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# State Water Pollution Control Policy Insights from a Reduced-Form Model

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**Abstract:** Regulatory policy analyses are often based on the results of computer-intensive models that have limitations resulting from their complexity, size, and run-time requirements. This paper describes and applies a reduced-form model (RFM) of a large-scale water quality model developed for regulatory decision support. The RFM addresses the needs of decision makers who are interested in assessing uncertainty in model estimates and developing prescriptive applications of the model. This paper describes the RFM and demonstrates its applicability to four U.S. states that vary in environmental and socioeconomic characteristics. An application to combined sewer overflow (CSO) policy is developed to illustrate how the RFM can improve decision support. Economic benefits of CSO controls are simulated using the RFM and compared with the U.S. Environmental Protection Agency's control cost estimates. The sensitivity of these benefits to assumptions of the benefit-cost analysis is tested. In terms of environmental decision making, the RFM reveals that it is more important to resolve what loading rates are most appropriate for benefit-cost analysis than it is to precisely model wet-weather hydrology.

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## Introduction

Needs of policy analysts and decision makers often stand in contrast to the features of large-scale environmental models intended to provide regulatory decision support. Policy analysts and decision makers need models that provide results in terms of appropriate decision metrics and that can be run many times for sequential decision making, heuristic analysis, replication among political or geographic areas, and uncertainty analysis. If run times are too long, output files too large, or postprocessing requirements too complex, then the utility of these models can be limited by the computational capacity of the analyst, which is frequently limited to a desktop computer. Reduced-form models (RFMs) reproduce decision-relevant results of large numerical models more efficiently, while implicitly preserving the original input data and the representation of hydrologic, chemical, and physical processes.

This paper describes an RFM for a large-scale water quality model, the National Water Pollution Control Assessment Model

(NWPCAM, Version 1.1) (Bondelid et al. 2000). The RFM, developed in Schultz (2002), overcomes several limitations of the NWPCAM. It reduces the time to complete Monte Carlo simulations for uncertainty analysis from several days to several seconds, and it provides a single, continuous function to explore the sensitivity of regulatory decisions, investigate regulatory options, and prescribe the level of controls needed to achieve water quality goals. This paper demonstrates the applicability of the RFM in four states that vary in demographic, climatic, and geophysical characteristics and implements the RFM in a benefit-cost analysis of regulations to reduce combined sewer overflows (CSOs) at the state level. The CSO issue is selected for its economic importance, its timeliness given the U.S. Environmental Protection Agency (EPA)'s regulations to reduce pollutant load from these sources, and the high level of compatibility between the EPA's compliance cost estimates and the economic benefits estimated using the RFM.

Other examples of RFMs are available in the literature. Small and Sutton (1986) and Small et al. (1988) develop direct distribution models describing the effect of acid deposition on regional lake acidification in the Adirondacks. In this direct distribution approach, parameters of a probability distribution describing the regional distribution of lake alkalinity are derived from mechanistic lake acidification models. Sinha et al. (1998) describe reduced-form modeling using the Model of Acidification of Groundwater in Catchments (MAGIC), a numerical model for predicting future changes in regional surface and soil water chemistry because of acid deposition. Cocca (2001) describes Mercury Maps, a model that relates changes in mercury air deposition rates to changes in fish tissue concentrations. Its form is derived from the steady-state formulations of three dynamic models that describe the mercury cycle, fate and transport in watersheds, and bioaccumulation. These three examples of RFMs provide scalable, portable substitutes for large-scale models while preserving the policy-relevant science, expressing results in policy-relevant terms, and facilitating uncertainty analysis.

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RFMs serve independently or as components of larger integrated assessment models designed for policy and decision support. For example, the Small et al. (1988) direct distribution RFM for lake acidification has been incorporated into integrated assessments that predict the effects of SO<sub>2</sub> emissions controls on lake acidification and the occurrence of specific fish species in the Adirondacks and the Boundary Waters region of Minnesota (Rubin et al. 1992). The RFM of Sinha et al. (1998) is a component of the Tracking and Analysis Framework (TAF) that evaluates implementation, effectiveness, and net-benefits of the acid-deposition control program. Mercury Maps is applied on a national scale to determine the proportional reduction in air deposition, by watershed, that is required to meet the new methylmercury criterion (Cocca 2001).

## National Water Pollution Control Assessment Model

Research Triangle Institute developed the NWPCAM with support from the EPA Office of Water. This steady-state fate and transport model, which is fully described in Bondelid et al. (2000), estimates the ambient levels of conventional water quality parameters, including biological oxygen demand (BOD), total suspended solids (TSS), fecal coliform (FC), and dissolved oxygen (DO) at approximately 1-mi intervals of a 632,000 mi computational stream network. This stream network, Reach File 1 (RF-1), was developed jointly by the EPA and the U.S. Geological Survey to represent the largest rivers and streams in the country. One run of the NWPCAM generates a 270-MB output file containing over 650,000 rows of data and 27 variables describing location, hydrology, and water quality in each modeling interval.

To observe the impacts of a regulatory intervention, users must generate and postprocess two model runs, one describing a baseline regulatory scenario, and another describing a regulatory counterfactual scenario. Regulatory impacts can be assessed by comparing water quality conditions in each stream mile of the counterfactual run with those in the baseline run. Recent applications of the NWPCAM include a retrospective evaluation of regulations to control conventional water pollutants under the Clean Water Act (Bingham et al. 2000) and a prospective evaluation of regulations to control pollution from concentrated animal feeding operations (EPA 2001). The NWPCAM is currently limited to conventional pollutants, but many surface water quality problems are caused by nutrients and toxics. Modules that address these pollutants are in development, and the RFM method could eventually extend to these models.

## Pollutant Loads

The NWPCAM accounts for conventional pollutant loads from over 8,000 municipal wastewater treatment plants, 23,000 industrial wastewater treatment plants, and 621 combined sewer systems (CSSs). Urban and rural nonpoint source (NPS) loads are based on county-level estimates and allocated as distributed loads to stream segments in each county. By manipulating loads from these sources, users can observe water quality response to changes in 5 day biological oxygen demand (BOD<sub>5</sub>), TSS, FC, and total Kjeldahl nitrogen (TKN), which is the oxidizable fraction of nitrogen in the water column that affects dissolved oxygen concentrations.

