USING MULTIPLE WATERSHED MODELS TO PREDICT WATER, NITROGEN, AND PHOSPHORUS DISCHARGES TO THE PATUXENT ESTUARY

Kathleen M.B. Boomer, Donald E. Weller, Thomas E. Jordan, Lewis Linker, Zhi-Jun Liu, James Reilly, Gary Shenk, and Alexey A. Voinov

ABSTRACT: We analyzed an ensemble of watershed models that predict flow, nitrogen, and phosphorus discharges. The models differed in scope and complexity and used different input data, but all had been applied to evaluate human impacts on discharges to the Patuxent River or to the Chesapeake Bay. We compared predictions to observations of average annual, annual time series, and monthly discharge leaving three basins. No model consistently matched observed discharges better than the others, and predictions differed as much as 150% for every basin. Models that agreed best with the observations in one basin often were among the worst models for another material or basin. Combining model predictions into a model average improved overall reliability in matching observations, and the range of predictions helped describe uncertainty. The model average was not the closest to the observed discharge for every material, basin, and time frame, but the model average had the highest Nash–Sutcliffe performance across all combinations. Consistently poor performance in predicting phosphorus loads suggests that none of the models capture major controls. Differences among model predictions came from differences in model structures, input data, and the time period considered, and also to errors in the observed discharge. Ensemble watershed modeling helped identify research needs and quantify the uncertainties that should be considered when using the models in management decisions.

(KEY TERMS: watersheds; watershed management; nonpoint source pollution; simulation; hydrological modeling; ensemble modeling; model comparison; model average; land use; model structure; model performance.)


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INTRODUCTION

We analyzed an ensemble of watershed models that can all predict water, nitrogen, and phosphorus discharges to the Patuxent River, which is a subestuary of the Chesapeake Bay and the sixth largest tributary to the Bay. Watershed models are essential tools for linking nonpoint sources with surface water pollution and for predicting the effects of management efforts on water quality (Miller et al., 2004). In the Patuxent, the larger Chesapeake Bay, and many other estuaries worldwide, efforts to reduce watershed nutrient discharges and restore degraded estuaries rely on watershed models to plan management actions and to help enforce water quality regulations (Boesch, 2002; Smith et al., 2006; USEPA, 2010a; NRC, 2011).

Despite their critical role in management programs, watershed models often perform poorly because of imperfect knowledge of hydrological processes, biogeochemical processes, and human activities (Radcliffe et al., 2009). The resulting uncertainty in model predictions is difficult to quantify and interpret, and that can undermine scientific and public confidence in model predictions (Radcliffe et al., 2009). In addition, most applications rely on a single model, and this provides no opportunity to evaluate the structural uncertainty inherent in choosing the conceptual and mathematical underpinnings of the model.

Analyzing a set of two or more models of a watershed (ensemble modeling) can help objectively evaluate model skill and the uncertainty in model predictions (Beven, 2007). Ensemble modeling is especially appropriate for environmental systems in which dynamic processes operate over a range of temporal and spatial scales (Clark, 2007). Each model represents a different set of hypotheses describing the dominant landscape processes affecting watershed discharge. Comparing models contrasts different hypotheses about system drivers (Bloschl, 2006) and helps to identify how models can be refined and improved (e.g., McIntyre et al., 2005; Dezetter et al., 2008). The multi-model approach has gained widespread acceptance in other disciplines, including financial forecasting, socioeconomics, weather and climate, and wildlife management (e.g., Givens, 1999; Koop and Tole, 2004; Gneiting and Raftery, 2005; Phillips and Gleckler, 2006). Initial applications in watershed modeling reported that multi-model synergies provide better estimates and a stronger basis for informing watershed management decisions than a single model (Vrugt and Robinson, 2007; Hsu et al., 2009; Huisman et al., 2009), but ensemble watershed modeling has not been used much outside of the European Union, possibly because of the higher cost of implementing multiple models and the reluctance of the watershed modeling community to embrace uncertainty analyses (Pappenberger and Beven, 2006).

The predictions from a set of models can also be combined into a model average, which can work better than relying on a single “best” model for supporting management decisions, especially when there is not enough information to identify the best model or when the data do not favor a particular model (Kadane and Lazar, 2004). Because of the reluctance to examine multiple models, the applications of model averaging in watershed analysis have also been limited (Vrugt and Robinson, 2007), but would likely advance knowledge of terrestrial hydrologic processes (Sivakumar, 2008) and improve model accuracy (Duan et al., 2007). The range of predictions for a defined endpoint provides an initial quantitative estimate of the overall uncertainty in the system processes.

In our study of Patuxent watershed models, we evaluated the abilities of the models to predict observed water and nutrient discharge data (model skill) and to estimate quantities that are important for management decisions, but not measured. Instead of seeking a best model, we focused on how an ensemble of models and model averaging can improve predictions of watershed discharges, help quantify model uncertainty, and increase understanding of terrestrial-aquatic linkages and the impacts of human activities on aquatic ecosystems.

We analyzed the watershed models as they were published because the models were not amenable to further standardization and because the published results have already been used to draw scientific inferences and to guide management decisions. Our analysis differed from a common approach to rigorous model comparison, which reruns a set of similar models with standardized inputs and calibration data, and then compares results for the same outputs and time periods (Breuer et al., 2009). Such an effort focuses on quantifying how model structure affects model output with everything else controlled. This approach is very discerning from a modeling perspective. It is not always feasible, it ignores important differences arising from user choices and constraints during model implementation, and it may not reveal the full contrast among models that is needed to understand their management implications. As we analyzed the models as published, some of the differences among models that we report are due to differences in input data, calibration data, or time period considered rather than to differences in model structure.
METHODS

Overview

We identified six watershed models that had been applied to the Patuxent River watershed or that predicted loads from the Patuxent watershed as a part of modeling the larger Chesapeake Bay basin. The models were published in peer reviewed literature or actively used in land use planning. Three models had more than one published version, so altogether there were 10 implementations of the six models (Table 1). The scope and complexity of the models vary widely, but all the models are intended to quantify how natural factors and anthropogenic stressors influence total nitrogen (TN) and total phosphorus (TP) discharges from the watershed.

We compared model predicted outputs for selected endpoints, where “endpoint” refers to the estimated discharge for a combination of material, basin, and time frame. There were three output materials (water, TN, and TP), four prediction basins (Laurel, Western Branch, Bowie, and the entire Patuxent watershed), and three time frames (average annual, annual time series, and monthly time series). We examined the average annual predictions because some of the models predict only average annual loads and because management decisions are often based on annual average loads to factor out the effects of extreme weather or other unusual events that may affect a single year. We also examined predictions of annual and monthly time series loads to quantify how the models perform in representing temporal variability in water and nutrient discharges. The analysis of monthly time series generally confirmed to the lessons learned from the annual time series, so the descriptions of the monthly analysis is reported only in the Supporting Information.

Two sets of endpoints had no measurements available to evaluate model performance: predictions of average annual and annual time series discharges from the entire Patuxent watershed and the predicted proportions of nonpoint TN and TP discharges allocated to agriculture and to developed land for all four watersheds. Making predictions for unmeasured endpoints is a major objective of watershed modeling, and these two endpoints are good examples of unmeasured endpoints that environmental decision makers need to estimate. Understanding the impact of the Patuxent watershed on the Patuxent and Chesapeake estuaries demands estimates of the total nutrient

<table>
<thead>
<tr>
<th>Model</th>
<th>Abbreviation</th>
<th>Year*</th>
<th>General Description</th>
<th>References</th>
</tr>
</thead>
<tbody>
<tr>
<td>Models predicting average annual TN and TP</td>
<td>MDP90</td>
<td>1990</td>
<td>Export coefficient model</td>
<td>MOP (1993, 1995); Maryland Department of Planning (MDP), Maryland Department of the Environment (MDE), and Maryland Department of Natural Resources (DNR) (2007); Tassone et al. (1998)</td>
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<tr>
<td></td>
<td>MDP97</td>
<td>1997</td>
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<td></td>
<td>SPARROW87</td>
<td>1987</td>
<td>Nonlinear statistical model</td>
<td>Smith et al. (1997), Preston and Brakebill (1999)</td>
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<td>SPARROW92</td>
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<td>SPARROW97</td>
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<td>PLM</td>
<td>1986-1993</td>
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*For MDP and SPARROW, year refers to the date of the geographic and load data used to predict average annual loads. For the other models, the range of years represents the period over which the time series of flow and nutrient discharges were simulated.
loads from the watershed, and developing strategies for reducing nutrient loads demands information on where the loads originate within the watershed. For every endpoint considered, we present the model average prediction, calculated as the simple average of estimates from the models capable of predicting that endpoint. We estimated the skill of the model average as if it were another model in the ensemble.

The following provides more detailed descriptions of the study area, the streamflow and nutrient data, the models themselves, and the methods of analysis.

Study Area

The 2,300 km² Patuxent River watershed is entirely in Maryland, U.S., mainly in the Coastal Plain physiographic province (72%) with the remainder in the Piedmont (Figure 1). The upper watershed is located between the cities of Washington, D.C. and Baltimore, Maryland. The 2001 National Land Cover Database (Homer et al., 2004, 2007) indicated that 17% of the watershed area was developed, 11% was cropland, 24% was grassland, and 46% was forest. Two reservoirs in the northern part of the watershed are managed for flood control and drinking water supply. From 1997 to 1999, 150 million cubic meters (Mm³) of water (about 9% of the 1,664 Mm³ freshwater flow to the estuary) was withdrawn for water supply purposes (Jordan et al., 2003), but a roughly equal amount (142 Mm³) was returned to the river network in the discharges from 8 major (>500,000 gallons/day) and 17 minor wastewater treatment facilities (Jordan et al., 2003; Weller et al., 2003).

