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Author(s): Haejin Lee and Michael K. Stenstrom
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Haejin Lee, Michael K. Stenstrom

ABSTRACT: Stormwater runoff is now a major contributor to the pollution of coastal waters in the United States. Public agencies are responding by requiring stormwater monitoring to satisfy the National Pollutant Discharge Elimination System stormwater permit. However, studies to understand the utility of the current programs or to improve their usefulness have not yet been performed. In this paper, we evaluate the land-use-based program, the industrial stormwater permit program, and beach water-quality monitoring in the County of Los Angeles, California, to determine if the results will be helpful to planners and regulators in abating stormwater pollution. The utility of the program has been assessed based on the programs' ability to accurately estimate the emissions for different classes of land use. The land-use program appears successful, while the industrial monitoring program does not. Beach water-quality monitoring suffers from a lack of real-time monitoring techniques. We also provide suggested improvements, such as sampling method and time, and parameter selection. *Water Environ. Res.*, **77,** 219 (2005).

KEYWORDS: stormwater, monitoring, neural network, land use, coastal water.

Introduction

California coastal waters are important recreational and economic resources, which make the safety of coastal waters of concern to both state and county health departments and beachgoers (Jiang et al., 2001). The completion of wastewater treatment plants mandated by the Clean Water Act has reduced conventional water pollution to California's beaches and bays. As a result, non-point-source pollution, such as stormwater runoff, is now a major contributor to the pollution of the coastal water, including Santa Monica Bay, which is among the most severely polluted bays in the United States (Wong et al., 1997). The problem of stormwater pollution is becoming worse because of population growth, which results in increased impermeable area. Storm drains entering the ocean are a main cause of permanent beach postings at many California beaches (State Water Resources Control Board, 2001).

Public agencies are responding by requiring stormwater monitoring to satisfy the National Pollutant Discharge Elimination System (NPDES) stormwater permit as authorized by the Clean Water Act. For example, the Los Angeles County Department of Public Works (LACDPW) has been monitoring stormwater under the 1990 NPDES municipal permit (No. CA0061654), and later the 1996 municipal permit (No. CAS614001), since the 1994–1995 wet season. Additional sampling is required by other agencies, such as the City of Los Angeles and the California Department of Transportation. Similar programs are underway in other areas of California and the United States.

The existence of stormwater-monitoring programs should represent progress towards achieving clean-water goals; however, studies have not yet been performed to understand the utility of the current programs or to improve their usefulness. In this paper, we evaluate several monitoring programs to determine if the results will be helpful to planners and regulators in abating stormwater pollution. Datasets from a major municipal program, beach monitoring, a large self-monitoring program, and a research project were used. The results suggest that parts of the current monitoring programs will not be helpful to regulators and planners, and we make proposals for improvement, along with projected cost increases.

Background

The LACDPW has been monitoring stormwater since the early 1970s. In 1994, it began an improved program, which was designed to determine total pollutant emissions to Santa Monica Bay and determine land-use-specific discharges (Stenstrom and Strecker, 1993). Total emissions are estimated from flow-weighted composite samples that are collected at five sampling stations (four stations are required under the 1996 permit and one station remains from an earlier permit.). These stations are ''mass emission'' stations in that they were selected to sample the greatest runoff mass with the least number of stations. The stations are equipped with flow-monitoring equipment and operate unattended in secure facilities. Samples from specific land uses are also required by the 1996 municipal permit and are collected with composite samplers at engineered sampling stations. A large suite of water-quality parameters is measured, including indicator organisms, general minerals, nutrients, metals, semivolatile organic compounds, and pesticides.

Additional monitoring is being conducted by other agencies to satisfy regulations or for research. The California Department of Transportation (Caltrans) has a large monitoring program for their highways. Our laboratory has monitored three highway locations near the University of California at Los Angeles (UCLA) (adjacent to the 101 and 405 freeways) since 1999 (Stenstrom et al., 2000 and 2001). The study is also sponsored by Caltrans, and an extensive suite of parameters is measured, including indicator bacteria, general minerals, nutrients, metals, polycyclic aromatic hydrocarbons, and oil and grease.

The previous programs monitor discharges to the bay, but there are also programs that monitor coastal waters. The California Assembly passed Bill 411(chapter 765 of Statutes of 1997; http://www.swrcb.ca.gov/beach/bills/ab_411_bill_19971008_chaptered.pdf) to address the problem of declining beach water quality and restore confidence in beach swimming. Three types of indicators organisms are monitored, and retesting in the event of an exceedence is also required. The more restrictive procedures by the bill have increased the frequency of beach postings and closures. The closure of Huntington Beach in Orange County, California, during the summer of 1999, was the first example of beach closures caused by the new regulations (Grant et al., 2001; Orange County Sanitation District, 1999). Many organizations are monitoring the microbiological water quality of Southern California coastal waters (Noble et al., 2000).

An example of a new monitoring activity is the Industrial Activities Stormwater General Permit, which mandates all industrial stormwater

Table 1—Selected eight major industries and its case number according to the different sets of input parameters after clipping outliers for 1998–2001 seasons.