Bondelid et al. (2000) obtained information on pollutant loadings at municipal wastewater treatment plants and major industrial dischargers from the EPA's Permit Compliance System

(PCS) database and other agency sources. Model developers obtained information on minor industrial dischargers from the EPA's Industrial Facility Discharger database (Bingham et al. 2000). For point sources where discharge loading rates were unavailable, model developers used industry-specific effluent flow rates and concentration means, or an overall mean value where standard industrial classification codes were unknown. According to model developers, these loadings represent mid-1990s loadings under prevailing pollution control policies. Developers obtained estimates of the level of pollutant load expected from CSO events caused by 5-year 1-h storms from background documents prepared for the EPA's 1992 Clean Water Act Needs Survey (CWANS). Since the NWPCAM is a steady-state model, model developers weighted these estimates by 0.167 to characterize long-term average CSO loading rates.

## Water Quality Modeling

The transformations of pollutants are modeled as temperature-sensitive, lumped-parameter, first-order decay processes that describe the degradation or loss of pollutants from the water column over time, following standard methods described in Thomann and Mueller (1987) and Chapra (1997). Model environmental conditions such as temperature and hydrology are representative of the period between July 1 and September 30 because summer conditions are often water quality limiting. The hydrologic modeling component is based on estimates of stream flow and velocity contained in the RF-1 database with stream depth imputed under the assumptions of stable channel analysis and an assumed side slope angle (Henderson 1966).

BOD<sub>5</sub>, FC, TSS, and TKN concentrations are estimated using a 1D steady-state plug-flow equation with a distributed source-load term for NPS loads and a fixed sediment oxygen demand (SOD). The NWPCAM assumes that under current prevailing conditions the BOD removal rate equals the BOD decomposition rate and that settling losses can be ignored because of the small fraction of particulate BOD in effluent from secondary treatment. The FC decay rate depends on both salinity and temperature. DO concentration is the difference between the oxygen saturation level (milligrams per liter) and the oxygen deficit (milligrams per liter). Oxygen saturation accounts for the effects of temperature, salinity, and atmospheric pressure. Oxygen deficit is calculated using the Streeter-Phelps equation accounting for the effects of BOD, TKN, SOD, and a surface reaeration rate that depends on stream velocity, depth, and temperature. The NWPCAM assumes that photosynthesis and respiration are balanced, so does not account for these processes (Bondelid et al. 2000).

## Use-Support Characterization

The NWPCAM characterizes water quality in terms of use support, which indicates the level of human contact for which a water body is suited given the ambient concentrations of pollutants in the water column. Use-support categories are, in decreasing level of quality and suitability for human contact, swimmable, fishable, boatable, and nonsupporting. Swimmable waters are the cleanest and designated safe for the highest level of human contact other than drinking. Fishable waters are safe for human contact, but for aesthetic or other reasons are not suitable for swimming. Water bodies that meet no more than the boatable standards are considered suitable for secondary contact recreation, but not for direct human contact. Nonsupporting water bodies are not even considered safe for secondary contact recreation.

**Table 1.** National Water Pollution Control Assessment Model Water Quality Ladder

Use-support level	BOD <sub>5</sub> (mg/L)	FC (MPN/100 mL)	TSS (mg/L)	DO saturation (%)
Swimmable	≤1.5	≤200	≤10	≥83
Fishable	≤3.0	≤1000	≤50	≥64
Boatable	≤4.0	≤2000	≤100	≥45

Note: Reproduced from Bondelid et al. (2000); BOD=biological oxygen demand; FC=fecal coliform; TSS=total suspended solids; and DO=dissolved oxygen.

A higher-level use-support classification implies that water quality satisfies all lower levels of use support. For example, fishable waters are also boatable, and swimmable waters are both fishable and boatable. The level of use support in a stream mile is determined with reference to the NWPCAM water quality ladder, which is based conceptually on Resources for the Future (RFF)'s water quality ladder (Vaughn 1986). The NWPCAM water quality ladder, shown in Table 1, lists four water quality criteria for each level of use support. To satisfy a particular level of use support, water quality must satisfy all four criteria; therefore, use support in each stream mile is assessed with respect to the limiting water quality parameter.

### Economic Impact Assessment

Environmental benefits and costs of regulation can be evaluated in terms of changes in consumer welfare, which are assessed through either indirect or direct methods. Indirect methods are those through which an analyst derives the value of environmental amenities from information about commodity prices and consumer choices, and direct methods are those through which the analyst elicits information about environmental values directly from consumers. Preferences for direct methods at the EPA and among some analysts are rooted in awareness that many amenities are not traded in the market and indirect methods have a tendency to underestimate these values. The most common of the direct methods is contingent valuation. Although a number of well-documented issues are associated with the method, contingent valuation has gained broader acceptance in recent years (NOAA 1993; Carson 2000).

To value changes in use support, Bondelid et al. (2000) adopted results from an existing contingent valuation study. Authors of that study presented respondents with detailed scenarios regarding hypothetical changes in water quality and asked respondents to answer questions concerning their willingness to pay (WTP) to raise the minimum level of use support in the nation through higher product prices and income taxes. Survey results were fit to a Hicksian income compensation function that accounts for differences in income, preferences, and attitudes among respondents (Mitchell and Carson 1986; Carson and Mitchell 1993). The 1986 estimates of WTP and their standard errors, expressed in 1983 dollars, are listed in Table 2, along with updates for 1996.

These WTP estimates for increments in use support are additive across the hierarchical use-support categories. On average, respondents allocated 67% of these estimates to a WTP for use-support improvements within their own state and 33% to a WTP for use-support improvements elsewhere in the nation. Given the numerous limitations of contingent valuation methods and these estimates in particular, there is currently much discussion among NWPCAM users regarding exactly how economic impacts should

**Table 2.** Household Willingness-to-Pay Estimates for Use-Support Increments

Currency	Nonsupporting to boatable		Boatable to fishable		Fishable to swimmable	
	Mean	S.E.	Mean	S.E.	Mean	S.E.
1983 Dollars <sup>a</sup>	93	8	70	6	78	9
1996 Dollars <sup>b,c</sup>	189	16	143	12	159	18

<sup>a</sup>Estimates from Carson and Mitchell (1993).

<sup>b</sup>Updated expected values are from Bingham et al. (2000).

<sup>c</sup>Updated standard deviations are obtained by scaling 1983 estimates.

be estimated using model results. Economic impact of changes to or from use-support level  $i$ ,  $L_i$ , is estimated here as a function of  $\pi_i$ , the ratio of the number of stream segments that improve or degrade in quality relative to use  $i$  to the number that do not support use  $i$  under the policy being evaluated. Within a particular state, economic impact is given by

$$L_i(\pi_i) = \pi_i \cdot 0.67 \cdot \text{WTP}_i \cdot \left( \frac{N}{2.62} \right) \quad (1)$$

where  $N$ =affected population in the state, divided by 2.62 people per household to obtain an estimate of the number of households in the state; and the coefficient 0.67=portion of WTP allocated to use-support improvements occurring within the state, which are considered "local." The total economic benefit attributed to any change in pollutant load within a state is the sum of  $L_i(\pi_i)$  (dollars/year) across the three hierarchical use-support levels,  $i = \{b, f, s\}$ ; and lower-case letters indicate boatable ( $b$ ), fishable ( $f$ ), and swimmable ( $s$ ) use support, respectively.

