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Determination of Surrogate Indicators for Phosphorus and Solids in Urban Stormwater: Application of Multivariate Data Analysis Techniques

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Abstract

Solids and phosphorus found within urban stormwater have the potential to cause environmental damage to ecological systems in receiving waters. The evaluation of these pollutants in urban stormwater is usually undertaken by physico-chemical monitoring programs which sample streamflow for laboratory assessment. In this study, data from two such monitoring programs have been examined for the catchment characteristics which influence solids and phosphorus discharge behaviour and the potential for the use of surrogate indicators to predict streamflow concentrations. The study involved partitioning of the components on the basis of the dissolved and particulate fractions. Suspended solids and particulate phosphorus were found to depend on the extent of impervious area within the catchment. Surrogate indicators were evaluated in order to provide supplementary key indicators that can be used for site based measurements with fewer requirements for laboratory based analysis. Investigation of the physical and chemical behaviour of solids and phosphorus by univariate and multivariate data analysis techniques allowed the identification of a number of parameters with the potential for interrelationship. Thus, relationships were developed for suspended and dissolved solids using turbidity and conductivity, and for dissolved and particulate phosphorus using suspended and dissolved solids. These relationships will enhance rapid generation of vital information on spatial and temporal variation of indicator concentrations in urban stormwater.

KEYWORDS: solids; phosphorous; surrogate indicators; urban stormwater, multivariate analysis,

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1. INTRODUCTION

In the context of effective urban resource planning and management, the recognition of the impacts of urbanisation on the water environment is crucial. The significance stems from the fact that water environments are greatly valued in urban areas as environmental, aesthetic and recreational assets. Arguably, it is the water environment which is most adversely affected by urbanisation. Any type of activity in a catchment that changes the existing land use will have a direct impact on its water quality characteristics [1, 2]. In an effort to mitigate the adverse impacts of urbanisation various management measures are being adopted by regulatory authorities. In this regard stormwater quality monitoring forms an important facet of most management strategies. Monitoring is needed to assess the effectiveness of the strategies adopted, to evaluate the impacts of pollutants and to obtain trends in the quality of the stormwater.

However stormwater water quality monitoring gives rise to two issues which act as major constraints in the implementation of effective monitoring programs. Firstly, monitoring exercises can be resource intensive. Consequently, there is an ever growing demand for the identification of parameters which are cost efficient such as field-based measurements to monitor and can act as surrogates for other pollutant indicators. Secondly, the large databases acquired as a result of monitoring studies usually contain many variables which preclude the use of standard univariate statistical methods for the derivation of useful outcomes. Therefore there is a need for the adoption of innovative analytical approaches such as Principal Component Analysis (PCA) and Partial Least Squares (PLS) to systematically and simultaneously interpret the derived data. These analytical methods are commonly being used to supervise and improve industrial processing [3,4]. It is hypothesized that these analytical methods can also aid the development of surrogate indicators, which would in turn enhance the efficiency of predicting pollution related properties from field data rather than using costly laboratory based measurements. Consequently, this would provide increased information on the spatial and temporal variation of indicator concentrations. Additionally, the multi-criteria decision aids of PROMETHEE and GAIA, enabled the further investigation of the data for identifying appropriate surrogate variables. PROMETHEE and GAIA are multivariate decision aids that rank actions according to specific criteria and thresholds. The details of PROMETHEE and GAIA are described elsewhere and outlined in the experimental section of this paper [5,6].

Unfortunately, there is paucity of evidence in research literature relating to the application of multivariate predictive modeling to estimate key water pollution indicators. This paper contributes to the current knowledge base, by reporting on the application of PLS to urban stormwater monitoring, in order: (i) to develop surrogate pollution indicators; (ii) to understand the relationship between the factors (X) and responses (Y); and (iii) to demonstrate the potential of PLS to model and predict parameters impacting on the quality of urban stormwater.

