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INTEGRATED MODULAR MODELING OF WATER AND NUTRIENTS FROM POINT AND NONPOINT SOURCES IN THE PATUXENT RIVER WATERSHED[1]

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ABSTRACT: We present a simple modular landscape simulation model that is based on a watershed modeling framework in which different sets of processes occurring in a watershed can be simulated separately with different models. The model consists of three loosely coupled submodels: a rainfall-runoff model (TOPMODEL) for runoff generation in a subwatershed, a nutrient model for estimation of nutrients from nonpoint sources in a subwatershed, and a stream network model for integration of point and nonpoint sources in the routing process. The model performance was evaluated using monitoring data in the watershed of the Patuxent River, a tributary to the Chesapeake Bay in Maryland, from July 1997 through August 1999. Despite its simplicity, the landscape model predictions of streamflow, and sediment and nutrient loads were as good as or better than those of the Hydrological Simulation Program-Fortran model, one of the most widely used comprehensive watershed models. The landscape model was applied to predict discharges of water, sediment, silicate, organic carbon, nitrate, ammonium, organic nitrogen, total nitrogen, organic phosphorus, phosphate, and total phosphorus from the Patuxent watershed to its estuary. The predicted annual water discharge to the estuary was very close to the measured annual total in terms of percent errors for both years of the study period (≤2%). The model predictions for loads of nutrients were also good (20-30%) or very good (<20%) with exceptions of sediment (40%), phosphate (36%), and organic carbon (53%) for Year 1.

(KEY TERMS: watershed modeling; nonpoint source pollution; nutrients; point source pollution; simulation; Chesapeake Bay.)

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INTRODUCTION

It has been over 20 years since nonpoint source (NPS) pollution was first recognized as a major contributor to the degradation of water resources in the United States (U.S.) (USEPA, 1985). Despite progress in understanding and controlling NPS over the years, pollution of sediment and plant nutrients in many of the nation's streams and rivers remains of great concern (Carpenter *et al.*, 1998; Howarth *et al.*, 2000). Given the diffuse nature of NPS, efforts have been made to assess and address the water quality and ecological conditions in streams from a watershed

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perspective. For example, the U.S. Environmental Protection Agency (USEPA) requires the establishment of total maximum daily load as a watershed-wide budget of pollutant load to watercourses (USEPA, 2000).

In efforts to understand and control water pollution from both nonpoint and point sources, watershed models have been used as one of the important tools for addressing research questions and for guiding watershed management (Singh, 1995; Srinivasan *et al.*, 1998; Beven, 2001; Diplas, 2002). A great number of watershed models can be found in the literature. Some of these models simulate only hydrologic processes in a watershed, such as Systeme Hydrologique Europeen (SHE) (Abbott *et al.*, 1986a,b), TOPMODEL (Beven and Kirkby, 1979; Beven *et al.*, 1995), and Soil Moisture Distribution and Routing (SMDR) (Walter *et al.*, 2001; Gérard-Marchant *et al.*, 2006; Hively *et al.*, 2006). Others simulate both hydrology and water quality of a watershed, such as Chemicals, Runoff, and Erosion from Agricultural Management Systems (Knisel, 1980) and AGNPS (Young *et al.*, 1989). Some watershed models simulate single storm events [e.g., Areal Nonpoint Source Watershed Environment Response Simulation (ANSWERS) (Beasley *et al.*, 1980) and Agricultural Nonpoint Source], while continuous-time models simulate both storm and non-storm conditions, such as Hydrological Simulation Program-Fortran (HSPF) (Johansen *et al.*, 1984; Donigian *et al.*, 1995), Simulator for Water Resources in Rural Basins (Arnold *et al.*, 1990) and Soil and Water Assessment Tool (SWAT) (Arnold *et al.*, 1998).

Many of the watershed models are physically based and spatially distributed models (e.g., ANSWERS, SHE, SMDR) that are designed to simulate a variety of physical processes (mainly hydrological and geomorphological processes) in detail both temporally and spatially. The processes are usually represented in the form of differential equations on a very small spatial support (usually a grid cell). The development of physically based comprehensive watershed models demands a great deal of time, manpower, and resources. The application of such a model is complex and computationally demanding because of a large number of model parameters. This is especially the case when a spatially detailed comprehensive watershed model is applied in large-scale regional studies that may involve hundreds of thousands of parameters in model simulations. With ever increasing computer power, the computation requirements *per se* may not be a limiting factor for general model applicability. However, the availability of data or lack thereof, for such a large number of parameters can become a bottleneck in model applications. Alternatively, many parameters are guesstimated or simply lumped average values, sometimes over the whole watershed, are used. This introduces a great deal of uncertainty into model simulations, which in turn propagates into model predictions. As a result, though conceptually superior, complex comprehensive watershed models may not provide better predictions than simpler models (Beven, 1989; Grayson *et al.*, 1992; Jakeman and Hornberger, 1993). There is an increasing need for spatially explicit models with less intensive data requirements. In response to this need, watershed modeling has shifted from single complex comprehensive models to modular systems with multiple simple model components (Leavesley *et al.*, 1996a,b; Jackson *et al.*, 2001).

One of the advantages of modular model design is its simplicity and flexibility. Each component model is just for one set of processes, and usually is much simpler than a comprehensive model. For any particular application, one can develop new model components, use existing models, or combine the two to simulate different sets of processes separately and then integrate the results from those component models (Leavesley *et al.*, 1996a,b). Simple models may be more tractable in terms of parameter estimation, calibration, and uncertainty analysis. For many modeling problems, simple models may give more precise predictions because they have fewer parameters and associated parameter uncertainties. This is the case for mechanistic as well as empirical models (e.g., Steenhuis *et al.*, 1999). In addition, simple and modular models better meet the need of watershed managers and decision makers for assessment tools that are relatively simple, user friendly and can be applied to broad landscapes (Jackson *et al.*, 2001).

In this paper, we present a modular landscape simulation model for prediction of runoff, sediment, and nutrients from a watershed. The model is a continuous-time model with three separate model components for different sets of processes that operate in a watershed with a defined stream network. Unlike many other modular watershed models that consist of processes-based model components, all the components of our landscape model are simple conceptual or empirical models because we wanted to achieve simple dynamic simulations at the landscape scale. The landscape model is similar to the conceptual modeling framework presented by White *et al.* (1992) in which a watershed is partitioned into subwatersheds that are linked by a stream network. The concept of using different models for different sets of processes, however, was not implemented in their work. Smith *et al.* (1997) presented the SPARROW model based on the same modeling framework, but that model was developed primarily as a nonlinear regression model instead of a simulation system.

Our landscape model is designed to be applicable to watersheds of various sizes, including large ones,

while some models are specially designed for applications on small watersheds, such as SMDR model. Our model is conceptually simple and, due to its modular structure, is easy to update compared with other watershed models, such as HSPF and SWAT. Our model accounts for finer-scale temporal variability, unlike many other simple models, such as SPARROW, which is mainly used for annual predictions (Alexander *et al.*, 2000). The model structure is characterized by the combination of conceptual models (semi-mechanistic) for better understood watershed processes (such as rainfall-runoff relationships) and data-driven empirical models for less understood parts of the system (e.g., the interaction factors controlling nutrient concentrations).

Our landscape model was developed as part of the Complexity and Stressors in Estuarine Systems (COASTES) project conducted in the watershed of the Patuxent River in Maryland. The purpose of the project was to understand the effects of multiple stressors in coastal systems and the interaction of the complexity of such systems with stressors (Breitburg *et al.*, 2003). Weller *et al.* (2003) developed a set of empirical linear regression models to predict NPS sediment and nutrients in the Patuxent watershed. These models have been applied to predict nutrient inputs to the Patuxent estuary under different watershed land use scenarios and the model predictions have been used by other estuarine models (Lung and Bai, 2003; Weller *et al.*, 2003). Despite their fairly successful applications, the models by Weller *et al.* can only be used for a particular period of time because the weather conditions and temporal variation of material concentrations in that period are embedded in the model parameters. For more general applicability, we developed the landscape model presented in this paper for applications in the Patuxent watershed for different periods of time and weather conditions. The landscape model could also be applied to other watersheds after some modifications. In the following sections, we will describe the landscape model, evaluate model performance, and then present the application of the model to the Patuxent River watershed to predict discharges of water, sediment, and various nutrients from the watershed to the river's estuary.

STUDY AREA

The Patuxent River Watershed

The Patuxent River is a tributary to the Chesapeake Bay near the cities of Washington, District of Columbia, and Baltimore, Maryland (Figure 1). The entire 2,300-km^2 Patuxent watershed lies in the state of Maryland. Most of the watershed falls in the Coastal Plain physiographic province (72%) and the remainder is in the Piedmont. Despite its proximity to two major metropolitan areas, only 12% of the watershed area is developed (urbanized). Nearly half of the watershed remains forested (49%). The remainder is cropland (10%) and grassland (28%) (USEPA, 1994a). The two reservoirs in the watershed, maintained for flood control and drinking water supply, drain about 55% of the Piedmont section of the watershed.

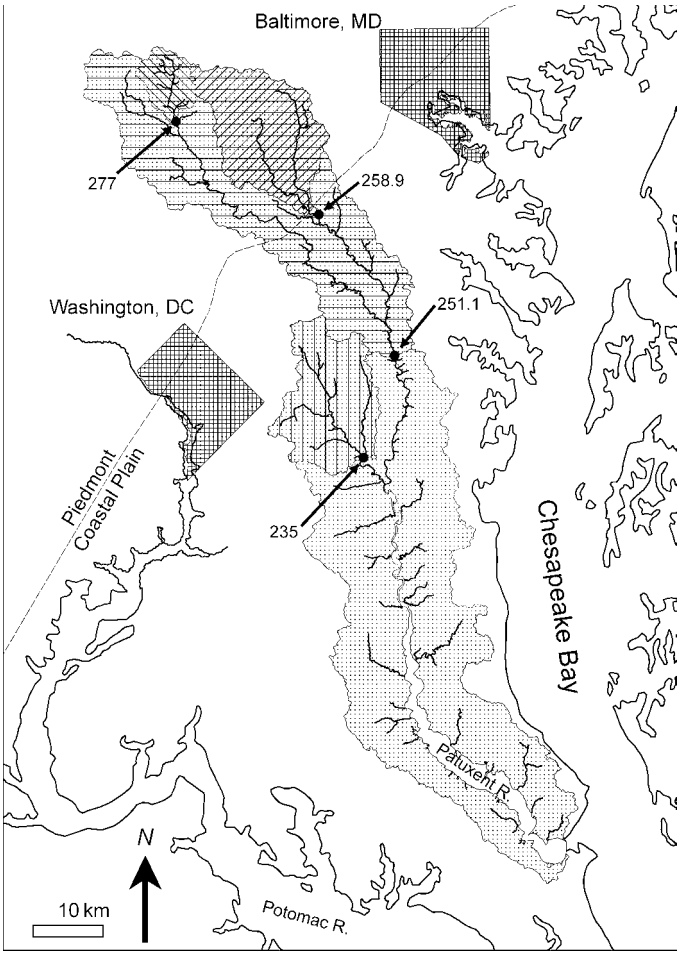

FIGURE 1. Location of the Patuxent River Watershed. The four subwatersheds draining to SERC sampling Stations 277, 235, 258.9, and 251.1 are outlined and stippled.

