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Raul Lejano
New York University

Oladele A Ogunseitan
University of California, Irvine

Aaron Hipp
North Carolina State University

Cost Effectiveness of Regulation-Compliant Filtration To Control Sediment and Metal Pollution in Urban Runoff

C. SCOTT SMITH,[†] RAUL P. LEJANO,[†] OLADELE A. OGUNSEITAN,*[,‡,§] AND J. AARON HIPP[‖]

Department of Planning, Policy, and Design, Program in Public Health, College of Health Sciences, Department of Environmental Health, Science, and Policy, and School of Social Ecology, University of California, Irvine, California 92697

The implementation of Total Maximum Daily Load (TMDL) to control urban runoff presents major structural and managerial challenges for cities. We developed a decision support system (DSS) for TMDL compliance at the city level to solve for a phased, least-cost strategy toward meeting four TMDLs using stormwater filtration. Based on a case-study city, we modeled wet weather flows and associated discharge of Total Suspended Sediment (TSS), cadmium, copper, and zinc to receiving waters by coupling U.S. EPA's Storm Water Management Model (SWMM v. 5.0) with the geographic dataset of the urban drainage network. We linked a mixed integer linear programming algorithm to the watershed model for deriving cost-effective selection and placement of curb inlet filters to meet mass- and concentration-based TMDL requirements. The least cost solution for meeting the city's TMDL waste load allocations for TSS (73.9% reduction), Cd (50.6% reduction), Cu (30.0% reduction), and Zn (55.7% reduction) would require 1071 filter inserts at a cost of \$1.7 million. In contrast, random placement of 1071 filters or uniform placement of 1266 filters is effective only for TSS and would cost \$4.0 million and \$4.8 million, respectively. Our results demonstrate the increases in cost-effectiveness of using an optimization-based DSS for urban watershed management.

Introduction

Managing nonpoint source (NPS) pollution is a daunting environmental challenge for urban watershed management. This challenge is complicated by physical phenomena such as dynamic weather patterns, diffuse sources of pollution, and the complex functioning of drainage systems (*1*−*6*). Managing NPS pollution also has an often underappreciated social and political dimension, because cities are required to meet regional, state, and federal water quality objectives while simultaneously providing other essential municipal services (*1, 7, 9*).

* Corresponding author phone: (949)824-6350; fax: (949)824-2056; e-mail: Oladele.Ogunseitan@uci.edu.

[†] Department of Planning, Policy, and Design.

[‡] Program in Public Health, College of Health Sciences.

[§] Department of Environmental Health, Science, and Policy.

[‖] School of Social Ecology.

Although the concept of Total Maximum Daily Load (TMDL) were included in the Clean Water Act of 1972 (CWA), their implementation was marginalized in favor of more pressing demands of controlling point sources of water pollution. The rekindling of interest in TMDLs was caused in part by the fact that approximately 40% of U.S. waters remain chronically impaired despite 35 years of implementing the federal CWA. Inasmuch as treatment technologies for point sources of pollution have not been sufficient to bring these waters to full compliance, regulators can now affix numerical limits (i.e., TMDLs) to total pollutant loadings for the entire watershed. Furthermore, TMDLs are meant to be apportioned among the different sources in the watershed (point and nonpoint), which means that each source will have to, by means of selected Best Management Practices (BMPs), limit its release of pollutants to quantitative threshold concentrations. In some cases, existing means of pollution control will not allow a source to attain these new limits, thus TMDLs represent a big step beyond the more well-defined technology standards.

TMDLs are embedded in Section 303(d)(1)(C) of the CWA. All states have impaired water bodies represented on the 303(d) list, and for each designated impaired water body, a TMDL must eventually be established. The negotiation process around each TMDL is typically lengthy, and only a fraction of these waters currently has established TMDLs. Typically, agencies are given multiple years to comply with a TMDL although penalties for noncompliance can be severe. For example, California Water Code Section 13385(c) stipulates a fine of at least \$10 000 per day of violation.

According to the most recent 303(d) list (2006), California has 1883 individual reaches, or segments, of bodies of water designated as impaired, but only 150 TMDLs have been established with 120 under development. In most cases, TMDLs are established for multiple pollutants in one watershed. For example, the San Diego Creek−Newport Bay watershed has 17 established TMDL targets representing reach 1 and reach 2 for San Diego creek and upper and lower segments of Newport Bay based on toxics, sediment, and nutrients for all four water segments and pathogens for the Upper and Lower Newport Bay.

As cities struggle with a new generation of stormwater management issues initiated by newly instituted TMDLs, it is becoming clear in many localities that ad hoc practices for selecting and employing BMPs (best management practices) may not allow for full compliance (*2, 10, 15*). At the same time, the stringency of these recently instituted TMDLs magnifies the suboptimal nature of present NPS programs. We have not conducted a systematic survey of city managers, but we are aware of no examples where an optimization framework is being used to design BMPs. Interviews with various stormwater program managers in Southern California suggest full compliance with all relevant TMDLs is not anticipated in the foreseeable future. We believe that this skepticism arises partly from the failure of municipalities to optimize BMPs using a rational procedure within an overall compliance strategy.