		Input parameters		
Major industries	**SIC code**	**pH, TSS, SC, TOC, and O&G**	**pH, TSS, SC, and O&G**	**Lead, copper, and Zinc**
Food and kindred products (FKP)	20	184	472	10
Chemical and allied products (CAP)	28	305	850	35
Primary metal industries (PMI)	33	144	773	100
Fabricated metal products, except machinery and transportation equipment (FMP)	34	417	1325	155
Transportation equipment (TE)	37	193	601	187
Motor freight transportation and warehousing (MFTW)	42	263	731	76
Electric, gas, and sanitary services (EGSS)	49	182	505	198
Wholesale trade-durable goods (WT)	50	120	723	471
Number of total cases		1808	5980	1232

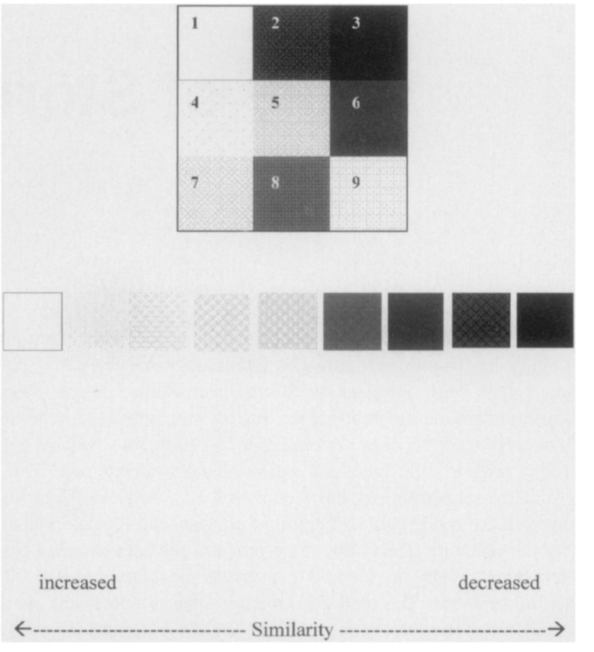

Figure 1—Activation map having 3 × 3 neurons obtained by a Kohonen neural model, which was trained with four input parameters (pH, TSS, SC, and O&G). The shading intensity indicates the degree of similarity to their neighbor nodes. Numbers indicate node in the Kohonen layer.

permittees to analyze stormwater samples, twice per year, for at least four analytical parameters. The industries are classified by Standard Industrial Classification (SIC) code (www.swrcb.ca.gov/rwqcb4/html/programs/stormwater/sw_industrial.htmlreference). The monitored analytical parameters are pH, total suspended solids (TSS), specific conductance (SC), and total organic carbon (TOC). Oil and grease (O&G) may be substituted for TOC. In addition, the permittees must monitor any other pollutants, which they believe to be present in their stormwater discharge as a result of industrial activity (www.swrcb.ca.gov/stormwtr/docs/induspmt.doc). Permittees, in some cases, may be required to sample at more than one location.

It is natural to ask if the monitoring programs are valuable. Is the resulting water-quality database useful to planners and regulators to identify acute problems, improve long-term water quality, and understand land-use and water-quality relationships? An improved understanding of the relationship of land use to stormwater quality is an expected result, because land-use-specific sampling is required by the NPDES permit. The original purposes of the monitoring programs were to identify larger sources (e.g., ''hot spots'') and to create a database to help develop total maximum daily loads (TMDLs) and other management tools. To answer this question, we reviewed the current industrial stormwater permit program. We also comment on other monitoring programs, and suggest improvements in sampling strategies and water-quality-parameter selection, with their anticipated cost increases.

Monitoring Program Utility

It is generally recognized that different human activities will create different types and varying concentrations of stormwater contaminants (Stenstrom et al., 1984). For example, runoff from transportation-associated land use is a primary source of metals and hydrocarbons (LACDPW and Woodward-Clyde, 1998). Vehicles release hydrocarbons from leaks, engine byproducts and unburned fuel, and various metals from corrosion, fuel combustion, and wearing surfaces, such as brake pads (Rogge et al. 1993; Sansalone and Buchberger, 1997). Differences in land-use patterns will likely result in different pollutant concentrations, and, therefore, land-use-related control strategies are essential to control stormwater pollution effectively.

Land-Use-Monitoring Data. The land-use-based program administered by the LACDPW is a useful example. The land-use-monitoring program, required by the 1996 Municipal Permit, was examined to determine if different land uses produce different stormwater quality. If the monitoring program is successful, land uses should be identifiable from the collected data. We developed a neural network approach to identify the various types of land use (commercial, residential, industrial, transportation, and vacant) as a function of stormwater-quality data (Ha and Stenstrom, 2003). The neural model uses a Bayesian network, and was trained using LACDPW data collected during 1996–2001 wet seasons. Among approximately 90 water-quality parameters that were measured, 42 candidate parameters were initially selected because they were detected in more than 25% of the storm events. We then selected the top 10 most useful parameters for classifying the target land-use classes using a discriminant analysis. The 10 water-quality parameters are potassium, sulfate, alkalinity, dissolved phosphorus, nitrite-N, total dissolved solids, volatile suspended solids, TSS, dissolved copper, and dissolved zinc. The model was successful at classifying 92% of the cases. The model was useful in that a data set

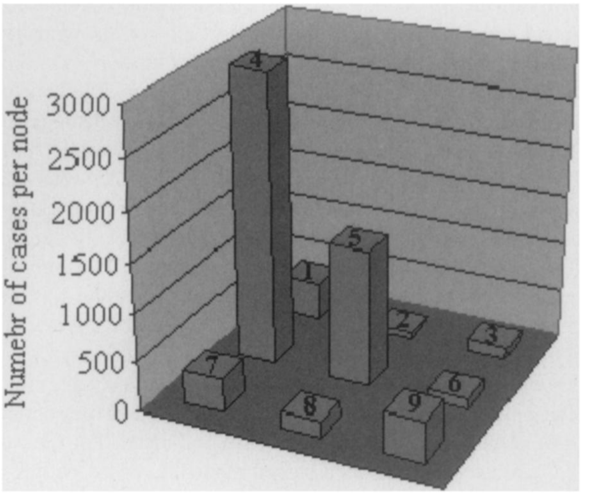

Figure 2—Number of cases per node obtained by the Kohonen neural model explained in Figure 1.

could be manipulated by changing various water-quality parameters, and the changes in classifications could be observed. It is also possible to determine which parameters are most sensitive for the classification and which are most active in a particular case. The model will eventually be useful to automatically examine many datasets to identify abnormally high or low parameters for a particular land use and label these as opportunities for investigation or improvement.

