia require close working relationships with local soil and water conservation districts (SWCDs), farmers and conservation groups working in the watersheds to validate the accuracy of spatial data used in planning local strategies. Lack of collaboration and involvement of local stakeholders may result in poor planning that may lead to unnecessary BMP effort by implementers in one subwatershed while underestimating the effort required in the next subwatershed within the same watershed. Further, familiarization with the local subwatershed and watershed conditions and existing practices is important to better represent the watershed during watershed modeling and management planning. To achieve accurate model results, it is necessary to document voluntary BMPs implemented

by the individual landowners within the subwatersheds. This will help to more accurately determine the required BMP effort at the local scale. In cases where data are overestimated, there may be unnecessary expenses to be incurred and such would need additional financial support while in cases of underestimation may result in a compromised load reduction effort.

3. The trade-off between use of county-level aggregated and site-specific spatial data should be determined based on a cost-benefit analysis of acquiring and utilizing the site-specific data.

Watershed management planning should emphasize use of available planning resources. Care must be taken if disaggregated land use and BMPs are used to estimate load reductions, as these may provide higher required reductions in some watersheds that translate to unnecessary expenses compared to the use of site-specific data. On the contrary, the predicted loads may be lower in some other subwatersheds where land use or BMP data are underestimated, which may result in inaccurate load reductions that do not meet the required target loads.

4. The on-going efforts by some state agencies like the VADCR to make available local information on target TMDL loads, current watershed loads, land use, BMPs and other spatial and water quality data should be encouraged by all jurisdictions.

This is important to promote transparency and accountability of the USEPA local TMDL target goals. Providing the model input data used in developing the TMDL target loads for a locality can be useful in determining variations in the actual watershed conditions. Willing donors in the states should also be encouraged to participate in water quality management initiatives. This will provide the necessary financial resources needed to allow BMP implementers to determine the required watershed management effort to meet the Bay TMDL goals.

7.3 Conclusions

In this study:

- Modeled responses showed that sediment, TN and TP were all affected by the differences in the land use and BMP data sources.

- Disaggregated land use provided higher cropland and loafing lot estimated areas than site-specific land use for the study watershed, which contributed to high simulated loadings. On the other hand, site-specific BMP data resulted in lower load unit area yields than disaggregated BMP data. It is concluded that for local watersheds, depending on the accuracy required for modeled responses, use of the disaggregated data is less suitable than the use of site-specific data. Combining local satellite land use imagery and the aggregated data may provide a better option than using aggregated data alone and future research should study how this can be done in an effective manner.
- The use of disaggregated data resulted in higher levels of existing NMPs and lower levels of streamside fencing and cover crops BMP implementation.
- The HSPF model suggested that for the study watershed, current BMP implementation levels and even the 100% hypothetical BMP implementation scenario do not meet the CBP TMDL target loads for sediment, TN and TP for the Upper Opequon Watershed and additional management measures may be required.
- This study used N-based land application of manure based on information acquired from stakeholders in the watershed. Future work with P-based NMPs may be useful.

In summary, this study yielded quantitative information on the alternative spatial datasets in modeling pollutant loads used in developing TMDLs and TMDL implementation plans to meet water quality goals. There are economic consequences to government, landowners and local business communities associated with use of county-level aggregated data. Actions by local stakeholders in controlling sediment, N, and P to achieve desired water quality goals must be informed by best science using cost-effective methods to achieve the expected water quality standards. The use of county-level aggregated spatial data must also take into account economic consequences to states, landowners, private industries and such. The trade-off in the use of disaggregated spatial data should be determined by the cost of acquiring site-specific data. Watershed implementation plans must also consider the voluntary conservation efforts by landowners.