WTP (dollars) estimates and their application deserve several additional comments. In particular, the partitioning of in-state and out-of-state benefits may be somewhat arbitrary because it ignores the essential issue of proximity in the notion of local use-support improvements—individuals in some parts of the state may reside closer to use-support improvements in other states than they do within their own state. In addition, this approach implies equality of WTP and willingness to accept (WTA), and the application assumes that the WTP estimates can be applied to the RF-1 network, which represents only a portion of the nation's waters in which Carson and Mitchell (1993) valued changes in water quality.

### General Form of Response Surface

The response surface approach reduces a large-scale numerical model to a single function that mimics its output response to changes in selected input variables (Box et al. 1978; Downing 1985; Box and Draper 1987; Law and Kelton 1991). Input variables are screened to assess their uncertainty importance, and the  $n$ -dimensional output variable hyperspace is sampled by varying the most important input variables according to a carefully constructed experimental design. Empirical relationships between the input variables and the output variable(s) are then established by fitting a function.

The response surface function estimates  $R_i$ , the fraction of stream miles satisfying use support level  $i$ ;  $R_i$  is the cumulative sum of the marginal proportion of stream miles satisfying use-support level  $i$  and its lower-level uses. For any assessment of use-support changes, two estimates of  $R_i$  are necessary;  $R_i$  is the fraction of stream miles supporting use  $i$ , and  $R_i^{\text{Mod}}$  is the fraction

**Table 3.** National Water Pollution Control Assessment Model Variables and Probability Distributions Used in Simulation

Variable	Nominal value	Distributional form	Parameter values	Median value <sup>a</sup>	Arithmetic $\mu$ and $\sigma$	Relative uncertainty importance
PRURAL	1.0	Lognormal	$\xi=0$ ; $\phi=1.0$	1.0	$\mu=1.649$ ; $\sigma=2.161$	92.55
$F$	1.0	Lognormal	$\xi=0.019$ ; $\phi=0.513$	1.0	$\mu=1.163$ ; $\sigma=0.638$	6.65
$T$ (Celsius)	21.9	Normal	$\mu=21.9$ ; $\sigma=3.71$	21.9	$\mu=21.9$ ; $\sigma=3.71$	0.46
PURBAN	1.0	Lognormal	$\xi=0$ ; $\phi=1.0$	1.0	$\mu=1.649$ ; $\sigma=2.161$	0.12
$D_E$	1.0	Asymmetric triangular	Minimum=0.5; mode=0.93; maximum=1.25	1.0	$\mu=1.000$ ; $\sigma=0.166$	0.13
PSOD	1.0	Uniform	Minimum=0; maximum=2	1.0	$\mu=1.000$ ; $\sigma=0.577$	0.04
VTSS (m/day)	0.3	Log-uniform	Minimum=0.1; maximum=0.9	0.3	$\mu=0.364$ ; $\sigma=0.226$	0.04
$V_E$	1.0	Asymmetric triangular	Minimum=0.5; mode=0.93; maximum=1.25	1.0	$\mu=1.000$ ; $\sigma=0.166$	0.02
PCSO	1.0	Lognormal	$\xi=0$ ; $\phi=1.0$	1.0	$\mu=1.649$ ; $\sigma=2.161$	<0.01

Note: PRURAL=rural nonpoint source load scale parameter; PURBAN=urban nonpoint source load scale parameter; PSOD=sediment oxygen demand scale parameter; VTSS=total suspended solids settling velocity (m/day); and PCSO=combined sewer overflow load scale parameter.

<sup>a</sup>Median value is that of the parameter under the stated distribution.

of stream miles supporting use  $i$  under a proposed or modified policy. These estimates of  $R_i$  are then used to calculate the regulatory performance measure,  $\pi_i$ , while holding the values of any uncertain variables constant:

$$\pi_i = \frac{R_i^{\text{Mod}} - R_i}{1 - R_i} \quad (2)$$

This performance measure is the fraction of stream miles not supporting use  $i$  that change in use support, either to or from use-support level  $i$  under the policy being evaluated. The numerator is the change in the fraction of stream miles supporting use  $i$  under the proposed policy, and the denominator is the fraction of stream miles that do not support use  $i$  in the absence of the policy.

Most econometric textbooks document the problems of estimating proportions and probabilities using linear functions. To avoid these pitfalls, the cumulative proportion  $R_i$  is transformed to an empirical logit so that it is bounded between zero and one. In this context, the logit is the natural log of the odds ratio of the probability that use-support level  $i$  is satisfied. In the response surface model, the logit is a function of a set of independent variables:

$$L_i = \ln\left(\frac{R_i}{1 - R_i}\right) = f(z_c, z_u) \quad (3)$$

The independent variables include control variables ( $z_c$ ) used to adjust pollutant loads and nine uncertain hydrologic and environmental variables ( $z_u$ ). These nine variables are a subset of NWPCAM variables selected for their relative importance in assessing uncertainty in NWPCAM outputs. Uncertainty importance is calculated as the product of the squared output variable sensitivity and the variance of the probability distribution characterizing uncertainty in the NWPCAM input variables (Morgan and Henrion 1990). Output variable sensitivity is defined as the change in the number of stream miles at least supporting each use-support level. Since there are three use-support levels, the absolute values of these three sensitivities were summed across the three use-support levels to obtain a single aggregate measure of model sensitivity.

Probability distributions characterizing uncertainty in input variables were developed from information in the literature and expert judgment (Thomann and Mueller 1987; Chapra 1997; Schultz 2002). Table 3 lists the variable symbol, gives its nominal

value in the NWPCAM, lists the distributional form and parameter values adopted for this uncertainty analysis, and lists the median, mean, and standard deviation of transformed values under the stated distribution. The final column in Table 3 lists the proportion of total uncertainty importance accounted for by each variable.

Response surfaces can take many functional forms. A main-effects model, a polynomial expansion, and two versions of an RFM were considered for the NWPCAM. These four candidates were developed using a joint control variable for municipal and industrial point sources (PS) to reduce dimensionality. However, the experimental design permits separation of municipal and industrial point source effects as described above, and independent control variables are used in applications. Evaluation and selection of the response surface form is based on the ability to estimate decision-relevant outputs including  $R_i$ ,  $\pi_i$ , and their uncertainty distributions, as discussed in Schultz (2002). The RFM presented in this paper consistently provided the best estimates with the highest degree of interpretability when compared to the alternative forms.