Industrial Stormwater Monitoring. Based on this experience, a similar approach was applied to the industrial stormwater discharge data for the 1998–2001 wet seasons. This dataset contains approximately 14,000 cases. Neural networks were trained to differentiate between several industrial categories, based on SIC code and water-quality data. It was hoped that the trained model would be help to identify industrial "hot sources" or outliers. Eight industrial categories were selected, based their prevalence in Los Angeles County, which means some SIC codes have many more cases than others. The selected eight industrial categories, and each category's case number for the three years, are shown in Table 1. The data cases that contain both the mandatory water-quality parameters (pH, TSS, SC, TOC, and O&G) and metals are limited. Because of this reason, a neural model trained separately with the water-quality data and metal data. Outliers in this study were defined as the upper 2% of the whole range of the data set for each parameter, and these cases were removed.

In this study, Neural Connection 2.1 (SPSS, Inc. and Recognition Systems, Inc, Chicago, Illinois) was used to build the neural models. Three supervised, feed-forward neural networks, namely, Multi-Layer Perceptron, Radial Basis Function, and Bayesian Network were used to differentiate the various types of industries. The neural models were extensively trained with various architectures; however, the performance of all models was very poor. This indicates a weak or almost no relationship between the industrial categories based on the SIC code and the available water-quality data.

To further seek a relationship between water-quality data and various land uses of industries, an unsupervised Kohonen neural network was used. The goal of Kohonen network is to map the spatial relationships among clusters of data points into hyperdimensional space (Aguilera et al., 2001). Once trained successfully, it may be used to identify unknown data patterns, and it was hoped that useful patterns between water quality and industrial categories would be identified.

A Kohonen neural model with two dimensions in the Kohonen layer was trained with different node sizes of 3×3, 5×5, and 7×7. The method performs square normalization, which normalizes the original input data patterns to zero mean and unit variance. The results were generally unsatisfactory, and it was difficult to make a decision to cluster from the activation maps by the neural model.

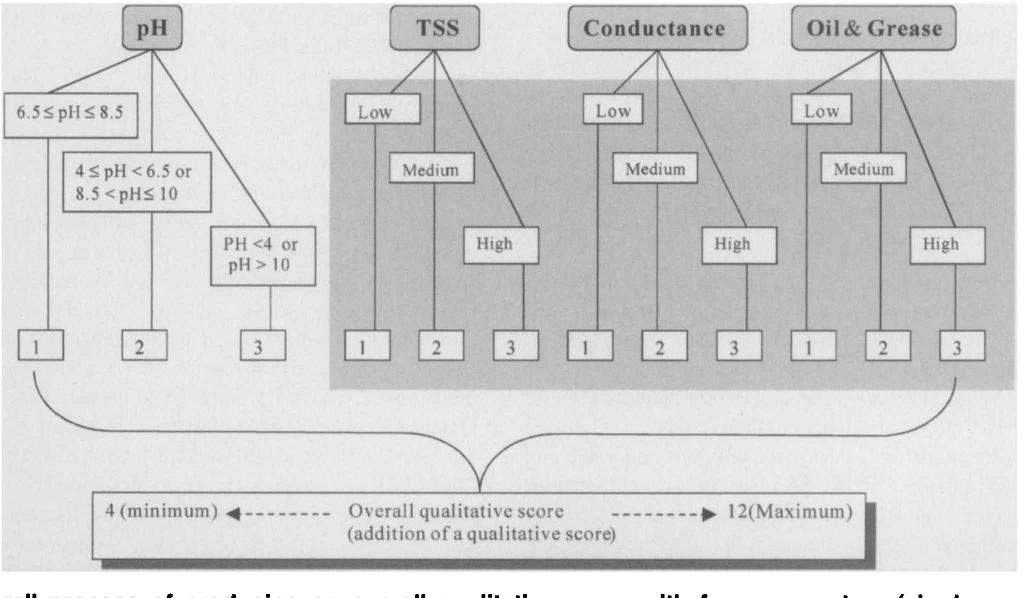

Figure 3—Overall process of producing an overall qualitative score with four parameters (shade area: a Kohonen network having three nodes in the Kohonen layer was trained for each parameter).