We interviewed several city officials in Southern California and found, in most cases, the citywide BMP measure was often limited to a single type of technology—e.g., in one city, the strategy centered around filter inserts, while in another the entire strategy was constructed wetlands. There is a logic to why a particular measure was favored (e.g., in the latter city, there is more open space for wetlands), but no strong rational framework appeared to inform why single-strategy approaches were taken or how they were employed. We also

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observed, in one of the cities employing filter inserts, a degree of ad hoc decision making such that inserts were not necessarily placed where they would have the greatest impact, but, rather, they were placed along streets where paving or other repair work was underway.

In this paper, we simulate the decision problem and demonstrate how a decision support system (DSS) can assist with a phased approach toward TMDL compliance. Specifically, this study conceptualizes and solves for an optimal, phased strategy toward meeting four TMDLs using curb inlet stormwater filtration BMPs while minimizing total costs to the city. We should note that the phased compliance approach proposed herein is not part of the TMDL requirement but, rather, a means we developed to maximize the cost-effectiveness of any BMP program.

In a previous paper in this journal, we constructed a first-generation DSS that demonstrates how ad hoc BMP strategies, typically used by municipalities, produce suboptimal NPS programs that may fail to fully comply with TMDLs (*11*). That analysis employed simplifying assumptions, including generic filter BMP performance and static hydraulic loadings, in order to simulate how optimal spacing of such BMPs might be achieved. Here, we address a more realistic representation of the decision-maker's problem, namely the following:

Given a range of competing BMPs (with widely differing costs and levels of performance), dynamic hydraulic loading conditions, and flow-based TMDLs, how can a municipality solve for a least-cost BMP strategy that can be phased in over a reasonable period of time?

Toward this end, we described three objectives. First, we model stormwater quantity and quality within a particular urban setting, the city of Costa Mesa in Orange County, CA. To do this, we adapt hydrologic and geographic information for use in the United States Environmental Protection Agency's (EPA) Stormwater Management Model (SWMM v. 5.0). SWMM's simulation tools are used to estimate hydrographs (water quantity over time) and the spatio-temporal variations in mass emissions and ambient concentrations for four regulated constituents—total suspended solids (TSS), cadmium, copper, and zinc—throughout Costa Mesa.

Next, we link the watershed model with an economic optimization routine, the latter based on mixed integer linear programming (MILP). Using actual price information and flow/pollutant measurements in receiving waters, we construct a DSS and solve it for the least-cost filter BMP strategy, phased over a period of time. The next consideration, which is program phasing, is an important element of the compliance process that is sometimes unacknowledged and certainly not formally analyzed. In this paper, we include this element deliberately so as to best simulate the actual decision process. Because it is unlikely that all BMPs can be implemented instantly, it is useful to structure the optimization problem in phases. If the problem were not structured in phases, then the solution would indicate the optimal combination of BMPs to meet the ultimate TMDL requirements. But with only this solution in hand, the manager does not know in what order to implement the BMPs to maximize the rate of approach to the final optimal configuration. Structuring the problem in phases solves this problem by indicating not only what final configuration of BMPs is optimal but also what intermediate configurations are optimal given the current level of expenditures. Therefore, we show how rational methodologies, represented by the DSS, can be integrated with a phased compliance approach that allows decision-makers to actually construct BMP strategies that comply with a host of increasingly stringent TMDLs. Moreover, the use of the DSS allows us to analyze feasibility more thoroughly. Furthermore, we use the model to construct Pareto efficiency curves for increasing levels of TMDL compliance.

The final objective is to describe various ways to reform regional and municipal regulatory/compliance structures to support employment of these rational methods by watershed management agencies.

Data and Methods

The Case Study City. The salient characteristics of the city of Costa Mesa (the city) and adjoining watershed have been described previously (*11*). As a permitted effluent discharger, the city must comply with federal NPDES (National Pollutant Discharge Elimination System) guidelines and waste load allocations specified in the TMDLs for water features designated on the EPA's 303(d) list (*16*). The city discharges polluted stormwater directly or indirectly into three formally designated impaired watersheds: (1) Santa Ana River, (2) San Diego Creek, and (3) Newport Bay. The concrete-lined Santa Ana River marks the western border of the city, and the Upper Newport Bay—an ecological reserve fed by the San Diego Creek—serves as part of the city's eastern boundary. The San Diego Creek and its downstream water feature, Newport Bay, presently have TMDLs in place for the monitoring and mitigation of sediments and toxics (*17, 18*).