Since colonial times, human activities have changed the landscape and affected the biogeochemical processes that operate in the Chesapeake drainage basin. As a result, discharges of water and materials from the watershed to the Bay are often increased (Correll *et al.*, 1994; Boynton *et al.*, 1995; Jordan *et al.*, 1997a,b,c; Carpenter *et al.*, 1998). The deterioration of water quality in the Bay has mainly resulted from increased influx of anthropogenic chem-

icals to the Bay from streams in the drainage basin. Increases in watershed inputs of nutrients have led to eutrophic conditions in the system, causing algal blooms, demise of submerged aquatic vegetation, low levels of dissolved oxygen, and declining stocks of living resources (Officer *et al.*, 1984; Correll, 1987; Haire *et al.*, 1992; Boesch *et al.*, 2001).

As one of the main tributaries to the Chesapeake Bay, the Patuxent River is a well-studied system and is often chosen as the site for testing environmental study methods and models (Costanza *et al.*, 2002; Binder *et al.*, 2003; Breitburg *et al.*, 2003; Lung and Bai, 2003). Watershed-scale models have been used in studies of the Patuxent River and the Chesapeake Bay to simulate both hydrology and water quality, such as the USEPA Chesapeake Bay Program's Bay Watershed Model and the Maryland Department of the Environment's Patuxent Basin Scenario Generator, both of which are applications of the HSPF model (Donigian *et al.*, 1995).

Partitioning of the Watershed

As part of the COASTES project and an extension of its long-term watershed research program in the Chesapeake Bay drainage, the Smithsonian Environmental Research Center (SERC) undertook an extensive sampling campaign of the streamflow, sediment, and plant nutrients in the Patuxent River watershed from 1997 to 1999 (Jordan *et al.*, 2003). The contributing area of each sampling site was defined as its drainage watershed, or subwatershed with regard to the whole Patuxent watershed. As such, the Patuxent River watershed is partitioned into subwatersheds based on the sampling sites. In addition, unsampled land areas, mainly along the estuary, are divided into equivalent-size subwatersheds. The resultant 210 subwatersheds are used in our model simulations as spatial units of runoff generation and NPS of sediments and nutrients (Figure 2). These subwatersheds range in size from 0.3 to 78 km^2 and vary in land cover from nearly totally forested to completely rural to dominantly urbanized (Table 1).

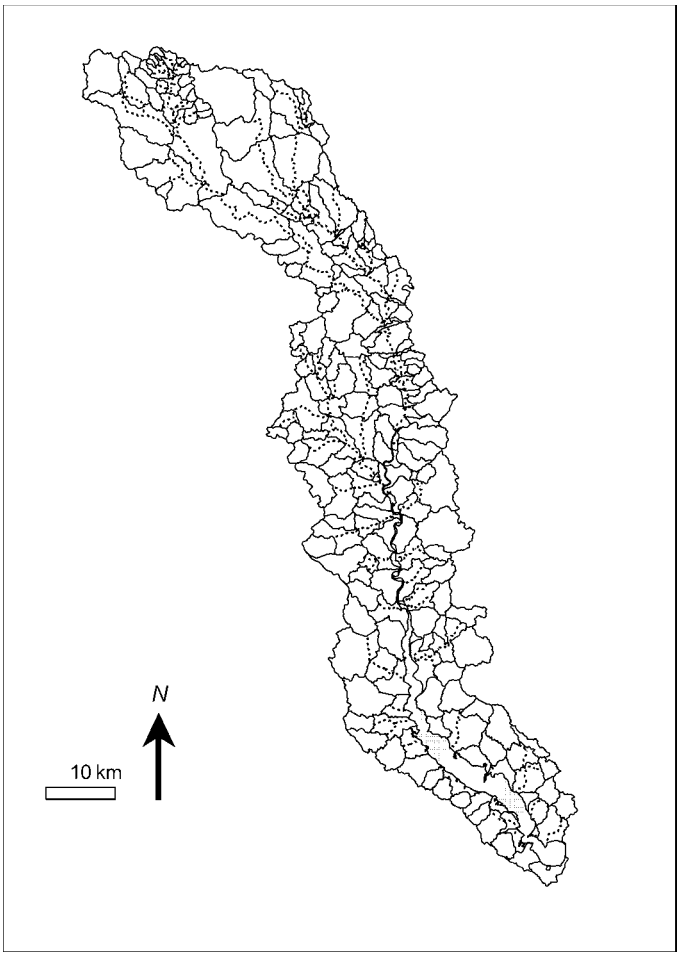

FIGURE 2. The Partitioning of the Patuxent River Watershed Into 210 Subwatersheds, the Units of the Landscape Model Simulation. The dotted lines are major streams.

TABLE 1. Descriptive Statistics of Watershed Area and Major Land Cover Types for 210 Subwatersheds in the Patuxent River Watershed.

	Mean	Median	Minimum	Maximum	Standard Deviation
Watershed area (km^2)	10.9	8.1	0.3	78.5	11.2
Urbanized (%)	14.3	4.5	0.0	79.9	20.2
Cropland (%)	10.7	8.4	0.0	53.6	10.5
Forest (%)	45.6	43.2	0.1	97.3	19.2
Grassland (%)	28.5	27.1	0.6	69.1	14.0

METHODS

The Landscape Model

The landscape model is based on the conceptual model described by Liu and Weller (2008). The conceptual model applies to a generic watershed that consists of a set of subwatersheds connected to their corresponding anchor reaches in a stream network. The subwatersheds are sources of runoff and NPS of water pollutants, which can be predicted using separate submodels. The integration of point sources and NPS in the watershed is implemented through a stream network submodel (Figure 3).

The landscape model consists of three components: a rainfall-runoff submodel, a nutrient submodel, and

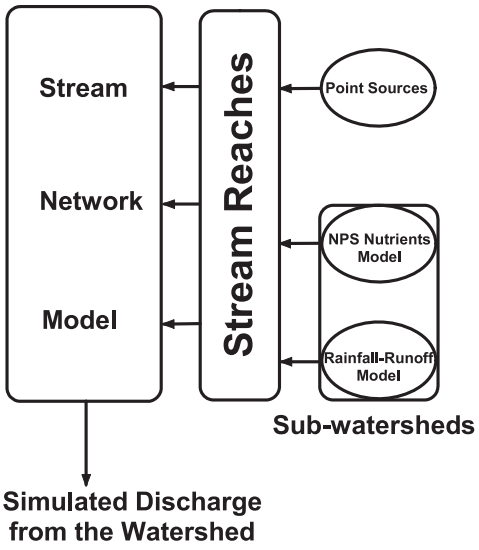

FIGURE 3. A Conceptual Modular Watershed Model.

a stream network submodel. The rainfall-runoff submodel, TOPMODEL, estimates runoff from subwatersheds. The nutrient submodel is a set of empirical statistical models for estimation of sediment and nutrients from NPS in subwatersheds. Outputs from TOPMODEL and the nutrient model, together with point source data, are input to the stream network submodel, which integrates point sources and NPS and routes water and nutrients through the stream network to the estuary (Figure 4).

The landscape model combines conceptual models (semi-mechanistic) for better-understood watershed processes with data-driven empirical models for less-understood parts of the system. TOPMODEL is a conceptual hydrological model that simulates runoff generation in a watershed, but does not account for streamflow routing, which is simulated in the stream network model. The nutrient module, as a set of

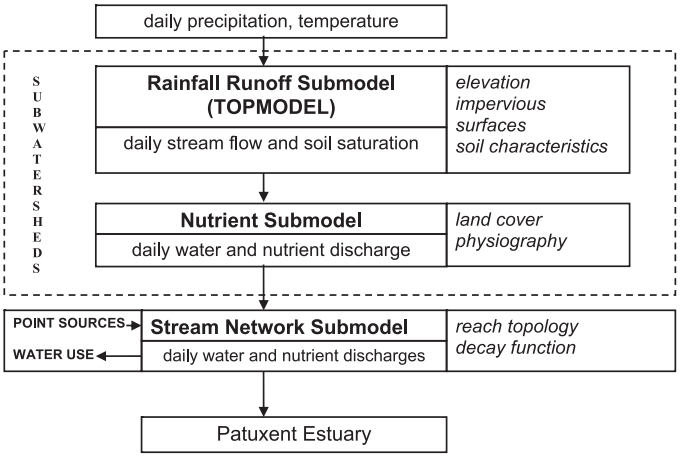

FIGURE 4. Components and Structure of the Landscape Model.

regression models, is a data-driven model that does not quantify processes, but instead predicts sediment and nutrient concentrations from empirical equations derived by relating measured concentrations to watershed characteristics and streamflow. For each subwatershed, the outputs from both TOPMODEL and the nutrient module are used as inputs to the stream reach the subwatershed drains to. Through a decay function, the stream network model explicitly accounts for instream processes that may remove some of the nutrients discharged from the subwatersheds. However, the measured nutrient concentrations and the regression models fitted to those observations may be influenced by instream effects that occur upstream of sampling sites. The regression equations of the nutrient module would then implicitly account for some instream nutrient processing within individual sampled subwatersheds, and as such the decay coefficients in the stream network model should not be interpreted as representing the total instream loss of nutrients.

TOPMODEL

TOPMODEL (Beven and Kirkby, 1979) is a conceptual rainfall-runoff model that simulates the variable contributing area concept of streamflow generation (Dunne and Black, 1970a,b; Dunne and Leopold, 1978). The application of TOPMODEL in hydrological modeling abounds in the literature (Hornberger *et al.*, 1985; Wolock and McCabe, 1995; Franchini *et al.*, 1996; Dietterick *et al.*, 1999). This model predicts runoff and streamflow from precipitation based on the topographic features and soil properties of a watershed. The topographic features in a watershed are represented in TOPMODEL by a topographic index. Using a topographic index in hydrological modeling has attracted a great deal of attention partly because of the increasing availability of digital elevation data (Band, 1986, 1993; O'Loughlin, 1986; Quinn *et al.*, 1991, 1995; Ambroise *et al.*, 1996; Woods *et al.*, 1997). The topographic index used in TOPMODEL is $\ln(a/\tan\beta)$, which is the logarithm of ratio of the upslope drained area (a) to the slope in the downhill direction ($\tan\beta$). Locations in a watershed with the same value of the index are assumed to be hydrologically similar in their response (Wolock, 1993; Beven *et al.*, 1995). As such, individual spatially distributed values (topographic index values of individual cells) can be aggregated into intervals, and then the frequency distribution of the midpoints of the intervals (in percent of watershed area) can be calculated (Wolock, 1993). By using the frequency distribution of the topographic index, TOPMODEL can be run at a scale other than grid cells.

For each of the 210 subwatersheds in the Patuxent watershed (Figure 2), individual cell values of the topographic index were first calculated from digital elevation model (DEM) data using a geographic information system (ArcInfo GRID subsystem) that has implemented the algorithms of the topographic index described by Jenson and Domingue (1988). The frequency distributions of the index were then calculated for each subwatershed. One of the parameters in TOPMODEL is the impervious surface area. Data on the impervious surface area were obtained from the Mid-Atlantic Regional Earth Science Applications Center (RESAC) at the University of Maryland (Goetz *et al.*, 2004). The inputs in TOPMODEL simulations include daily precipitation and temperature, and the outputs are simulated runoff from a watershed. The model is run separately for each of 210 subwatersheds. A file is created to save runoff predictions for each subwatershed, resulting in 210 separate files of runoff data for the subsequent phases of simulation, that is, the simulation of the nutrient submodel and the stream network submodel (Figure 4).

