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Identification of land use with water quality data in stormwater using a neural network

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Abstract

To control stormwater pollution effectively, development of innovative, land-use-related control strategies will be required. An approach that could differentiate land-use types from stormwater quality would be the first step to solving this problem. We propose a neural network approach to examine the relationship between stormwater water quality and various types of land use. The neural network model can be used to identify land-use types for future known and unknown cases. The neural model uses a Bayesian network and has 10 water quality input variables, four neurons in the hidden layer, and five land-use target variables (commercial, industrial, residential, transportation, and vacant). We obtained 92.3 percent of correct classification and 0.157 root-mean-squared error on test files. Based on the neural model, simulations were performed to predict the land-use type of a known data set, which was not used when developing the model. The simulation accurately described the behavior of the new data set. This study demonstrates that a neural network can be effectively used to produce land-use type classification with water quality data.

Keywords: Artificial neural network; Stormwater; Land use; Classification; Bayesian network; Water quality data

1. Introduction

Stormwater is a major non-point source contributor to coastal water pollution including Santa Monica Bay, which is among the most severely polluted Bays in the United States [1]. Storm drains and urban runoff accounted for 34 percent of the beach mile-day beach closures and warnings [2]. The problem of stormwater pollution is becoming worse because of population growth, which results in increased impermeable surfaces. Stormwater runoff picks up natural and human-made contaminants that accumulated on surfaces during the dry days and transports them to the coastal waters.

The forms and concentrations of contaminants from runoff are closely related to various types of land use because human activity is different according to land use. To control stormwater pollution effectively, development of innovative land-use-related control strategies will be required. An approach that could differentiate land-use types in stormwater would be a first step to solving this problem. We propose a neural network approach to examine the relationship between water quality variables and various types of land use. The neural network model could then be used to identify land-use type for future cases where only the inputs are known. We could also apply the neural model to water quality data sets from known land uses. If the network cannot confirm the known land use, it suggests that something else is occurring such a spill, leakage, illegal discharge, or that monitoring data are suspect. Such information could provide opportunities for better land-use management to control stormwater pollution.

A neural network (NN), more specifically an artificial neural network, is a computational tool that operates similarly to the biological processes of human brain. Many researchers have discussed the history, capability,

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kinds, structure, and learning algorithm of neural networks [3–10]. NN is in the "black-box" class of models. These models do not require detailed knowledge of the internal functions of a system in order to recognize relationships between inputs and outputs [11]. Because of this feature, NN modeling is being increasingly applied in various aspects of science and engineering, including the environmental field. NNs have been used to predict wastewater inflow rate [11], sanitary sewer flows [12], the flux during ultrafiltration and after backwashing [13], peak *Cryptosporidium* and *Giardia* concentrations [14], and metal bioleaching in municipal sludge [9]. In addition, NNs have been applied to simulate nitrate leaching [15], model solid transport in sewers [16] and to identify non-point sources of fecal contamination [17]. In this study, a NN was applied to the identification of land-use types as a function of stormwater quality data.

Our objectives were to develop a neural network model to examine the relationships between stormwater quality variables and land-use types. We evaluated three approaches: multi-layer perceptron, radian basis function and Bayesian network. A model was developed using the Bayesian network which was then used to identify land-use types for known cases.

We envision that this tool could be used in identifying targets for water quality improvement. Regulators in the United States are now faced with many additional stormwater permits and no resources to review the water quality data. A tool such as a NN classifier could be used to review either monitoring reports or water quality studies to identify situations were the water quality is not appropriate for the stated land use. This might occur if an unknown or unintended activity is occurring. An extreme example is sometimes called a "hot spot." If regulators can identify such opportunities, they may be able to affect greater water quality improvement.

2. Overview of Bayesian networks

A Bayesian network (BN) is the application of probability theory in Bayesian statistics to a multi-layer perceptron (MLP), the most common supervised neural network. Therefore, a BN has many common features with MLP. The major difference is the way error is measured during training. In an MLP, only the weights between neurons are adjusted during training. In a BN, both these weights and a set of parameters can be altered to reduce error measure during training. This enables BN to produce a generalized model without a validation data file, which is particularly useful for relatively small data sets such as ours.