According to the waste load allocations specified in the San Diego Creek and Newport Bay TMDLs and monitored data, the city must reduce mass emissions of TSS into these receiving waters by 50%, Cd by 50.6%, Cu by 50%, and Zn by 55.7%. In this paper, we assume discharges emptying into the Santa Ana River must also meet emissions reductions specified for the San Diego Creek and Newport Bay water features given that a Santa Ana River TMDL is presently under development. In addition to reductions in pollutant mass emissions, the TMDLs require discharges to meet certain water quality standards according to the California Toxic Rule, or CTR—establish maximum acute or instantaneous concentrations for dissolved heavy metals as a function of flow rate and water hardness (i.e., hardness in mg/L as calcium carbonate) (*19*). For example, acute numeric targets for copper and zinc under medium flow conditions (defined by EPA as 5−23 $m^3\ s^{-1}$) and an assumed water hardness of 236 mg L^{-1} are 10.8 mg L^{-1} and 243 mg L^{-1}, respectively. According to the water quality data published in the 2004 and 2005 Unified Annual Monitoring Reports, stormwater in the Costa Mesa Channel exceeded the acute standard for Cu 19 times and Zn twice (*20*). Zn and Cu exceedances were also identified in the Santa-Ana Delhi Channel over this period (*20*).

Modeling and Optimization Strategies. Previous attempts to optimize NPS pollution mitigation strategies have integrated spatial analysis, hydrologic modeling, linear programming, and genetic algorithm techniques (*11, 21, 22*). We used EPA's SWMM, a dynamic rainfall-runoff simulation model used for single event or continuous simulation of runoff quantity and quality from primarily urban areas, to model hydrologic patterns within the case study city (*23*). SWMM reports total runoff and mass emissions by location for user-specified wet weather events. We acquired data from the Orange County Watershed and Coastal Resources division which collects hydraulic information at regular intervals for two channels within our study area: the Santa Ana−Delhi Channel and the Costa Mesa Channel. For each of these drainage areas, we acquired hourly rainfall and flow rates for a 2-year period beginning July 2003 through July 2005 (i.e., the 2003/2004 and 2004/2005 rainfall seasons). The agency also publishes water quality data such as mass emissions and ambient concentrations in its Unified Annual Report (*20*). These water quantity and quality data were used to calibrate our SWMM-based application.

The city provided us detailed Geographic Information System (GIS) data layers that were essential for SWMM applications. The city's storm drain GIS layer, for example, includes the category (e.g., open or closed; concrete lined or earthen), length, and other attributes for each network segment. We adapted these data along with curb inlet locations to calibrate the propagation of flows through the modeled drainage network. The GIS model was translated into an array of nodes and links that were input into SWMM. SWMM uses a kinematic wave formula to simulate the cascading of upstream to downstream flows. Detailed land use data provided by the city were also input into SWMM in order to specify impervious surfaces and estimate pollution generation. Typical infiltration and permeability coefficients for differing land use categories were obtained, and the midpoints of these ranges were used as starting values for calibrating SWMM (*24, 25*).

The delineation and topology of subcatchments defined as hydrologic units for which drainage system elements direct surface runoff to discharge points (i.e., curb inlets and drainage outfalls) are essential for SWMM simulations. We relied on the Army Corps of Engineers Hydrologic Engineering Center's Geospatial Hydrologic Modeling Extension to delineate subcatchments (*26*). Specifically, we used digital elevation models or DEMs made available by the United States Geologic Survey and street centerlines provided by the city to create hydrologically corrected subcatchments for every segment of the storm drain network. In order to comply with SWMM formatting, each curb inlet was associated with a single subcatchment. Our fully specified SWMM application includes 1331 subcatchments, 5 primary outfall nodes, 3193 junctions (of which 1266 are curb inlets), and 3193 conduit links (Figure 1).

SWMM Calibration. To estimate stormwater flow rates and pollutant mass emissions, we used hourly precipitation and flow monitoring data for wet weather events during 2004–2005 seasons. We selected four peak rainfall events, which, collectively, account for 203 h of continuous simulation. We used typical infiltration and permeability coefficients as well as Manning's roughness coefficient to estimate flow volumes and the time of presentation of peak flows at monitoring points in the Santa Ana–Delhi and Costa Mesa channels. In this case, the optimum fit was determined by minimizing the continuity error, i.e., the percent difference between the initial storage plus total inflow and final storage plus total outflow for the entire drainage system. The simulated peak and average flows for each simulated storm event are within an error range of 5–10% of the monitored values reported by Orange County Watershed & Coastal Resources, and the continuity errors for each storm event, as reported by SWMM, were considerably less than the EPA-recommended maximum threshold of 10%. Measured and simulated hydrographs for the Santa Ana–Delhi channel (SABF01, shown in Figure 1) for the four storm events are presented in the Supporting Information (Figure A). We note that only minimal adjustments of the parameters were required (i.e., within 5% of the range midpoints).