Nutrient Model

The SERC sampling campaign included continuous monitoring with automated stations established at 17 sites in the Patuxent River watershed. The automated stations monitored streamflow continuously and controlled the compositing of volume-integrated water samples. The composited water samples were collected weekly and analyzed for sediment and nutrients. In addition to the 17 stations, six automated stations were located in the adjacent Rhode River watershed (Jordan *et al.*, 2003; Weller *et al.*, 2003). The monitoring data from 22 automated stations for the period of July 27, 1997, through August 2, 1999, were used to develop statistical models that describe the concentrations of materials (sediment or nutrients) from NPS in a watershed as a function of streamflow and the watershed's land cover and physiographic province.

Land cover data for the Patuxent watershed were obtained from the USEPA's Environmental Monitoring and Assessment Program (EMAP) (USEPA, 1994a). This database was developed for the Chesapeake Bay basin using remotely sensed land cover data from Landsat Thematic Mapper images. We aggregated 12 EMAP land cover categories to seven categories (cropland, forest, grassland, developed, herbaceous wetland, bare, and water). The physiographic province data were obtained from Langland *et al.* (1995). The proportion of each land cover category in a subwatershed was obtained by overlaying the land cover with subwatershed boundaries (Liu *et al.*, 2000). Studies show that among all the land cover categories, cropland and developed land (urbanized areas) are the most useful predictors for nutrient concentrations (Jordan *et al.*, 1997a,b,c; Jordan *et al.*, 2003; Weller *et al.*, 2003) and that the effects of land cover on nutrient concentrations vary in different physiographic provinces (Jordan *et al.*, 1997a,b,c; Liu *et al.*, 2000). Most of the 210 Patuxent subwatersheds lie completely in either the Piedmont (44) or Coastal Plain province (158). A few subwatersheds (8) straddle the borderline (the fall line) of the two physiographic provinces. The percentages of cropland and developed land and the physiographic locations of subwatersheds are included as predictors in the nutrient model.

The nutrient model consists of a set of regression models, each of which was separately developed for one of the following materials: total suspended sediment (TSS), total nitrogen (TN), nitrate (NO_3), total ammonium (NH_4), total organic nitrogen (ON), total phosphorus (TP), total phosphate (PO_4), total organic phosphorus (OP), total organic carbon (OC), and dissolved silicate (Si). All the regression models have the following general form:

$$C_{ij} = \beta_0 + \beta_1 Q_{ij} + \beta_2 \sin(2\pi T_{ij}) + \beta_3 \cos(2\pi T_{ij}) + \beta_4 \mathrm{CCROP}_j + \beta_5 \mathrm{FDEV}_j + \beta_6 \mathrm{PCROP}_j + \beta_7 \mathrm{FPIEDUP}_j + \beta_8 Q^2{}_{ij} + \varepsilon_{ij}, \quad (1)$$

where C_{ij} is concentration of nutrient or sediment on day i and at site j; $i = 1,\ldots,n$, n is the number of days in the study period; $j = 1,\ldots,m$, m is the number of sampling sites and $m = 22$ in this study; β_0, $\beta_1,\ldots,\beta_8$ are regression coefficients; Q_{ij} is daily mean flow on day i and at site j (m^3/ha-day); T_{ij} is the ratio of (Julian Day on day i - 1)/(the number of days in the year) for day i at site j; CCROP_j is fraction of watershed area covered by Coastal Plain cropland at site j; FDEV_j is fraction of watershed area that is developed (urbanized) at site j; PCROP_j is fraction of watershed area covered by Piedmont cropland at site j; $\mathrm{FPIEDUP}_j$ is fraction of watershed area that is in the Piedmont at site j; $Q^2{}_{ij}$ is the square of daily mean discharge (m^3/ha-day) on day i and at site j and is included only in the models for sediment, TP, OP, TN, and ON; and ε_{ij} is the error term. For terms of watershed characteristics, only site subscript, j, is used in the equation because those terms do not vary from day to day.

The effect of developed land was not listed separately in the model for the two physiographic provinces, as in the case of cropland, because the proportion of developed land in the Piedmont subwatersheds varied only from 0 to 6%, which was not enough to differentiate the effects of development

between the two provinces (Weller *et al.*, 2003). The inclusion of trigonometric functions (sine and cosine terms) in the regression models is to describe the seasonal changes in the time series. Similar use of these terms can be found in other studies. For example, Cohn *et al.* (1992) studied nutrient loads entering the Chesapeake Bay using a simple statistical model that included sinusoidal functions for the effects of annual seasonality.

The errors, ϵ_{ij}, are usually assumed in regression analysis to be independent and normally distributed. In this study, some sampling sites are upstream of others and the draining areas of upstream sites are nested within watersheds of downstream sites. Given the spatial distribution of sampling sites and the nature of time series data measured at those sites, interdependence of the observed values may exist between sites and over time. Some predictor variables included in the regression model can explain some of the spatial and/or serial dependence in the data, such as the trigonometric terms for serial autocorrelations, and streamflow for both spatial and serial autocorrelations. When the model errors are not independent, they will not affect the estimates of regression coefficients (still unbiased), but the variances of those estimates will be underestimated, causing the *t*-tests for model coefficients to be more statistically significant than they actually are. This will affect the interpretation of the relations of the response variable with explanatory variables, but will not affect the predictability of the model (Neter *et al.*, 1985; Draper and Smith, 1998).

Many models for estimating concentrations (or equivalently loads) of water constituents take a form of linear relationship between the logarithm of constituent concentration and the logarithm of flow and/or other explanatory variables (Cohn *et al.*, 1989, 1992; Clarke, 1990; Gilroy *et al.*, 1990). The assumption for this log-linear relationship between concentration and flow is mainly based on the empirical data that result from daily measurement of water discharge and instantaneous measurement of concentration (usually several times a year). Both discharge and constituent concentration may vary significantly during the day, especially under storm flow conditions, and their relationship can be highly nonlinear (Gilroy *et al.*, 1990). However, because flow data at finer time scales are not easily available, many of the estimating methods rely on daily averages of flow. As such, flow and concentration need to be log-transformed to convert a nonlinear relationship to a log-linear one. There are concerns with regard to use of log-linear models, such as retransformation bias (Cohn *et al.*, 1989, 1992; Gilroy *et al.*, 1990).

In developing the nutrient submodel, we did not use instantaneous concentration data from synoptic samples. Instead, we used the weekly monitoring data collected at the automated monitoring stations, which each have an automated sampler. The samplers continuously monitor discharge of water and take samples of stream water after a set amount of flow has occurred. Samples are collected more frequently at higher flow rates up to once every 5 min during storm flow (Jordan *et al.*, 2003). The concentrations measured from such samples are flow-integrated and accurately reflect the relationship with water discharge at finer-than-daily time scales. We built and examined both linear and log-linear regression models for the nutrient model. The linear models outperformed their log-linear counterparts.

In simulation of the landscape model, runoff from each subwatershed estimated by TOPMODEL is used as streamflow input to the nutrient model. The nutrient model is run separately for each of 210 subwatersheds as shown in the following equation:

$$\begin{aligned} C_{iw} = {} & b_0 + b_1 Q_{iw} + b_2 \sin(2\pi T_{iw}) + b_3 \cos(2\pi T_{iw}) \\ & + b_4 \mathrm{CCROP}_w + b_5 \mathrm{FDEV}_w + b_6 \mathrm{PCROP}_w \\ & + b_7 \mathrm{FPIEDUP}_w + b_8 Q^2{}_{iw}, \end{aligned} \tag{2}$$

where b_0, b_1,...,b_8 are estimated coefficients given in Table 2, $w = 1,\ldots,p$, where p is the number of subwatersheds and $p = 210$ in this study. Other notations are the same as those in Equation (1).

The outputs from the nutrient model are concentrations of sediment and nutrients from NPS in each subwatershed. The application of this model to the Patuxent watershed resulted in 210 separate files of nutrient concentration data, which were used as part of the input files for the next phase of simulation, the stream network submodel (Figure 4).

Point Source and Reservoir Management Data

In addition to NPS of sediment and nutrients, the Patuxent watershed also contains point sources of water pollution that contribute to the discharge of water, sediment, and nutrients. There are a total of eight major and 17 minor point sources in the watershed (Weller *et al.*, 2003). For point source discharges, the Maryland Department of Environment provided the locations and monthly data on volume and material concentrations for each source (Jeff Liang and Priya Papali, personal communication). The two reservoirs in the Piedmont section of the watershed affect the downstream hydrology and water quality. The Washington Suburban Sanitary Commission provided data on operations of the two reservoirs, including water discharge at the dams

TABLE 2. Coefficient Estimates and Standard Errors (SE) of Nutrient Regression Models.

Variable	n	R^2	Intercept		CCROP		PCROP		FDEV		FPIEDUP		Flow(Q)		Flow^2(Q^2)		cos(2πT)		sin(2πT)	
			Coeff.	SE	Coeff.	SE	Coeff.	SE	Coeff.	SE	Coeff.	SE	Coeff.	SE	Coeff.	SE	Coeff.	SE	Coeff.	SE
TSS	1617	0.075	−35.80	24.20	560.47	124.75****	708.27	270.05**	33.11	49.55	−85.79	53.04	6.97	1.24****	−0.03	0.02	−27.86	9.29**	−25.59	10.17*
TP	1619	0.094	−128.94	73.61	3004.68	379.41****	2727.90	819.50***	219.65	150.69	−338.29	160.86*	16.38	3.78****	−0.11	0.05*	−46.70	28.25	−68.34	30.85*
PO_4	1620	0.080	−34.14	43.59	1671.17	228.35****	1387.94	492.61**	90.73	90.44	−191.95	96.58*	4.18	0.99****	NA		−36.56	16.75*	−29.37	17.82
OP	1619	0.049	−83.63	48.52	1344.48	250.07****	1337.17	540.14*	139.30	99.32	−139.56	106.02	9.37	2.49**	−0.06	0.03	−6.09	18.62	−31.72	20.34
TN	1613	0.651	−189.81	144.65	6830.52	745.43****	45094.54	1609.55****	2388.38	295.94****	−3342.69	315.93****	32.54	7.43****	−0.27	0.10**	−101.38	55.56	−104.31	60.69
NO_3	1616	0.803	−193.19	92.58*	4013.33	484.95****	34715.80	1045.62****	1267.86	191.98****	−1902.46	205.02****	−0.85	2.10	NA		80.34	35.62*	−32.15	37.84
NH_4	1488	0.154	5.53	9.89	445.30	51.33****	746.57	145.01****	245.44	21.09****	−68.37	26.11**	0.39	0.23	NA		−20.78	3.91****	13.18	4.17**
ON	1617	0.063	90.30	102.90	2154.74	530.39****	5174.38	1145.82****	557.34	210.67**	−737.01	224.88**	29.69	5.29****	−0.24	0.07**	−153.47	39.49***	−42.15	43.19
OC	1620	0.053	4.45	1.31***	19.85	6.88**	44.90	14.84**	4.12	2.72	−9.20	2.91**	0.17	0.03****	NA		−0.99	0.50*	−0.62	0.54
SI	1607	0.829	2.64	0.13****	40.91	0.66****	4.81	1.44***	1.35	0.26****	0.63	0.28*	−0.02	0.00****	NA		−0.16	0.05**	−0.32	0.05****

*$p < 0.05$, **$p < 0.01$, ***$p < 0.0001$, ****$p < 0.0001$.

and water withdrawal from the reservoirs (Karen Wright and Lloyd Wold, personal communication). The point source data and reservoir operation data were used, together with outputs from TOPMODEL and the NPS nutrient model, in the next phase simulation, the stream network model (Figure 4).