7.4 Study Limitations

This study focused on spatial distribution of land use and agricultural BMPs. Other than variability in weather input that influenced watershed pollutant losses, future land use changes

and BMP effectiveness degradation over-time also play an important role in pollutant losses. For instance, BMP load reductions vary with, among other factors, the storm size, operating condition of the BMPs, and future land use changes. The Upper Opequon Watershed has additional BMPs (urban, forest management and agricultural) that were implemented voluntarily and which do not appear in state BMP databases, which mainly document cost-shared BMPs. This results in an underestimation of BMPs actually in place. For example, in the Upper Opequon approximately 90% of the cropland is in no-till which is considered to be a BMP, but because it is not cost-shared, it is not included in the BMP database. Similarly in urban areas, urban BMPs like bio-retention, infiltration swales, etc., that are required to develop a site are not listed in the BMP databases because they are not cost-shared. Urban BMPs were not considered in this research. Some urban BMPs are reported in the county-level BMP database, but they were not reported in the site-specific database.

7.5 Recommendations for Future Work

During model evaluation, the HSPF model was observed to predict excessively high and unrealistic nutrient concentration outputs under low flow conditions. The behavior associated with the unrealistically high concentrations during dry weather is likely to be associated with an internal HSPF model structure problem that calls for further investigation.

This research was performed on a single watershed, the Upper Opequon Watershed it should be repeated on multiple watersheds to determine if the results of this study apply to similar local watersheds. Detailed understanding of the significance of the differences in the land use spatial scales, BMP data and their effects on TMDL implementation plans on small watersheds may help decision-makers for future planning.

Variations were found to exist between site-specific and disaggregated BMP modeled water quality responses. In the study watershed, the use of disaggregated BMP data likely overestimated the extent of BMP implementation and their impacts in the watershed. In other watersheds, the effects may be the opposite and the impacts would likely cancel out at a larger scale. However, at the local scale, which impacts individual landowners and stakeholders, the results suggest that the use of county-level data can result in inaccurate estimates of current and needed BMP implementation and, therefore, landowner BMP implementation efforts that are more than or less than required. It is recommended that more research is conducted on different

watersheds to determine if the trends observed for this study watershed are representative of other watersheds.

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Appendix 1: Consolidated Site-Specific Land Use Categories

This Research Land Use Categories	Pervious/Impervious (%)	VADCR Land Use Categories (Class No.)
Cropland	Pervious (100)	Cropland (211) Rotational Hay (2114) Orchard (22)
Pasture	Pervious (100)	Improved Pasture/Hayland (2121)/Unimproved Pasture (2122)/Grazed Woodland (461)/ Overgrazed (2123)
Loafing Lot	Pervious (100)	Cattle Operation (231)
Forest	Pervious (100)	Forested (4) Water (5) Harvested Forest Land (44) Unmanaged Grass / CRP (2432)
Residential	Pervious (90) Impervious (10)	Farmstead (241) Wooded Residential (118) Open Urban (18) Mobile Homes (115) Mixed Urban (16) Low Density Residential (111) Medium Density Residential (112)
	Pervious (85) Impervious (15)	High Density Residential (113) Barren (7)
Urban	Pervious (40) Impervious (60)	Commercial (12) Industrial (13) Transportation (14)

Appendix 2: Consolidated County Aggregated Land Use Categories

This Research Land Use Categories	Pervious/Impervious (%)	Bay Model Land Use Categories and Codes
Cropland	Pervious (100)	Alfalfa (alf)
		Conventional tillage w/out manure (hom)
		Conventional tillage with manure (hwm)
		Conservation tillage with manure (lwm)
		NM* conventional tillage with manure (nhi)
		NM* conventional tillage w/o manure (nho)
		NM* conservation tillage with manure (nlo)
		Nursery(urs)
Pasture	Pervious (100)	Pasture (pas)
		NM* pasture that is part of a farm plan (npa)
		Small grain hay and failed cropland/hay with nutrients (hyw)
		NM* hay with nutrients (nhy)
		Wild hay/idle cropland/fallow land (hyo)
		Degraded riparian pasture (trp)
Loafing Lot	Pervious (100)	Animal feeding operation (afo)
Forest	Pervious (100)	Forest (for)
		Open Water (wat)
		Harvested Forest(hvf)
Residential	Pervious (90)	Pervious Urban Low Developed (pul)
	Impervious (10)	
	Pervious (85)	Pervious Urban High Developed (puh)
	Impervious (15)	Bare Ground (bar)
Urban	Pervious (40)	Impervious High Developed (imh)
	Impervious (60)	Impervious Low Developed (iml)
		Transportation (ext)