Streamflow and Nutrient Measurements

To test the models, we used measurements of water flow, nitrogen loads, and phosphorus loads for three U.S. Geological Survey (USGS) gauging sites (Figure 1) with continuous flow data and routinely measured TN and TP concentrations (Langland et al., 1995; Darrell et al., 1998; Michael Langland, USGS, August 24, 2009, personal communication; Langland et al., 1999; USGS, 2011a). We used the available measurements for 1984-2000 from three basins: Laurel (gauge 01592500, 342 km² basin area), Western Branch (01594526, 232 km²), and Bowie (01594440, 907 km²). The Laurel basin is in the Piedmont physiographic province and contains the two water supply reservoirs, and the Western branch basin is in the Coastal Plain. The Bowie basin is 70% Piedmont and includes the Laurel basin (Weller et al., 2003). The USGS applied the ESTIMATOR model (Cohn et al., 1989) to estimate monthly annual, and average annual nutrient loads from continuous discharge data and nutrient concentrations in water quality samples. For the Laurel and Bowie basins, the USGS also provided 95% prediction intervals for the annual and monthly nutrient load estimates produced using ESTIMATOR.

Watershed Models

This section provides brief descriptions of the six watershed models in our ensemble, along with references to more detailed information. The models are presented in rough order of increasing complexity: an uncalibrated export coefficient model, two statistical models, two spatially lumped simulation models, and a spatially distributed simulation model. All the models estimate point source contributions from wastewater treatment plants from discharge monitoring reports or from permitted discharges when monitoring reports are not available.
Maryland Department of Planning Assessment and Accounting. The Maryland Department of Planning (MDP) model is an export-coefficient model for the state of Maryland (MOP, 1993, 1995; MDP, 2007; Tassone et al., 1998). Export coefficient models assume a constant TN or TP yield (kg per ha per year, the “export coefficient”) for each land use class and estimate watershed load by summing the products of land use area and export coefficient across all land use classes. The MDP model has been used throughout Maryland to assist local town and county planners in developing growth strategies that minimize impacts to surface water bodies. The export coefficients were derived from the Chesapeake Bay Program’s HSPF Model, Version 4 (CBP4) (described below) for each land use in the Department of Planning multi-year land use database and adjusted by the average amount of impervious surface area associated with different developed land densities. The model does not predict water discharge, and the model was not calibrated to match observed TN or TP loads. There are two implementations, one for 1990 and one for 1997. Land use areas for 1997 were estimated using linear interpolation over time between the 1990 and 2002 land use maps (MDP, 2003a,b; U.S. Department of Commerce and U.S. Census Bureau, 2005).

Smithsonian Environmental Research Center. The core of the Smithsonian Environmental Research Center (SERC) model of the Patuxent watershed is a set of statistical models fit to measured water discharge and N and P concentrations collected weekly for 2 years from 22 study watersheds in the Patuxent River and adjacent Rhode River basins between July 1997 and August 1999 (Jordan et al., 2003; Weller et al., 2003). Annual rainfall was below average in the first year and above average in the second (Jordan et al., 2003). The statistical models predicted discharge and nonpoint source nutrient concentrations from proportions of cropland and developed land, physiographic province, and time (Jordan et al., 2003; Weller et al., 2003). Landsat-derived land cover estimates (EPA-EMAP, 1994) were lumped to three categories (cropland, developed land, and other land) for use in the models. The Patuxent watershed was divided into 23 sections, and the fitted models were applied to the land cover and physiographic province data to predict weekly water discharge and weekly average nutrient concentrations leaving each section. Weekly nonpoint source material discharges were calculated by multiplying the weekly flow and average weekly concentration predictions. The effects of point sources and reservoir management were included by assimilating data on monitored discharges from two reservoirs and from wastewater treatment plants. The SERC model was applied to explore the effects of land use change and future development on watershed discharges (Weller et al., 2003). The SERC model has also been linked to an estuarine water quality model (CE-QUAL-W2) to explore the effects of weather, watershed characteristics, and alternate land use scenarios on estuarine water quality and biological responses (Breitburg et al., 2003; Lung and Bai, 2003; Lung and Nice, 2007).

SPAtially Referenced Regressions on Watershed Attributes. The USGS developed a set of nonlinear regressions called SPAtially Referenced Regressions On Watershed attributes (SPARROW) to relate observed TN and TP loads to spatially explicit nutrient sources reduced by losses to land-surface and in stream processes (Smith et al., 1997; Preston and Brakebill, 1999). The nutrient sources include atmospheric deposition, urban land area, fertilizer application, livestock production, and point sources. The model statistically fit directly to TN and TP loads observed at points throughout the stream network, and does not estimate water discharge. The nonlinear regression procedure fits source coefficients for each nutrient source and delivery coefficients that relate nutrient losses to watershed characteristics, such as slope, soil permeability, stream density, and wetland area. Stream nutrient removal is represented as an exponential decay function of stream length and discharge volume. SPARROW models have been developed for several U.S. basins and analyzed to quantify nutrient sources, to estimate nutrients lost in river transport, to estimate nutrient delivery to estuaries, and to develop regulatory limits for implementing total maximum daily load (TMDL) regulations (see http://water.usgs.gov/nawqa/sparrow/).

We analyzed results from three versions of SPARROW models developed for the Chesapeake Bay watershed. Nutrient loads for the first version (SPARROW87) were estimated from 1950 to 1995 concentration and daily flow measurements from 109 Chesapeake watershed sites (79 for TN and 84 for TP), including 6 sites in the Patuxent watershed (Brakebill and Preston, 2003). The loads were normalized (Smith et al., 1997) for 1987, the year for which input data were assembled (Preston and Brakebill, 1999). Land cover in 1 km pixels was mapped by integrating three data sets (U.S. Environmental Protection Agency Environmental Monitoring and Assessment Program [EPA-EMAP] [1994], National Oceanographic and Atmospheric Administration Coastal Change and Analysis Program [NOAA-CCAP] [2006], and USGS Geographic Information Retrieval and Analysis System [GIRAS] [Gutierrez-Magness et al., 1997]). Stream networks were modified from the River Reach File 1 to derive hydrologic units (RF1, 1:500,000 scale) (Alexander et al., 1999).
For the second version (SPARROW92), water quality data for 1950 to 1995 came from 132 sites (103 for TN and 121 for TP), including 6 sites in the Patuxent watershed. Data were normalized (Smith et al., 1997) for 1992 (SPARROW Version 2.0) (Brakebill et al., 2001; Brakebill and Preston, 2003). Land cover came from integrating two data sets (EPA-EMAP [1994] and the 1990 National Land Cover Data [NLCD] [Vogelmann et al., 2001]), and the watershed network came from the National Hydrography Data (NHD), 1:100,000 scale (USGS, 1999).

For the third version (SPARROW97), 1950 to 2000 load estimates from 125 sites (87 for TN and 103 for TP), including 6 Patuxent sites, were normalized (Smith et al., 1997) for 1997 inputs (SPARROW Version 3.0) (Brakebill and Preston, 1999, 2004). Land cover data from the circa 1990 NLCD (Vogelmann et al., 2001) were updated to 1997 using a change detection process based on spectral change between individual Landsat images. The watershed network was based on the stream network used in SPARROW92, with minor modifications, such as the addition of major reservoirs.

**Smithsonian Environmental Research Center Landscape.** Smithsonian Environmental Research Center Landscape (SERCLM) is a modular simulation model of the Patuxent watershed that was developed to generalize the analysis and application of the SERC model (described above) beyond the 2-year time domain and Patuxent only spatial domain of the SERC model. The SERCLM model includes three sub-components (Liu and Weller, 2008; Liu et al., 2008). First, the TOPMODEL rainfall-runoff model (Beven and Kirby, 1979) is applied to estimate daily water discharge from 210 watersheds composing the Patuxent basin. TOPMODEL was manually calibrated to match observed flow at SERC and USGS monitoring stations (described previously). Second, two statistical models predict TN and TP concentrations from the proportions of cropland and developed land, physiographic province, time of the year, and water discharge estimated using TOPMODEL. The TN and TP models were fit to the water quality data set (Jordan et al., 2003) described above. Finally, a stream routing model (Liu and Weller, 2008) combines the predicted discharges from the 210 watersheds with monitored data on reservoir and point source discharges, and then routes water and nutrients to the estuary while also accounting for nutrient uptake during transport. The stream routing parameters were calibrated manually (Liu and Weller, 2008; Liu et al., 2008) to achieve the best match of streamflow, TN, and TP concentrations from SERC and USGS monitoring stations (described earlier).

**Chesapeake Bay Program Model.** The Chesapeake Bay Program (CBP) model of the Chesapeake Bay watershed is an adaptation of the Hydrologic Simulation Program — Fortran (HSPF) (Bicknell et al., 2001), which was derived from the Stanford Watershed Model (Crawford and Linsley, 1966). HSPF uses a mass-balance approach to solve a linked set of equations representing natural and anthropogenic mechanisms that control nutrient transport and delivery to streams (USGS, 2011b). For the Chesapeake Bay application, the hydrologic simulation model is linked to a regional atmospheric deposition model (Linker et al., 1996, 2000, 2008). Four increasingly refined versions have been released since 1994. Each version offered a more detailed segmentation, longer simulation period, and increasingly detailed representation of land use and best management practices (BMPs). The model was developed to quantify nutrient loads and their sources and to estimate load reductions from improved management practices. Model analyses of the impacts from alternative land management scenarios have helped to guide federal and state policy development, and loading estimates from CBP4 are used by regional, county, and municipal land managers to estimate loading rates associated with different land use types (e.g., the MDP model).