Stream Network Model

The stream network model generates a stream network in a watershed using the USEPA's Reach File 3, a network-oriented, spatially referenced geographic database of surface water features of the U.S. (USEPA, 1994b, 1995). We modified the original reach file by adding each point source to its "anchor reach" and each subwatershed to the stream reach it drains to. In simulation of the stream network model, streamflow, sediment, and nutrients are routed downstream reach by reach from headwater streams to the outlet of the watershed. In the routing process, the inputs to a particular reach include input from upstream reaches, point sources (if there are any), and NPS in the subwatershed draining directly to the reach. The output from a reach provides one of the inputs to its immediate downstream reach. Integration of the point sources and NPS is accomplished in the process of routing through the stream network. Specifically, for each stream reach, a line of daily data are read separately from a runoff file and a nutrient file for a subwatershed draining to the reach, and also a record of data from each point source file if there is any attached to the reach. The inputs from these data files are added to the input from upstream reaches as the total input to the reach. Then, a routing procedure is performed to estimate the output from the reach to its immediate downstream reach. This routing procedure applies to both streamflow and water constituents. In addition, the following decay function is applied to sediment and nutrients to account for loss caused by instream processes

$$O = I\mathrm{e}^{-kL/Q}, \tag{3}$$

where O is the flux of material from the reach in question, I is the input of material, L is the reach length, Q is the flow rate (discharge measured in volume/time), and k is a coefficient that controls the rate of decrease in the magnitude of material for given ratio of L and Q. Generally speaking, the fraction of nutrients removed is inversely related to stream channel depth and positively related to travel time (residence time). Although Reach File 3 does not include data on these two variables, the channel depth can be described as a function of flow rate and the residence time can be expressed as the ratio of

reach length to flow velocity (Horn and Grayman, 1993; Alexander *et al.*, 2000; Seitzinger *et al.*, 2002). Data on reach length and flow rate are available for simulation, but velocity data are not. Velocity can be expressed as the ratio of flow rate to the area of channel cross section, which varies along the stream and is not available in the simulation. Based on these relationships, the fraction of nutrient input removed by instream processes can be estimated by a function in which the removal rate is inversely related to flow rate and positively related to reach length. This relationship is usually described in some form of a decay function as shown in Equation (3). The percentage of sediment and nutrients removed from a stream reach can be calculated in the following equation:

$$R = \frac{I - O}{I} \times 100\% = (1 - e^{-kL/Q}) \times 100\%, \quad (4)$$

where R is the removal rate (%) and other notations are the same as those in Equation (3). This function shows that the removal rate of sediment or nutrients is positively related to reach length and inversely related to stream discharge. A more detailed description of the stream network model is given in Liu and Weller (2008).

Model Calibration and Evaluation

The landscape model was calibrated to the Patuxent watershed for this study. Given the modular structure of the model, we calibrated the three model components separately in the sequence of rainfall-runoff model (TOPMODEL), nutrient model, and then stream network model. Most of the parameters in TOPMODEL were not calibrated, but calculated or obtained from available data, including all the topographic index-related parameters, watershed size, and percentage of impervious area. The values of these parameters were calculated separately for each of the 210 subwatersheds. For the remaining parameters with no available data, the model was calibrated to the gauged subwatersheds by comparing simulated flow with observed flow. The calibration of TOPMODEL to a watershed is accomplished by determining the combination of adjustable parameter values that give the best agreement between observed and simulated streamflow. The agreement is measured using the Nash-Sutcliffe coefficient, which is similar to the coefficient of determination (R^2) in a regression analysis (Nash and Sutcliffe, 1970; ASCE, 1993; Bergman *et al.*, 2002). Wolock (1993) provided a detailed description of TOPMODEL calibration to a specific watershed. For ungauged subwatersheds with no observed flow data, those parameter values were estimated from neighboring gauged subwatersheds. Descriptive statistics of adjustable parameters for the 210 subwatersheds are given in Table 3.

The nutrient model (regression models) was built and calibrated using concentration data observed at 22 monitoring sites. When working with a large sample of randomly collected data, it is preferred to split the sample into two subsets, one for model building and the other for model validation. In this study, however, a split-data approach is not suitable because of the small number of sampling sites and their nonrandom spatial distribution. Nevertheless, along the same line of reasoning, we did omit one monitoring site (251.1) (Figure 1) from the model building process, and used the data from that site for model validation. Site 251.1 is located on the mainstem of the Patuxent River at the head of its estuary. The drainage area of this site is approximately 40% of the entire Patuxent watershed and contains two reservoirs and several point sources. It is the only site where the ability of the model to integrate all the components of the overall nutrient estimation could be assessed. This site is also a calibration site for the USEPA Chesapeake Bay Program's watershed model (see comparison of our model with the CBP model below). Site 251.1 has the lion's shares of inputs to the estuary; for example, annual flow at this site is normally about one-third of water the estuary receives from its entire drainage. As the main purpose of the model application in this study was to predict discharges of water, nutrients, and sediment

TABLE 3. Descriptive Statistics of TOPMODEL Parameters for 210 Subwatersheds.

Parameters	Mean	Min	Max	Standard Deviation
SZM	47.3	15.4	92.3	24.7
CONMEAN	377.9	92.2	858.0	323.7
PMAC	0.3	0.3	0.3	0.0
ZTOT	2.4	2.4	2.4	0.0
ZAB	1.5	1.5	1.5	0.0
THFC	0.2	0.2	0.2	0.0
TOPMIN	4.3	3.5	5.9	0.4
TOPMAX	17.9	14.0	22.6	2.1
TOPMEAN	7.8	7.0	9.2	0.4
TOPVAR	4.6	2.8	7.3	0.8
TOPSKEW	1.7	1.0	2.5	0.3
ATOT	10.9	0.3	78.5	11.2
PIMP	5.6	0.1	30.9	7.1

Notes: SZM, scaling parameters based on soil properties; CONMEAN, saturated hydraulic conductivity of the C horizon of the soil; PMAC, fraction of precipitation bypassing soil zone; ZTOT, total soil depth; ZAB, depth of AB horizon; THFC, field capacity of soil; TOPMIN, minimum of ln(a/tanB) index value; TOPMAX, maximum of ln(a/tanB) index value; TOPMEAN, mean of ln(a/tanB) distribution; TOPVAR, variance of ln(a/tanB) distribution; TOPSKEW, skewness of ln(a/tanB) distribution; ATOT, total watershed area; PIMP, impervious area of watershed (Wolock, 1993).

to the estuary, the accurate predictions at site 251.1 are critical for accurate estimation of inputs to the estuary.

For the stream network model, only two parameters were calibrated: one in the routing procedure and the other in the decay function (Liu and Weller, 2008). The routing procedure delays the movement of water and other materials downstream, but does not cause any loss of mass. The decay parameter k in the decay function shown in Equation (3) describes the fraction of nutrients removed in a reach as the stream routes through the reach. For regular stream reaches, the calibration resulted in a value of 0.01 for the parameter k in the decay function. For reservoirs, a value of 1,000 was set for this parameter because the residence time in a reservoir is longer and the fraction of nutrients removed is higher. Figure 5 shows the percentage of nutrients removed for different values of the decay parameter under different flow rates. As the value of the parameter k increases, the percentage of nutrients removed also increases. For a given k value and the same reach length (e.g., the Patuxent's average reach length of 1,790 meters) the percentage of instream loss increases with decreasing stream discharge (Figure 5). The calibrated value of the parameter k in the decay function leads to low percentages (<5%) of nutrients removed under the normal streamflow conditions. For longer reaches and lower flow rates, the removal rate will be higher. According to Seitzinger *et al.* (2002), the removal rates of N in individual reaches are generally less than 20%.

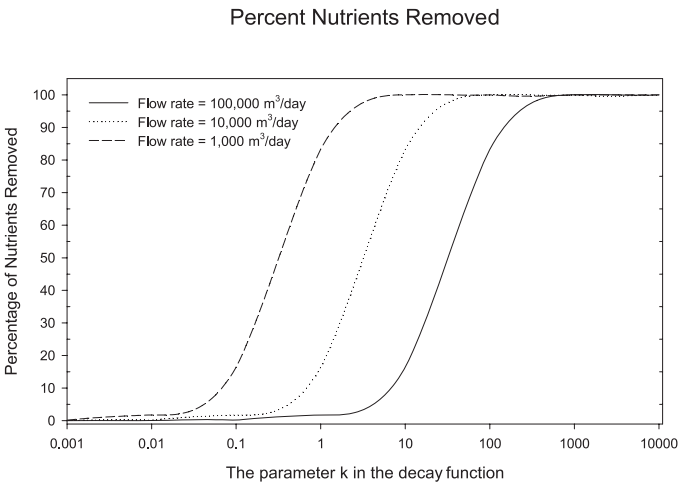

FIGURE 5. Percentage of Nutrients Removed Instreams Expressed by $1 - \exp(-kL/Q) \times 100\%$, Which Is Based on the Decay Function in the Stream Network Submodel. Exp is an exponential function, k a decay parameter, L the reach length, and Q the flow rate. The reach length used in creating the curves is 1,790 meters, the average reach length of the Patuxent River.

To evaluate the performance of the landscape model, we examined the simulation results at a number of sites in the Patuxent watershed using the following performance statistics as assessment criteria for prediction errors. The term prediction error is defined as the difference between the prediction and the actual measured value.

(a) Absolute mean deviation (AMD)

$$\mathrm{AMD} = \frac{1}{N}\sum_i |O_i - P_i| \tag{5}$$

(b) Bias (B)

$$B = \frac{1}{N}\sum_i (O_i - P_i) \tag{6}$$

(c) Root-mean-squared error (RMSE)

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_i (O_i - P_i)^2} \tag{7}$$

In the above equations, N is the number of observations in the time series. O is the observed value, and P is the model-predicted value. AMD measures the absolute departure of a model from observed value on average at each time step (Ye *et al.*, 1997). Bias is the average of model prediction errors and is indicative of possible systematic errors (under- or overprediction, if bias is not zero). RMSE is used to measure the magnitude of deviation of model predictions from observed values. RMSE and AMD, however, do not measure the direction of model deviation (i.e., under- or overprediction).

In addition to the overall evaluation of the model performance for the entire study period at selected sites, we also analyzed temporal patterns of flow and nutrients and their prediction errors at site 251.1 by examining their time series. To analyze the spatial pattern of streamflow prediction errors, we examined model-predicted streamflows at selected locations with varied drainage areas.