A range of stormwater pollution indicators are commonly measured based on the outcomes to be derived [7,8,9]. In this regard, solids and phosphorus are common parameters which are frequently monitored because of their potential, in high concentrations to cause environmental damage to ecological systems. Solids act as a mobile substrate for the transportation of other pollutants such as heavy metals and hydrocarbons whilst phosphorus is an essential plant nutrient which promotes eutrophication and algal growth in receiving waters [10, 11, 12, 13]. The study provides an insight into predictive models for solids and phosphorus in urban stormwater and a scientific basis for the reduction of the financial and opportunity cost associated with elaborate water quality monitoring studies.

2. MATERIALS AND METHODS

2.1 Study areas

North Lakes Development

The North Lakes urban project is located within the local government area of Pine Rivers Shire on the northern outskirts of Brisbane City, Queensland State, Australia. It is a major residential and commercial precinct proposed to cater for an eventual population of 30,000 persons. The development of the area has been staged with initial construction commencing in the south, in a catchment waterway referred to as Tributary ‘C’. This area is to be the commercial and retail centre of the development as well as catering for a substantial residential population. The Tributary ‘C’ catchment has an area of 314ha. Stormwater treatment requirements for this catchment were instigated by the current environmental legislation and the Local Government’s response to these requirements in the form of a stormwater infrastructure agreement with the developer. The agreement provides for sediment and nutrient control and limits have been defined as target outcomes for the treatment process. The agreement required that the performance of the stormwater treatment facilities be monitored for sediment and nutrient indicators and to assess the behaviour of these indicators.

Cabbage Tree Creek Tributary Catchment

The Cabbage Tree Creek catchment has an area of 4,400ha with the area of interest being the upper reaches within the same local government area of Pine Rivers Shire. This land consists mainly of State Forest on the northern bank and developed residential areas and remnant rural lands on the southern bank. A catchment wide monitoring program instituted by the Local Government in 1996 confirmed that the water quality had deteriorated in the reach of waterway downstream of the Cabrilla Street Tributary. This tributary has an area of 42ha and drains mainly residential properties via an underground piped drainage system along with overland flow in the street system. In the upper reaches of the tributary catchment, some major rural blocks with tree cover still exist and a band of commercial/light industrial premises is located on the boundary. In 1998 the Local Government instituted a detailed monitoring program and the construction of a major stormwater treatment facility on Cabrilla Street Tributary catchment in order to improve the downstream water quality. Additionally, water quality monitoring continued on the main Cabbage Tree Creek catchment.

2.2 Sample Collection

The Cabbage Tree Creek Tributary sampling program undertook the collection of samples from March 2000, whilst the North Lakes Development sampling program commenced in September 1999. Sample collection was performed using both grab and automatic procedures.

Grab procedures involved the collection of samples using a manually operated scoop and the program was scheduled on a seasonal basis or during base flow conditions. Automatic sampling was undertaken using a sampling device which was triggered by the rising runoff depth due to rainfall, and the number of samples was determined by the event magnitude and duration. The times for sample collection were reviewed in relation to the flow conditions and samples which provided representative coverage of the discharge conditions and the flow pattern were selected for laboratory analysis. Minor events involved the collection of only a few samples and generally all the samples were analysed. Major runoff triggered the collection in excess of the sampler 24 bottle capacity and testing was restricted to approximately half of the samples.

2.3 Field and Laboratory Testing

Based on the monitoring objectives, a number of physico-chemical parameters were identified as important key indicators of the runoff water quality from the catchments. The identified indicators in relation to solids and phosphorus are detailed in Table 1. In order to achieve the information objectives, a number of additional physico-chemical indicators were identified to supplement the key indicators and to enhance the understanding of the water quality behaviour. The selection criteria for these indicators are also detailed in Table 1.

The pH and electrical conductivity (EC) of the samples collected were recorded at the point of collection. Turbidity and various phosphorus and solids species were determined in accordance with procedures defined by Standard Methods for the Examination of Water and Wastewater [14]. The testing procedures for solids involved the assessment of the total solids component as well as the compartments based on particle size and origin.