CBP4 simulates hourly sediment and nutrient discharge for a period of 17 years (1984-2000) in 94 model segments with an average size of 1,900 km². Land use and land cover data were derived from satellite imagery (EPA-EMAP, 1994) and ancillary data and consolidated into nine land use classes: pervious and impervious urban areas; mixed developed land; high till and low till croplands; livestock feeding areas; hay fields; pasture; and forest. Additional input data included fertilizer and manure applications, point source discharges, septic system densities, atmospheric deposition, and BMP reduction factors. The model was calibrated to 1984-1997 flow and TN and TP concentration data from 20 monitoring stations in the Chesapeake watershed, including the Bowie station in the Patuxent watershed (described above). Data from the Bowie station dominated the calibration of model parameters for the Patuxent watershed.

The Chesapeake Bay Program’s HSPF Model, Version 5 (CBP5) is the current model version (USEPA, 2010a). It divides the Chesapeake Bay watershed into nearly 1,000 sub-units with an average size of 171 km². The model simulates discharges over a 21-year period (1984-2005), but we analyzed outputs for 17 years (1984-2000). The CBP5 expands the land use classification to 24 categories and incorporates annual land use change. The base land use data was derived from a combination of 2000 land cover data developed by the University of Maryland’s Regional Earth Science Applications Center (RESAC) (Goetz...
et al., 2004), the 1992 NLCD (Vogelmann et al., 2001), agricultural census data (http://www.agcensus.usda.gov/), and road network overlays (Tele Atlas, 2004). The model was calibrated to 1984-1995 flow and TN and TP concentration data from 296 stream monitoring stations in the Chesapeake watershed and nearby areas in Maryland and Virginia. Data from the same stations, but for the years 1995-2005 were used for model validation. There were seven stations in the Patuxent (including the three USGS sites described above) that dominated parameter estimates for the Patuxent watershed. The model has been applied to guide regulations to implement the Chesapeake Bay TMDL (USEPA, 2010c).

**Patuxent Landscape.** The Patuxent Landscape Model (PLM) is a spatially distributed simulation model for the Patuxent watershed that calculates daily hydrologic discharge and nutrient loads to streams (Costanza et al., 2002). PLM was developed to evaluate how human settlements and agricultural practices affect hydrology, plant productivity, and nutrient cycling; and the model was applied to different scenarios of land use change to help guide regional management decisions. Hydrological, ecological, and biogeochemical processes are simulated in each grid cell using a set of Structural Thinking Experimental Learning Laboratory with Animation (STELLA) (http://www.iseesystems.com) modules from the Library of Hydroecological Modules (LHEM) (http://www.likbez.com/LHEM/) (Voinov et al., 2004). The grid cells were linked within a Spatial Modeling Environment (Maxwell and Costanza, 1997) that used spatial data (land use, soil properties, climate, and nutrient input) to integrate the grid cell dynamics into regional-surface and groundwater hydrology and nutrient transport simulations (Voinov et al., 1999, 2007). For the Patuxent River application, the watershed was segmented into 2,352 one km² grid cells. Land use and land use change were derived from MDP data for the years 1985 and 1990, modified using agricultural census data (http://www.agcensus.usda.gov/), and consolidated into five classes: forest, agriculture, rural, residential, and urban. Each land use type was modeled using equations and parameters describing the local biogeochemical dynamics. The parameters were calibrated to flow and nitrogen concentrations collected at the USGS Bowie gauge station between January 1986, and December 1993 (Voinov et al., 2004).

**Land Type Inputs**

Nine different land use or land cover data sets were used in the 10 model implementations. We summarized the differences in land types among the models to provide background information needed to interpret differences among model load predictions. To describe the dominant land uses in the four study watersheds, we tabulated the average and ranges across the nine data sets for the percentages of four land types (cropland, grassland, developed land, and forest land) in each watershed. To document the differences in land cover percentages among models, we tabulated the percentages of the same land types used in the 10 model implementations for the entire Patuxent watershed.

**Comparing Model Estimates to Observed Loads**

**Average Annual Loads.** Every model implementation could predict some or all the average annual endpoints for flow, TN, and TP discharges from the three monitored watersheds (Table 2). The MDP and SPARROW implementations predict annual average TN and TP loads directly. The other models predict loads through time, but over different ranges of years (Table 1). Averaging across all the available years from each model produced annual average predictions for the time series models. The number of years available ranged from 2 (SERC) to 17 (CBP). The average annual predictions were tabulated and plotted against the observed annual averages from the 1984 to 2000 USGS monitoring data (above), and the range of predictions among models was reported as an initial characterization of uncertainty. We also tabulated the difference between each average annual prediction and the annual average observed values. We calculated the percent difference:

\[
\% \text{ difference} = 100 \left( \frac{P - O}{O} \right),
\]

where \( P \) is a predicted flux and \( O \) is the corresponding observed flux. For each endpoint, the models were also ranked in order of increasing absolute value of the percent difference from the data with model rank 1 assigned to the model with the lowest such difference.

TABLE 2. Numbers of Models Predicting Average Annual Material Fluxes Leaving Three Basins Monitored by USGS Sampling Stations.

<table>
<thead>
<tr>
<th>Material</th>
<th>Basin</th>
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<tr>
<td></td>
<td>L</td>
<td>B</td>
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<td>Flow</td>
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<tr>
<td>TP</td>
<td>9</td>
<td>9</td>
<td>8</td>
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Notes: Letters indicate basins: L (Laurel), B (Bowie), and W (Western Branch). Tables 8, 9, and 10 indicate the specific models associated with any number in the table.
Annual Time Series. The two SERC models, the two CBP models, and PLM could provide annual time series predictions (Table 3). The annual predictions from each implementation were plotted against annual observed values for the same years. For the nitrogen and phosphorus plots, we included the 95% confidence limits for the observed load. We plotted the confidence limits along the model prediction axis to reveal how the differences between model predictions and observations compare to the confidence limits on the observed loads. We summarized the difference from the observed value for each model and endpoint by applying Equation (1) in each year, then recording the average and range of percentage difference across years. We also calculated the Nash–Sutcliffe (NS) coefficient of model performance (Nash and Sutcliffe, 1970):

\[
    NS = 1 - \frac{\sum_{i=1}^{n} (O_i - P_i)^2}{\sum_{i=1}^{n} (O_i - \bar{O})^2},
\]

where \( O_i \) is the observed discharge (of water, TN, or TP) in year \( i \), \( P_i \) is the modeled discharge, \( \bar{O} \) is the mean observed discharge, and \( n \) is the number years. A NS value of 1 indicates a perfect fit, a value of 0 indicates that the model is predicting no better than the average of the observations (Nash and Sutcliffe, 1970). Negative values indicate the model is performing worse than using the average of the observations. We used the NS values to rank the model performance for each endpoint, assigning rank 1 to the model with the NS closest to one (e.g., Gordon et al. 2004).

Estimating Total Loads to the Estuary

We tabulated average annual predictions of flow, TN, and TP discharge from the entire Patuxent watershed (Table 4), and we plotted the annual time series of predicted flow, TN, and TP discharges together with annual precipitation amounts (http://ches.communitymodeling.org/models/CBPhase5/datalibrary/meteorological-data.php). We also tabulated the molar ratios of N and P discharged to the estuary. This ratio is often used to draw inferences about which nutrient is more limiting to aquatic production (Redfield, 1958; Glibert et al., 2006).

Allocating Loads to Land Types

We compared how the models attributed the nonpoint source nutrient loads to developed land, agriculture, and other land types (Table 5). For the MDP model, we estimated the total nutrient loads from developed land by adding the loads from residential, urban, commercial, industrial, transportation, and utility lands, and we estimated the total nutrient loads from agriculture by summing loads from row crops, pasture, orchards, and confined feeding lots. For the SERC models, statistical model coefficients for cropland and developed land and the areas of the two land covers were used to isolate crop land and developed loads, with the remaining nonpoint source load attributed to other land. For the CBP models, we summed the nutrient loads from agricultural areas (including conventional-till, conservation-till, hay fields, pasture, and confined animal operations) to estimate the agricultural contributions; and we summed the loads from low-, medium-, and high-intensity developed land and developed open space to estimate the total contributions from developed lands. The SPARROW models attributed nonpoint loads to...
fertilizer inputs, manure inputs, developed land area, and atmospheric deposition inputs; however, atmospheric deposition was integrated into the nutrient contributions from the different land types in the MDP, SERC, and CBP models. To make the SPARROW estimates more consistent with the other models, we apportioned its estimated loads from atmospheric deposition to agriculture, developed land, and other land using the proportions of these three categories in the land cover data. The agricultural load from SPARROW then included part of the atmospheric deposition load plus the loads attributed to fertilizer and manure, whereas the total nonpoint source load from developed land included the load attributed to developed land area plus the portion of the atmospheric deposition load that could be attributed to atmospheric deposition on developed land. It was not possible to attribute loads to agriculture and developed land with the PLM model because the model does not track the origins of the delivered nutrient loads.

RESULTS

Land Type Inputs

Land type proportions for the entire Patuxent basin differed considerably among the sources of land data used by the models (Tables 6 and 7). The proportion of developed land ranged from 11 to 37%, and the cropland proportion ranged from 9 to 31%. We summed row crop, grassland (called pasture in some data sets), and animal feeding areas (represented only in some data sets) to estimate agricultural area. The resulting agricultural areas ranged from 15 to 36% of the basin. Forest (43-62% of the basin) and all other land (barren areas and wetlands, 0-2% of the basin) were more similar among the land data sets.

The estimated proportions of cropland and developed land also differed widely among the land data sets for each of the three monitored watersheds (Table 7). Despite those differences, all the data sets consistently identify the Laurel basin as the most agricultural of the four watersheds (average of 26% cropland and 14% developed) and the Western Branch as the most developed (average 13% cropland and 33% developed, Table 7).