The BN used here is a three-layered, supervised feed-forward neural network with back-propagation algorithm. For supervised learning, the network can be trained using both input and target values. After training, when we present only the input values to the neural model, it will compute an output value that approximates the target value. In a feed-forward neural network, feed back loops are absent. Information is processed in a forward manner only from input to output, and thus it always gives the same output result for the same input. In a back-propagation algorithm, the prediction error is generated at the output layer of neurons and then propagates backwards through the network. It consists of an input layer, output layer and a hidden layer between the input and output layers. The number of neurons in the input layer is usually equal to the number of input variables. The number of output layer neurons is usually the same as the target variable number. The number of neurons in the hidden layer is determined to optimize performance.

3. Data collection

3.1. Development data

Development data are used for building a neural network model. We selected the Los Angeles County Department of Public Works (LACDPW) land-use stormwater monitoring data as development data because they are representative of this study purpose and are produced by a well-regarded agency. The LACDPW has been monitoring land-use stormwater in the County of Los Angeles since 1996. They provide flow and water quality data for various types of land use (commercial, educational, industrial, high-density residential, multi-family residential, mixed residential, transportation, and vacant) for every storm event. Flow-weighted composite samples were analyzed for many water quality variables including indicator bacteria, general minerals, nutrients, metals, semi-volatile organic compounds, oil and grease and pesticides. Records of the stormwater quality data in various types of land use were obtained online (http://www.ladpw.org/wmd/NPDES/report_directory.cfm) for the 1998–2001 seasons, and from the Los Angeles County Stormwater Monitoring Report, for the 1996–1998 seasons [18,19].

The development data set was divided into three data files: a training file, a validation file, and a test file. Validation data were used to monitor the neural model's performance during training to prevent problems such as overtraining. Test data were used to measure the performance of the trained neural model.

3.2. Run data

Run data, similar to test data, but not used when developing a neural network model, were used to test the developed model's suitability for identifying land-use types. Highway monitoring data being collected in our laboratory were used as a run data set. Three sites from interstate highways near UCLA have been monitored since 1999 [20,21]. The sites in Los Angeles are adjacent to the 101 and 405 freeways, which are among the busiest freeways in the United States (280,000–330,000 average daily traffic). Runoff samples during storm events were analyzed for a large suite of parameters such as indicator bacteria, general minerals, nutrients, metals, polycyclic aromatic hydrocarbons, and oil and grease.

4. Data screening and preprocessing

4.1. Target variables and input variables

Commercial, industrial, residential, transportation, and vacant land-use types were chosen as the target variables because they cover most types of land use in urban areas. For residential land use, we selected high-density residential sites because they have been monitored longer than the multi-family residential and mixed residential sites. Table 1 shows the land-use distribution in their sampling sites by LACDPW. The Santa Monica Pier site, representative of commercial land use, was not monitored in the 1999–2001 storm seasons because the City of Santa Monica was constructing a stormwater treatment plant.

Among approximately 90 water quality variables in stormwater, 42 candidate variables were initially selected because they were detected in more than 25 percent of the events. After clipping the data cases that contained missing values, 184 samples or cases remained. We next considered the maximum number of input variables within the available data set to develop a general neural network model. The following rough rule was used: "The minimum number of training data cases should be ten times the total number of input variables and target variables" [22]. Taking into account the five target variables and 85 percent of the available data for the training file, the maximum number of input variables was ten. Among the 42 water quality variables, the 10 input variables were selected using discriminant analysis as a preliminary classification approach (Systat 9, SPSS Inc., Chicago, IL). Discriminant analysis was used initially to determine the most useful variables for classifying the target classes. We selected the top 10 most useful variables among 42 water quality variables. The selected 10 input variables were potassium, sulfate, alkalinity, dissolved phosphorus, nitrite-N, total dissolved solids, volatile suspended solids, dissolved solids, dissolved copper, and dissolved zinc.