To evaluate how well our model performed in comparison with more complex models, we compared streamflow, and sediment and nutrient loads predicted by the landscape model with the predictions of the USEPA Chesapeake Bay Program's (CBP) Chesapeake Watershed Model (CWM Phase 4.3), which is an application version of the HSPF model (Linker *et al.*, 1999). The dataset obtained from the CBP (Gary Shenk, personal communication) contains daily predictions of streamflow, sediment, and selected

nutrients for the same location in the Patuxent watershed as the SERC Station 251.1. We converted the CBP daily data to weekly load sums and then compared them with our model predictions and SERC monitoring data for the same period of July 29, 1997 through August 2, 1999 (105 weeks). For each material, there are three sets of 105-week time series: observed values, predictions of the landscape model, and predictions of the CBP-HSPF model. We calculated correlations between the observed and predicted weekly loads by each of the two models, which are an indicator of strength of association between any two sets of time series.

In addition to comparing daily and weekly observed and simulated data, we also evaluated the annual simulation results for both the landscape model and the CBP-HSPF model. The study period is divided into two years with Year 1 from July 29, 1997, through July 28, 1998, and Year 2 from July 29, 1998, through August 2, 1999. We used the general guidelines for evaluating annual simulation results of the HSPF model to assess the relative performance of the landscape model (Donigian *et al.*, 1984; Bergman *et al.*, 2002). Based on the percent difference between the model predictions and observed annual total loads, the guidelines rank the performance of a model in one of three categories: very good, good, or fair. The definitions of the three categories are different for flow, sediment, and water quality (Table 1 in Bergman *et al.*, 2002).

The landscape model was applied to predict the discharges of water, sediment and nutrients to the Patuxent River estuary. As there are no available measured data on loads to the Patuxent estuary, we used as reference the annual load totals to the estuary for the same time period presented in Weller *et al.* (2003) to evaluate the load predictions of the landscape model. The *measured* data on loads to the estuary given in their paper were actually a combination of monitoring data for half of the Patuxent drainage and modeled data for the other half for which there were no monitoring data available. The models used in their work were regression models that contained a time variable (week) as one of explanatory variables. As such, the models were able to capture fine-scale temporal variability of concentrations. Nine of their 10 models for weekly NPS material concentrations had an R^2 value higher than 0.57 with the highest at 0.83. On a yearly scale, all the 10 models had an R^2 value ranging from 0.5 to 0.86. Thus, these models provide relatively more accurate predictions than the nutrient submodel of the landscape model for the study period.

RESULTS

Model Performance for the Study Period

For analysis of model performance using AMD, bias, and RMSE, we present results from three sites (Stations 277, 235, and 251.1), which are representative of differences in location, drainage area, and land cover (Figure 1, Table 4). The watershed that drains to Station 277, located in the Piedmont physiographic province, is a small, low-order rural watershed (58 km^2) with 19 subwatersheds and no point sources. The watershed of Station 235 located in the Coastal Plain province is a more urbanized watershed with a drainage area of 234 km^2, 24 subwatersheds, and no point sources. Station 251.1 is at the head of the Patuxent estuary with a drainage area of 908 km^2 that contains 79 subwatersheds with 13 point sources. The sediment and nutrient concentrations measured at Station 251.1 were not used in building the nutrient model (regression models). Evaluation of the model performance at this site is an actual independent cross-validation of the model.

In calculating the three performance statistics, observed streamflow data were from three USGS stations, which are at the same locations as the three SERC stations (USGS 01594440 at 251.1, USGS 01594526 at 235, and USGS 01591400 at 277). Observed sediment and nutrient data were from the three SERC monitoring stations. The bias of predicted streamflow (Table 5) is positive at Sites 277 and 251.1 (3.0 and 88.4, respectively), indicating, on average, underprediction of the model. The bias at

TABLE 4. Area, Land Cover, Point Sources, and Physiographic Province for Watersheds 277, 235, and 251.1 (Weller *et al.*, 2003).

	Area (km^2)			Land Cover (%)				
Watersheds	Total	Land Only	Number of Point Sources	Developed Land	Cropland	Grassland	Forest	Percent in Piedmont Province
277	58.4	58.3	0	1.6	16.9	46.6	34.9	100
235	233.8	233.3	0	23.0	6.9	32.7	37.2	0
251.1	908.4	901.2	13	19.0	7.8	29.4	43.8	70
Patuxent	2294.6	2260.9	25	12.0	9.9	28.0	49.3	28

Site 235 is −96.4, which shows that the model on average overpredicted streamflow at that site. The watershed of Site 235 is more urbanized with a relatively large percentage of impervious area used in the TOPMODEL simulations for that site. The AMD and RMSE measurements of streamflow increase from Watershed 277 to 235 to 251.1, or increase with watershed size.

With regard to concentrations and loads, most bias values are positive, indicating underprediction of the model. However, the magnitudes of bias are usually small, most of which are less than 1 mg/l for concentrations or 1 Mg/week for loads, with a few exceptions mainly in TSS and OC. There is no clear spatial pattern of prediction errors for concentrations by any of the three criteria. That is, the prediction errors of concentration did not seem to vary significantly across watersheds with different drainage areas. As for loads, larger watersheds generally show a greater value of all of the three criteria. For example, Site 251.1 has a larger prediction bias than Site 277 for almost all the materials, except for TP. The former also has consistently higher AMD and RMSE than the latter for sediment and all the nutrients. Apparently, this results from the fact that load is calculated as the product of streamflow and concentration, and that the prediction errors of streamlow propagate into the prediction of loads.

Spatial-Temporal Analysis of Streamflow and Prediction Errors

Figure 6 shows the daily time series and scatter plots of simulated and observed streamflows at Site 251.1. The simulated streamflows are in good agreement with the observed data. The correlation coefficient between the observed and predicted streamflows is 0.92. The main discrepancy between predicted and observed streamflows appears to be in the major peak flows. Predicted major peak flows are generally lower than their observed counterparts. In addition, the landscape model overestimated the base flows or low flows generated by light rains. The underestimation of peak flows is more dominant, resulting in a positive bias value (88.4) (Figure 7f). This discrepancy was inherited from TOPMODEL, which exhibited similar patterns in its runoff output

TABLE 5. Analysis of Prediction Errors (Observed-Predicted) for Streamflow (1,000 m^3/day), and Weekly Avearge Concentrations (mg/l) and Load (Mg/week) of Sediment and Nutrients, Measured by Absolute Mean Divation (AMD), Bias, and Root Mean Squared Error (RMSE).

	Flow	TSS	TN	NO_3	ON	NH_4	TP	OP	PO_4	OC	SI
Watershed 251.1											
AMD											
Conc.	233.8	47.3	0.39	0.25	0.29	0.07	0.12	0.06	0.07	3.10	1.10
Load		316.7	4.15	2.24	1.87	0.30	0.62	0.39	0.46	20.17	7.13
Bias											
Conc.	88.4	14.5	0.14	−0.03	0.13	0.01	0.03	0.02	0.003	2.13	1.07
Load		−76.5	1.92	0.71	0.87	0.02	0.05	0.09	−0.24	1.25	6.18
RMSE											
Conc.	510.9	61.0	0.92	0.31	0.71	0.23	0.15	0.09	0.10	4.13	1.26
Load		580.9	7.16	3.35	3.99	0.54	0.93	0.64	1.13	42.67	11.91
Watershed 235											
AMD											
Conc.	139.5	82.9	0.47	0.19	0.32	0.04	0.26	0.10	0.17	4.46	1.25
Load		371.9	1.35	0.39	0.94	0.16	0.70	0.35	0.61	21.86	3.87
Bias											
Conc.	−96.4	−6.0	−0.21	−0.08	−0.10	−0.01	0.03	−0.01	0.04	−2.40	0.93
Load		−8.3	−0.54	−0.07	−0.41	−0.09	−0.04	−0.07	−0.22	−17.75	0.23
RMSE											
Conc.	252.0	161.9	0.66	0.27	0.52	0.06	0.49	0.18	0.35	6.02	1.49
Load		1,161.7	2.27	0.59	1.75	0.33	1.56	0.81	1.59	58.06	5.88
Watershed 277											
AMD											
Conc.	19.5	115.9	0.66	0.76	0.56	0.04	0.18	0.12	0.07	4.03	0.61
Load		72.9	0.67	0.55	0.34	0.03	0.12	0.09	0.05	2.97	0.49
Bias											
Conc.	3.0	72.4	−0.002	−0.29	0.35	0.01	0.09	0.07	0.01	1.97	0.35
Load		54.1	0.28	−0.03	0.29	0.02	0.08	0.06	0.002	1.13	0.42
RMSE											
Conc.	70.6	203.5	0.86	0.97	0.87	0.06	0.29	0.22	0.10	6.93	0.76
Load		217.4	1.09	1.19	0.89	0.07	0.34	0.28	0.16	9.09	0.73

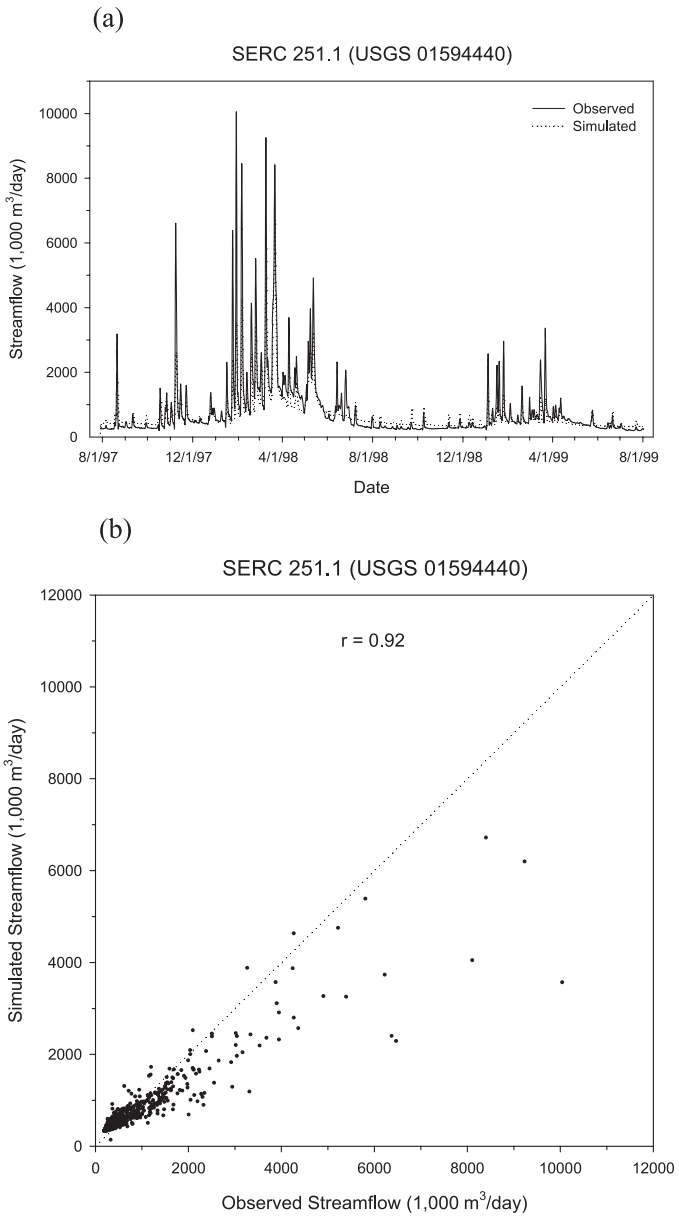

FIGURE 6. Daily Time Series and Scatter Plots of Simulated and Observed Streamflows at SERC Station 251.1 (USGS 01594440). The diagonal dotted line in the scatter plot shows the ratio of 1:1 of predicted to observed flows.

for individual subwatersheds. Other studies also found that TOPMODEL underestimated major peak flows and overestimated low flows (e.g., Durand *et al.*, 1992). As shown in the scatter plot of streamflow (Figure 6), the predicted flows deviate further from the 1:1 line in the plot as the volume of flow increases. Most high peak flows fall below the 1:1 line in the scatter plot for Station 251.1, indicating underestimation of these flows.