3. MULTIVARIATE ANALYSIS

3.1 Data Pre-treatment

The data obtained was subjected to multivariate analysis using SIMCA-P 10 [15]. Samples taken at different locations and runoff events were treated as objects and the measured parameters were regarded as variables. A typical matrix consisted of 119 objects and up to 18 variables. Thus the matrix has adequate degree of freedom based on any of the common criteria (e.g 16). To minimize skewness of the data caused by missing numbers in the matrix, a constant number was added to all of the variables and the data was log transformed, mean-centred and scaled to unit variance before multivariate modelling

3.2 PROMETHEE and GAIA Procedures

The algorithm and application of PROMETHEE and GAIA procedures is available in the literature [6, 17, 18,19]. PROMETHEE facilitates the ranking or ordering of a number of objects (in this work, the water samples) according to preference and weighting conditions which have been pre-selected by the user and are applied to the variables (e.g. concentration of phosphorus, pH, temperature, conductivity and total dissolved solids etc).

PROMETHEE provides a choice of six preference functions, which supply the mathematical basis for selecting one object in preference to another. In this work the V-shaped function (P), described mathematically below was applied to each stormwater quality indicator.

P = 1 for $d \leq z$ (1)

P = d/z for $0 < d < z$ (2)

P = 0 for $d \geq 0$ (3)

where '*d*' is the difference for each pairwise comparison and '*z*' is the threshold, which was set at the highest value of an indicator in a particular column. Regardless of the function selected, for each indicator, all entries in the data matrix were compared pairwise in all possible combinations by subtraction and this resulted in a difference, '*d*', for each comparison. It was also necessary to specify whether higher or lower variable values are preferred by choosing to 'minimise' or to 'maximise' each variable. Since a lower value indicates a more accepted stormwater quality, each water quality-indicator was considered as a variable and its value 'minimised'. The preference function selected for each variable was used to allocate a preference value for each difference, resulting in a preference table. The sum of preference values for each object gives a value called a 'global preference index', 'π', which indicates the preference of one object over another.

To refine the selection process, positive and negative outranking flows ϕ^+ and ϕ^- respectively, were computed. The former expresses how each object outranks all others whilst the latter indicates how each object is outranked by all the other objects. By applying a set of rules described previously [6,18], a partial ranking order, called PROMETHEE I, and a complete ranking, known as PROMETHEE II were obtained. The former highlights one of the following three possible outcomes, viz: (i) one object is preferred to another; (ii) there is no difference between the two objects; or (iii) the objects cannot be compared. As a rule, comparable objects are joined by one or more arrows, incomparable objects are unconnected by arrows and comparable objects to the left of any action are preferred to that action. PROMETHEE II, on the other hand, eliminates the incomparability based on the value of the net out ranking flow, $\phi = \phi^+ - \phi^-$. Therefore PROMETHEE II appears to be more efficient, but the information obtained from it may be less reliable.

GAIA evaluates and visually displays PROMETHEE results. Like other Principal Component Analysis (PCA) procedures, GAIA reduces a large number of variables into a smaller number of principal components and shows visually how variables relate to each other and the objects. But unlike other typical PCA results, it displays a decision aixs, 'π', which guides the selection of the best performing objects. The interpretation of the GAIA analysis results obtained in this study was undertaken according to the guidelines summarised by Keller et al. [6] and Espinasse et al. [18].

3.3 Principal Component Analysis (PCA)

PCA is an unsupervised projection method that facilitates the extraction of information about the relationships among objects and variables in a data matrix. The projection is obtained by linear combinations of the original variables along orthogonal axes, called principal components and affords new but fewer variable spaces that account for as much of the variation within the data set as possible. The amount of variance of the original data set that is explained by successive principal components (expressed as a percentage) decreases from the first to the last significant principal component. Graphically, the outcome of PCA is usually presented as scores and loadings plots, which reveal the patterns in the objects and variables, respectively. While the 'scores' plot describes the relationships among the objects; the 'loadings' plot describes the relationships of the original variables to one another. When 'scores' and 'loadings' plots are displayed on the same visual representation, a biplot is obtained, which provides additional information about the association between the objects and the variables. In particular, the loadings provide information of the variables that contribute most to the positioning of the objects on the scores plot.