In addition to water quantity, SWMM utilizes information on the quality of stormwater flows such as the magnitude and timing of emissions entering each curb inlet and the ambient concentrations at each outfall location. In order to estimate water quality, we parametrize SWMM's washoff characteristics using region-specific event mean concentrations (EMCs) that represent typical runoff pollutant concentrations found in overland flows across different land use types, as observed in the Los Angeles region (*26*). These EMCs were then applied to each land use polygon in the GIS database for the city to generate pollutant loading estimates. SWMM then routes these using a kinematic wave function and calculates concentrations of pollutants at each outlet. The quality of stormwater was calibrated by scaling up the EMC parameters equally to obtain the best fit between prediction and measured flow hydrographs. The model is underidentified which means that the equal scaling up of EMC parameters was done to optimize the fit between the two—in this case, the optimum fit was determined by minimizing the difference between final stored masses of pollutants as reported by SWMM and estimated emissions as specified in the 2004 and 2005 Unified Annual Reports (*23, 24*). EMCs for each of the modeled pollutants—TSS, Cd, Cu, and Zn—are listed in Supporting Information Table A by land use type. The effect of curb inlet filter BMPs on these flows and pollutant loadings are modeled by applying pollutant removal efficiencies for each particular type of filter on loadings entering each curb inlet. SWMM then routes these loadings as before and calculates pollutant concentrations at the outlets.

Spatial Optimization of Stormwater Filtration. The variability of the quantity and location of stormwater filtration equipment defined as a BMP at each curb inlet was explored using a mixed integer linear programming (MILP) model, where the objective was to minimize the total cost of installing and maintaining the filtration equipment and TMDL compliance was treated as a constraint. The least-cost selection and most effective placement of BMPs were obtained through this iterative process. The performance of various curb inlet fiters in removing pollutants from stormwater were obtained from a previous study (*11*). We obtained product cost estimates from five filter manufacturers, including initial capital cost and average costs for operation and maintenance (O&M) for six types of filters. The initial capital and O&M values were combined to create a per-filter implementation cost over a 50-year time frame in terms of total Present Value (PV). Capital replacement was assumed to occur every decade. The estimated costs range from $1296 to $10 662 per filter in PV for a 50-year implementation. The performance and cost data are presented in Supporting Information Table B. PV were estimated according to the following assumptions: (1) time horizon for analysis = 50 years, (2) life of filter housing = 10 years, (3) inflation rate = 4.3% (http://www.bls.gov/cpi/ accessed July 25, 2006), and (4) discount rate = 6.75% (http://www.federalreserve.gov/RELEASES/H15/update/ accessed July 25, 2006).

The mass loading, BMP price, and performance values described above were used to parameterize a series of MILP equations that were subsequently solved using LPSolve IDE v. 5.5—an open source solver application (*27*). We simulated the decision problem, including the phased strategy, under two different scenarios. The first scenario simulates the case when the city selects one contractor to supply all the filters for the program. We solve this by assuming only one type of filter insert is available and optimizing its placement. The second scenario simulates the case when the city has the flexibility to install different filter types in different curb inlets. We solve this by optimizing the placement of filter inserts across all filter types, meaning that, in each location, the most cost-effective type of filter is installed.

The first series of equations identifies the optimal placement of filters by calculating the minimum number of filter inserts (of a similar type) necessary to meet desired reductions in waste load allocations for all four pollutants simultaneously (eq 1)