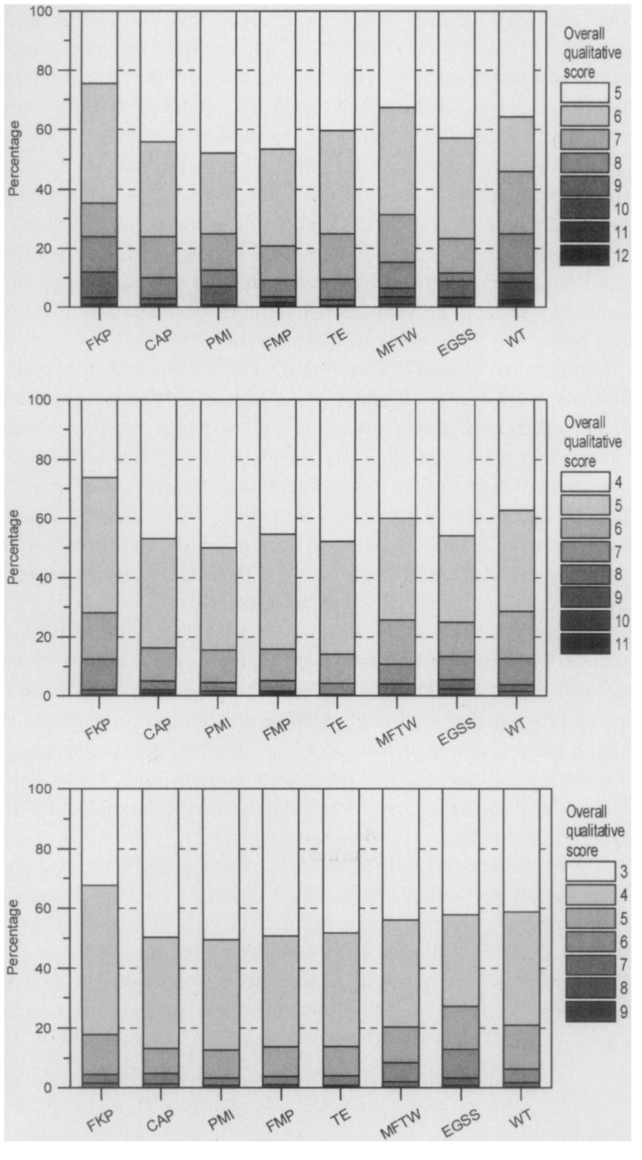

Figure 4—Distribution of the overall qualitative score for each industrial category. Higher scores indicate low water quality. Number of cases per category with different sets of parameters was shown in Table 1 (top: five parameters [pH, TSS, SC, TOC, and O&G] were used; middle: four parameters [pH, TSS, SC, and O&G] were used; bottom: three parameters [Pb, Cu, and Zn] were used).

Figure 1 shows an activation map having 3 × 3 neurons obtained by a Kohonen model that was trained with four parameters: pH, TSS, SC, and O&G. The shading intensity indicates the degree of similarity to their neighbor nodes; lighter shades indicate similar characteristics as the neighboring node, and darker patterns indicate greater differences. There are two possible clusters. The first contains nodes 1, 4, 5, and 7, and the second contains nodes 2, 3 and 6. Figure 2 shows the number of cases assigned to the various nodes. Nodes 4 and 5 contain most of the cases, and the majority (82%) would be assigned to the first cluster. A classification system that assigns such a large fraction to a single cluster is not useful; basically, the classification system is saying that it can find no difference in the available water-quality parameters among the majority of the SIC codes. Nodes 4 and 5 tend to have the lowest pollutant concentrations, but the members are not distinguished by SIC codes. Similar results were obtained using 5 × 5 or 7 × 7 neurons and with different set of input parameters. The conclusion from this analysis is that stormwater quality is not distinguishable by SIC code using the current water-quality parameters.

To further investigate possible relationships, the water-quality data were transformed into a three-member fuzzy set with categories of low, medium, and high. Each of the resulting data sets (except for pH) was examined using a Kohonen neural model. Each model had three nodes in the one-dimensional Kohonen layer and was trained for each parameter separately. The output result of the model was assigned a specific node number, from 1 to 3, for every case. The nodes were reordered so that higher node numbers always indicated greater pollutant concentration, with the number 3 representing the highest pollutant concentration for each parameter. For the case of pH, a qualitative score was assigned manually, based on deviation from neutrality. An overall qualitative score was created by summing the fuzzy states. Figure 3 shows the overall process. For example, when we used four parameters, the possible minimum and maximum overall qualitative score is 4 and 12, respectively, with 12 representing the worst water quality.

Figure 4 shows the distribution of the overall qualitative score for the various types of industries with different sets of input parameters. The upper figure used all five water-quality parameters (pH, TSS, SC, TOC, and O&G). The middle part shows the classifications when TOC is left out. The bottom shows the classification using the metal analysis. In general, no distinguishing differences were found among industrial categories and with different sets of input parameters. The food and kindred product facilities have the least abundance of low scores for the three different sets of input parameters, suggesting that it has worse stormwater quality. When five water-quality parameters were used (Figure 4, top), the wholesale trade-durable goods category had least abundance of small scores, if scores up to 6 are considered.

In general, no distinguishing differences were found among industrial categories for metals (Figure 4, bottom), if scores up to 4 are considered. However, it was necessary to remove more outliers in lead and zinc concentrations for primary metal industries and copper for transportation equipment industries than for other categories. This suggests that these two industries have the worst stormwater quality, with respect to metals. The statistical significance of these findings has not been evaluated, and it all likelihood, a new or different method would need to be used.

The industrial data set was also examined to determine if a seasonal first flush could be identified. Los Angeles has two distinct rainfall seasons. The late spring to late fall or early winter is generally dry. Most rainfall occurs in winter and early spring. This rainfall pattern creates a long period for pollutant buildup, and the first storm of the season generally has abnormally high pollutant concentrations, which is called a seasonal first flush. The industrial permit requires the first storm to be sampled and one later storm to be sampled, which was required to identify the seasonal first flush.

To determine if the industrial stormwater monitoring program was successful in identifying the seasonal first flush, the data (for 2000–2001 season only) were divided into first and second sample datasets. In some cases, the first sample does not represent the first rainfall event. In cases when there were more than two samples collected, the later samples were ignored. Cases with only one sample were also ignored. The first to second samples for the 2000–2001 season are compared in Figure 5 using notched bar plots.