3.4 Partial Least Squares (PLS)

PLS is a regression extension of Principal Component Analysis, which works with two matrices X and Y. Its main objectives are to: (i) well approximate X and Y and (ii) to model the relationship between them. The predictive block (X) is described by X scores, T, while the response block is represented by the Y scores, U. PLS maximises the covariance between T and U, where T and U are defined as shown in the equations given below [15].

$$X = TP^T + E \qquad (4)$$

$$Y = TC^T + F \qquad (5)$$

T is the matrix scores that summarises the X variables, P is a matrix of loadings, C is the matrix weights expressing the correlation between Y and T (X) and E and F are residuals.

PLS is extensively used in multivariate analysis to explain or predict a set of dependent variables from a set of predictors, especially when the number of predictors is large and the number of observations is not so large.

4. RESULTS AND DISCUSSION

Each sampling program had information objectives applicable to the particular waterway and these programs allowed the study objectives to be achieved. Key indicators were selected to achieve monitoring outcomes. The monitoring programs offered a range of information in relation to low flow and high flow conditions. The study involved the investigation of solids and phosphorus concentrations in stormwater runoff using information obtained from two sampling programs. A specific requirement of the monitoring programs was to evaluate surrogate indicators suitable for the prediction of solids and phosphorus concentrations and forms the primary focus of this paper.

The Cabbage Tree Creek catchment was studied principally as an example of a low density residential development. Re-development within the catchment was ongoing during the monitoring period, but the influence on the overall residential density of the catchment was negligible. The catchment therefore represents a stable regime in relation to land use considerations where the discharge of solids and phosphorus are determined by rainfall and hydrological processes. Details of the land use characteristics are given in Table 2.

The North Lakes development, on the other hand, is of mixed use and includes native eucalypt and melaleuca forest, agricultural and grazing rural lands and urban residential development. The residential areas are similar to the Cabbage Tree Creek catchment. The developing areas have been subject to continuous change with the land surface varying from the B horizon after topsoil stripping and excavation to a revegetated surface after road and dwelling construction. The discharge from these areas has been subject to erosion and sediment control measures, both on-site and in stormwater treatment facilities. This would have mitigated the impact from disturbance to some degree. Details of the land use characteristics at the catchment are also given in Table 2.

4.1 Stormwater Quality

Information obtained from the monitoring programs at Cabbage Tree Creek tributary catchment (CT) and North Lakes development (NL) are summarised in Table 3. It is evident from the table that the phosphorus and suspended solids loads are consistently higher for CT when compared to NL. The reasons for this catchment behaviour can be hypothesised as follows. Firstly, NL has a relatively lower percentage of built-up area and hence impervious area when compared CT. As previous research has shown (for example 1, 2, 13), it is the impervious area which is the primary contributor of pollutants to stormwater runoff. Secondly, the stormwater runoff from NL is subjected to erosion and sediment control measures as pointed out above. This in turn would help to reduce the transport of pollutants with stormwater runoff.

4.2 Univariate data analysis

The investigation of surrogate indicators for solids and phosphorus was based on the correlation of a variety of parameters which have the potential to illustrate linked or interrelated performance (Table 4). The indicators were selected based on past research and the relevance to the solids and phosphorus pathways within the catchment and the aquatic environment. The potential interrelationship of various water quality indicators were assessed by combined and individual comparison of data sets. This allowed mathematical relationships to be established and the bounds of those relationships to be defined. Indicator matching was performed by consideration of the various characteristics and movement pathways of solids and phosphorus. This information was considered in relation to the requirements for surrogate indicators to be preferably site assessed. Typical plots are illustrated with plots of suspended solids vs turbidity for grab and automatic samples obtained for the two study areas as given in Figure 1. Selected indicators with potential to match solids and phosphorus concentrations are detailed in Table 5 along with the predicted equations, correlation coefficients and error estimation.