### Reduced-Form Response Surface Model

The RFM incorporates interaction terms representing explicit physical relationships known from NWPCAM model equations. In terms of pollutant transport, the NWPCAM is essentially based on a 1D steady-state plug-flow model, although it contains numerous other features. The plug-flow model estimates pollutant concentration,  $C$  [milligrams per liter or most probable number per liter (MPN/L)], at distance  $x$  (meters) downstream from a waste source as a function of the waste loading rate,  $W$  (kilograms), the stream flow,  $Q$  (cubic meters per day), and a decay term:

$$C(x) = \frac{W}{Q} \exp\left(-k\theta^{(T-20)}\frac{x}{U}\right) \quad (4)$$

In the decay term,  $k$  ( $\text{day}^{-1}$ )=nominal decay rate;  $\theta$ =coefficient reflecting sensitivity of  $k$  to temperature;  $T$  (Celsius)=mean summer temperature; and  $U$  (m/day)=stream velocity. The RFM incorporates the variable interactions in the plug-flow model as an index of environmental sensitivity,  $K$ . This impact coefficient has functional similarity to the plug-flow model but is constructed using dimensionless hydrologic and environmental scale parameters associated with nonload variables:

**Table 4.** Integrated Model Coefficients for Arizona and Iowa

Variables	Arizona						Iowa					
	Boatable		Fishable		Swimmable		Boatable		Fishable		Swimmable	
	Coefficient	S.E.	Coefficient	S.E.	Coefficient	S.E.	Coefficient	S.E.	Coefficient	S.E.	Coefficient	S.E.
INTERCEPT	0.798 <sup>a</sup>	0.018	0.243 <sup>a</sup>	0.026	-1.139 <sup>a</sup>	0.036	2.383 <sup>a</sup>	0.037	1.309 <sup>a</sup>	0.044	-0.327 <sup>a</sup>	0.014
$K$	0.336 <sup>a</sup>	0.041	0.780 <sup>a</sup>	0.058	0.748 <sup>a</sup>	0.079	0.103	0.082	0.567 <sup>a</sup>	0.099	0.279 <sup>a</sup>	0.031
$PMUN \cdot K$	-0.013	0.026	-0.014	0.037	-0.010	0.050	-0.089	0.051	-0.085	0.061	-0.045 <sup>a</sup>	0.019
$PIND \cdot K$	-0.011	0.026	-0.014	0.037	-0.022	0.050	-0.023	0.051	-0.020	0.061	-0.018	0.019
$PRURAL \cdot K$	-1.035 <sup>a</sup>	0.016	-1.412 <sup>a</sup>	0.022	-1.252 <sup>a</sup>	0.031	-1.976 <sup>a</sup>	0.031	-1.648 <sup>a</sup>	0.037	-0.264 <sup>a</sup>	0.012
$PURBAN \cdot K$	-0.120 <sup>a</sup>	0.011	-0.135 <sup>a</sup>	0.015	-0.271 <sup>a</sup>	0.021	-0.180 <sup>a</sup>	0.021	-0.223 <sup>a</sup>	0.025	-0.111 <sup>a</sup>	0.008
$PCSO \cdot K$	—	—	—	—	—	—	-0.028	0.021	-0.013	0.025	-0.015	0.008
PSODT	-0.066 <sup>a</sup>	0.008	-0.135 <sup>a</sup>	0.011	-0.236 <sup>a</sup>	0.015	-0.044 <sup>a</sup>	0.015	-0.132 <sup>a</sup>	0.018	-0.111 <sup>a</sup>	0.006
KTSS	0.524 <sup>a</sup>	0.018	0.968 <sup>a</sup>	0.026	1.135 <sup>a</sup>	0.036	-0.087 <sup>a</sup>	0.036	0.278 <sup>a</sup>	0.043	0.170 <sup>a</sup>	0.014
$R$ -squared	0.858		0.850		0.757		0.842		0.708		0.549	

Note: PMUN=municipal load scale parameter; PIND=industrial load scale parameter; PRURAL=rural nonpoint source load scale parameter; PURBAN=urban nonpoint source load scale parameter; PCSO=combined sewer overflow load scale parameter; PSODT=temperature-adjusted sediment oxygen demand scale parameter; and KTSS=effective total suspended solids settling velocity (m/day).

<sup>a</sup>Indicates significance at  $\alpha=0.05$  level; number of observations in each regression is 1,027.

$$K = \frac{1}{F} \exp\left(-\bar{k}\bar{\theta}^{(T-20)} \frac{1}{V}\right) \quad (5)$$

where  $Q$  is replaced by  $F$ , the NWPCAM flow scale parameter that induces proportional adjustments to stream flow throughout the stream network, and  $U$  is replaced by  $V$ , which is the ratio of the run-time velocity to nominal stream velocity;  $V$  depends on the user-specified scale parameters  $F$  and  $V_E$  that control stream flow and velocity, respectively (Schultz 2002). Downstream distance from the waste source,  $x$ , is replaced by the modeling interval, which is approximately 1 mi. The nominal decay rate,  $\bar{k}$ , takes a representative value of 0.5 day<sup>-1</sup> since all NWPCAM decay rates are between 0 and 1 day<sup>-1</sup>. Similarly,  $\bar{\theta}$  has a representative value of 1.05, which is consistent with NWPCAM values between 1 and 1.1.

Representative values are used for decay rates and temperature sensitivities because the uncertainty importance for these variables indicated that they were much less important than some other variables. Including them in the impact coefficient as representative values with appropriate magnitude and sign ensures that the index responds appropriately to the other variables while reducing RFM development costs. Larger values of  $K$  indicate greater environmental sensitivity to load, and smaller values of  $K$  indicate less sensitivity. In the RFM,  $K$  serves to weight the independent pollution control variables so that the effect of pollutant load on use support varies with factors that affect environmental sensitivity to pollutant loads.