Comparing Model Estimates to Observed Loads

Average Annual Loads. Predictions differed widely among models for all the average annual endpoints (Figure 2; Table 8). Streamflow predictions from the SERC and CBP models were more accurate for Western Branch (maximum absolute difference from observed flow of 11% or less, Table 9) than at Bowie and Laurel (up to 26–61% absolute difference from observed, respectively). The models tended to overestimate observed annual average flows for the Western Branch watershed, where there was a higher proportion of developed land and no reservoirs.

<table>
<thead>
<tr>
<th>Implementation</th>
<th>Crop</th>
<th>Grass</th>
<th>Developed</th>
<th>Forest</th>
<th>Year</th>
<th>Data Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>MDP90</td>
<td>25</td>
<td>4</td>
<td>20</td>
<td>46</td>
<td>1990</td>
<td>MDP (2003a,b)</td>
</tr>
<tr>
<td>MDP97</td>
<td>24</td>
<td>3</td>
<td>27</td>
<td>43</td>
<td>1997</td>
<td>MDP (2003a,b)</td>
</tr>
<tr>
<td>SPARROW87</td>
<td>12</td>
<td>7</td>
<td>37</td>
<td>44</td>
<td>1990</td>
<td>Geographic Information Retrieval and Analysis System (GIRAS) (Gutierrez-Magness et al., 1997); EPA-EMAP (1994); 1992 NLCD (Vogelman et al., 2001)</td>
</tr>
<tr>
<td>SPARROW 97</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>1997</td>
<td>1990 NLCD (Vogelman et al., 2001); Landsat image change detection (Brakebill and Preston, 2004)</td>
</tr>
<tr>
<td>CBP4</td>
<td>12</td>
<td>7</td>
<td>37</td>
<td>44</td>
<td>1990</td>
<td>EPA-EMAP (1994); NOAA-CCAP (2006); USGS GIRAS (Gutierrez-Magness et al., 1997)</td>
</tr>
<tr>
<td>SERC</td>
<td>10</td>
<td>28</td>
<td>12</td>
<td>49</td>
<td>1990</td>
<td>EPA-EMAP (1994)</td>
</tr>
<tr>
<td>SERCLM</td>
<td>10</td>
<td>28</td>
<td>12</td>
<td>49</td>
<td>1990</td>
<td>EPA-EMAP (1994)</td>
</tr>
<tr>
<td>PLM</td>
<td>31</td>
<td>5</td>
<td>11</td>
<td>51</td>
<td>1973</td>
<td>MDP (2003a)</td>
</tr>
<tr>
<td></td>
<td>25</td>
<td>4</td>
<td>20</td>
<td>46</td>
<td>1990</td>
<td>MDP (2003a,b)</td>
</tr>
<tr>
<td></td>
<td>24</td>
<td>3</td>
<td>27</td>
<td>43</td>
<td>1997</td>
<td>MDP (2003a,b)</td>
</tr>
<tr>
<td>CBP5</td>
<td>13</td>
<td>11</td>
<td>18</td>
<td>57</td>
<td>1984</td>
<td>1990 NLCD (Vogelman et al., 2001); 2000 RESAC</td>
</tr>
<tr>
<td></td>
<td>9</td>
<td>7</td>
<td>22</td>
<td>62</td>
<td>2000</td>
<td>Land cover (Goetz et al., 2004); Agricultural Census Data (<a href="http://www.agcensus.usda.gov">http://www.agcensus.usda.gov</a>)</td>
</tr>
</tbody>
</table>

Notes: Land cover numbers for the SPARROW 1992 and 1997 implementations were not included in the SPARROW publications (–). For all the data sets, the land not occupied by cropland, grassland, developed land, or forest was less than 3% of basin area.
or point source contributions. For Laurel and Bowie, the models tended to underestimate streamflow. The SERCLM model best predicted flow at Laurel and Bowie, whereas CBP5 best predicted flow at Western Branch (Table 10), but both of these models also made relatively poor predictions for other basins. The SERC statistical model did not provide the best estimates for any endpoint, but consistently provided reasonable flow estimates (5–26% absolute difference from observed flow) for all three watersheds. The CBP4 model more significantly overestimated flow for Laurel and Bowie than did the other models, possibly because it did not account for water removed from the two reservoirs.

Predicted average annual TN loads were less accurate than flow predictions, with differences from observed TN ranging between –83 and 42%. Underestimates were more common for Laurel and Western Branch, the two smaller basins, than for Bowie (Table 9). With the exception of the SERC model, the export coefficient and statistical models predicted TN loads more accurately than the simulation models. For example, the MDP90 and MDP97 models best predicted TN loads at Laurel and Western Branch, and the SPARROW97 version best predicted average annual loads at Bowie. Although the SERC model provided accurate flow predictions, it underestimated TN loads by more than the other models, possibly because its 2-year time frame (August 1997–July 1999) provides a poor representation of average annual conditions (see Discussion).

As in the flow comparison, models that predicted well for one watershed often predicted poorly for others. For example, the MDP90 model predictions were closest to the observed values at Western Branch, but were poor at Bowie (rank 7.5 out of 11). The SPARROW97 model predictions most closely matched the observed annual average TN load at Bowie, but provided the poorest estimate at Western Branch.

Model performance in predicting observed TP loads was generally poorer than for TN, and the range of TP predictions among models was wider. Predictions for Laurel generally were more than 100% greater than

<table>
<thead>
<tr>
<th>Basin</th>
<th>Crop</th>
<th>Grass</th>
<th>Developed</th>
<th>Forest</th>
</tr>
</thead>
<tbody>
<tr>
<td>Laurel</td>
<td>26 (11-47)</td>
<td>15 (7-40)</td>
<td>14 (3-24)</td>
<td>44 (34-62)</td>
</tr>
<tr>
<td>Bowie</td>
<td>17 (8-32)</td>
<td>10 (5-30)</td>
<td>28 (16-43)</td>
<td>43 (36-56)</td>
</tr>
<tr>
<td>Western Branch</td>
<td>13 (3-23)</td>
<td>10 (2-33)</td>
<td>33 (22-45)</td>
<td>42 (36-50)</td>
</tr>
<tr>
<td>Entire Patuxent</td>
<td>18 (9-31)</td>
<td>9 (3-28)</td>
<td>22 (11-37)</td>
<td>50 (43-62)</td>
</tr>
</tbody>
</table>

Notes: Table 6 provides citations and details on how the 10 model implementations represented the entire Patuxent basin. The MDP analysis did not separate cropland and grassland, so the cropland + grassland sum for each model is shown for comparison to MDP. Land not occupied by cropland, grassland, developed land, or forest was always <3% of every basin. The cropland means and ranges summarize three land data sets for Western Branch and four data sets for the other basins. For the other land types, seven land data sets are summarized for Western Branch and eight for the other basins.
the USGS observed loads, possibly because the models did not adequately account for P retention by the reservoirs. Only SPARROW97 and CBP5 were within 15% of the observed load. In contrast, the models tended to underestimate TP loads to Western Branch and Bowie. As with flow and TN, the highest ranked models differed among basins. At Laurel and Western Branch, the CBP5 model best matched the observed annual average TP load, whereas the MDP97 model best predicted TP loads observed at Western Branch and Bowie. The best performing TP models for a basin were not the models that were best for flow or TN.

In summary, the average annual analysis revealed several key patterns. No model consistently excelled across the materials and watersheds considered, and the models that best matched the observations at one endpoint were often among the worst models for another endpoint. Model skill in predicting the observed data was best for flow, intermediate for TN, and poor for TP. There was no relationship between how well the simulations predicted flow and how well they predicted TN or TP loads. The export coefficient and statistical models (MDP, SPARROW, and SERC) were generally better predictors of TN loads than the simulation models (SERCLM, CBP, and PLM). All the models were poor predictors of TP loads. For all materials, models were closest to the observations at Bowie (the largest basin) and most different from the observations at Laurel (the smallest basin), suggesting that model performance improved with watershed size.

**Annual Time Series.** The analysis of annual time series endpoints (Table 3) supported the findings from the average annual analysis. Model performance again differed among materials and locations (Figure 3; Tables 11-13). For example, SERCLM best predicted flow at the Laurel outlet (NS = 0.9), but was the least accurate at Western Branch (NS = −8.2). The

---

**TABLE 8. Average Annual TN and TP Discharges from Three Monitored Watersheds Predicted by 10 Model Implementations and Measured.**

<table>
<thead>
<tr>
<th>Implementation</th>
<th>Flow Mm$^3$/yr</th>
<th>TN Mg N/yr</th>
<th>TP Mg P/yr</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>L</td>
<td>W</td>
<td>B</td>
</tr>
<tr>
<td>MDP90</td>
<td>–</td>
<td>–</td>
<td>–</td>
</tr>
<tr>
<td>MDP97</td>
<td>–</td>
<td>–</td>
<td>–</td>
</tr>
<tr>
<td>SPARROW87</td>
<td>–</td>
<td>–</td>
<td>–</td>
</tr>
<tr>
<td>SPARROW92</td>
<td>–</td>
<td>–</td>
<td>–</td>
</tr>
<tr>
<td>SPARROW97</td>
<td>–</td>
<td>–</td>
<td>–</td>
</tr>
<tr>
<td>SERC</td>
<td>54.8</td>
<td>92.4</td>
<td>315</td>
</tr>
<tr>
<td>SERCLM</td>
<td>72.7</td>
<td>98.3</td>
<td>349</td>
</tr>
<tr>
<td>CBP4</td>
<td>119</td>
<td>–</td>
<td>430</td>
</tr>
<tr>
<td>CBP5</td>
<td>49.5</td>
<td>88.5</td>
<td>316</td>
</tr>
<tr>
<td>PLM</td>
<td>–</td>
<td>–</td>
<td>299</td>
</tr>
<tr>
<td>Model average</td>
<td>73.9</td>
<td>93.2</td>
<td>342</td>
</tr>
<tr>
<td>Observed</td>
<td>73.7</td>
<td>88.3</td>
<td>339</td>
</tr>
</tbody>
</table>

Notes: Letters indicate basins: L (Laurel), B (Bowie), and W (Western Branch). The MDP and SPARROW models did not predict flow, and some models did not predict TN and TP for all basins (–). Observed data are means for the years 1984-2000.