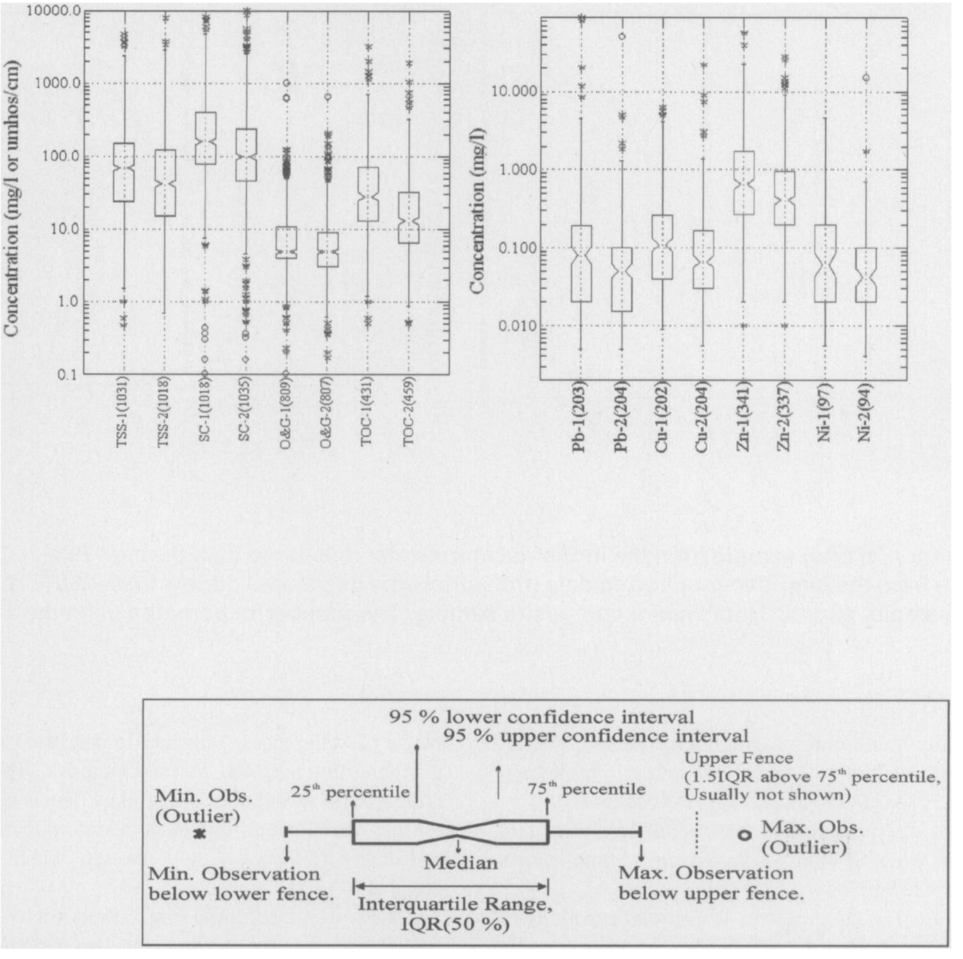

Figure 5—Comparison of first to second sample for the 2000–2001 wet season. All outliers are now shown. The "1" in the x-axis indicates the first sample, and "2" indicates the second sample. Number in a parenthesis in x-axis indicates number of cases.

Concentrations for all parameters were higher in the first sample than the second sample by 0 to 120% for the median and 20 to 85% for the mean. The TOC showed the greatest difference between first and second samples; O&G showed the smallest difference. Statistically significant differences can be observed in the notched bar plot.

Beach Monitoring. Assembly Bill 411 created improved beach water-quality-monitoring requirements. The improved monitoring was mandated after an epidemiological study of Santa Monica Bay swimmers suggested increased health risk associated with swimming near storm drains (Haile et al., 1999). Daily samples for total and fecal coliforms and enterococcus were mandated with new, lower levels that trigger a beach posting or closure. Leecaster and Weisberg (2001) examined sampling data from 24 sites in Los Angeles County between 1995 and 1999. They report that over 70% of the water-quality exceedences were for only one day.

The time required to analyze indicator organism data is generally more than 24 hours. This created a chronology as follows:

(1) Day 1—a sample is collected and analysis begins.
(2) Day 2—the sample is analyzed and an exceedence is noted, with a beach posting; a new sample is collected and analysis begins.
(3) Day 3—the second sample result is negative 70% of the time, and the beach posting is removed.

The chronology creates a situation that beaches are posted when the samples do not exceed standards and open when they do. Clearly, the problem is a monitoring program that cannot be implemented with current technology. Rapid indicators are needed. Furthermore, the utility of conventional indicator organisms for fecal contamination in beach waters is in question.