Table 1
Land-use distribution of the monitored stations by LACDPW

Station name	Drainage Area (km^2)	Land-use distribution[a] (%)
Santa Monica Pier	0.33	**Commercial/retail** (53.6) Other (36.7) Multi-family residential (5.1) Transportation (4.6)
Sawpit Creek	13.41	**Vacant** (98) Other (2)
Project 620	0.49	**High-density residential** (100)
Dominguez Channel	3.65	**Transportation** (75.2) Light industrial (17) Other (7.1) High-density residential (0.6) Retail/commercial (0.1)
Project 1202	2.77	**Light industrial** (67.1) Other (26.9) Transportation (4.7) Vacant (1) Retail/commercial (0.3)

4.2. Clipping outliers

In a preliminary test, poor classification was obtained between target variables and the output because of data cases that contained unusually high values in the input variables. These high values were identified as outliers and the data cases with outliers we removed (clipped) from the data sets. Outliers were defined as any observation exceeding 10 times its median value in the whole range of the data set. We found 11 data cases that contained outliers. After clipping, 173 storm events from the five land-use monitoring stations remained for the 1996–2001 seasons.

4.3. Data file and multiple data sets

The 173 cases were divided into three data files. The training file contained 121 cases or 70% of the total cases; the validation file contained 26 cases or 15% of the total cases, which left 26 cases or 15% of the total cases for the test file. The cases for each file were selected randomly from the overall data set. For the BN, which does not require a validation file, the data that would have been used for validation was grouped with the training data.

Lack of data is a common problem in developing neural networks and data sets with a relatively small number of data cases such as ours are a typical. To partially overcome this problem, additional combinations were created by randomly selecting different new test data sets from the original data set. The remaining 85% of the data were then used as training and validation files. Three data sets were created, called A, B and C, from the original data and were used to measure the overall performance of the neural network model.

5. Building a neural network model

5.1. Selection of neural network

In this study, Neural Connection 2.1 (SPSS Inc. and Recognition Systems Inc, Chicago, IL) was used to build the neural model. Three supervised, feed-forward neural networks, namely, multi-layer perceptron (MLP), radial basis function (RBF), and Bayesian network (BN) were used. In the early work, the neural networks were trained at their default settings. Both MLP and BN used eight neurons in their hidden layer. The BN automatically normalizes the input data. The RBF network started with 5 centers, and increased in steps of 5–50 centers using a spline radial function. The performance of the networks was measured using correct classification in percentage and the root-mean-square error (RMSE), which is the mean square difference between the target and the actual output value. An ideal neural network model would correctly classify all cases and have zero RMSE. The overall performance of the neural networks, as the average over each of the three data sets, is presented in Fig. 1. The best performing network in the preliminary evaluation was BN. For this reason, BN was selected for further development.

5.2. Architecture of the neural model

For all cases the number of neurons in the input layer was equal to the number of water quality input variables and the number of neurons in the output layer was equal to the number of land-use types. In many problems, a second hidden layer does not produce a large improvement in performance, and varying the number of hidden neurons in the one hidden layer is usually sufficient [11]. We evaluated the benefits of one to nine hidden neurons. The model had a significant improvement in the RMSE and classification accuracy as the neurons were increased from one to four. After four neurons, additional neurons had no benefit (see Fig. 2). In general, the number of neurons in the hidden layer should be as low as possible to make a generalized neural model. Therefore, the model that utilizes four neurons in the hidden layer was chosen to be the final model. The BN model had nineteen total neurons: 10 in the input layer, four in the hidden layer, and five in the output layer (see Fig. 3).

Fig. 4 shows the error reduction as a function of the number of training epochs. The interval for checking error improvement was varied from 10 to 100 epochs. A value of 80 was selected for the remaining studies, and a relative improvement of less than 0.01 was selected for termination. In general, there was no improvement after 400 epochs.