$$\text{minimize} \sum_{i=1}^{1266} x_i \tag{1}$$

Subject to the following constraints

$$[\text{constraint 1}] \sum_{i=1}^{1266} x_i m_{ik} r_{jk} \geq R_k$$

for a particular filter *j*, for all *k* pollutants

$$[\text{constraint 2}]\ x_i \subset \{0,1\}$$

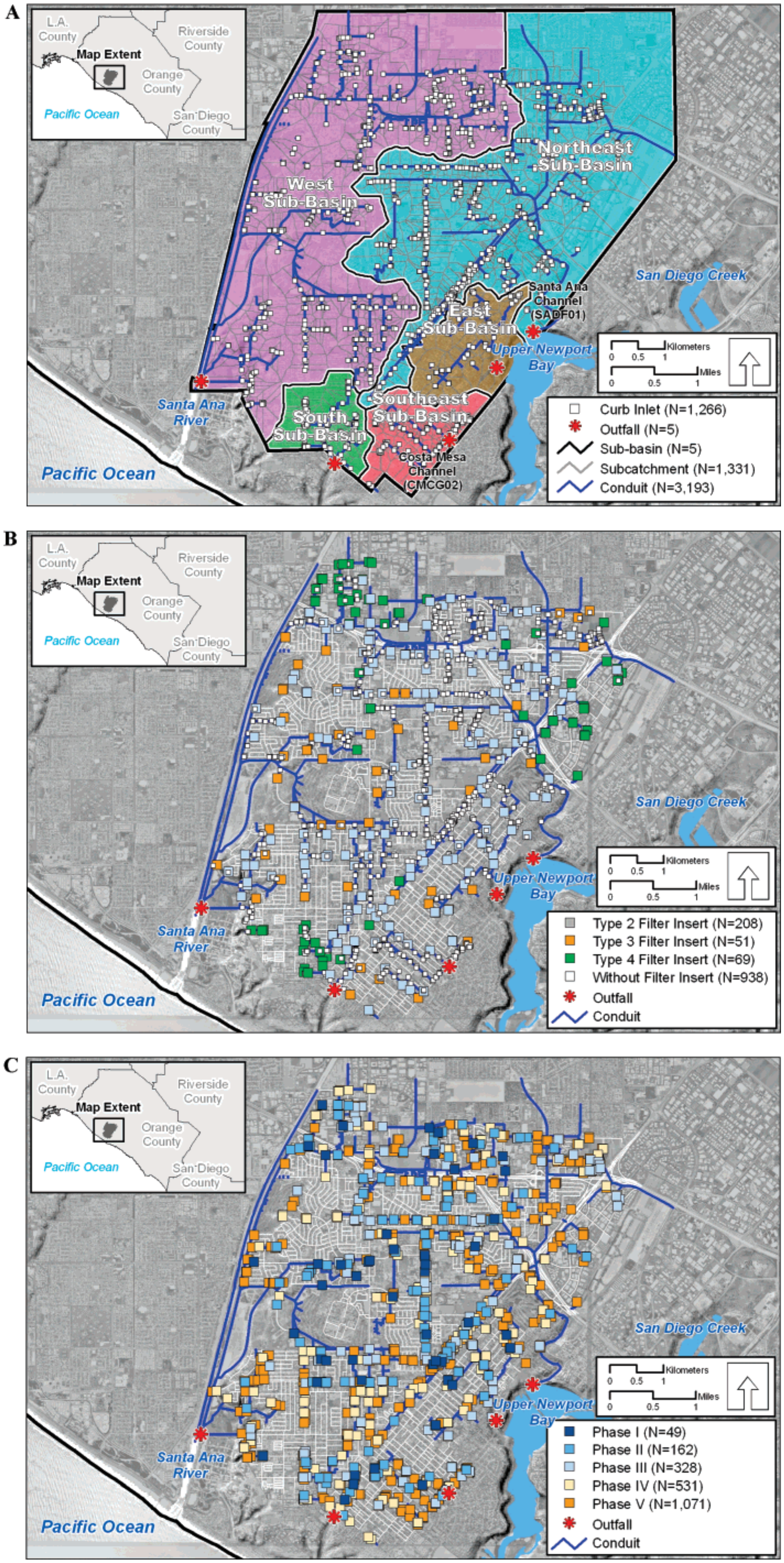

FIGURE 1. A: Map of study area sub-basins, subcatchments, conduits, curb inlets, and outfalls. B: Map of optimized filter insert selection (phase III). C: Location of filters across the city in complete compliance with all TMDLs (phase V).