Suspended solids, turbidity, dissolved solids and conductivity coefficients indicate a close correlation between the evaluated linear regression line and the various data sets. The error estimates also support the correlation prediction by indicating a relatively close distribution of data points around the regression line and therefore the various surrogate relationships are considered to provide a suitable predictive tool. Total particulate phosphorus, suspended solids, total dissolved phosphorus and dissolved solids coefficients are at the lower end of reliability with around 50 percent of the variation accounted for by the evaluated regression equation.

The results for individual catchments indicate that the relationships can be either catchment specific or generic. For example, the relationships between phosphorous and its surrogate indicators are specific to particular catchment conditions and could be specific to the particular waterway environment. This may be due to the fact that particles of similar geological origin and form are more likely to demonstrate similar physical characteristics. The recommended relationships for phosphorus and their limitations are detailed in Table 6. On the other hand, the recommended relationships for solids are both generic and catchment specific in application; the suitable equations under each condition depend on the accuracy prediction range required. The relationships considered suitable for waterways within the Pine Rivers Shire and its environs are also detailed in Table 6.

4.3 Multivariate Data Analysis

When the entire data set (N= 119 and K = 18) was analysed by PCA, a total of four components were significant on the basis of cross-validation. 79.9 % of the data variance was accounted for and 49.3% predicted (Q^2X= 0.493). Like other parametric projection methods, PCA are sensitive of outlying objects. Therefore, after the removal of two outliers (ie objects which were outside the T^2 Hotelling ellipse, encloses all objects that lie within 95% confidence level), the remaining objects formed two main clusters corresponding to the catchments studied (Figure 2). Objects from North Lakes had negative PC1 and those from Cabbage Tree had positive PC1 scores. A close examination of the clusters revealed that the objects are further separated according to the sampling methods (ie automatic and grab). These patterns clearly demonstrate the variability in the levels of stormwater quality influencing parameters at different sites. The loadings plot show that total solids, turbidity (TU) and suspended solids (SS) correlate with each other. Similarly, the total volatile solids (TVS), total phosphorus (TP), total phosphorus (TP), conductivity and acid hydrolizable phosphorus (AHP) also correlate (Figure 3). This suggests that parameters in the former group can be used as surrogates for suspended solids while those in the latter may be used as surrogate for phosphorus.

The differences in the results from North Lakes and Cabbage Tree Tributary catchments were examined closely to see whether they reflect fundamental differences in the two catchments. Thus separate models were developed for the two catchments**.** The first two components explained 53.7% of the variance for the North Lakes data (N= 57 and K = 11). The grab samples mainly had negative PC1 scores while the automatic samples had positive PC1 scores. The loadings for SS, TU and TS correlated while the loadings for Temp, Cond, MRP, TDP, AHP and TVS correlate. Only the first component for the Cabbage Tree data (N=61 and K = 11) was significant and this accounted for 40.4% of the data variance.

Next, a Coomans' plot for the two models along with the critical distances is given in Figure 4. It is evident from Figure 4 that with the exception of three North Lake samples (NLG3AU21, NLAU1M, and NLAU1M NLG1Au21) and three Cabbage Tree samples (CTGD23A, CTAD24A and CTG5Au22) all other samples are clearly separated on the basis of their catchments of origin. It is quite clear that the existing land use influences the pollutant concentrations in a catchment. Cabbage Tree Tributary catchment is an existing urban area whilst North Lakes Development is undergoing initial urbanisation only now.

When variables like residential, commercial/industrial allotments, road reserve, forest, park, pervious area and impervious area were excluded ie PCA was performed on the basis of measured indicators only and the data set (N= 119 and K = 11) analyzed by PCA, 50.3 % of the data variance was accounted for and 20.5% predicted (Q^2X= 0.205) . The objects were not cleanly separated on basis of the catchments studied. However, objects from North Lakes mainly had positive PC1 scores and those from Cabbage Tree had negative PC1 scores. The loadings plot showed that total solids, turbidity (TU) and suspended solids (SS) correlated with each other. Similarly, the total volatile solids (TVS), molybdate reactive phosphorus (MRP), total volatile phosphorus (TVS), conductivity and acid hydrolysable (AHP) also correlate. This again suggests that parameters in the former group can be used as surrogates for suspended solids while those in the latter may be used as surrogate for Total phosphorus.