We analyzed predicted streamflow at locations with varied drainage areas to examine the downstream propagation patterns of prediction errors. Here we present and compare streamflow predictions and their errors for Station 251.1 and two sites nested within its drainage, Stations 277 and 258.9. The latter two have a drainage area of 58 and 255 km^2, respectively. As with Sites 277 and 251.1, data from a USGS station at the same location as 258.9 (USGS 01594000) were used as observed streamflow. As shown by the time series plots of predicted and observed streamflows and prediction errors at these three sites (Figure 7), the model on average underestimated at all three sites. The main discrepancy between observed and predicted streamflows is in the highest peak flows. As reflected in all three performance criteria, the magnitude of prediction errors increased downstream with increasing drainage area. Bias increased from small to large watersheds [i.e., from 3.0 (Site 277) to 22.1 (Site 258.9) to 88.4 (Site 251.1)]. The AMD and RMSE also increased in the same order from (19.5, 70.6) for 277 to (86.4, 216.1) for 258.9 to (233.8, 510.9) for 251.1.

Temporal Analysis of Loads

We examined time series plots of weekly loads of nutrients and sediment, and their prediction errors at Site 251.1 (Figure 8). In general, the simulation results for dissolved materials are in better agreement with the observed data than those for particulate nutrients. Specifically, predicted loads of nitrate ($r = 0.89$) and silicate ($r = 0.90$) are closer to the observed than those for organic N ($r = 0.75$), organic P ($r = 0.73$), and sediment ($r = 0.55$). All forms of nitrogen have better simulation results than their phosphorus counterparts, such as nitrate ($r = 0.89$) *vs.* phosphate ($r = 0.47$), organic N ($r = 0.75$) *vs.* organic P ($r = 0.73$), and total N ($r = 0.88$) *vs.* total P ($r = 0.73$).

By contrast, although the model predictions matched well on average with the observed concentrations as shown by the bias measurements in Table 5, the model did not predict well the short-scale temporal variability of concentrations (e.g., as shown in the time series plot of nitrate concentrations for Site 251.1) (Figure 9). This observation is consistent with the predictions of the nutrient submodel for individual subwatersheds (Table 2). In general, the simulated loads of sediment and nutrients are better correlated with their observed values than the predicted concentrations with their observed counterparts. In terms of temporal pattern of prediction errors, most nutrients varied in a similar way as streamflow (Figures 7 and 8); mainly, the largest prediction errors of loads occurred at the highest peak flows when the model mostly underpredicted flows. A

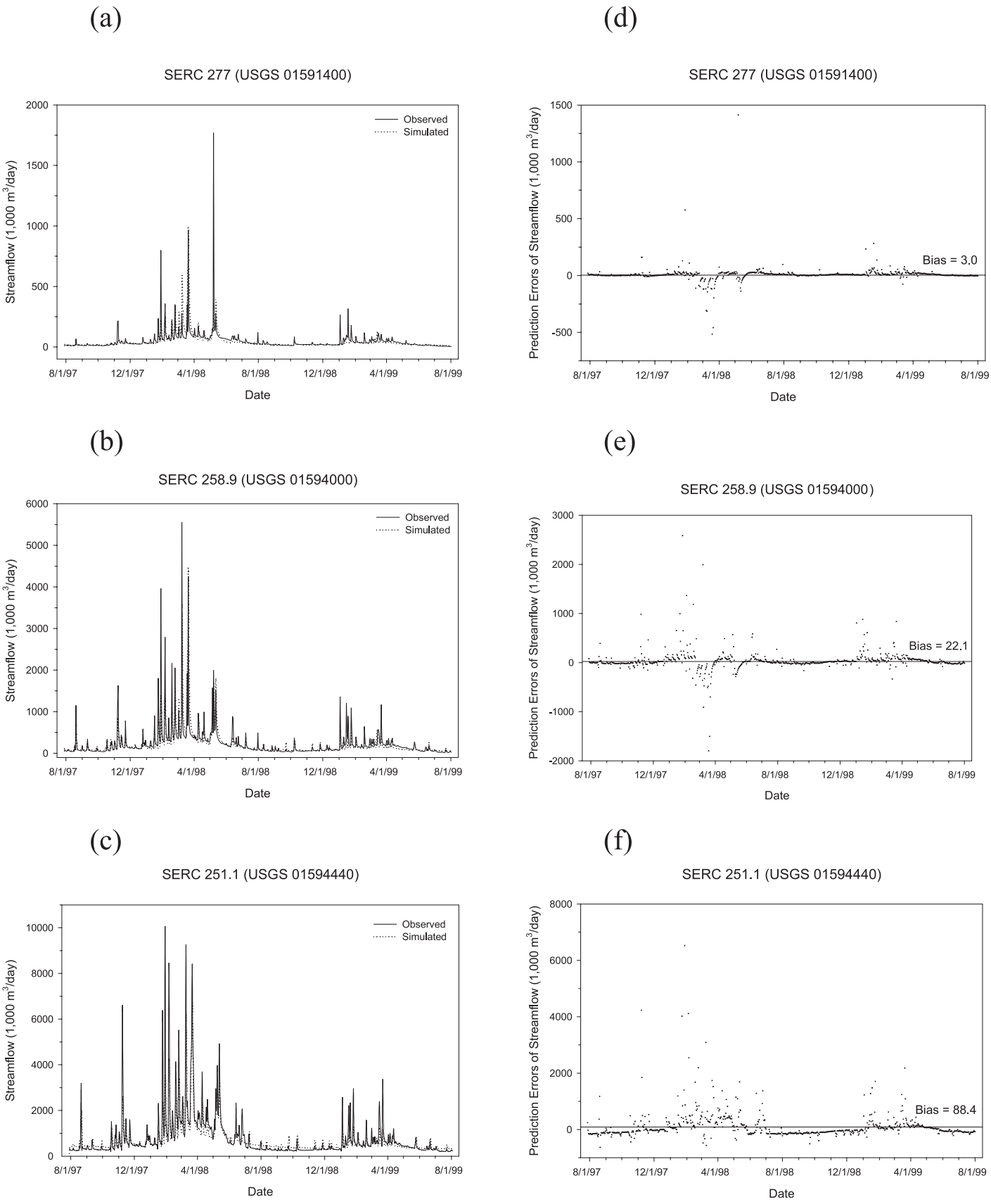

FIGURE 7. Streamflow Rates (a-c) and Prediction Errors (d-f) at SERC Stations 277, 258.9, and 251.1 (USGS 01591400, 01594000, and 01594440, respectively). The horizontal line in an error plot is the bias of prediction errors.

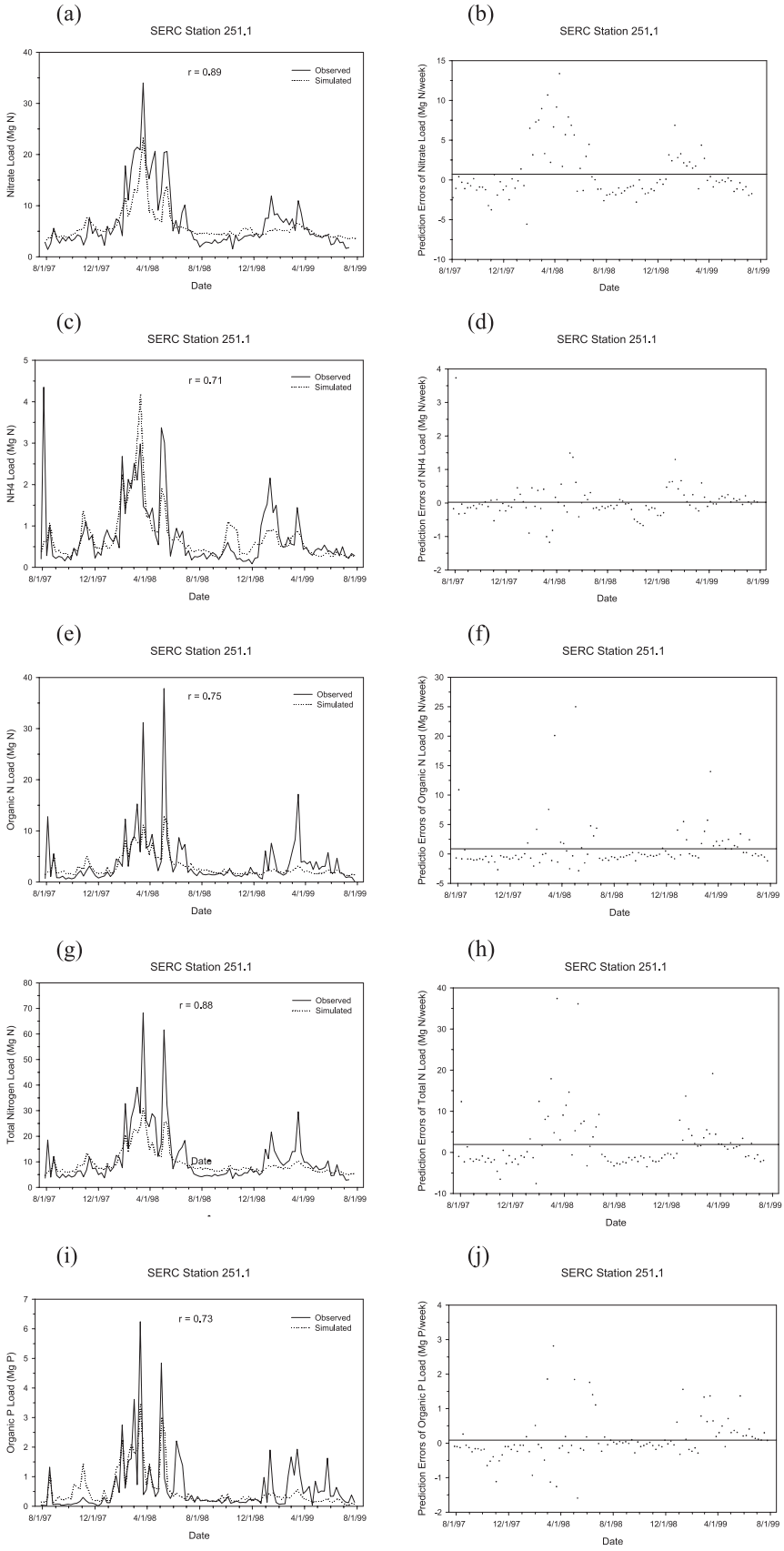

FIGURE 8. Weekly Observed and Simulated Loads of Sediment and Nutrients and Prediction Errors at SERC Station 251.1. The horizontal line in an error plot is the bias of prediction errors.