**TABLE 9. Percent Difference from USGS Observed Discharges (Equation 1) for Average Annual Model Predictions.**

<table>
<thead>
<tr>
<th>Model</th>
<th>Flow</th>
<th>TN</th>
<th>TP</th>
</tr>
</thead>
<tbody>
<tr>
<td>MDP90</td>
<td>–</td>
<td>–</td>
<td>–</td>
</tr>
<tr>
<td>MDP97</td>
<td>–</td>
<td>–</td>
<td>–</td>
</tr>
<tr>
<td>SPARROW87</td>
<td>–</td>
<td>–</td>
<td>–</td>
</tr>
<tr>
<td>SPARROW92</td>
<td>–</td>
<td>–</td>
<td>–</td>
</tr>
<tr>
<td>SPARROW97</td>
<td>–</td>
<td>–</td>
<td>–</td>
</tr>
<tr>
<td>SERC</td>
<td>–26</td>
<td>5</td>
<td>–7</td>
</tr>
<tr>
<td>SERCLM</td>
<td>–1</td>
<td>11</td>
<td>3</td>
</tr>
<tr>
<td>CBP4</td>
<td>61</td>
<td>27</td>
<td>–3</td>
</tr>
<tr>
<td>CBP5</td>
<td>–33</td>
<td>1</td>
<td>–7</td>
</tr>
<tr>
<td>PLM</td>
<td>–</td>
<td>–</td>
<td>–12</td>
</tr>
<tr>
<td>Model average</td>
<td>0</td>
<td>6</td>
<td>1</td>
</tr>
</tbody>
</table>

Notes: Negative values indicate underpredictions; positive values indicate overprediction. Letters indicate basins: L (Laurel), B (Bowie), and W (Western Branch). Some models did not predict some endpoints (–).
TABLE 10. Ranked Performance of Models for Average Annual Predictions Based on the Absolute Value of Percent Difference from USGS Observed Discharges (Table 9).

<table>
<thead>
<tr>
<th>Model</th>
<th>Flow TN</th>
<th>Flow TP</th>
<th>TN Mean Rank</th>
<th>TP Mean Rank</th>
<th>Overall Rank</th>
</tr>
</thead>
<tbody>
<tr>
<td>MDP90</td>
<td>2</td>
<td>1</td>
<td>6.5</td>
<td>3.2</td>
<td>4.4</td>
</tr>
<tr>
<td>MDP97</td>
<td>1</td>
<td>2</td>
<td>3.5</td>
<td>2.2</td>
<td>3.7</td>
</tr>
<tr>
<td>SPARROWS7</td>
<td>3</td>
<td>5.5</td>
<td>10</td>
<td>6.2</td>
<td>6.6</td>
</tr>
<tr>
<td>SPARROW92</td>
<td>4</td>
<td>8</td>
<td>11</td>
<td>7.7</td>
<td>7.0</td>
</tr>
<tr>
<td>SPARROW97</td>
<td>5</td>
<td>9</td>
<td>1</td>
<td>5.2</td>
<td>5.8</td>
</tr>
<tr>
<td>SERC</td>
<td>3</td>
<td>2</td>
<td>3.5</td>
<td>2.8</td>
<td>4.6</td>
</tr>
<tr>
<td>SERCLM</td>
<td>2</td>
<td>4</td>
<td>2.7</td>
<td>6.8</td>
<td>5.6</td>
</tr>
<tr>
<td>CBP4</td>
<td>5</td>
<td>10</td>
<td>5.5</td>
<td>6.8</td>
<td>6.0</td>
</tr>
<tr>
<td>CBP5</td>
<td>4</td>
<td>8</td>
<td>1</td>
<td>7</td>
<td>4.2</td>
</tr>
<tr>
<td>PLM</td>
<td>1</td>
<td>3</td>
<td>1</td>
<td>5</td>
<td>5.0</td>
</tr>
<tr>
<td>Model average</td>
<td>1</td>
<td>3</td>
<td>1.7</td>
<td>3.5</td>
<td>2.8</td>
</tr>
</tbody>
</table>

Notes: Letters indicate basins: L (Laurel), B (Bowie), and W (Western Branch). Some models did not predict some endpoints (–).

FIGURE 3. Annual Time Series Predictions from Five Model Implementations vs. Measured Annual Discharges of Water, TN, and TP. Predictions would equal observations along the solid diagonal line. For the Laurel and Bowie watersheds, the dotted lines on the TN and TP plots are the 95% confidence limits for the USGS estimates of observed loads. The confidence limits are plotted against the vertical axis to show how differences between model predictions and observed loads compare to the 95% confidence limit of the observed loads.
CBP5 best predicted flow at Western Branch (NS = 0.77), but provided relatively poor predictions at Laurel (NS = 0.3). TN loads predictions were again less accurate and more different among models than flow predictions. The SERC and SERCLM models performed well in predicting annual TN loads (NS > 0.8) at Laurel, but all the models performed poorly in predicting annual TN loads at Bowie (NS < 0).

The ranges of differences between the TP load predictions and observations were again higher than those for TN. At Laurel, TP loads were generally overestimated, and all the models had years with predictions >100% of the observed annual loads (Table 11). Differences between observations and the model predictions were smaller for the larger Bowie watershed. The NS coefficients (Table 12) indicate that none of the models are good predictors of TP loads. NS values were below 0 for all but one TP endpoint, indicating the models were less reliable than using the average observed loads as a predictor. The CBP4 model had a positive coefficient (NS = 0.25) at Bowie, but the value (NS = 0.25) was still below the threshold of good performance (i.e., NS > 0.5) (Moriasi et al., 2007). The SERC and SERCLM models tended to overestimate observed TP loads by more than 100% because of the measured TP loads used to fit the SERC models were higher than the USGS TP observations (see Discussion).

For both TN and TP, most model predictions fell outside the 95% confidence limits for the observed loads (Figure 3) produced using the ESTIMATOR.
model (Cohn et al., 1989), suggesting that the differences between model predictions and observations are statistically significant. A few model predictions fell within the 95% confidence limits of the observations, but such agreement was again not consistent among materials and locations for any model.

In summary, the analysis of annual time series predictions supported the key patterns identified in the analysis of average annual endpoints: no model consistently excelled across the endpoints, model skill was highest for flow, intermediate for TN, and poor for TP; and skill in predicting one material seemed unrelated to the skill in predicting the others. In addition, models that performed well in predicting an average annual endpoint were not necessarily among the best models for predicting the annual time series for the same material and basin. In some cases, this may partly reflect the limited number of years available to estimate the annual average (see Discussion).

Performance of the Model Average. We compared the performance of the model average to the individual models for every endpoint. For many of the endpoints considered above, at least one model provided a better estimate than the model average, but across all the endpoints, the model average performed more consistently and more reliably than any single model (Figures 2 and 3, Tables 8-13). The model average had the best overall rank across all the average annual and annual time series endpoints (Tables 10 and 13). The model average worked well partly because each individual model performed poorly for some endpoints. For example, the annual average TN load predicted by SPARROW97 was most similar to the observed long-term average at Bowie, but least similar at Western Branch. The MDP90 TN predictions agreed closely with the long-term data at Laurel and Western Branch, but not at Bowie. Model performances also varied among response variables. For example, the MDP97 model effectively predicted long-term TN loads but not TP loads; and the reverse was true for CBP5. The model average did perform poorly for particular endpoints where a single, very poorly performing model dominated the average (as when the CBP4 model greatly overestimated annual average flow at Laurel) or where all the models either over- or under-predicted the observations (e.g., annual TP loads at Laurel). The model average performed better for the annual time series endpoints (and monthly time series endpoints, Supporting Information) than for the average annual endpoints.

Total Loads to the Estuary

Across the model set, predicted average annual flow from the entire watershed to the Patuxent estuary ranged between 840 and 9,100 Mm$^3$/yr, and the model average flow was 2,900 Mm$^3$/yr (Table 14). Predicted average annual TN loads to the sub-estuary ranged between 1,400 and 2,900 Mg N/yr. Estimates from the SERCLM and CBP5 models were remarkably similar (1,750 Mg N/yr), whereas estimates from MDP, SPARROW92, and CBP4 were consistently higher than the other models. The model average was 2,115 Mg N/yr. Predicted average annual TP loads ranged between 60 and 340 Mg P/yr, and the model average was 191 Mg P/yr.

The molar ratio of TN to TP in the average annual discharge ranged from 11 to 78, with a model average of 24 (Table 14). The ratio for the two SERC models was 11, which is less than the Redfield ratio of 16 (Redfield, 1958; Glibert et al., 2006), suggesting a possible excess of phosphorus over nitrogen relative to the needs of phytoplankton. The other seven model implementations had TN:TP ratios above 16, suggesting a relative excess of nitrogen in watershed discharges to the estuary. The SPARROW92 implementation had the most extreme TN to TP ratio (78, Table 14).