Appendix 3: Site-Specific Cost-Shared BMPs for Upper Opequon Watershed

Practice Name and Code	Target Area	Units	Type of Target Area	Benefitted Area (Ha)	Type of Benefit	Date of Installation
Permanent vegetative cover on cropland (SL-1)	25.0	Ha	Area planted	12.76	Area planted	2009-11-09
NMPs revisions (NM-1)	51.21	Ha	Area installed in planned system	51.21	Area benefitted from planned system	2009-06-01
NMPs revisions (NM-1)	22.0	Ha	Area installed in planned system	12.76	Area benefitted from planned system	2009-06-01
Fencing with off-stream watering (SL-6)	609.6	m	Length of streambank protected	8.1	Area where grazing is improved & stream bank protected	2004-05-10
Permanent vegetative cover on cropland (SL-1)	35.0	Ha	Area planted	14.2	Area planted	2007-03-05
Small grain cover crop (SL-8H)	25.0	Ha	Area in planted crop	10.1	Area in planted crop	2009-04-02
Permanent vegetative cover on cropland (SL-1)	30.0	Ha	Area planted	12.1	Area planted	2009-11-17
Small grain cover crop (SL-8H)	35.2	Ha	Area in planted crop	14.3	Area in planted crop	2008-04-17
	44.6	Ha	Area in planted crop	18.1	Area in planted crop	2009-04-02
Integrated pest management (WQ-10)	90.0	Ha	Area being scouted	36.4	Area benefitted from being scouted	2004-01-22
Permanent vegetative cover on cropland (SL-1)	17.5	Ha	Area planted	7.1	Area planted	2008-02-08
	18.2	Ha	Area planted	7.4	Area planted	2010-11-30
	49.7	Ha	Area planted	20.1	Area planted	2007-01-23
	15.0	Ha	Area planted	6.1	Area planted	2007-01-23
Small grain cover crop (SL-8H)	18.9	Ha	Area in planted crop	7.7	Area in planted crop	2008-04-17
Permanent vegetative cover on cropland (SL-1)	7.3	Ha	Area planted	3.0	Area planted	2009-05-13
	25.5	Ha	Area planted	10.3	Area planted	2008-02-08
	57.7	Ha	Area planted	23.4	Area planted	2009-11-17
	12.5	Ha	Area planted	5.1	Area planted	2009-11-17
Small grain cover crop (SL-8H)	38.8	Ha	Area in planted crop	15.7	Area in planted crop	2009-04-02
	7.9	Ha	Area in planted crop	3.2	Area in planted crop	2009-04-02
	36.8	Ha	Area in planted crop	14.9	Area in planted crop	2009-04-02
Stream exclusion fencing (WP-2)	381.0	m	Length of streambank protected	4.9	Area of stream bank fenced out	1999-10-05
Permanent vegetative cover on cropland (SL-1)	9.6	Ha	Area planted	3.9	Area planted	2009-04-02
Integrated pest management (WQ-10)	67.0	Ha	Area being scouted	27.1	Area benefitted from being scouted	2004-01-22