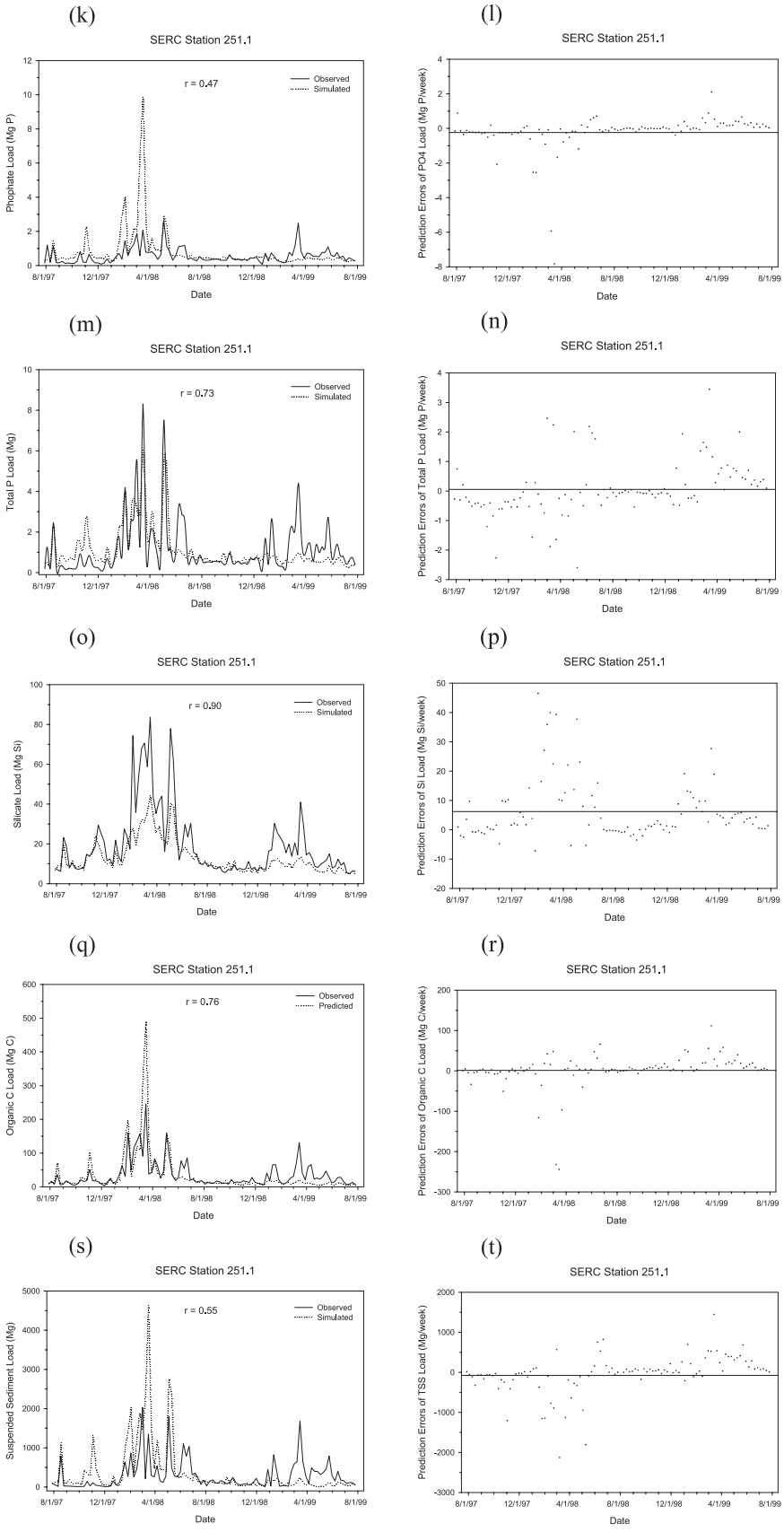

FIGURE 8. Continued.

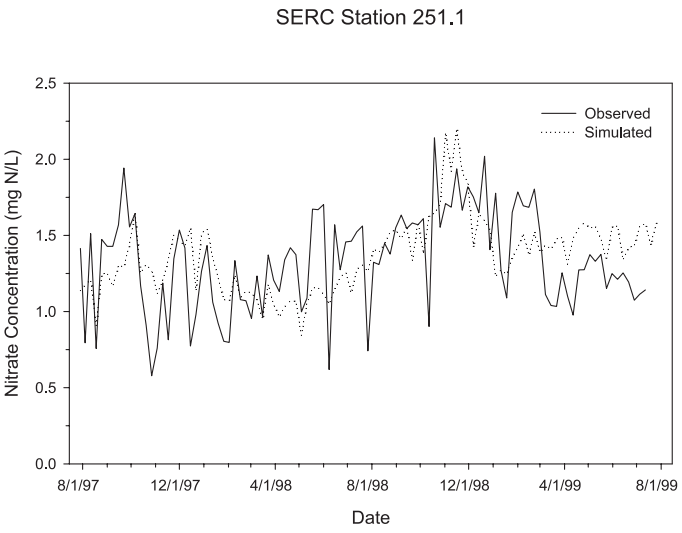

FIGURE 9. Observed and Simulated Nitrate Concentrations (mg/l) at SERC Station 251.1.

few exceptions to this observation include phosphate, OC, and suspended sediment, where the model overpredicted loads at peak flows.

Comparison to the CBP-HSPF Model

For streamflow, TSS, and each of the nutrients compared, the predictions of the landscape model (the SERC model in Table 6) had a higher correlation with the observed values than the predictions of the CBP-HSPF model. Plots of the three sets of weekly time series for each of the same materials are given in Figure 10, which shows that the landscape model (labeled as the SERC model in the figures) performed as well as or better than the CBP-HSPF model in terms of agreement between model predictions and observed values. For streamflow (Figure 10a), both models underestimated the largest peak flows. The landscape model was in better agreement with the observed values than the CBP-HSPF model for most of the study period except for the two peak flows in year 1999, the relatively dry year of the two. This is also the case for TSS. The CBP-HSPF model overestimated three peak loads of sediment by at least twofold (Figure 10b). As with streamflow, both models underestimated the largest peaks of loads for TN, nitrate, and organic nitrogen (Figures 10c, 10d, and 10e). For ammonium (NH_4), except for a couple of peak values, the landscape model performed better than the CBP-HSPF model (Figure 10f). The CBP-HSPF model completely missed (significantly underestimated) all the major peaks of phosphate load while the landscape model significantly overestimated two or three peak loads (Figure 10g). Both models performed better for organic P and total P with the landscape model in closer agreement with the observed values (Figures 10h and 10 i). The landscape model also outperformed the CBP-HSPF model for OC except for a couple of overestimated peaks (Figure 10j).

TABLE 6. Correlations of Observed Weekly Loads at Station 251.1 With Predictions by the SERC Landscape Model and the Chesapeake Bay Program's (CBP) Chesapeake Watershed Model (based on 105 weeks of data from July 29, 1997, Through August 2, 1999).

	SERC Model	CBP-HSPF Model
Flow (m^3)	0.92	0.76
Total suspended sediment (Mg)	0.55	0.40
Nitrate (Mg N)	0.89	0.67
Organic N (Mg N)	0.75	0.58
Ammonium (NH_4) (Mg N)	0.71	0.56
Total N (Mg)	0.88	0.77
Phosphate (PO_4) (Mg P)	0.47	0.38
Organic P (Mg P)	0.74	0.48
Total P (Mg)	0.73	0.49
Organic C (Mg C)	0.76	0.57

The predicted annual totals by both models of water discharge and loads of sediment and nutrients at Station 251.1 are presented and compared with the observed data in Table 7. According to the evaluation guidelines (Bergman *et al.*, 2002), the predictions of the landscape model (labeled as the SERC model in Table 7) for annual total of water discharge at Station 251.1 were good (10-15%) for Year 1 and very good (<10%) for Year 2. The predictions of the CBP-HSPF model were fair (15-25%) for Year 1 and good for Year 2. The predictions of both models for sediment (TSS) were fair (25-35%) or worse (>35%). For all forms of nitrogen, the landscape model predictions were either very good (<20%) or good (20-30%); the same was true of the CBP-HSPF predictions except for NH_4 for Year 1, which was fair (30-40%). The two models did not perform as well in predicting phosphorus. The predictions of the landscape model were very good for total P and organic P for Year 1, but were fair or worse for Year 2. The model's predictions for phosphate (PO_4) were less than fair (>40%) for Year 1, but good for Year 2. The CBP-HSPF model performed worse than the landscape model for phosphorus nutrients except for OP in Year 2 and PO_4 in Year 1. The OC predictions by the landscape model were good for Year 1 and less than fair for Year 2. The CBP model predictions of OC for both years were less than fair.

Loads to the Patuxent River Estuary

The predicted annual totals to the estuary by the landscape model for the same two-year period are

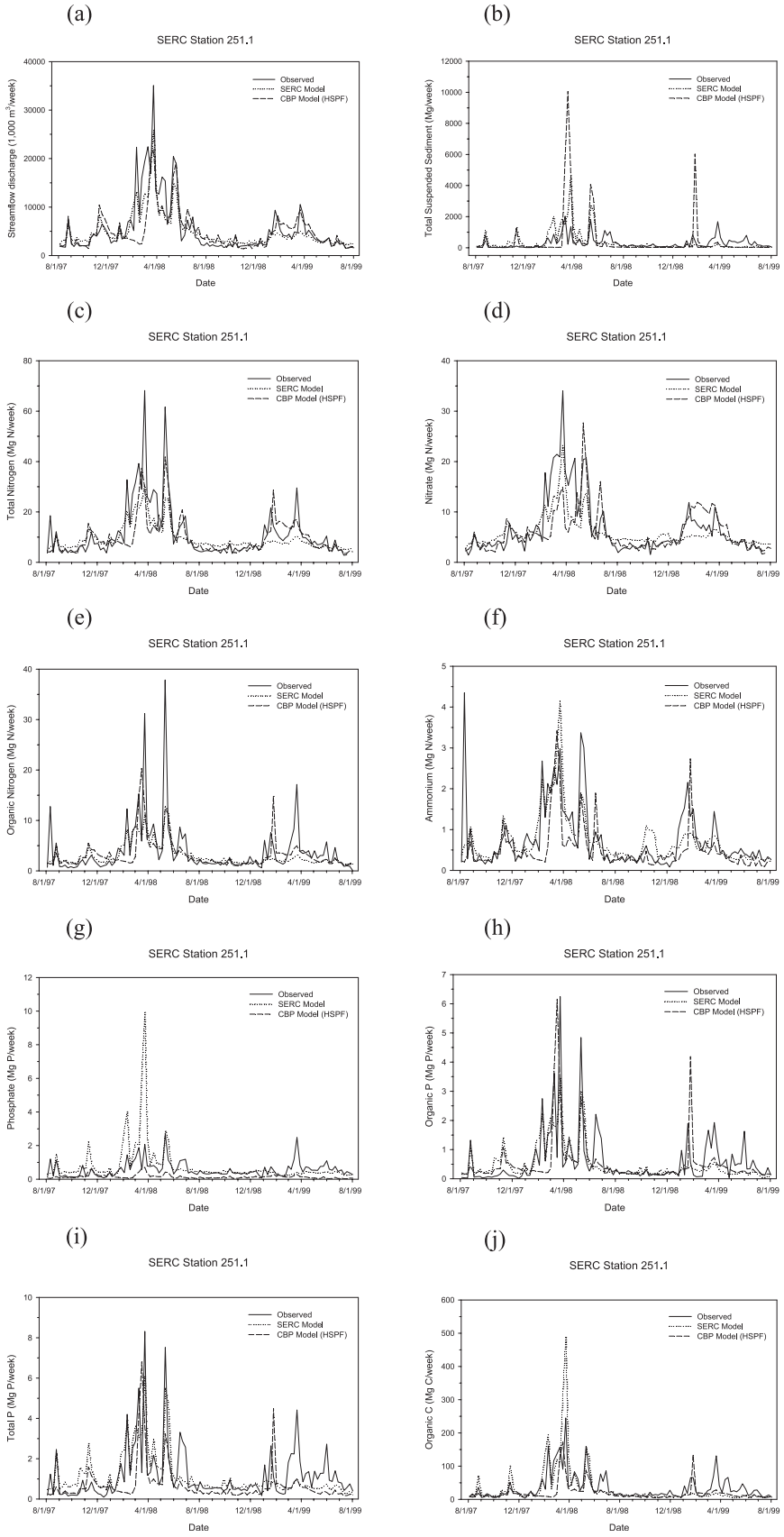

FIGURE 10. Comparison of Observed and Simulated Loads of Sediment and Nutrients at SERC Station 251.1 With Simulation Predictions of Chesapeake Bay Program's Bay Model (HSPF).