5.3. Results of the final model

The performance of the final neural model on the training and test data files in RMS error and correct classification is shown in Table 2. In general, the statistical quality of the neural model was high. We obtained 92.3 and 94.5 percent overall correct classifications and 0.157 and 0.154 overall RMSE on the test and training files, respectively.

Fig. 5 shows the overall performance for each land-use type as indicated by the percentage correctly classified. The percentages represent the average of classifications of three data sets. Vacant and residential land-use types were 100 percent correctly classified,

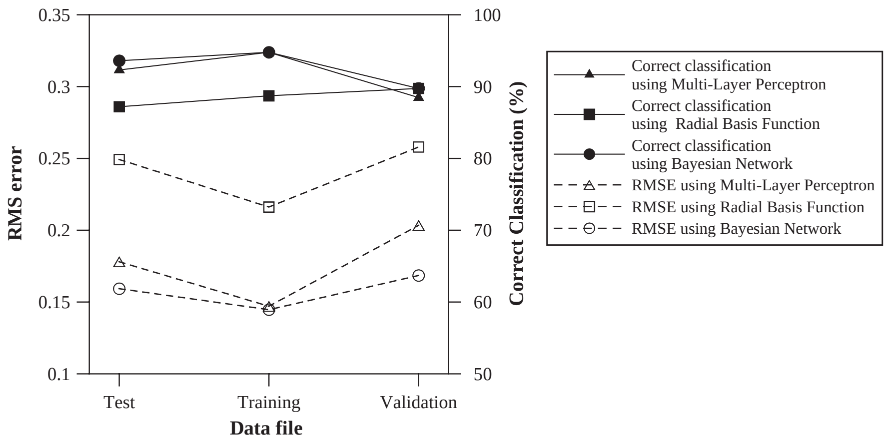

Fig. 1. The overall performance of the various neural networks in the preliminary tests. The overall performance measured average over each of the three data set A, B, and C.

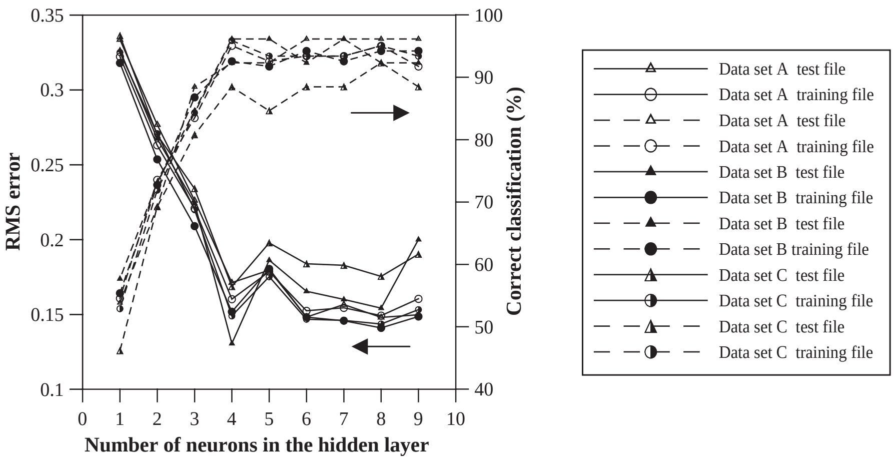

Fig. 2. The effect of neuron number in the hidden layer.

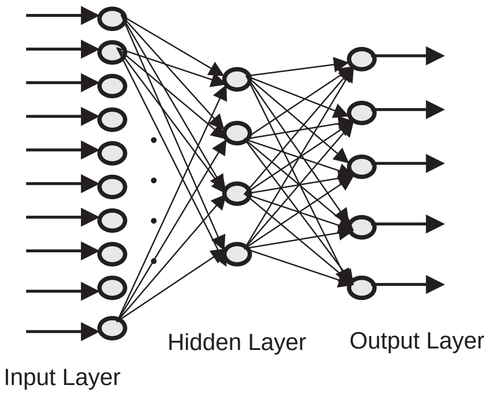

Fig. 3. A schematic diagram of the final neural model.