The analysis of uncertainty importance also showed that the stream depth scale parameter,  $D_E$ , and the TSS settling velocity, VTSS (meters per day), are also important variables to include in the RFM. These variables are incorporated into an effective TSS settling velocity, KTSS (meters per day), which depends on VTSS and  $D_E$ :

$$KTSS = \frac{VTSS}{D} \quad (6)$$

where  $D$ =ratio of run-time stream depth to nominal stream depth and is calculated from  $F$ ,  $V$ , and the user-specified  $D_E$  in a manner consistent with hydrologic assumptions in the NWPCAM (Schultz 2002). There is a logical interaction between KTSS and the pollutant load scale parameters because the higher its value,

the more quickly sediment is removed from the water column. Although TSS is an important determinant of use support, including this as an interaction with pollutant load scale parameters led to poor results; therefore it is included as an intercept shift. The sediment oxygen demand scale parameter, PSOD, interacts with temperature and is included as another intercept shift:

$$PSODT = PSOD \cdot \theta^{(T-20)} \quad (7)$$

The RFM estimates the logit of the proportion of stream miles satisfying use-support level  $i$  as a function of pollutant load scale parameters and environmental modeling terms:

$$\begin{aligned} \hat{L}_i = \ln\left(\frac{R_i}{1-R_i}\right) \\ = \beta_{i0} + \beta_{i1}K + \beta_{i2}PMUN \cdot K + \beta_{i3}PIND \cdot K + \beta_{i4}PRURAL \cdot K \\ + \beta_{i5}PURBAN \cdot K + \beta_{i6}PCSO \cdot K + \beta_{i7}KTSS \\ + \beta_{i8}PSODT \end{aligned} \quad (8)$$

The variables PMUN and PIND are deterministic scale parameters for municipal and industrial point source loads, respectively. PRURAL, PURBAN, and PCSO are uncertain scale parameters that control the level of loadings from rural NPSs, urban NPSs, and CSOs, respectively. The impact coefficient,  $K$ , controls for changes in the sensitivity to pollutant load as environmental variables change. RFM coefficients are estimated using weighted least squares, a procedure that minimizes the sum of squares of weighted residuals. Residuals have been weighted by  $1/PRURAL^2$  to reduce heteroscedasticity that is inversely proportional to rural NPS loads. This heteroscedasticity reflects the fact that it is harder to predict use-support gains and losses when the water quality is relatively good. The RFMs estimated in this paper were fit to 1,027 experimental NWPCAM runs that produced 295 GB of model output and required several months of continuous run time to generate and process.

RFMs were developed for Arizona, Iowa, Maryland, and Pennsylvania to demonstrate the applicability of this approach. Results for Arizona and Iowa in Table 4 show that point sources are an insignificant determinant of the use-support fraction. While changes in load from these sources have an unambiguous effect

**Table 5.** Integrated Model Coefficients for Maryland and Pennsylvania

Variables	Maryland						Pennsylvania					
	Boatable		Fishable		Swimmable		Boatable		Fishable		Swimmable	
	Coefficient	S.E.	Coefficient	S.E.	Coefficient	S.E.	Coefficient	S.E.	Coefficient	S.E.	Coefficient	S.E.
INTERCEPT	4.408 <sup>a</sup>	0.035	2.310 <sup>a</sup>	0.050	0.323 <sup>a</sup>	0.021	3.795 <sup>a</sup>	0.038	2.174 <sup>a</sup>	0.043	0.321 <sup>a</sup>	0.020
$K$	0.575 <sup>a</sup>	0.080	1.086 <sup>a</sup>	0.112	0.422 <sup>a</sup>	0.046	0.277 <sup>a</sup>	0.084	1.053 <sup>a</sup>	0.096	0.436 <sup>a</sup>	0.045
$PMUN \cdot K$	-0.159 <sup>a</sup>	0.049	-0.093	0.070	-0.142 <sup>a</sup>	0.029	-0.268 <sup>a</sup>	0.053	-0.229 <sup>a</sup>	0.059	-0.094 <sup>a</sup>	0.028
$PIND \cdot K$	-0.464 <sup>a</sup>	0.049	-0.278 <sup>a</sup>	0.070	-0.075 <sup>a</sup>	0.029	-0.235 <sup>a</sup>	0.053	-0.235 <sup>a</sup>	0.059	-0.100 <sup>a</sup>	0.028
$PRURAL \cdot K$	-1.516 <sup>a</sup>	0.030	-1.244 <sup>a</sup>	0.042	-0.481 <sup>a</sup>	0.018	-1.496 <sup>a</sup>	0.032	-1.197 <sup>a</sup>	0.036	-0.311 <sup>a</sup>	0.017
$PURBAN \cdot K$	-0.567 <sup>a</sup>	0.020	-0.361 <sup>a</sup>	0.029	-0.273 <sup>a</sup>	0.012	-0.335 <sup>a</sup>	0.022	-0.328 <sup>a</sup>	0.024	-0.214 <sup>a</sup>	0.011
$PCSO \cdot K$	0.009	0.020	-0.060 <sup>a</sup>	0.028	-0.044 <sup>a</sup>	0.012	-0.072 <sup>a</sup>	0.021	-0.065 <sup>a</sup>	0.024	-0.043 <sup>a</sup>	0.011
PSODT	-0.105 <sup>a</sup>	0.014	-0.287 <sup>a</sup>	0.020	-0.104 <sup>a</sup>	0.008	-0.117 <sup>a</sup>	0.015	-0.239 <sup>a</sup>	0.017	-0.145 <sup>a</sup>	0.008
KTSS	0.033	0.035	0.291 <sup>a</sup>	0.049	0.199 <sup>a</sup>	0.020	0.026	0.037	0.360 <sup>a</sup>	0.042	0.159 <sup>a</sup>	0.020
$R$ -squared	0.837		0.575		0.661		0.798		0.636		0.547	

Note: PMUN=municipal load scale parameter; PIND=industrial load scale parameter; PRURAL=rural nonpoint source load scale parameter; PURBAN=urban nonpoint source load scale parameter; PCSO=combined sewer overflow load scale parameter; PSODT=temperature-adjusted sediment oxygen demand scale parameter; and KTSS=effective total suspended solids settling velocity (m/day).

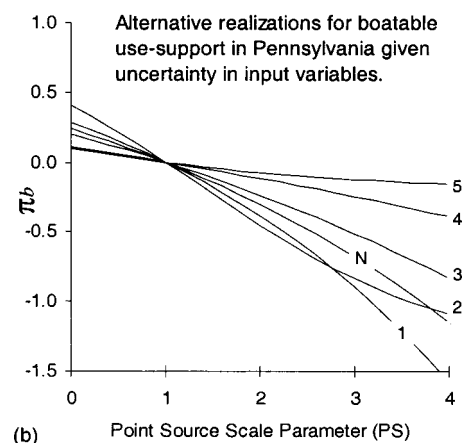
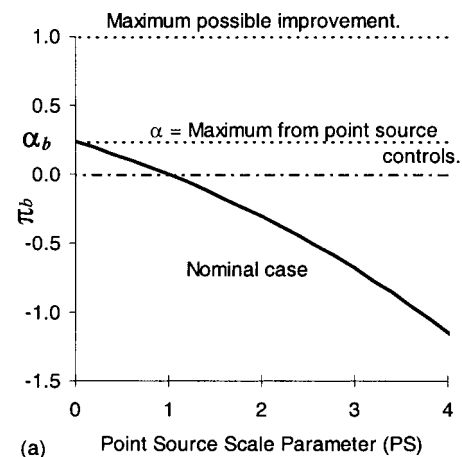
<sup>a</sup>Indicates significance at  $\alpha=0.05$  level; number of observations in each regression is 1,027.

on water quality, the effect in terms of an aggregate statewide measure of water quality condition,  $R_i$ , could not be inferred from experimental model runs. Results for Maryland and Pennsylvania in Table 5 show that point sources are a significant factor affecting  $R_i$ . Point source load coefficients are negative, indicating that increases in pollutant load cause use-support losses.