Annual time series predictions of flow, TN, and TP increased directly with annual precipitation, but the response to precipitation differed among models (Figure 4). Absolute and relative differences among the model predictions were greater during wetter years. CBP4 estimates of flow were consistently higher and increased more with additional precipitation than did flow estimates from the SERCLM or CBP5 models, which were consistently similar throughout the study period. Between 1984 and 2000, flow estimates from the SERCLM, CBP4, and CBP5 models ranged between 500 to 1,500 Mm$^3$/yr, 5,000 to 16,000 Mm$^3$/yr, and 850 to 2,700 Mm$^3$/yr, respectively. All three models predicted their highest annual discharge during the wettest year (1996), but they did not all predict the lowest annual flow during

<table>
<thead>
<tr>
<th>TABLE 14. Predicted Average Annual Flow, Total Nitrogen Load, and Phosphorus Load to the Patuxent Estuary and Atomic N to P Ratios.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Model</td>
</tr>
<tr>
<td>MDP90</td>
</tr>
<tr>
<td>MDP97</td>
</tr>
<tr>
<td>SPARROW92</td>
</tr>
<tr>
<td>SPARROW97</td>
</tr>
<tr>
<td>SERC</td>
</tr>
<tr>
<td>SERCLM</td>
</tr>
<tr>
<td>CBP4</td>
</tr>
<tr>
<td>CBP5</td>
</tr>
<tr>
<td>Model Average</td>
</tr>
</tbody>
</table>
the driest year (1991). Among years, the model average annual P load ranged between 2,400 and 6,700 Mm\(^3\)/yr.

Patterns in the predicted annual time series nutrient loads were similar to the patterns in the predicted annual flow. For TN, the SERCLM and CBP5 models consistently predicted lower loads (range: 1,100-2,600 and 1,400-2,600 Mg N/yr, respectively) than the CBP4 (range: 1,200-4,800 Mg N/yr). The model average ranged between 1,400 and 2,800 Mg N/yr. For TP, the SERC and SERCLM models predicted higher annual loads (range: 85-540 and 175-560 Mg P/yr, respectively) than the CBP4 and CBP5 models (75-460 and 110-270 Mg P/yr, respectively), probably because of differences in the underlying measurements used for model calibration (see Discussion). The model average ranged between 135 and 365 Mg P/yr.

Allocating Loads to Land Types

The attribution of nonpoint source (NPS) annual average TN loads to agriculture and to developed land differed among models (Tables 5, 15, and 16). In the Laurel watershed, all models identified agriculture as the majority TN source (range 51-95% of NPS load). The SERCLM model predicted the highest agricultural contribution despite using the lowest estimated proportion of agricultural land area, indicating that the differences among models in source allocation reflect more than just the differences in land type proportions. In the other three watersheds, some models attributed the majority of the TN load to agriculture, whereas other models attributed the majority to developed land. For Bowie, the SPARROW and SERC models attributed more nitrogen to agriculture, whereas the MDP and CBP models attributed more...
to developed land. For all four watersheds, the model average contribution from agriculture was larger than the model average contribution from developed land.

The allocation of NPS TP loads differed even more among the models than did the TN allocations. For the Laurel basin, the agricultural contribution to NPS TP loads ranged from 40 to 91% among models, and all models estimated that developed land contributed a much smaller fraction (<17%) of the NPS TP load. For Bowie, the MDP90, SERC, and SERCLM models predicted that more TP came from agriculture than developed land, whereas the MDP97, SPARROW, and CBP models predicted the reverse. For three basins, the model average indicated that agriculture contributed more TP than developed land, but the developed land contribution at Bowie was higher than the agricultural contribution.

**DISCUSSION**

Our ensemble analysis of watershed models yielded insights that could not have been revealed by examining a single model. We found that none of the individual models was consistently best in matching observed loads across the set of endpoints that we examined. Instead, the model average prediction was the most consistently reliable predictor, and the range of predictions among models provided a first order estimate of uncertainty. For nutrients, the range among model predictions was much larger than the confidence limits for the observed loads, suggesting that the uncertainties in modeling are much larger than the uncertainties in load measurement. In some cases, consensus among the models would justify confidence in the model predictions and the underlying knowledge, but other analyses revealed large differences among the models. Those differences suggest areas where more research is needed to provide better data or better understanding of watershed processes. These insights from ensemble modeling support the importance of considering multiple models and the need to adaptively manage land use practices to protect water resources. The following sections provide more details on each of these findings.

There Is No “Best” Model

No single model consistently outperformed the other models across the endpoints for which we compared predictions to observations. The models that most closely matched the data for one endpoint often were among the worst models for another endpoint (Tables 10 and 13, Figures 2, 3, and 4). Such an outcome is not inevitable, and some ensemble analyses could identify a model that is generally superior to the alternatives across particular sets of predictions. However, our finding of “no best model” matches the experience of a more intensive watershed model comparison implemented across the European Union (Bormann et al., 2007, 2009; Breuer and Huisman, 2009; Breuer et al., 2009; Huisman et al., 2009; Viney et al., 2009).

The Range of Predictions Helps Quantify Model Uncertainty

The range among models in an ensemble provides a first order estimate of model uncertainty for predicting

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**TABLE 15.** Model Average and Range Among Models (in parentheses) for the Percentages of Predicted Average Annual TN and TP Discharges Allocated to Cropland and Developed Land in Four Watersheds.

<table>
<thead>
<tr>
<th>Basin</th>
<th>TN Cropland</th>
<th>Developed Land</th>
<th>TP Cropland</th>
<th>Developed Land</th>
</tr>
</thead>
<tbody>
<tr>
<td>Laurel</td>
<td>72 (51 to 95)</td>
<td>12 (1 to 24)</td>
<td>64 (40 to 91)</td>
<td>12 (3 to 17)</td>
</tr>
<tr>
<td>Bowie</td>
<td>46 (23 to 69)</td>
<td>39 (17 to 59)</td>
<td>35 (21 to 51)</td>
<td>48 (34 to 59)</td>
</tr>
<tr>
<td>Western Branch</td>
<td>47 (18 to 62)</td>
<td>37 (17 to 56)</td>
<td>47 (19 to 81)</td>
<td>38 (17 to 67)</td>
</tr>
<tr>
<td>Entire Patuxent</td>
<td>49 (27 to 72)</td>
<td>35 (18 to 54)</td>
<td>47 (23 to 75)</td>
<td>35 (12 to 48)</td>
</tr>
</tbody>
</table>

**TABLE 16.** Percentages of Predicted Average Annual TN and TP Discharges from the Bowie Basin Allocated to Cropland and Developed Land by Nine Model Implementations.

<table>
<thead>
<tr>
<th>Model</th>
<th>TN Agriculture</th>
<th>Developed Land</th>
<th>TP Agriculture</th>
<th>Developed Land</th>
</tr>
</thead>
<tbody>
<tr>
<td>MDP90</td>
<td>37</td>
<td>50</td>
<td>51</td>
<td>46</td>
</tr>
<tr>
<td>MDP97</td>
<td>31</td>
<td>58</td>
<td>44</td>
<td>54</td>
</tr>
<tr>
<td>SPARROW87</td>
<td>63</td>
<td>27</td>
<td>30</td>
<td>37</td>
</tr>
<tr>
<td>SPARROW92</td>
<td>56</td>
<td>40</td>
<td>27</td>
<td>55</td>
</tr>
<tr>
<td>SPARROW97</td>
<td>71</td>
<td>25</td>
<td>26</td>
<td>52</td>
</tr>
<tr>
<td>SERC</td>
<td>49</td>
<td>36</td>
<td>46</td>
<td>44</td>
</tr>
<tr>
<td>SERCLM</td>
<td>66</td>
<td>27</td>
<td>50</td>
<td>34</td>
</tr>
<tr>
<td>CBP4</td>
<td>25</td>
<td>54</td>
<td>21</td>
<td>52</td>
</tr>
<tr>
<td>CBP5</td>
<td>32</td>
<td>50</td>
<td>30</td>
<td>56</td>
</tr>
<tr>
<td>Model average</td>
<td>48</td>
<td>41</td>
<td>36</td>
<td>48</td>
</tr>
</tbody>
</table>
an endpoint, thus helping to objectively assess confidence in model predictions (Beven, 2007; Clark, 2007). As the range accounts for differences among models, it reflects uncertainty in the model structure (Tobias and Li, 2004). In our model set, the SERC and SPARROW models were statistical models that could provide predictions with confidence limits, but the loading coefficient (MDP) and simulation models (SERCLM, CBP, and PLM) provided no estimates of prediction uncertainty. Indeed, most watershed simulation models do not provide uncertainty estimates (Pappenberger and Beven, 2006). The uncertainty range from ensemble modeling can help describe prediction uncertainty while research continues on better methods to quantify uncertainty in complex simulation models. There has been some success in quantifying prediction uncertainty in simple watershed models (e.g., Alexander et al., 2002). Increases in computer power and ongoing research in uncertainty analysis methods may eventually enable more complete uncertainty analyses of more complex simulation models, like the CBP or PLM models in our ensemble, but such analyses of individual models cannot capture uncertainty in the underlying model structure.

The Model Average Is the Most Consistent Predictor

Averaging across the model ensemble provided more reliable predictions across the set of endpoints than any single model. Unlike any of the individual models, the model average estimates generally were within the top 10% across all endpoints and always within the top 50% of the ranked performances of individual models (Tables 10 and 13). The model average was not always the closest to the observed data for every endpoint, so it should not be enshrined as a “best” model (see previous section). However, when data are not available to test model predictions, the model average is likely to be a better estimate than any single model. Other studies have also reported that the model average is more consistently reliable than a single model (Breuer and Huisman, 2009; Viney et al., 2009).

We used the simple average of model predictions in our investigations of model averaging, but model averaging is most successful when it incorporates penalties for model complexity, considers uncertainties of model predictions, and weights models by past performance (i.e., Bayesian model averaging) (Kadane and Lazar, 2004; Tobias and Li, 2004). These measures minimize the influence of poor or overly complicated models. Bayesian model averaging has gained widespread application in financial forecasting and socioeconomics (e.g., Wright, 2008; Tobias and Li, 2004), weather (e.g., Koop and Tole, 2004; Gneiting and Raftery, 2005), and more recently, in hydrology (e.g., Gourley and Vieux, 2005). We could not apply penalties for model complexity, because we did not have measures of model complexity and uncertainty (see above) for most of the models in our ensemble. Better methods quantifying model complexity and uncertainty for large simulation models (see above) would enhance the interpretation of individual models and the power of multi-model approaches like model averaging.