TABLE 7. Comparison of the Predicted Loads by the Landscape Model and the CBP-HSPF Model With the Measured Loads to Station 251.1 and to the Estuary of the Patuxent River.

			Loads in mg/Year								
	Year	Flow 10^6 m^3	TSS	TN	NO_3	ON	NH_4	TP	OP	PO_4	OC
Watershed 251.1											
Measured	1	403	17,923	773	457	264	52	72	40	32	2363
	2	175	13,279	409	235	147	27	50	23	27	1301
SERC Model	1	351	34,503	619	379	217	50	84	41	64	2978
	2	170	4735	375	248	103	26	33	13	20	555
Percent errors relative to measured	1	−13	93	−20	−17	−18	−4	17	3	100	26
	2	−3	−64	−8	6	−30	−4	−34	−43	−26	−57
CBP-HSPF Model	1	334	33,522	600	356	211	34	47	36	10	1286
	2	194	8997	422	277	126	19	25	19	6	723
Percent errors relative to measured	1	−17	87	−22	−22	−20	−35	−35	−10	−69	−46
	2	11	−32	3	18	−14	−30	−50	−17	−78	−44
Loads to the Estuary											
Measured	1	1268	150,126	2139	1078	851	140	521	228	293	10,764
	2	403	19,671	812	506	259	54	104	40	65	2419
SERC Model	1	1275	210,828	1865	830	965	143	574	271	398	16,449
	2	412	20,434	768	493	238	48	121	44	77	2314
Percent errors relative to measured	1	1	40	−13	−23	13	2	10	19	36	53
	2	2	4	−5	−3	−8	−11	16	10	18	−4

Notes: Year 1 is from July 29, 1997 through July 28, 1998, and Year 2 from July 29, 1998, through August 2, 1999. The measured loads to the estuary are from Weller *et al.* (2003).

presented in Table 7, together with the measured data from Weller *et al.* (2003). The predicted annual water discharge to the estuary was very close to the measured annual total in terms of percent errors relative to the measured data for both years (≤2%). The model predictions for loads of nutrients were also good (20-30%) or very good (<20%) with exceptions of sediment (40%), phosphate (36%), and OC (53%) for Year 1.

Year 1 was a wet year with an annual discharge to the estuary about three times as much as in Year 2, a relatively dry year. The loads of sediment and all the nutrients were consistently significantly higher in Year 1 than in Year 2. Both monthly and annual loads of sediment and nutrients were highly related to water discharge, indicating the dominant role of streamflow in predicting sediment and nutrient transport to the estuary.

DISCUSSION

The landscape simulation model presented in this paper represents a watershed modeling framework in which different sets of processes occurring in a watershed can be simulated separately with different models. The landscape model consists of loosely coupled model components that are conceptually simple and require less development time and cost than comprehensive watershed models. The simplicity of the model did not compromise the quality of model performance. Our model predictions of water discharge, and sediment and nutrient loads were as good as, or better than the predictions of the USEPA CBP's CWM, an application version of the HSPF model. We chose the HSPF model as a system of reference representative of complex comprehensive watershed models because the HSPF model is one of the most widely used watershed models of its kind. Generally speaking, the predictions of the landscape model for dissolved materials, such as nitrate and silicate, were in better agreement with the observed data than for particulate materials. In addition, model predictions for different forms of nitrogen were better than for their phosphorus counterparts. Similar findings have been reported by other studies (Johnson *et al.*, 1997; Lee *et al.*, 2000; Jones *et al.*, 2001; Weller *et al.*, 2003).

The landscape model predictions of loads were in better agreement with observed values than were predictions of concentrations. The model predicted the average nutrient concentrations well, but seemed unable to capture fine-scale temporal variability (daily or weekly). There are a number of reasons for the model not being able to capture fine-scale temporal variability of nutrient concentrations even if the streamflow is already included in the model. The temporal variability of nutrient concentrations is not solely controlled by streamflow, but also by antecedent watershed conditions, such as nutrient storage in

the soil that is determined, among other things, by land use activities (e.g., fertilizer applications) and the interval between two precipitation events. These factors control the variation of influx of materials into stream and in turn change concentrations even under the same flow regime, but not on the same time scale as streamflow does. In addition, the relationship between streamflow and concentration may not be monotonic. For example, actual nitrate concentration usually increases with increased streamflow under low flow conditions, but it may also decrease with increased streamflow under certain high flow conditions because of the dilution effect. Because the coefficient of streamflow in the regression model for nitrate concentration is fixed (either positive or negative), this actual nonmonotonic relationship may not be explained by the model, depending on the range of streamflows. The possible effect of watershed size has already been taken into account by scaling the flow by watershed area as shown in its unit of measurement (m^3/ha-day).

Increased streamflow generally leads to an increase in load (mass transport), but not necessarily an increase in concentration. In addition, the load is calculated as the product of water discharge and concentration. As the magnitude and variability of streamflow are usually much greater than those of concentration, the temporal variation of loads is associated more with changes in flow than concentrations. For example, the temporal variation of nitrate load at Station 251.1 shown in Figure 8a more resembles that of water discharge in Figure 6a than the temporal pattern of nitrate concentration in Figure 9. Because of the dominance of flow in load predictions, good flow predictions usually lead to good load predictions (Weller *et al.*, 2003), overshadowing the influence of concentration on load estimation, as shown in this study. The landscape model's good simulation of streamflow variation on the fine-time scales enabled the model to capture the temporal variability of loads on these scales. The model predictions of loads of sediment and nutrients into the Patuxent estuary matched closely with stream inflows during the study period. Similar findings are reported by others. For example, Hively *et al.* (2006) found that predicted loads agree well with observed loads when streamflow is modeled accurately. This discrepancy between concentration and load in terms of prediction accuracy has also been found in other studies (e.g., Cohn *et al.*, 1992). Weller *et al.* (2003) examined the accuracy of the regression models for both concentrations and loads of sediment and various nutrients by comparing the models' coefficient of determination (R^2). They found that the models for loads (labeled as flux in their paper) all had a higher R^2 value than their counterparts for concentrations.

The quality of the landscape model predictions depends on the quality of its submodel components. The runoff generation submodel, TOPMODEL, is a conceptual model, has been widely used and tested in many studies, and provides generally good predictions of streamflow, as shown in this study. On the other hand, TOPMODEL inherently overestimates low flows and underestimates peak flows as shown in this and other studies. This discrepancy can result from an insufficiently detailed topographic analysis and the lack of soil spatial variability in model simulation (Quinn *et al.*, 1991; Durand *et al.*, 1992; Franchini *et al.*, 1996). Franchini *et al.* (1996) indicated that as a major sensitive parameter in TOPMODEL, the hydraulic conductivity is linked to soil properties and the DEM grid size. They showed that it is inevitable in practical applications to have high values of this parameter, which increases with the DEM grid size. The errors in the output of TOPMODEL for individual subwatersheds propagate downstream through the stream network and through the subsequent model components into the output of the landscape model. Our study shows a clear spatial pattern of streamflow prediction errors, that is, the magnitude of prediction errors increases downstream with increasing drainage area. This may reflect the fact that streamflow usually increases with watershed size, and the magnitude of prediction errors usually increases with the magnitude of the predicted quantity.

In contrast, the nutrient submodel consists of empirically derived regression equations that predict nutrient concentrations based on watershed characteristics and streamflow. Some terms in the model do not change with time on a short time scale, such as land cover and physiographic location. The trigonometric terms in the model are included for capturing seasonal variability. The only term in the model that changes on a shorter temporal scale, such as day or week, is streamflow. As discussed above, however, nutrient concentrations do not always change in a linear or even a monotonic fashion with changes in streamflow. Unlike streamflow, which accretes downstream as a result of contributions from subwatersheds, concentrations do not necessarily increase downstream, but vary according to relative rates of flow and material influx. Because of these reasons, the nutrient submodel often seems unable to capture the short-scale temporal variability in the concentrations of sediment and nutrients for individual subwatersheds. An explanatory variable for short-time-scale variation could be added to the model as shown in Weller *et al.* (2003), in which the variable week was included to express weekly variation. However, such models can only be applied for the same period of time during which monitoring data were collected

and used for model building. By contrast, the nutrient submodel of the landscape model presented in this paper is not limited to a particular period of time and certain weather conditions. Our study shows that the prediction errors of concentration did not propagate in the same way as the prediction errors of streamflow. That is, they did not increase downstream with increasing drainage area.

Compared with the other two components, the landscape model's third component, the stream network model, has a relatively small impact on the quality of predictions of the landscape model. The stream network model simulates instream loss using an exponential decay function, which is the only mechanism in that model that could affect the predictions of concentrations. The main terms in the decay function are reach length and flow rate, which vary from stream to stream. Flow rate also changes from time to time. As such these two terms cannot be predefined for simulations. What can be set by the user of the model is the decay parameter determined through model calibration to the stream network under study. As shown in this study (Figure 5), the instream loss can vary greatly given different combinations of reach length, flow rate, and decay parameter. This provides general applicability of the model for different stream systems with a variety of instream loss rates. When the instream loss is small compared to the runoff and nutrient contributions from individual subwatersheds, which are predicted by the rain-runoff and nutrient submodels, the proportion of the prediction errors of the whole landscape model that can be attributed to the stream network submodel will be small. On the other hand, when a stream has a high rate of instream loss, the contribution of the stream network model to the prediction errors of the landscape model can be substantial if an inappropriate value of the decay parameter is used. It is beyond the scope of this paper and the underlying field observations to study the removal rates on a watershed scale. Nevertheless, it is expected that the removal rates from all streams in the watershed will be higher than the removal rates at stream reach level because of the cumulative effect of continued removal of material along the stream network (Seitzinger *et al.*, 2002).

In general a watershed can be compartmentalized spatially or topologically in different ways, depending on the purpose of research. Spatial processes in different compartments can be simulated with different component models. A watershed model designed this way facilitates model update and customization, as new component models can be added or existing ones removed without much effort. For example, a new nutrient model with improved predictability when available can replace the one currently included in the landscape model. No change needs to be made to the other components of the landscape model. There will be no need to rerun TOPMODEL for the same watershed. The same sets of streamflow predictions for individual subwatersheds generated by the rain-runoff model can still be used for future simulations with the new nutrient model.

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