Practice Name and Code	Target Area	Units	Type of Target Area	Benefitted Area (Ha)	Type of Benefit	Date of Installation
Permanent vegetative cover on cropland (SL-1)	19.2	Ha	Area planted	7.8	Area planted	2009-11-17
	11.4	Ha	Area planted	4.6	Area planted	2008-02-08
Small grain cover crop (SL-8H)	40.3	Ha	Area in planted crop	16.3	Area in planted crop	2009-04-02
Legume cover crop (WQ-4)	19.8	Ha	Area in planted crop	0.0	Area in planted crop	2009-06-09
NMPs revisions (NM-1)	136.1	Ha	Area installed in planned system	55.89	Area benefitted from planned system	2009-06-01
Small grain cover crop (SL-8H)	56.6	Ha	Area in planted crop	22.9	Area in planted crop	2008-04-17
Integrated pest management (WQ-10)	548.0	Ha	Area being scouted	221.9	Area benefitted from being scouted	2004-01-22
Permanent vegetative cover on cropland (SL-1)	43.1	Ha	Area planted	17.4	Area planted	2008-02-08
	41.4	Ha	Area planted	16.8	Area planted	2008-12-03
Small grain cover crop (SL-8H)	41.4	Ha	Area in planted crop	16.8	Area in planted crop	2008-04-17
Legume cover crop (WQ-4)	13.8	Ha	Area in planted crop	5.6	Area in planted crop	2009-06-09
Buffer restoration (CRFE-3)	40.4	Ha	Area of buffer planted	16.4	Area buffer restored	2006-05-16
Harvestable cover crop (SL-8B)	7.7	Ha	Area in planted crop	3.1	Area in planted crop	2008-05-12
Permanent vegetative cover on cropland (SL-1)	23.5	Ha	Area planted	9.5	Area planted	2010-05-11
Fencing with off-stream watering (SL-6)	444.4	m	Length of streambank protected	2.4	Area where grazing is improved & stream bank protected	2008-05-13
Fencing with off-stream watering (SL-6)	914.4	m	Length of streambank protected	40.5	Area where grazing is improved & stream bank protected	2002-02-21
Permanent vegetative cover on critical areas (SL-11)	3.0	Ha	Area stabilized	4.6	Area stabilized	2005-12-31
Harvestable cover crop (SL-8B)	119.8	Ha	Area in planted crop	52.9	Area in planted crop	2010-05-18

Source: Courtesy of VADCR (McRae, 2011, personal Communication)

Appendix 4: Upper Opequon Watershed County-Level Aggregated BMPs

(The BMPs for River Segment PU2_4730_4220)

(Definition of land use type codes provided in Appendix 5)

Item No.	Landuse Category	Short Name	Area (Ha)
1	rpd	UrbanNutMan	55.92
2	npd	UrbanNutMan	1347.99
3	nhi	DecisionAg	14.36
4	nlo	DecisionAg	96.51
5	alf	ConPlan	5.88
6	hom	ConPlan	15.67
7	hwm	ConPlan	1.44
8	hyw	ConPlan	49.70
9	lwm	ConPlan	9.65
10	nal	ConPlan	111.63
11	nhi	ConPlan	14.36
12	nho	ConPlan	297.81
13	nhy	ConPlan	944.35
14	nlo	ConPlan	96.51
15	npa	ConPlan	346.84
16	pas	ConPlan	1387.35
17	urs	CaptureReuse	2.51
18	afo	BarnRunoffCont	13.69
19	cfo	BarnRunoffCont	0.50
20	for	ForHarvestBMP	0.00
21	hvf	ForHarvestBMP	38.73
22	hom	CoverCropSDW	1.65
23	hwm	CoverCropSDW	0.15
24	lwm	CoverCropSDW	1.02
25	nhi	CoverCropSDW	2.87
26	nho	CoverCropSDW	31.35
27	nlo	CoverCropSDW	19.30
28	hom	ComCovCropEDW	1.78
29	hwm	ComCovCropEDW	0.16
30	lwm	ComCovCropEDW	1.10
31	nhi	ComCovCropEDW	3.10
32	nho	ComCovCropEDW	33.86
33	nlo	ComCovCropEDW	31.44
34	hom	CoverCropEDW	2.97
35	hwm	CoverCropEDW	0.27
36	lwm	CoverCropEDW	1.83
37	nhi	CoverCropEDW	5.17
38	nho	CoverCropEDW	56.43
39	nlo	CoverCropEDW	39.96
40	rid	WetPondWetland	38.05
41	nid	WetPondWetland	49.73
42	rpd	WetPondWetland	118.46
43	npd	WetPondWetland	131.87
44	rid	DryPonds	10.95
45	nid	DryPonds	14.31
46	rpd	DryPonds	52.83
47	npd	DryPonds	66.89
48	rid	ExtDryPonds	19.98
49	nid	ExtDryPonds	26.11
50	rpd	ExtDryPonds	123.95
51	npd	ExtDryPonds	142.92
52	rid	Infiltration	13.51
53	nid	Infiltration	17.65
54	rpd	Infiltration	50.18
55	npd	Infiltration	68.12
56	rid	Filter	11.65
57	nid	Filter	15.23
58	rpd	Filter	47.68
59	npd	Filter	60.91
60	rcn	EandS	85.64
61	ccn	EandS	0.00
62	npa	PrecRotGrazing	233.66
63	pas	PrecRotGrazing	876.22
64	nal	EnhancedNM	117.51
65	nhi	EnhancedNM	14.36
66	nho	EnhancedNM	313.49
67	nhy	EnhancedNM	994.05
68	nlo	EnhancedNM	96.51
69	npa	GrassBuffersTrpN	0.27
70	npa	GrassBuffersTrpPS	0.13