Table 2
Result of the neural model on the test and training files

Data set	Correct classification (%)		RMS error	
	Test file	Training file	Test file	Training file
Data set A	92.3	95.0	0.171	0.160
Data set B	96.2	92.6	0.131	0.152
Data set C	88.5	95.9	0.169	0.149
Average	92.3	94.5	0.157	0.154

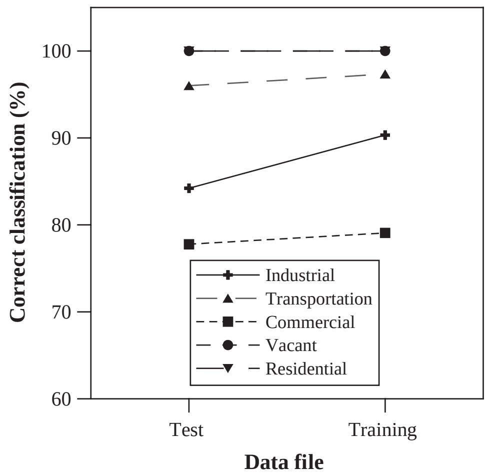

Fig. 5. The overall performance in correct classification on each target land-use type.

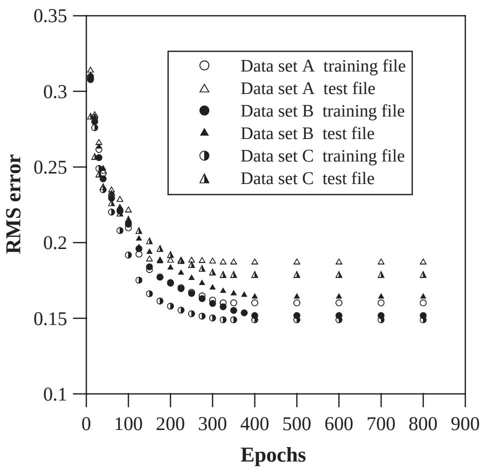

Fig. 4. RMS error on the training and validation file as a function of the number of epochs.

which shows that they are the most distinct among the five land uses. In contrast, commercial land-use classification was the most inaccurate, which might be expected since the land use is mixed with other land-use

Table 3
Example output with data set A

Case number	Potassium	Sulfate	Alkalinity	Dissolved phosphorus	Nitrite-N	TDS	SS	VSS	Dissolved copper	Dissolved zinc	Target	Output
1	0.00	2.82	10.60	0.09	0.00	28	116	22	0.116	0.022	Industrial	Industrial
2	0.90	5.26	19.30	0.13	0.06	50	31	16	0.031	0.016	Transportation	Transportation
3	0.96	3.59	16.10	0.10	0.05	50	29	16	0.029	0.016	Commercial	Transportation
4	1.05	6.67	21.40	0.12	0.05	72	98	39	0.098	0.039	Commercial	Commercial
5	1.05	11.70	164.00	0.00	0.03	228	43	12	0.043	0.012	Vacant	Vacant
6	1.29	2.26	8.48	0.13	0.00	22	26	15	0.026	0.015	H-D-Resident	H-D-Resident
7	1.10	37.00	8.80	0.16	0.04	36	17	11	0.017	0.011	Transportation	Transportation
8	1.42	2.73	7.70	0.35	0.06	36	14	12	0.014	0.012	H-D-Resident	H-D-Resident
9	1.41	16.10	187.00	0.04	0.00	262	26	15	0.026	0.015	Vacant	Vacant
10	1.52	4.19	13.80	0.12	0.03	40	90	21	0.09	0.021	Industrial	Industrial
11	1.52	16.30	184.00	0.00	0.03	260	6	5	0.006	0.005	Vacant	Vacant
12	1.69	2.30	10.60	0.00	0.00	36	16	6	0.016	0.006	Industrial	Industrial

The unit of the input variables is mg/l. TDS: total dissolved solids; SS: suspended solids; VSS: volatile suspended solids.

activity (see Table 1). Table 3 shows a typical result using Data Set A. The water quality inputs are shown in the left 11 columns along with the case number. The known land use is shown in column 12, and these first 12 columns are an example of the training data set. The result from the neural network classification is shown in column 13. For this case, there is one incorrect classification (case 3), which is commercial land use.