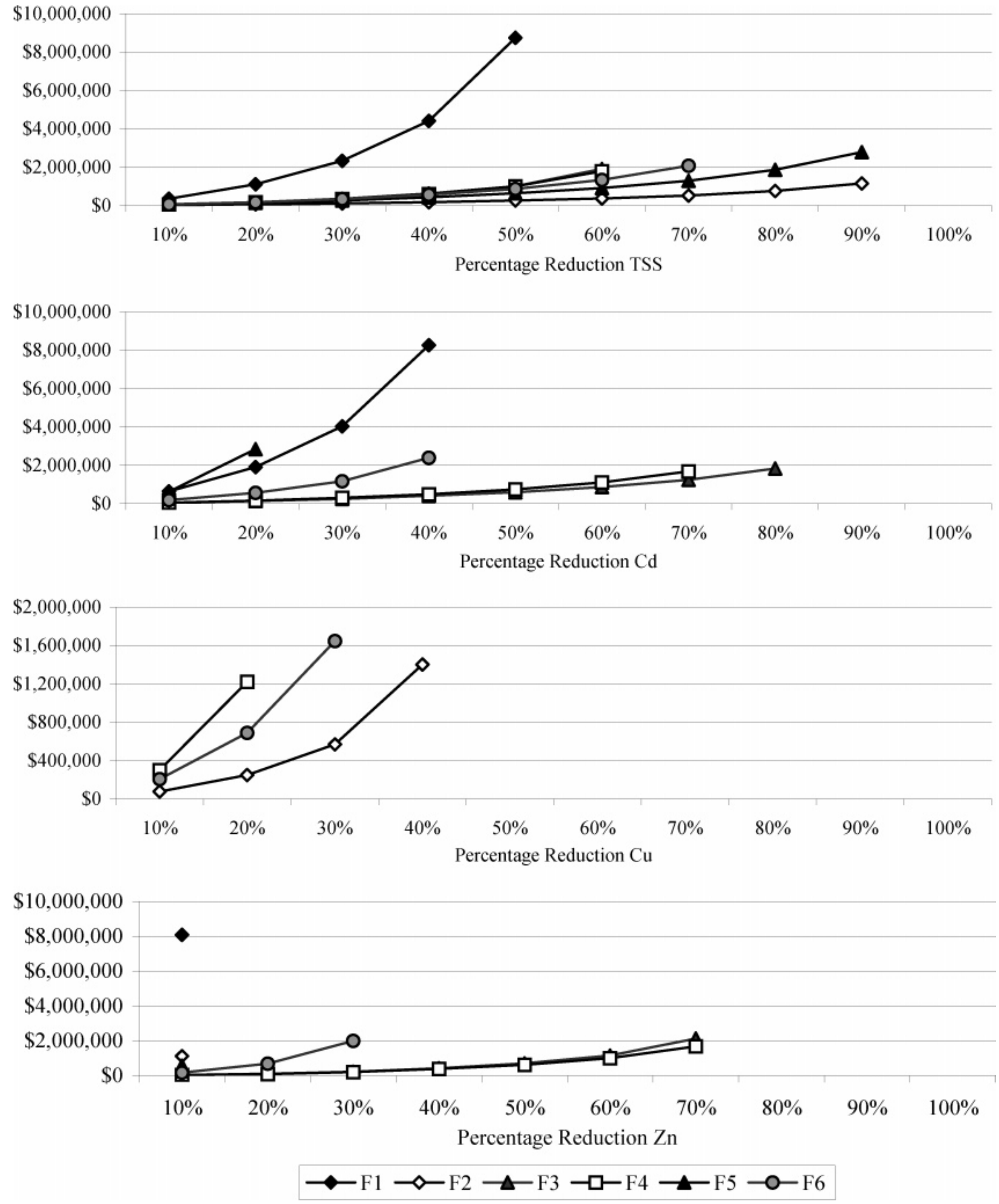

FIGURE 2. Estimated costs for reducing mass loadings by pollutant and filter insert types (F1−F6).

where i represents curb inlets (ranging from 1 to 1266), j represents filter type (of 6 possible choices), k represents pollutant type (of 4 target pollutants), x_i is the binary intervention decision to apply a filter at inlet i (where no=0, yes=1), m_{ik} is the mass emissions (kg) of pollutant k at inlet i, r_{jk} is the average percentage reduction of pollutant k by filter j, and R_k is the desired city-wide reduction of pollutant k (kg).

Since x_i is a discrete variable (i.e., we do not allow for half a filter), we cannot use a regular linear programming model but, instead, require an MILP formulation. Solutions to the MILP problem, e.g., using a branch-and-bound algorithm, are considered routine.

A second series of linear equations is used to optimize both the placement and selection of multiple filters to meet specified reductions of multiple pollutants simultaneously at the lowest cost (eq 2). Note that, in eq 2, the objective function is now expressed as a cost function. Here the optimization function minimizes the cost of filters based on filter price and performance to satisfy parametrized constraints. With these specifications, a decision maker is able to identify a geographically explicit, least-cost solution for reducing one or more pollutants city-wide.

Let us, briefly, consider why the multiple-filter, multiple-pollutant optimization problem is so challenging. If we had the simple problem of one pollutant and one filter type, we would directly locate filters by installing the first filter in the inlet receiving the highest mass loading, the second in the inlet receiving the second highest mass loading, etc. But if we have two pollutants, it is possible that the first inlet has the highest loading of pollutant X but the lowest of pollutant Y, and the second inlet has the opposite—in this case, it is not straightforward to determine where to put the insert first. Now, if we have multiple filter types, this further complicates the decision problem, as we are not only uncertain as to which inlet to serve first but also which filter

TABLE 1. Percentage Pollutant Reductions and Implementation Costs for Optimized, Random, and Uniform BMP Selection and Placement Strategies