Consistencies and Differences Among Models

Nutrient Source Areas. Our ensemble analysis found some patterns of agreement among the models. Despite the differences in land data and nutrient generating activities considered, all the models indicate that agricultural lands release more N and P per unit area than do developed lands. Empirical watershed studies have also reported higher rates of nutrient release from croplands than from developed lands (Beaulac and Reckhow, 1982; Jordan et al., 1997a,b, 2003; Liu et al., 2000).

Watershed models often are analyzed to identify the source areas for nutrient discharges. In our comparison, the models allocated different fractions of the nutrient loads to agriculture and to developed land. In some watersheds, some models identified agriculture as the dominant source area, whereas other models identified developed land as the more important source (Tables 15 and 16). Other model comparisons also have reported widely different partitioning among nutrient sources for different models (Valiela et al., 2002; Jordan et al., 2003; Weller et al., 2003). The differences are important because the estimates could affect how management efforts are targeted to the two land types (Valiela et al., 2002). Together, the models we studied indicate that agriculture and developed land both contribute substantially to nutrient loads, and both land types should be managed to improve water quality.

Watershed Estuary Linkages. Watershed models have been linked to estuarine models to help understand and manage the impacts of human activity and management efforts on estuarine water quality and living resources (e.g., Cerco, 1995; Brandt and Mason, 2003; Lung and Nice, 2007). These efforts often estimate the atomic ratio of nitrogen and phosphorus in estuarine inputs and compare that estimate to the Redfield ratio 16, which represents the average atomic ratio of N to P in phytoplankton (Redfield, 1958; Glibert et al., 2006). TN to TP ratios greater than 16 may mean that N is abundant relative to P, so that P is the nutrient more limiting to
phrytoplankton production. TN to TP ratios less than 16 imply the reverse, that N supply is more limiting to primary production.

The predicted TN to TP ratio varies widely among the models (Table 14), ranging from 78 (SPARROW2) to 11 (SERC and SERCLM). Only the two SERC models suggest N limitation by predicting ratios below 16. The other six model implementations, all predict TN to TP ratios greater than 16, suggesting that P is the more limiting nutrient. Inferences based on TN to TP ratios are not conclusive because phrytoplankton respond to dissolved inorganic nutrient concentrations (not total concentrations), and because much of the TP in watershed discharges is attached to particles that may become buried in sediment and remain unavailable to phrytoplankton (Hartzell et al., 2010). The wide range of predicted TN to TP ratios does indicate that knowledge of the linkage between watershed discharges and estuarine nutrient limitation remains uncertain. Relying on a single watershed model would limit our understanding of that uncertainty, whereas using multiple models can improve our confidence in the overall model predictions.

Relative Predictably of Flow, TN Load, and TP Load. There were consistent patterns across models in the relative uncertainties of predictions for different materials. For all the models that had published calibration results, the performance of the calibrated model was better for water discharge than for TN load and worst for TP load (Linker et al., 2000; Costanza et al., 2002; Weller et al., 2003; Liu et al., 2008). Our ensemble analysis confirmed those patterns. For all three time frames that we considered (average annual, annual time series, and monthly), performance metrics were best for flow, intermediate for TN, and worst for TP; and the ranges of estimates among models were narrowest for flow, intermediate for TN, and widest for TP (Tables 8 and 11, Figures 2, 3, and 4, Supporting Information). Nutrients are harder to predict than flow partly because nutrient release, transport, and removal are all strongly driven by factors that are temporally episodic and spatially heterogeneous, making them hard to represent with deterministic models.

Controls of Phosphorus Delivery. The poor performance and high uncertainty in predicting TP loads suggests that the models do not capture the dominant watershed processes controlling the transport and delivery of phosphorus. The P in streams is mostly associated with sediments (Jordan et al., 1997a,b), so effectively modeling P loads requires a good representation of sediment generation and transport. Most watershed models assume that hillslope erosion is the proximal source of sediment (and associated particulate P) in stream loads, although empirical tests have demonstrated that hillslope erosion models are poor predictors of suspended sediment loads (Boomer et al., 2008; Wilkinson et al., 2009) and that other processes likely control sediment generation and transport (de Vente and Poesen, 2005). Important processes identified in field studies include: gully erosion (Wells et al., 2009), seepage erosion (Fox and Wilson, 2010), stream bank erosion (e.g., Walter and Merritts, 2008; Devereux et al., 2010; Mukundan et al., 2010), in-stream erosion and deposition (Dearing and Jones, 2003), and floodplain deposition (e.g., Noe and Hupp, 2009). Models that move beyond hillslope erosion to account for more of these processes (Prosser et al., 2001; Wilkinson et al., 2009) may provide more accurate and precise TP predictions. Application of inorganic fertilizer or manure can also promote soil P saturation and increase delivery of dissolved P to streams (Staver and Brinsfield, 2001). The poor performance of most watershed models in predicting P loads suggests a critical need for field and modeling research to understand the relative importance of different sediment and phosphorus transport processes.

Errors in Model Implementation. Our independent review of output from each model also helped identify and correct many errors and inconsistencies in the model implementations. For every model, we found errors in the model output caused by oversights in running the model or in summarizing its output for analysis. These included errors in data entry, database queries, or unit conversions. The mistakes were not evident when examining a single model, but became clear when predictions from several models were compared.

Sources of Differences Among Models

Land Use or Land Cover Data. Some of the differences among models in load predictions came from large and systematic differences among the land type data sets used to drive different models (Tables 6 and 7). Clearly, there are fundamental differences in land classification that yield differences in the proportions of cropland and developed land among model inputs. These are the land types responsible for most non-point TN and TP, so the differences in their proportions are likely an important source of differences in modeled TN and TP discharges. Some of the differences among the data sets arose from processing land type maps to provide model input. The SERC, SERCLM, and PLM models used published data without any modifications. The SPARROW and CBP input
data were synthesized from several land cover maps combined with county agricultural census data and counts of septic systems. The modified data sets had higher proportions of developed land and less crop-land than the unmodified land cover maps. The MDP data sets, which were interpreted from aerial photography, also had higher percentages of developed land than the unmodified data sets derived from satellite imagery, such as the EPA-EMAP (1994) data (Table 6). The differences remind us that land type data do not come from simple, direct measurements, but are instead derived from interpreting aerial photography or from applying classification models to remotely sensed data.

The dates of the land data sets range from 1973 to 2000 (Table 6); so some of the differences among them come also from land use change. Most watershed models use information from a single land use or land cover data set. Even many models that include detailed representation of temporal responses to precipitation and temperature still assume that land use remains constant through time. In our model set, only the CBP5 and PLM models incorporated information on land use change to dynamically account for its effects in multi-year simulations (but the estimated temporal changes in land use proportions are similar in magnitude to the differences in proportions among data sets for similar dates; Table 6). Given the important effects of land types on water and nutrient discharges, more models need to account for land changes, especially in applications over multi-year periods.

More research is needed to classify land use and land cover more accurately and consistently, to quantify the uncertainty in those classifications, and to propagate those uncertainties through watershed models to measure how they affect the uncertainty of predicted loads. The current uncertainties in land characterization confound our interpretation of predicted nutrient source allocations or impacts from alternative land use management scenarios (Huisman et al., 2009). Recent progress in refining land classification models with ancillary data (e.g., Pyke, 2010; P. Claggett, USGS, unpublished data) may provide more reliable land type data for the Chesapeake Bay region.

**Stream Measurements of Nutrient Loads.** Disparities in measured loads also contributed to differences among model predictions. In particular, the SERC model was a poor predictor of the USGS observed TP loads (Table 12), despite the model’s strong calibration results (Jordan et al., 2003; Weller et al., 2003). This discovery led us to compare the USGS streamflow and nutrient load data with the independent SERC measurements used to calibrate the SERC and SERCLM models. Nutrient loads reported by the USGS are derived from a log-linear regression model that estimates nutrient loads from measured nutrient concentrations, measured streamflow, and a function of time that represents seasonality and possible linear trends (Cohn et al., 1992). The USGS measured nutrient concentrations during periodic short sampling events using a spatially integrated approach in which samples were collected across the stream width and depth and then composited. Streamflow was monitored continuously. The SERC data came from automated samplers, which measured stream depth continuously and collected weekly flow-weighted composite samples for nutrient analysis (Jordan et al., 1997c), a method which has been reported to provide direct and accurate estimates of loads (Stone et al., 2000; Harmel et al., 2006). Weekly mean flow rates and flow-weighted mean concentrations were multiplied to estimate weekly loads for the sampling period between August 1997 and July 1999.

A comparison of SERC and USGS monthly observed TN loads revealed that many of the SERC measurements fell outside the 95% prediction interval for the USGS observations provided using ESTIMATOR (Cohn et al., 1989), but there was still a strong correlation ($R^2 = 0.90$) and data were grouped symmetrically around the 1:1 line (Figure 5). However, the observed TP loads were less strongly correlated ($R^2 = 0.71$) and the USGS and SERC loads were systematically different. The geometric mean slope (appropriate when two variables are both measured with error) (Sprent and Dolby, 1980) of SERC TP vs. USGS TP is 1.97, indicating that SERC-measured TP discharges are roughly twice the USGS-measured TP discharges. The relationship also explains why the SERC and SERCLM models (which were calibrated with the SERC measurements) made predictions that were strongly correlated with, but systematically greater than the USGS measurements (see Figure 3). If the SERC TP measurements are correct, then models calibrated with the USGS TP measurements would significantly underestimate TP loads. The ESTIMATOR modeling approach applied using USGS to estimate TP loads from flow and concentration data may underestimate loads during high flow periods. Further research comparing volume-integrated composite sampling using ESTIMATOR modeling and quantifying the uncertainties in both types of measurements would help identify the most accurate way to measure TP loads.