6. Analysis of the final model

6.1. Sensitivity of input variables

To evaluate the sensitivity of the model to different water quality variables, each variable was omitted ("leave-one-out method") and the network was re-trained with all other conditions as before. In this way, the impact of each variable on the final result can be evaluated. The percent difference in RMSE between 10 and the 9 input variables is shown in Table 4. If the error increases after removing a variable, it means that the removed variable was helpful in improving classification. If the error is unchanged, it means that the variable was not helpful for classification. A negative percentage in Table 4 suggests that the variable was harmful and might not be related to land use. All cases in Table 4 are positive except sulfate in data set A. The neural model was the most sensitive to the level of dissolved copper, and the least sensitive to the level of sulfate. The values shown in Table 4 are useful in that they suggest ways of differentiating land use in future monitoring programs.

6.2. Simulation

The utility of a neural network model, and our reason for developing it, is to confirm land uses from a large number of data sets. An agency seeking to reduce stormwater pollution can review monitoring data from known land uses and compare them to benchmark data used in developing the neural network. If the network cannot confirm the known land use, it suggests that something else is occurring or that monitoring data are suspect. Such a tool could be useful watershed-based approaches to stormwater management. Large data sets could be screened to identify opportunities for water quality improvement.

To demonstrate this concept, simulations were carried out on a known data set (motor vehicle highways) that was not used in developing the model. Table 5 shows the monitoring data for the selected input variables. All data were from flow-weighted composite samples for 2000–2001 wet season, and collected by our laboratory. Two variables present in the LACDPW, potassium and

Table 4
Leave-one-out impact analyses based on all 10 input variables

Input variables	Impacts (%)			
	Data set A	Data set B	Data set C	Average
Potassium	7.6	31.8	13.9	17.8
Sulfate	−5.4	32.1	1.7	9.4
Alkalinity	7.1	20.7	22.7	16.8
Dissolved phosphorus	5.4	24.9	7.9	12.7
Nitrite-N	9.6	12.8	9.0	10.5
Total dissolved solids	8.8	20.5	16.2	15.2
Suspended solids	11.0	25.1	16.8	17.7
Volatile suspended solids	10.1	12.1	8.0	10.1
Dissolved copper	24.5	33.8	31.2	29.8
Dissolved zinc	11.2	29.9	22.4	21.2

Table 5
Water quality results from the highway monitoring

Input variables	Storm date and station number and storm event number					
	2/9/2001 S2–E4[a]	2/18/2001 S3–E5	2/23/2001 S3–E6	4/6/2001 S2–E8	4/6/2001 S3–E8	4/19/2001 S1–E9
Potassium (mg/l)	NA[b]	NA	NA	NA	NA	NA
Sulfate (mg/l)	24.82	3.84	1.73	373.16	4.78	8.66
Alkalinity (mg/l)	17	9.5	11	112.1	10	28.5
Dissolved phosphorus (mg/l)	0.243	0.161	0.061	0.126	0.152	0.154
Nitrite-N (mg/l)	0.162	0.119	0.048	0.103	0.075	0.151
Total dissolved solids (mg/l)	NA	NA	NA	NA	NA	NA
Suspended solids (mg/l)	86.87	80.57	62.7	127.1	56.4	33.69
Volatile suspended solids (mg/l)	37.6	25.80	18.3	38.5	21.3	14.27
Dissolved copper (μg/l)	20.55	6.98	5.4	25.8	16.2	27.35
Dissolved zinc (μg/l)	90.5	54.85	42	100.8	107.4	151.99

[a] S indicates station number and E indicates storm event number.
[b] NA indicates sample was not analyzed.