In all four states,  $R_i$  is more sensitive to PRURAL than to PURBAN. This might be attributed either to the amount of rural NPS loads relative to urban NPS loads or to the broader distribution of rural NPS loads in the NWPCAM. However, one cannot infer a preference for controlling one source of load relative to another without information about control costs. For example, if rural NPS loads are less concentrated than urban NPS loads, it is conceivably cheaper to obtain a 10% reduction in urban NPS load than a 1% reduction in rural NPS load. Significant coefficients for PCSO are relatively small and negative. Although the overall effect of CSOs on the use-support fraction statewide is small, CSOs may be relatively important sources of degradation locally. There are no CSOs in Arizona, so this coefficient is not estimated in that state. As expected, PSODT has a negative impact on use-support, and KTSS has a positive effect.

The size and significance of coefficients depend upon characteristics such as geography, population, and climate. Arizona and Iowa are rural states with low population density and a relatively high level of agricultural activity. This explains the relative importance of rural NPS loads and the limited benefits realized by controlling point source loads, although individual sources may be relatively important locally. Point sources have larger effects in Maryland and Pennsylvania. In Maryland, changes in PIND have greater effect on  $R_b$  and  $R_f$  than changes in PMUN, but changes in PMUN have a greater effect on  $R_s$ . In Pennsylvania, coefficients for PMUN and PIND indicate that these sources have similar effects at all use-support levels.

Environmental factors and loading patterns affect how  $R_i$  and  $\pi_i$  respond to changes in point source load. Fig. 1(a) illustrates the response of  $\pi_b$  in Pennsylvania to changes in point source load under nominal environmental conditions and loading patterns. The y-axis shows  $\pi_b$ , the fraction of stream miles not supporting boatable use that improve or degrade relative to the boatable use-support criterion. PS, on the x-axis, has a value of 1 in the baseline loadings case and ranges in value from 0 to 1 in the case of point source load reductions or from 1 to much greater



**Fig. 1.** Reduced-form model results for boatable use-support response  $\pi_B$  to point source loads  $PS$  in Pennsylvania; (a) shows nominal case  $N$  and (b) illustrates sensitivity to input variables in realizations 1–5.

**Table 6.** State Variable Values for Realizations of Reduced-Form Model (RFM) in Fig. 1(b)

RFM realization	State variables of RFM						Implicit scale parameters <sup>c</sup>		Impact coefficient
	$T$	$Q$	$V_E$	$D_E$	VTSS	PSOD	$V$	$D$	$K$
Nominal	21.9	1.00	1.00	1.00	0.3	1.0	1.00	1.00	0.5778
1	15.0	1.00	1.00	1.00	0.3	1.0	1.00	1.00	0.6759
2	21.9	0.30	1.00	1.00	0.3	1.0	0.70	1.20	1.5170
3 <sup>a</sup>	21.9	1.20	1.00	1.00	0.5	1.0	1.06	0.97	0.4957
4	21.9	1.75	0.50	1.00	0.7	1.0	0.59	0.41	0.2260
5 <sup>b</sup>	21.9	0.60	1.25	1.20	0.3	1.0	1.07	1.68	0.9993

Note: All other variables are at their nominal levels except as noted: (<sup>a</sup>) PRURAL=2; (<sup>b</sup>) PRURAL=3; (<sup>c</sup>) Implicit scale parameters vary among stream segments. These values are for a representative stream segment. VTSS=total settling velocity (m/day); and PSOD=sediment oxygen demand scale parameter.

than 1 in the case of point source load increases, which may be the result of either reduced treatment levels or increased discharge volume.

Prospective use-support losses are potentially much greater than prospective use-support improvements because point source controls are already relatively stringent. Under baseline loadings, when PS=1 on the  $x$ -axis,  $\pi_b=0$ , indicating that no change in water quality occurs without changing PS from its baseline level. The maximum improvement possible is to eliminate all nonsupporting stream miles, at which point  $\pi_b=1$ . The point  $\alpha_b$  at the  $y$ -axis intercept shows the improvement in boatable use support that can be achieved by eliminating point source loads. For this nominal case,  $\alpha_b=0.24$ , indicating that 24% of nonboatable stream miles improve to boatable when point source loads are eliminated. Additional improvement must be obtained by controlling other sources of pollution, such as rural and urban NPSs, CSOs, or sediment.

The slope of the  $\pi_b$  curve at PS=1 reflects the sensitivity of the regulatory performance measure to point source controls. This sensitivity varies with state variables describing environmental conditions and the level of other pollutant loads. Fig. 1(b) shows the response of  $\pi_b$  under nominal environmental conditions and pollutant loads, labeled "N," and five realizations of the response for selected combinations of state variable values, as listed in Table 6. These combinations are chosen to illustrate the flexibility and range of the  $\pi_b$  response and they therefore tend to represent low probability states. However, all are possible representations of steady-state conditions given the specifications of uncertainty in input variable values in Table 3.

Realization 1 shows that  $\pi_b$  becomes more sensitive as  $T$  decreases and causes  $K$  to increase. Realization 2 shows that a 70% reduction in  $Q$  greatly increases  $\pi_b$  sensitivity to PS. Sensitivity to PS also depends upon factors that are not reflected in the impact coefficient, such as the level of urban and rural NPS loads. Realizations 3 and 5 show that sensitivity of  $\pi_b$  decreases when NPS loads are higher than their nominal levels. Realization 4 has the lowest impact coefficient because of increases in  $Q$  and VTSS. In realization 5,  $\pi_b$  is less sensitive to PS than in realization 4 despite a high impact coefficient because rural NPS loads are high.