Discussion and Recommendations

Three stormwater monitoring programs were discussed. The land-use-monitoring program was generally successful and showed the anticipated differences in water quality, based on land use. This program used automatic, flow-weighted composite samplers with trained personnel. The second program, the industrial-monitoring program, used grab samples collected at various times for two storms with SIC codes as land-use or industrial-use descriptors. The program is generally unsuccessful in identifying relationships between water quality and land use. It was successful in showing a seasonal first flush, and its utility for identifying acute problems is questionable, based on outliers, to be discussed later. The third is

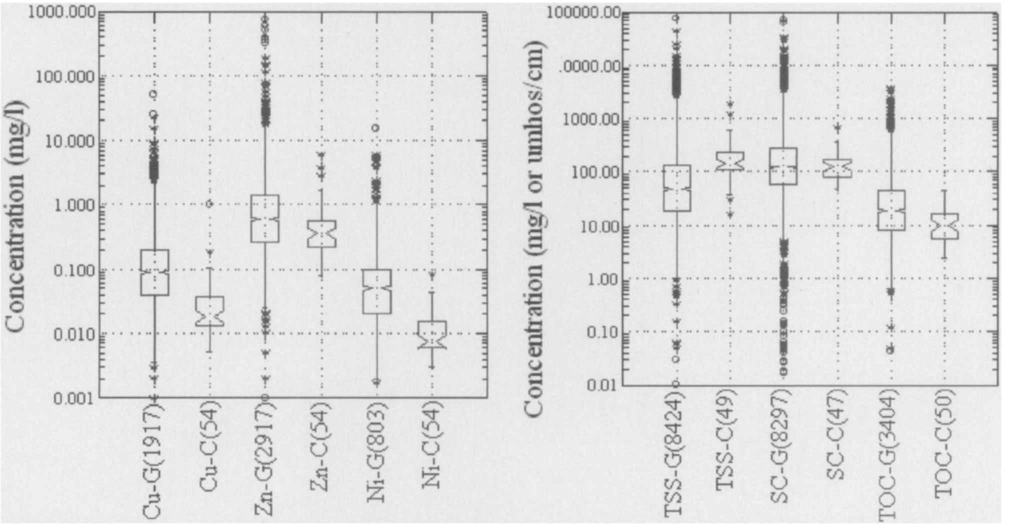

Figure 6—Comparison of grab sample from the industrial stormwater discharge data during 1998–2001 to flow-weighted composite sample from the land-use-monitoring data (industrial land use alone) during 1996–2001. The "G" in the x-axis indicates a grab sample, and "C" indicates a composite sample. The number in parenthesis in the x-axis indicates the number of cases.

the beach water-quality-monitoring program, which uses grab samples and analyses that are not real-time. This creates problems of beach postings, which are out of phase with exceedences.

In this section, we discuss possible reasons for less successful program and suggest ways to improve monitoring. Some suggestions will require new technology.

Sampling Method. For the industrial stormwater permit monitoring, grab samples are allowed, and facility operators are instructed to collect the sample during the first hour of discharge from the first storm event for the wet season (October to May) and at least one other storm event in the wet season. A grab sample is a discrete sample taken within a short period of time, typically less than 15 minutes. Flow-weighted composite samples were collected in the land-use program, which requires instrumentation and, perhaps, site preparation to create a channel for flow measurement and security for equipment. The flow-weighted samplers collect a composite by combining a series of discrete samples of specific volume, collected at specific flow-weighted intervals over the duration of a storm event (LACDPW and Woodward-Clyde, 1998).

It is useful to compare the results of the two programs. They are analogous in that both programs attempt to measure the emissions from a particular human activity, although the industrial program also attempts to identify high dischargers. The results of the 1998–2001 industrial permit using grab samples were compared to the 1996–2001 land-use monitoring that used flow-weighted composites. Figure 6 is a notched bar plot that shows the differences.

There are a large number of outliers among the grab samples and only a few outliers among the composite samples. The number of outliers suggests the need for a quality assurance program, and is helpful in understanding why the neural networks could not identify significant differences in stormwater from SIC codes.

The standard deviations of the concentrations are much lower among the composite samples (Table 2). For example, the standard deviation for TOC is 174 for grab samples and 9.7 for composite samples, or a ratio of 18. The other parameters have ratios of standard deviations from 2.3 (pH) to 66 (zinc). With this large range of differences, one has to question to the utility of such a monitoring program for any purpose. The application of any normalization method of the original data is not useful to generalize for use with a neural model. In addition, there are too many upper and lower outliers in the data set, which results in excessive clipping.

A flow-weighted composite sample for a storm event generally better represents the storm event than a single grab sample, which may be biased because of the collection time. The results of the flow-weighted composite sample can be considered as an event mean concentration (EMC), which can be multiplied by the flowrate to calculate overall mass emissions. This is useful for spreadsheet load models (Wong et al., 1997), which are finding widespread use for planners and TMDL development.

A grab sample suffers from a variety of errors and biases, but one that has not been fully explored is the effect of first flush. Many parameters exhibit a first flush, which is typified by a declining concentration from storm beginning to storm end (Ma et al., 2002a). When the grab sample is collected early in the storm, it will be higher than the EMC; conversely, if collected too late, it will be lower than the EMC. The industrial-monitoring program suggests collecting a sample within the first hour. To improve the results from grab samples, it is necessary to find the best time to sample. For example, the best time for sampling O&G from highway land use is between two and three hours and is related to cumulative rainfall and duration (Ma et al., 2002b). There might be some improvement in the existing program with better definition of collection times.

It is almost universally recognized that composite samplers are better for stormwater monitoring; however, to collect a flow-weighted composite sample, an automatic sampler must be installed and operated properly before a storm event. It would be a burden to all industrial permittees to construct composite sampling facilities. Additionally, several water-quality parameters, such as O&G and indicator bacteria, are not easily measured by a composite sample.

Table 2—Comparison of grab to composite sample (0 indicates level below detection limit).