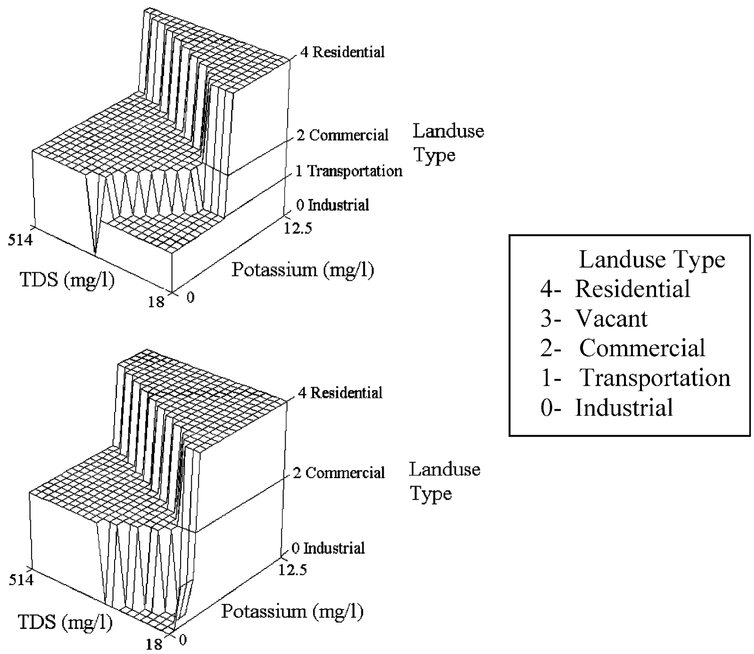

Fig. 6. Land Use classification as a function of Potassium and Total Dissolved Solids concentration for the case of S1–E9 (the top) and S3–E5 (the bottom), calculated by the neural model using data set B.

total dissolved solids (TDS), were not collected as part of the highway monitoring program. The two missing variables provide an opportunity to evaluate classification sensitivity by substituting hypothetical data for the missing values.

The model correctly classifies the land use if TDS and potassium concentrations typically associated with highway land use are substituted into the data set for the missing values for all samples except S3-E5 and S3-E6. By substituting a large range of possible values, the sensitivity of classification can be observed. Fig. 6 shows the changes in classification caused by changing TDS and potassium concentrations. Low values of TDS and potassium are associated with transportation land use. If potassium concentrations increase, the classification changes to commercial and finally residential land use. The TDS concentration "pushes" the classification towards commercial at higher concentrations.

Samples S3–E5 ad S3–E6 in Table 5 did not classify correctly with typical values of TDS and potassium; they were incorrectly classified as industrial, commercial or residential. The most likely reason is the low values of copper and zinc. To test this suggestion, the values of copper and zinc were increased. The classification changes to transportation as the copper, or copper and zinc concentrations are changed to 22.5 μg/l and 112.7 μg/l, respectively. The classification changes to industrial if only the zinc concentration is changed.

The simulation demonstrates the utility of the model for understanding why land-use classifications change as a function of water quality variables. Further usage of the model may be helpful in identifying "problem" sites or developing a better classification system—a system that creates land-use types based upon water quality as opposed to observable human activities or the needs of public agencies (e.g. tax records).

7. Conclusions

A neural network model for identifying the various types of land use with stormwater quality data was successfully developed using LACDPW stormwater monitoring data, collected during 1996–2001. A Bayesian network model was best and had 10 water quality input variables, four neurons in the hidden layer and five land-use target variables. The statistical quality of the neural model was high. We obtained 92.3 and 94.5 percent of correct classification, and 0.157 and 0.154 in the RMSE on the test and training files (173 cases). The model was used as a simulation tool to predict land-use type from highways stormwater monitoring data that was not used to develop the model. The simulations showed the sensitivity to classification and demonstrated a method to identify water quality variables that affect classification.

This research has demonstrated that a neural network can be used to classify land uses from water quality data, and that the technique can be automated. An approach for identifying opportunities for water quality improvement could be developed using this concept. Such information could provide opportunities for better management to control stormwater pollution.

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