**Time Period Considered.** Differences in the modeled time period also contributed to differences among model predictions. The clearest example of possible confusion arises in evaluating the performance of the SERC model. This simple statistical
model was calibrated using extensive empirical information from the Patuxent, so it is not surprising that it is among the best models for annual time series predictions of flow, TN, and TP (Table 13). Given its good performance for annual time series predictions, its much poorer performance for average annual predictions seems surprising. However, the explanation is simple. The two years predicted using the SERC model (August 1997–July 1999) are not typical and provide a poor estimate of average annual loads. This problem does not arise for the other models because they were designed to predict the annual average (MDP or SPARROW) or because they estimate the annual average from much longer annual time series (7–17 years, PLM, CBP, and SERCLM). In general, simulation periods need to be long enough to capture climatic variation, especially when calculating the long-term mean discharges most often used in applying watershed models to management questions.

Comparing Models as Published

We were not able to compare our models using exactly the same inputs and outputs. The models we compared could not be fully standardized because they took very different approaches to modeling nutrient discharges from watersheds. For example, the models use fundamentally different kinds of information on land types and nutrient sources (Tables 6 and 7), and some models attribute nutrients directly to particular activities, such as fertilizer or manure application rather than using land type as a surrogate (Preston and Brakebill, 1999). Across the model ensemble, the land type data sets are not commensurate (see Weller et al., 2003), so each model must be run with the land data for which it was developed. It would be wrong to apply a model calibrated with one type of land data to predict nutrient loads for watersheds described with a different source of land data (Weller et al., 2003). The different choices of land data or nutrient generating activities to consider represent different ideas of how to represent nutrient sources, and the choices are essentially elements of model structure that cannot be eliminated. Similarly, we could not compare model outputs for exactly the same time periods. Some models (MDP, SPARROW) made only average annual predictions, not estimates for specific years. The SERC statistical model can only produce estimates during the years of its underlying empirical data (August 1997 through July 1999) and cannot make predictions for other years.

Our analysis, then, did not focus strictly on differences due to mathematical structure. Instead, we compared the predictions as published and as interpreted for management implications. This approach does demand some care in interpretation, such as the caution noted previously about annual average results based on different ranges of years, particularly, the short 2-year range of the SERC model. However, despite the limitations, comparing models as published is necessary and useful. All the models have been analyzed to make published inferences about the sources and magnitudes of nutrient loads, and some of the model predictions have been used to guide management decisions. We need to understand where the models agree and disagree, regardless of whether differences arise from mathematical structure or from differences in input data or time period considered. Considering all these differences provides

FIGURE 5. Comparison of USGS and Smithsonian Environmental Research Center (SERC) Observations of Monthly Nutrient Discharges from the Bowie Watershed. The SERC and USGS measurements would be equal along the diagonal line. The dotted lines are the 95% confidence limits for the USGS estimates of observed loads. The confidence limits are plotted against the vertical axis to show how differences between the SERC and USGS observations compare to the 95% confidence limits of the USGS loads.
the most complete information on uncertainty and confidence that the accumulated knowledge of all the models together can provide.

**Multiple Models in Watershed Management**

We must emphasize that the models we compared were designed for different purposes, had very different structures, and considered different geographic extents. Some of our models were for the Patuxent only (SERC, SERCLM, and PLM), one applied to the state of Maryland (MDP), and two modeled the entire Chesapeake Bay watershed (SPARROW and CBP), an area roughly 70 times larger than the Patuxent watershed. It is not surprising that empirical models customized for the Patuxent sometimes performed better in matching measured Patuxent discharges than did simulation models calibrated for the entire Chesapeake Bay watershed.

The CBP models have capabilities that none of the other models can provide, and those capabilities reflect its unique role in regional planning, decision making, and environmental regulation. The CBP models have been linked to a model of nutrient deposition from the atmosphere and to a model of estuarine circulation and ecological processes in the Bay. The combined modeling system estimates the maximum watershed nutrient loads that still support legally acceptable water quality in the Bay (the Chesapeake Bay TMDL, see USEPA, 2010b). The CBP model has been applied to partition the necessary watershed load reductions to states and local governments. The model accounts for a broad array of nutrient sources and watershed management actions, and it can predict the nutrient load reductions that might be achieved by different management alternatives. For these reasons, the CBP model is central to past and ongoing management and regulation in the Chesapeake Bay, and none of the other models in our ensemble could replace it in the regulatory process.

The existence of a dominant and very capable model, however, does not mean that a single model is sufficient and other models should be ignored. Our ensemble analysis demonstrates that there is much to be learned from comparing models, even for a system in which model development and application has focused strongly on a dominant model. Examining the range of estimates for common endpoints provided a way to quantify uncertainty in the model predictions, and averaging across all models generated more reliable estimates of flow and nutrient discharge than selecting and relying on any single model. Comparing the models also helped identify and correct problems and revealed gaps in scientific knowledge that require further research. Furthermore, considering a single model and not presenting its uncertainties can damage credibility if implemented strategies fail to meet the predicted outcomes (Breuer et al., 2009). Ensemble modeling provides a robust, transparent mechanism for building public credibility (Leamer, 1983; Layton and Lee, 2006).

The Patuxent is a much studied watershed (see review in Weller et al., 2003), so our ensemble analysis benefited from having published results available from many modeling programs. This reduced the cost of our analysis, overcoming one of the main limits on applying multiple models in watershed management (Pappenberger and Beven, 2006). However, analyzing the models as published also limited our ability to quantitatively attribute the differences among model predictions to the possible causes: differences in model structure, differences in the input data, or differences in the time period considered. Developing and sharing more standardized input data would improve ensemble modeling and its ability to inform science and management.

An ongoing program of ensemble modeling cannot be sustained by a single research group, but instead requires long-term funding and support of collaborative research (Jakeman et al., 2006). In the Chesapeake Bay region, recent reports have called for adopting a multiple model approach to watershed management (Friedrichs et al., 2011; STAC, 2011), and the proposal to create a Chesapeake Bay modeling laboratory (NRC, 2011; STAC, 2011) could provide the collaborative environment needed to support effective applications of multiple modeling.

**Adaptive Management**

The uncertainty documented by the large ranges among model predictions is definitely not an excuse for forgoing or delaying watershed management actions. The proper response to uncertainty is adaptive management (Boesch, 2002; Stankey et al., 2005; Williams et al., 2007), not inaction. In the case of the Chesapeake Bay, the legal mandate to address impairments is clear (USEPA, 2010c), major sources of nutrients are well known, and management actions that can reduce those sources have been identified. Proceeding through successive adaptive management cycles provides an effective way to move forward and address impairments in the face of uncertainties like those evident in our model comparison. As discussed above, using multiple models helps reinforce confidence in some model predictions and helps identify where additional monitoring or research is needed to reduce uncertainty and increase confidence. With these advantages, using multiple models can improve
the outcomes of adaptive management more efficiently over time than relying on a single model (Williams et al., 2007).

**SUPPORTING INFORMATION**

Additional results of our modeling analysis can be found in the online version of this article.

**Data S1.** Monthly Time Series Analysis. Methods. Results.

**Figure S1.** Time series predictions of monthly water, TN, and TP discharges from the Bowie basin vs. measured monthly discharges.

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**LITERATURE CITED**


USEPA (U.S. Environmental Protection Agency), 2010b. Chesapeake Bay Total Maximum Daily Load for Nitrogen, Phosphorus and Sediment, U.S. Environmental Protection Agency, Annapolis, Maryland.


Supporting Information

USING MULTIPLE WATERSHED MODELS
TO PREDICT WATER, NITROGEN, AND PHOSPHORUS DISCHARGES
TO THE PATUXENT ESTUARY

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Monthly Time Series.

Methods. We summarized monthly time series predictions of Bowie discharges for the
SERC, CBP, and PLM implementations. We plotted monthly discharge estimates against
observed values and calculated Nash-Sutcliffe values of model performance (Eq. 2, but with \(i\)
indexing months rather than years).

Results

Results. Five models could predict monthly loads at Bowie. The best model again varied by
constituent (Figure S1), and the patterns of model performance were different from the average
annual and annual time series patterns. The PLM model best predicted flow (NS = 1), although
all models (except CBP4, which overestimated monthly flow) produced good predictions (NS > 0.8). In contrast, the PLM was least reliable (NS = -0.58) for predicting monthly TN loads, and the SERC statistical model best predicted TN loads (NS = 0.82). For TP, the CBP4 and CBP5 models performed best compared to the other models, though only slightly better than simply using the mean observed TP (NS = 0.07 and 0.09, respectively). The models generally over-predicted monthly TP, especially during high discharge months. In particular, the SERC model consistently over-predicted TP loads (NS = -3.62), but the predictions were strongly correlated with USGS observed TP loads ($R^2 = 0.92$). The systematically higher monthly TP load estimates from the SERC and SERCLM models can be traced to a difference in TP measurements used to calibrate the SERC models and the USGS TP measurements (see Discussion).
FIGURE S1. Time series predictions of monthly water, TN, and TP discharges from the Bowie basin versus measured monthly discharges. The numbers are Nash-Sutcliffe (NS) performance coefficients. Predictions would equal observations along the diagonal line. The dotted lines on the TN and TP plots are the 95% confidence limits for the USGS estimates of observed loads. The confidence limits are plotted along the vertical axis to show how differences between model predictions and observed loads compare to the 95% confidence limit of the observed loads.