Item No.	Landuse Category	Short Name	Area (Ha)
71	pas	GrassBuffersTrpN	1.06
72	pas	GrassBuffersTrpPS	0.53
73	hom	GrassBuffersN	36.75
74	hom	GrassBuffersPS	36.75
75	hyw	GrassBuffersN	47.64
76	hyw	GrassBuffersPS	23.82
77	lwm	GrassBuffersN	120.96
78	lwm	GrassBuffersPS	60.48
79	pas	GrassBuffersN	436.71
80	pas	GrassBuffersPS	218.35
81	alf	WetlandRestore	0.25
82	hom	WetlandRestore	0.66
83	hyw	WetlandRestore	3.15
84	lwm	WetlandRestore	0.41
85	pas	WetlandRestore	5.49
86	npa	ForestBufferstrpN	0.17
87	npa	ForestBufferstrpPS	0.09
88	pas	ForestBufferstrpN	0.69
89	pas	ForestBufferstrpPS	0.34
90	hom	ForestBuffersN	6.54
91	hom	ForestBuffersPS	3.27
92	hyw	ForestBuffersN	132.03
93	hyw	ForestBuffersPS	125.36
94	lwm	ForestBuffersN	64.97
95	lwm	ForestBuffersPS	32.49
96	pas	ForestBuffersN	178.25
97	pas	ForestBuffersPS	89.12
98	rid	StreetSweep	21.83

Source: (CBP, 2010c (ftp://ftp.chesapeakebay.net/Modeling/phase5/Phase532/bmpacres/))

Appendix 5: Definition of County-Level Land Use Code

Land Use Code	Bay Model Land Use Categories
alf	Alfalfa
afo	Animal feeding operations
ext	Transportation
for	Forest
hom	Conventional tillage without manure
hvf	Harvested Forest
hwm	Conventional tillage with manure
hyo	Wild hay/idle cropland/fallow land
hyw	Small grain hay and failed cropland/hay with nutrients
imh	Impervious high developed
lwm	Conservation tillage with manure
nal	Nutrient management alfalfa
nhi	Nutrient management conventional tillage with manure
nho	Nutrient management conventional tillage without manure
nhy	Nutrient management hay with nutrients
nlo	Nutrient management conservation tillage with manure
npa	Nutrient management pasture that is part of a farm
pas	Pasture
pul	Pervious urban low developed
trp	Degraded riparian pasture
urs	Nursery
wat	Open water