### Application of Reduced-Form Response Surface Model

An ideal application of the response surface model would compare the marginal benefits of a pollution control strategy with short-run marginal costs, defined as all compliance costs that are variable within the planning horizon. Since we presently lack a

cost function to estimate the short-run marginal costs of control at individual sources or groups of sources, neither a marginal analysis nor an optimization of pollution control parameters is feasible. Therefore, this paper compares estimates of the marginal benefit of pollution control with EPA's point estimates of the marginal cost to comply with the CWA. Compliance cost estimates from the 1996 CWANS (EPA 1997) were regarded as most appropriate for comparison with these benefit estimates because pollutant loading rates in the NWPCAM are based on information contained in databases documenting mid-1990 loadings.

Several caveats should accompany comparisons of CWANS compliance cost estimates with RFM benefit estimates. CWANS compliance cost estimates account for only a portion of pollution control costs. They include capital costs required to prevent or abate existing water quality problems attributed to publicly owned treatment works (POTWs) and other grant-eligible sources at the time of the estimate and over the next 20 years, and they exclude capital costs at industrial sources, which are not eligible for federal construction grants, and operations and maintenance costs at all sources. Secondly, CWANS estimates are made under assumptions about how service needs might change in response to population changes that affect the volume of discharge. However, the RFM assumes that populations remain constant. Therefore, if net increases in service populations occur over the CWANS planning horizon, the RFM will underestimate future benefits.

A third caveat involves disparities in the definitions of need and compliance. CWANS cost estimates reflect costs to remedy existing water quality problems and prevent anticipated problems at specific sites. In contrast, RFM benefit estimates reflect a uniform adjustment in load at those sources controlled by scale parameters, and all adjustments in load are independent of water quality conditions in receiving waters below each source. When comparing CWANS cost estimates to RFM benefit estimates, it is important to remember that CWANS estimates are also uncertain. Uncertainty in costs was not considered in this analysis because the EPA's CWANS report does not document that uncertainty.

### Economic Benefits of Combined Sewer Overflow Controls

Applications of the RFM presented in this paper analyze benefits and costs of regulations to reduce CSO load. CSO loads are untreated discharges from CSSs located in approximately 880 municipalities, primarily in the Mid-Atlantic and Midwestern states. CSSs collect and divert for treatment both surface runoff and sewage and are designed to discharge raw sewage during storm events when runoff and sewage flow exceed capacity. The EPA has mandated an 85% reduction in CSO loads from each CSS, allowing municipalities to demonstrate regulatory compliance at

**Table 7.** Present Value of Benefits from 85% Combined Sewer Overflow (CSO) Load Reduction (in Millions of U.S. Dollars, 1996)

Benefit	Estimate	Steady-state CSO loading			Storm-level CSO loading		
		Iowa	Maryland	Pennsylvania	Iowa	Maryland	Pennsylvania
Benefit <sup>a</sup>	$E$ [Benefit]	30	99	513	154	478	2,275
	$\sigma$ [Benefit]	44	136	666	202	506	2,163
	90%-CI	0–99	4–338	29–1,820	1–541	2–2,973	147–6,849
Cost <sup>b</sup>		475	114	3,978	475	114	3,978

<sup>a</sup>Benefits are present value of annual benefits over the 20-year Clean Water Act Needs Survey (CWANS) planning horizon.

<sup>b</sup>Cost estimates from EPA's 1996 CWANS (EPA 1997).

CSSs by (1) restricting the frequency of overflows to between four and seven events per year; (2) eliminating or capturing for a minimum of primary treatment no less than 85% of the volume of annual rainfall flow through the system; or (3) eliminating or reducing the mass of pollutants equivalent to the above 85% volume control (EPA 1997).

The benefits of regulations to reduce CSO load by 85% are simulated using the RFM and compared to the EPA's CWANS compliance cost estimates. These CWANS cost estimates fit the RFM benefit estimates well because CWANS states the reduction in CSO load necessary to achieve compliance and assumes a uniform level of control at all CSSs. To estimate benefits of CSO controls using the RFM, a deterministic CSO control variable is introduced to weight PCSO, the uncertain pollutant load scale parameter for CSOs. A weight of 1 is consistent with baseline conditions and a weight of 0.15 is consistent with EPA's 85% control objective. The Monte Carlo simulation consists of 1,000 realizations. One realization of the RFM is obtained by sampling from the probability distributions for independent variables, as shown in Table 3, estimating  $R_i$ , adjusting the weight on PCSO from 1 to 0.15, estimating  $R_i^{\text{Mod}}$  using the same input values, and then calculating  $\pi_i$ .

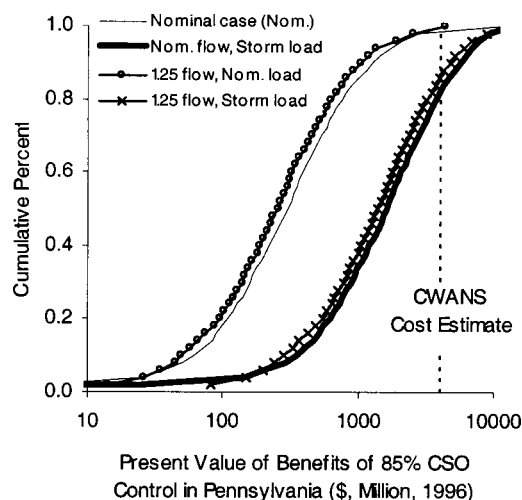
Table 7 compares the present value of benefits in Pennsylvania, Maryland, and Iowa with the CWANS cost estimates in those states. Pennsylvania is impacted by approximately 104 CSSs, Maryland by 9 CSSs, and Iowa by 19 CSSs. In Iowa and Pennsylvania, cost estimates are clearly outside the 90% confidence interval for benefits. However, in Maryland, a 90% confidence interval for the economic benefit estimate contains the CWANS compliance cost estimate. This suggests that, given the uncertainty in input variables, investments in CSO control infrastructure in Maryland may pass a benefit-cost test.

However, confidence intervals in Table 7 capture only input uncertainty, which is that portion of uncertainty attributed to specification of the input variable values. There are additional sources of uncertainty. In particular, NWPCAM is only one possible model, and these confidence intervals do not account for uncertainty associated with model choice. When implementing the benefit-cost analysis, there is yet another layer of uncertainty related to the characterization of regulatory controls, the specification of design conditions for environmental modeling, and similar assumptions under which the benefit-cost analysis is implemented. The RFM enables the analyst to test the sensitivity of benefit-cost results to such assumptions very quickly. This paper assesses sensitivity of benefit-cost results in Pennsylvania and demonstrates that these assumptions can have large effects on the outcomes.