Water-quality parameters	Grab Industrial stormwater permit sample 1998–2001	Flow-weighted composite Landuse monitoring sample 1996–2001 (industrial site alone)
pH		
Number	8584	51
Minimum	0.1	6.04
Maximum	12.7	8.32
Median	6.88	6.82
Mean	6.91	6.83
Standard deviation	0.96	0.41
Total suspended solids (mg/L)		
Number	8424	49
Minimum	0	16
Maximum	101 000	1865
Median	48	140
Mean	219.11	232.55
Standard deviation	1693	298
Specific conductance (μmhos/cm)		
Number	8297	47
Minimum	0.017	48.9
Maximum	71 000	691
Median	121	126
Mean	365.17	150.06
Standard deviation	1555	111
Oil and grease (mg/L)		
Number	6685	
Minimum	0	
Maximum	6640	
Median	5	Not analyzed
Mean	13.63	
Standard deviation	95	
Total organic carbon (mg/L)		
Number	3404	50
Minimum	0	2.4
Maximum	3700	45.62
Median	18	9.85
Mean	56.01	12.67
Standard deviation	174	9.7
Lead (mg/L)		
Number	171	Low detection
Minimum	0	frequency
Maximum	90	
Median	0.06	
Mean	0.402	
Standard deviation	3.5	
Copper (mg/L)		
Number	1917	54
Minimum	0	0.0053
Maximum	49.5	0.99
Median	0.084	0.0185
Mean	0.337	0.047
Standard deviation	1.6	0.13
Zinc (mg/L)		
Number	2917	54
Minimum	0	0.079
Maximum	2200	5.97
Median	0.6	0.36

Table 2—(Continued).

Water-quality parameters	Grab Industrial stormwater permit sample 1998–2001	Flow-weighted composite Landuse monitoring sample 1996–2001 (industrial site alone)
Mean	4.86	0.63
Standard deviation	64.4	0.97
Nickel (mg/L)		
Number	803	54
Minimum	0	0
Maximum	15.1	0.0804
Median	0.05	0.005995
Mean	0.196	0.0082
Standard deviation	0.76	0.013

To improve sampling, it might be reasonable to randomly select a small subset of industrial users for composite sampling. This might be funded by fee permittees or by allowing a reduced number of grab samples to be collected. A trained team would also increase quality assurance to eliminate outliers. Such an approach might be a better or less-expensive method of determining stormwater emissions on receiving waters.

Parameter Selection. A variety of metal-related industries are included among the SIC codes in the industrial monitoring program. Many industries should be sources of metals, such as chromium, copper, lead, nickel, and zinc (Woodward Clyde, 1992). Figure 7 shows the mean concentration of the basic analytical parameters and metals as a function of their industrial categories for the 1998–2001 seasons. Outliers, defined earlier, have been removed. The numbers of cases for all parameters vary with as many as 800 for conventional parameters and only approximately 80 for metals. The conventional water-quality parameters show much less relation to industrial category than metals. The mean concentrations of lead, zinc, and nickel were highest for the primary metal industries category, and copper was highest at the transportation equipment facilities category. Mean concentrations of O&G and TOC were highest for whole trade-durable good industries and mean concentration of conductivity and suspended solids were highest for electric, gas, and sanitary-service facilities.

In addition, concentrations of metals exceeded the stormwater benchmark values suggested by the U.S. Environmental Protection Agency (U.S. EPA) more frequently than the basic water-quality parameters (Table 3). The concentrations of metals (except nickel) are mostly above the benchmark levels. For the cases of zinc, approximately 90% of observations exceeded the benchmark.

The addition of metals to the basic permit's requirement for basic water-quality parameters would be a useful way of adding information to the dataset. A neural model trained with both metals and basic parameters will perform better than that trained with existing water-quality parameters or metals alone. The addition of metals will increase the monitoring cost. Table 4 shows the current costs for laboratory analysis. The addition of metals to the permit will approximately double or triple the laboratory costs. The cost of collecting the samples should be quite similar. Cost increases are probably inevitable, but this approach may be less expensive than other approaches.