The main conclusions from the above analyses are turbidity and conductivity correlated with suspended solids and phosphorus. The next step was to test whether these can be used as surrogates for solids and phosphorus. As pH has the potential to correlate with phosphorus reaction conditions and sediment precipitation rates it was also evaluated as a surrogate indicator for these pollutants. Thus a predictive PLS model was applied to the combined data. Turbidity, pH and conductivity were modeled as X variables while SS, TS, TP, TDP, TVS MRP and AHP were modeled as Y variables. A two component model was obtained. Its R^2X_{cum} (fraction of sum of squares of the X-block explained) was 0.91; R^2Y_{cum} (fraction of the sum of squares of the Y-block explained) 0.24 and the Q^2_{cum} (fraction of the total variation of the X's that can be predicted by the components) was 0.21. The inner relationship of the Y-block scores denoted as u[1] in SIMCA software against the X-block scores (t[1] (Figure 5) shows a PLS correlation coefficient of 0.77 at 95% confidence level. Thus the relationship between the Y and X blocks is significant at 95% confidence level and the X variables can be used to predict the Y variables.

PROMETHEE and GAIA analyses

PROMETHEE ranking of the combined North Lakes and Cabbage Tree catchments showed that the North Lakes samples were generally better performing than the Cabbage Tree samples. Thus the top ten performing samples are exclusively samples from North Lakes and most of the samples from this catchment are ranked among the best 50% samples (Table 7). On the other hand, most of the Cabbage Tree samples are ranked among the least performing samples although a considerable number of samples from North Lakes are also in the least performing samples. It is evident from Table 4 that Cabbage Tree has higher percentages of impervious and residential areas than North Lakes catchment. These parameters may be influencing the loading of stromwater quality indicators at the catchments. GAIA analysis showed that the most important variables influencing the ranking were, TS, TDP, Cond, pH, TU and SS while the least important were AHP and TVS. Loadings vectors for the SS, TU, TDP and TS correlate, highlighting the potential of TU to serve as a surrogate for SS and

TDP.

5. CONCLUSIONS

The study has derived relationships for suspended solids based on turbidity and for dissolved solids based on conductivity. The results presented suggest that the predictions can be made with a high level of confidence although care must be taken in the application of the equations universally. The preferred approach in the application of surrogate indicators would be to undertake a site based testing program for a short duration to determine waterway specific parameters or to establish the applicability of the equations recommended in this study to the specific situation.

The investigation also determined the relationships between total particulate phosphorus and suspended solids and total dissolved phosphorus and dissolved solids. The results obtained by the univariate method generally agree with those obtained with multivariate data analysis techniques. In addition to its ability to assist the development the relationships, PROMETHEE and GAIA produced ranking information which were used to evaluate other parameters that are important in this type of study. The relationships proposed in this study are specific to particular catchment conditions and could be specific to the particular waterway environment. Nevertheless they have the potential to enhance the acquisition of vital information on urban stormwater quality without the resource intensive laboratory based analysis of key indicators.