BMP (filters) implementation strategy	pollutant[a] TSS	Cd	Cu	Zn	cost
			Optimized Placement		
phase I; $n = 49$	16.3%	10.3%	6.1%	11.2%	*$80,444*
phase II; $n = 162$	33.7%	20.4%	12.0%	22.4%	*$261,619*
phase III; $n = 328$	49.2%	30.4%	18.0%	33.4%	*$526,728*
phase IV; $n = 531$	**59.9%**	40.5%	24.0%	44.6%	*$861,811*
phase V; $n = 1071$	**73.9%**	**50.6%**	30.0%	**55.7%**	*$1,692,089*
			Random Placement[b]		
phase I; $n = 49$	2.9% (6.0E-03)	1.8% (4.1E-03)	0.7% (2.2E-03)	0.7% (2.5E-03)	*$185,492 ($22,292)*
phase II; $n = 162$	9.5% (1.1E-02)	6.1% (7.3E-03)	2.3% (3.9E-03)	2.3% (4.5E-03)	*$611,930 ($40,637)*
phase III; $n = 328$	19.2% (1.4E-02)	12.3% (9.8E-03)	4.6% (5.4E-03)	4.6% (6.1E-03)	*$1,241,647 ($56,937)*
phase IV; $n = 531$	31.2% (1.6E-02)	19.9% (1.2E-02)	7.4% (6.7E-03)	7.4% (7.7E-03)	*$2,008,941 ($72,844)*
phase V; $n = 1071$	**62.9% (1.3E-02)**	40.1% (1.3E-02)	14.9% (8.4E-03)	15.0% (9.5E-03)	*$4,047,055 ($102,967)*
			Uniform Placement[c]		
$N = 1266$	**74.3% (7.8E-03)**	47.5% (8.3E-08)	17.7% (2.3E-06)	17.6% (1.9E-05)	*$4,784,156 ($110,468)*

[a] Percentage reductions in bold meet TMDL waste load allocations. [b] Values represent random placement of a discrete number of randomly selected BMPs (i.e., one of the six filtration devices). [c] Values represent uniform placement such that a randomly selected BMP is placed within each of the 1266 of the modeled curb inlets. Random placements and/or BMP selections for the random and uniform placement strategies were drawn from 5000 independent samples. These independent samples were used to estimate distributions, with standard deviations in parentheses around average pollutant removals and BMP expenditures. Values reported for "optimized placement" are presented as generated through SWMM simulation without standard deviations.

type to install there (assume filter A treats pollutant X but not Y, and filter B treats Y but not X). Such a complex problem requires numerical analysis.

$$\text{minimize} \sum_{i=1}^{1266} x_{ij} p_j \tag{2}$$

Subject to the following constraints are the following

$$[\text{constraint 1}] \sum_{i=1}^{1266} x_{ij} m_{ik} r_{jk} \geq R_k$$

for all filters j, all pollutants k

$$[\text{constraint 2}] \sum_{j=1}^{6} x_{ij} \subset \{0,1\}$$

where p_j is the price of filter j (expressed as present value), and all other variables are as defined above.

Results and Discussion

In the case-study city, stormwater runoff accumulates within five sub-basins and is drained via five associated outfalls, as shown in Figure 1, panel A. The northeast, east, and southeast sub-basins discharge into the Upper Newport Bay, while the west sub-basin flows into the Santa Ana River. Stormwater flows originating in the south sub-basin are channeled through the adjacent city of Newport Beach and, ultimately, are discharged into Newport Bay.

We estimated 1.14 million kg of TSS, 7.1 kg of Cd, 268 kg of Cu, and 2216 kg of Zn were generated over the four-storm, 203-h simulation period, and 0.2−0.6% of these amounts were reabsorbed into soil strata. The distribution of these total emissions varies with respect to the area of each subcatchment and the proportional share of land use categories represented within them. Approximately 67% of the emissions are not treatable using filtration devices given that some subcatchments do not discharge runoff through a curb inlet. Thus we focus henceforth on mitigating the 33% of mass loadings of the candidate pollutants TSS, Cd, Cu, and Zn that are treatable using curb inlet filtration systems.

Figure 2 presents solutions for the first set of linear equations (eq 1). Specifically, the figures show Pareto frontiers, which plot the limited combinations of pollutant reductions and costs such that each point on the frontier represents the highest possible removal at a particular cost. The results indicate that the marginal costs for mitigating emissions increases with the share of pollutants treated—marked by an increase in slope. This is due to the heterogeneous generation or washoff of mass emissions throughout the urban watershed. It is also evident that the marginal costs differ across filter and pollutant types due to variations in filter price and performance. For example, filter F4 can potentially reduce 50% of TSS (the rate of reduction required by the San Diego Creek TMDL) for a cost of less than $1 million (PV). To achieve the same level of reduction would cost nearly $9 million using the F1 filter type.

The slope of the lower envelope of curves, in each figure, essentially gives an estimate of the marginal cost (or, the shadow price) of reducing each particular pollutant. In this case, we see from cursory inspection that Cu has the highest marginal cost (corresponding to the steepest slope), and TSS the lowest, across all four pollutants. In this sense, we see that compliance with Cu standards is the most problematic for this study area with respect to the particular BMP devices considered in this paper.