Selection of design conditions for loading rates and environmental variables that are highly variable in nature is an important issue for regulatory evaluation when using steady-state models. This issue manifests itself in the selection of an averaging time

for CSO discharges. The NWPCAM's default assumptions average CSO discharges over a 6-day period. This is appropriate if peak discharges occur at approximately 6-day intervals, and the regulatory intervention is perceived as abating the long-term average CSO load. However, CSO discharges occur during storm events, when discharge volumes are much higher than the long-term average. An alternative approach is to treat the regulatory intervention as an abatement of peak CSO load as it occurs during storm events. This approach is consistent with other modeling conventions that emphasize the importance of conducting the benefit-cost analysis assuming water quality limiting conditions. For example, the NWPCAM models water quality during the summer months, when in many places low stream flows and higher temperatures are a major factor contributing to water quality impairment. An assessment of the sensitivity of benefit-cost results to these types of assumptions provides no insight into which assumption is more appropriate; however, since these two alternatives represent extremes in terms of this issue, the analysis helps determine upper and lower bounds for the benefit-cost results.

To reframe the regulatory intervention in this benefit-cost analysis as an abatement of peak CSO storm loads, the averaging time is reduced to 1-day, causing an increase in the weight on PCSO to reflect emissions at 5-year, 1-h storm levels. This is accomplished by multiplying the uncertain CSO scale parameter (PCSO) by the inverse of the steady-state CSO control variable,  $1/0.167=5.98$ . CSO loads in the control scenario represent an



**Fig. 2.** Cumulative distribution functions for estimates of present value of benefits and costs of combined sewer overflow (CSO) load controls over 20 years for four baseline pollutant load and stream flow scenarios in Pennsylvania

85% reduction in load relative to this baseline. Table 7 shows that this framing of the problem increases the benefits of CSO controls and that CSO compliance costs are more clearly within the confidence intervals for benefits in the three demonstration states that contain CSOs. Therefore, choice of the CSO loading rate is an important consideration because it affects the interpretation of benefit-cost results.

A benefit-cost analysis of regulations to abate peak CSO load should also account for environmental conditions associated with that peak. In particular, peak loadings from CSOs are likely to occur during periods of wet-weather flow when high stream flows have a dilution effect. This analysis tests the importance of accounting for wet-weather flows by increasing stream flow in each of the two loading rate scenarios by 25%. Fig. 2 plots the results of these four scenarios as cumulative distribution functions (CDFs) on the present value of benefits over 20 years in Pennsylvania and compares these to the compliance cost estimate, shown by the vertical dotted line. The effect of increases in stream flow is to shift the distribution to the left, indicating a reduction in the expected value of benefits. However, the effect of changes in  $Q$  on the probability that net benefits will exceed control costs is small relative to the effect caused by changes in CSO loading rates. Assuming high loading rates increases the probability that benefits exceed costs by approximately 20%. The implication is that, in this analysis, the choice between nominal and wet-weather flows may be a relatively unimportant consideration, but efforts to identify the appropriate averaging time for CSO loading rates deserves a greater emphasis.

## Conclusion

This paper describes an RFM for a large-scale water quality model that EPA has recently used in developing a national policy regulating emissions from concentrated animal feeding operations. RFMs are estimated for four demonstration states, and the impact of different types of pollution sources on regulatory performance metrics is inferred from coefficients. The RFM complements the NWPCAM and expands its capabilities as a decision support tool because it is a single, continuous function and a more efficient Monte Carlo simulation tool. The flexibility and speed of the RFM enable useful insights into the response of the regulatory performance metric, as shown in Fig. 1. Two runs of the original model would be required to observe a single point in that plane, so such insights are not readily accessible from the original model. This paper employs these RFM capabilities to illustrate the importance of accounting for uncertainty in modeling water quality response to pollution controls and to characterize uncertainty in benefit estimates.

Another important enhancement to the capabilities of the NWPCAM is the ability of the RFM to prescribe what level of controls could achieve policy goals. RFMs described in this paper are estimated at the state level but could be estimated on any political or natural scale. Experience shows that the more gradual the output variable response to changes in input variables, the better the RFM predicts NWPCAM response. This can be achieved when the decision-support region contains a large number of stream segments. The RFM may also perform better in larger regions because there is less dependence among the many stream segments in the network.

Economic benefits of CSO controls are estimated in demonstration states for a range of CSO control levels. Under steady-state modeling assumptions, use-support impacts from CSO loads, evaluated in economic terms as the increase in consumer

welfare from abatement of the loads, appear low relative to expected control costs. However, this conclusion depends upon basic assumptions about how CSO loads should be modeled for benefit-cost analysis. The RFM provides the flexibility to test modeling assumptions and shows that CSO controls appear more economical if the regulatory evaluation is framed in terms of an abatement of peak CSO loads. The RFM also shows that, in terms of environmental decision making, it is more important to ascertain what level of baseline CSO loading should be assumed for benefit-cost analysis than it is to refine the modeling of wet-weather hydrology.

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## Notation

*The following symbols are used in this paper:*

- $C$  = concentration (mg/L or MPN/100 mL);
- $D$  = ratio of run-time stream depth to nominal stream depth;
- $D_E$  = stream depth scale parameter;
- $F$  = stream flow scale parameter;
- KTSS = effective TSS settling velocity (m/day);
- $K$  = impact coefficient;
- $k$  = decay rate at 20°C (day<sup>-1</sup>);
- $L$  = economic value of changes in use support (U.S. dollars/year);
- $N$  = affected population;
- PCSO = combined sewer overflow load scale parameter;
- PIND = industrial load scale parameter;
- PMUN = municipal load scale parameter;
- PRURAL = rural nonpoint source load scale parameter;
- PS = joint municipal and industrial point source scale parameter;
- PSOD = sediment oxygen demand scale parameter;
- PSODT = temperature-adjusted sediment oxygen demand scale parameter;
- PURBAN = urban nonpoint source load scale parameter;
- $Q$  = stream flow (m<sup>3</sup>/day);
- $R$  = use-support fraction;
- $T$  = temperature (degrees Celsius);
- $U$  = stream velocity (m/day);

VTSS = total suspended solids settling velocity (m/day);  
 $V$  = ratio of run-time stream velocity to nominal stream velocity;  
 $V_E$  = stream velocity scale parameter;  
 $W$  = waste load (kg);  
 $x$  = distance from source of waste load (m);  
 $z$  = independent variables of reduced-form model;  
 $\alpha$  = maximum improvement possible from point source load controls;  
 $\theta$  = temperature sensitivity coefficient; and  
 $\pi$  = proportional change in complement of use-support fraction.

### Subscripts

$c$  = index of control variables of reduced-form model;  
 $i$  = index of use-support level; and  
 $u$  = index of uncertain variables of reduced-form model.

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