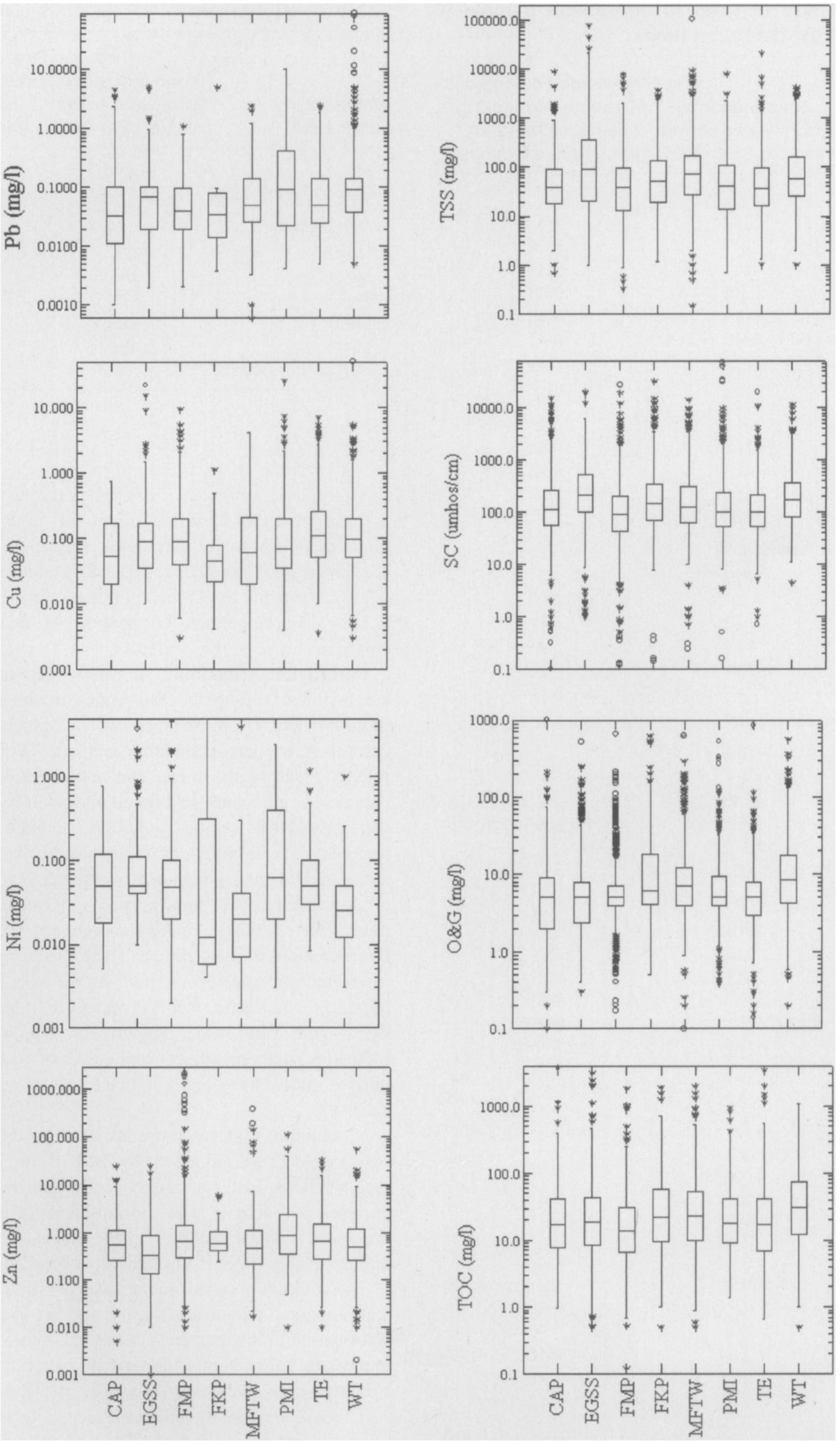

Figure 7—Distribution of the analytical parameters and metals for each industrial category. The number of cases is varied.

Table 3—Comparison with the U.S. EPA benchmark levels for parameters for the 1998–2001 wet seasons.

Water-quality parameters	No. of observations	No. of outside benchmark values	Percentage of outside benchmark values
pH	13 770	1571	11.4
Total suspended solids	13 527	4266	31.5
Specific conductance	13 155	4617	35.1
Oil and grease	10 780	1560	14.5
Total organic carbon	5406	499	9.2
Aluminum	1487	898	60.4
Copper	2505	1441	57.5
Iron	1762	1205	68.4
Nickel	1122	20	1.8
Lead	2230	906	40.6
Zinc	3615	3227	89.3

Conclusions

This paper has examined three stormwater monitoring programs. The utility of the programs have been assessed based on the programs' ability to accurately estimate the emissions for different classes of land uses and other obvious benefits. The following conclusions are made:

(1) Data collected by grab samples had much higher variability than composite samplers. The coefficients of variation (standard deviation divided by the mean) for the same parameters were generally 2 to 9 times higher for the grab samples. The variability suggests that composite samples should be collected, even if it means a reduction in the total number of samples or facilities that can be monitored.

(2) The time required to analyze a sample must be commensurate with the intended use of the results. Beach water-quality monitoring suffers from analysis time for indicator organisms. The data suggests that 70% of the beach postings are out of phase with the water-quality parameter exceedence.

(3) Metals are major pollutants in industrial land use and potentially more useful to distinguish industrial categories or land-use patterns. Metal concentrations frequently exceeded U.S. EPA benchmark concentrations. Adding them to existing permits might increase cost, but will add value to the resulting monitoring database.

Managing stormwater is a developing technology and much remains to be done. This paper has shown that, even with the limited experience we have thus far, there are improvements that can be made.

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Authors. At the time of this work, Haejin Lee was a post-doctoral researcher in the Department of Civil and Environmental Engineering at University of California at Los Angeles (UCLA). Michael K. Stenstrom is a professor in the Department of Civil and Environmental Engineering at UCLA. Correspondence should be addressed to Michael K. Stenstrom, Prof., Department of Civil and Environmental Engineering, 5714 Boelter Hall, University of California, Los Angeles, CA 90005; e-mail: stenstro@seas.ucla.edu.

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Table 4—Comparison of the current requirement parameters to the complementary parameters on the costs of laboratory analysis (data source: Los Angeles County Department of Agricultural Commissioner/Weights and Measures Environmental Toxicology Laboratory, Arcadia, California).

Water-quality parameters	Cost per sample ($)	Current requirement parameters		Complementary parameters	
		pH, TSS, SC, and TOC	pH, TSS, SC, and O&G	pH, TSS, lead (Pb), copper (Cu), and zinc (Zn)	pH, TSS, SC, O&G, Pb, Cu, Zn, aluminum (Al), and iron (Fe)
pH	3.50	3.50	3.50	3.50	3.50
Total suspended solids (TSS)	7.68	7.68	7.68	7.68	7.68
Specific conductance (SC)	6.40	6.40	6.40	6.40	6.40
Total organic carbon (TOC)	23.46	23.46		23.46	23.46
Oil and grease (O&G)	36.25		36.25		
Copper (Cu)	20.29			20.29	20.29
Lead (Pb)	20.29			20.29	20.29
Zinc (Zn)	20.29			20.29	20.29
Aluminum (Al)	20.29				20.29
Iron (Fe)	20.29				20.29
Total cost per sample ($)		41.04	53.83	101.91	142.49

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