While solutions to eq 1 are useful for implementing a cost-effective, single pollutant strategy, cities such as Costa Mesa are more often required to mitigate multiple pollutants simultaneously. Equation 2 closely simulates this scenario. Supporting Information Table C presents the cost estimates of five incremental phases of compliance (i.e., five incremental and progressive degrees of compliance, corresponding to phases I−V). This type of phased, stepwise compliance is typical in TMDL implementation plans. For example, the Newport Bay/San Diego Creek TMDL for sediment specifies quantifiable, time-specific targets including a 50% reduction in the current load of sediment in the receiving water within 10 years. The corresponding TMDL for toxics, while it does not specify a discrete time frame for reaching implementation goals, encourages the designation of interim targets or benchmarks in terms of pollutant mitigation actions and pollutant loadings to help ensure that control actions are taken and progress is being made toward attaining the specified water quality standards. Clear interim targets for both the watershed and dischargers are crucial for a phased implementation approach in that they assist in the evaluation of whether TMDLs or implementation strategies need to be adjusted in the future.

In eq 2, Table 1, and Supporting Information Table C, we introduce a hypothetical, iterative strategy toward the city attaining water quality standards specified in the Newport Bay/San Diego Creek sediment and toxics TMDLs. The benchmarks could also be informed by discrete time-specific penalties for noncompliance and the city's budget. For instance, the objective of phase I is to find the least cost solution for reducing TSS by 16.3%, Cd by 10.3%, Cu by 6.1%, and Zn by 11.2% by identifying the optimal selection and placement of filters. This strategy would require the city to apply 49 curb filter inserts at a present value cost of $80 444. In order to meet TMDL waste load allocation requirements for TSS, Cd, and Zn simultaneously (phase V), the city would need to apply 1071 filter inserts at a present value cost of nearly $1.7 million. Figure 1, panel B maps the optimized selection and placement of filter inserts with respect to phase III, as an example. The results showing how successive placement of filter inserts would proceed from phases I–V, the latter representing compliance with all four TMDLs, is presented in Figure 1, panel C.

In addition to reductions in waste load allocations, we considered another measure of environmental performance relating to acute toxics concentrations requirements as stated in the CTR. By adjusting the analytical time step in SWMM, we were able to simulate ambient concentrations on a minute-to-minute basis. Therefore, the 203-h simulation period yielded 60 900 data points for the five outfalls identified in Figure 1, panel A. According to our estimates the city experienced 5394 acute or instantaneous exceedances (Zn = 4,423; Cu = 971) over the study period. A majority of these exceedances were estimated to be in the south and northeast sub-basins. Upon implementation of phase I, our model suggests that that the number of total exceedances would drop to 3588 (a 33.5% decrease) all of which would be acute violations of Zn. By implementing phase II, the city would not violate any of the maximum acute standards specified in the CTR (*19*).

The model presented here is quite robust, but some caveats should be highlighted. First, we focused on one case-study city, and we acknowledge that additional cost savings could be realized through cooperative agreements across municipal or regional boundaries that simultaneously discharge into common watersheds. Second, our estimates of costs associated with installation maintenance may vary by site, and we did not include transaction costs such as contract administration and permits. Third, our model relies on monitoring of ambient concentrations of pollutants and surface flow information that allows estimates of pollutant loadings for each curb inlet. Such data-intensive models require capital expenditure for cities to collect and organize necessary information. Last, where funds are lacking or where geographical features limit the installation or effectiveness of drainage system filters—such as in the case study, where only 33% of the mass loadings are treatable using curb inlet filtration devices—alternative BMPs or mixtures of BMPs also will need to be considered.

Implications for the Regulatory Framework to Protect Urban Watersheds. Despite these caveats, the model presented allows for greatly reduced cost burdens for TMDL compliance at the individual city level. For example the model estimates $1.7 million worth of BMPs to meet TMDL waste load allocations for TSS, Cd, and Zn and to approach compliance for Cu to the degree shown. Alternately, a random placement strategy for these same BMPs will cost $4.05M, more than double what we estimated using the least-cost solution, and satisfies only one (TSS) waste load allocation (Table 1). We expect that further refinement of the model and the apparent cost-saving advantages and approach presented here can overcome the management challenges attributable to a lack of firm regulatory direction received by municipalities regarding the employment of BMPs. Both federal and state NPS guidelines require municipalities to employ BMPs on a good-faith effort basis, where the default emphasis is cost minimization, rather than pollution abatement. Our approach allows both cost and environmental quality concerns to be on equal pedestals. Our results favor a phased compliance approach that involves, first, firmly setting TMDL compliance requirements without equivocation and with some firm timeline for compliance (*28–30*). Such an approach is necessary for full compliance with multiple TMDLs within increasingly tax-base and revenue challenged municipal programs.

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Supporting Information Available

Details of average hourly flow for Santa Ana–Delhi channel for rainfall events occurring during the study period and additional input data for the model. This material is available free of charge via the Internet at http://pubs.acs.org.

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