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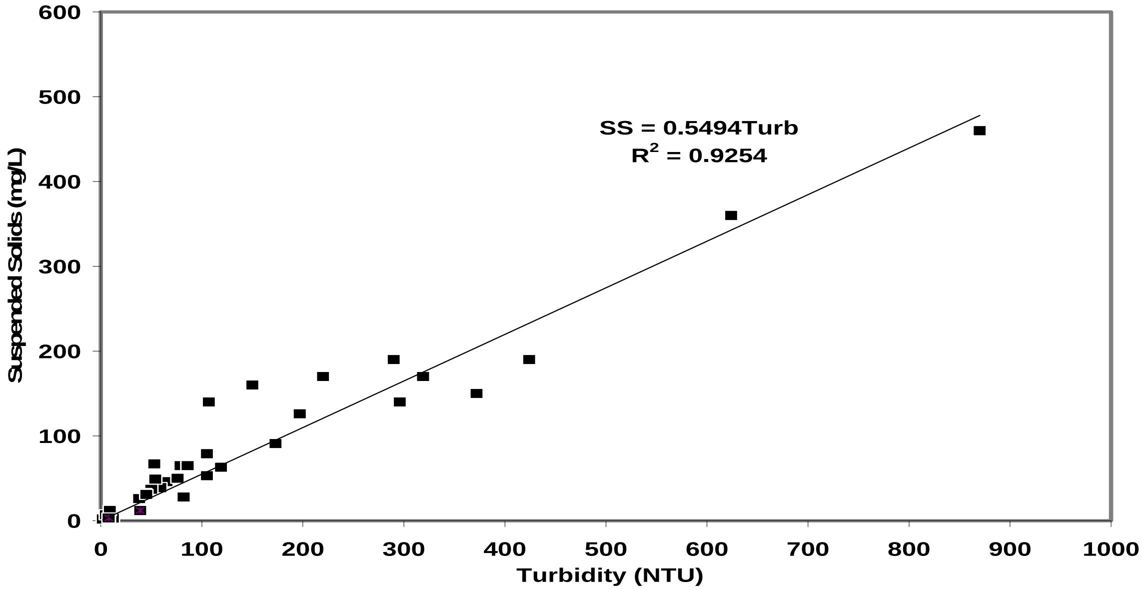
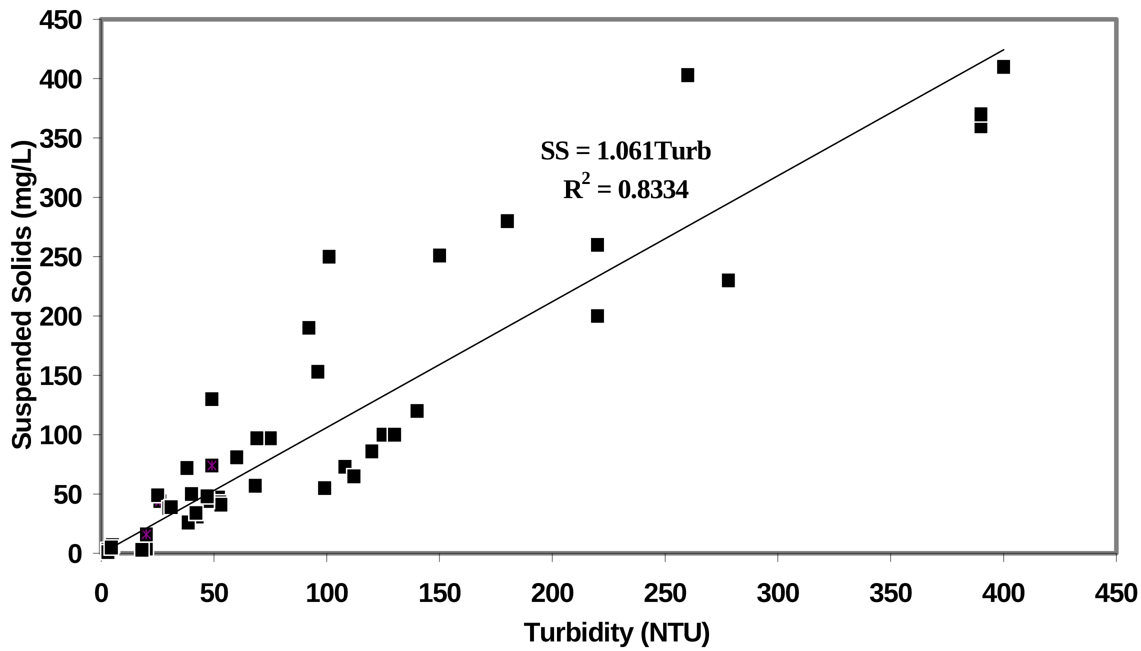
Figure 1: Correlation of suspended solid with turbidity at (a) North Lakes and (b) Cabbage Tree



(a)



(b)

Figure 2: The scores plot for the overall data from Cabbage Tree and North Lakes (Number of objects =117 and number of variables 18). t[1] and t[2] are Principal Components 1 and 2 and they explain 45% and 16% of the data variance respectively.

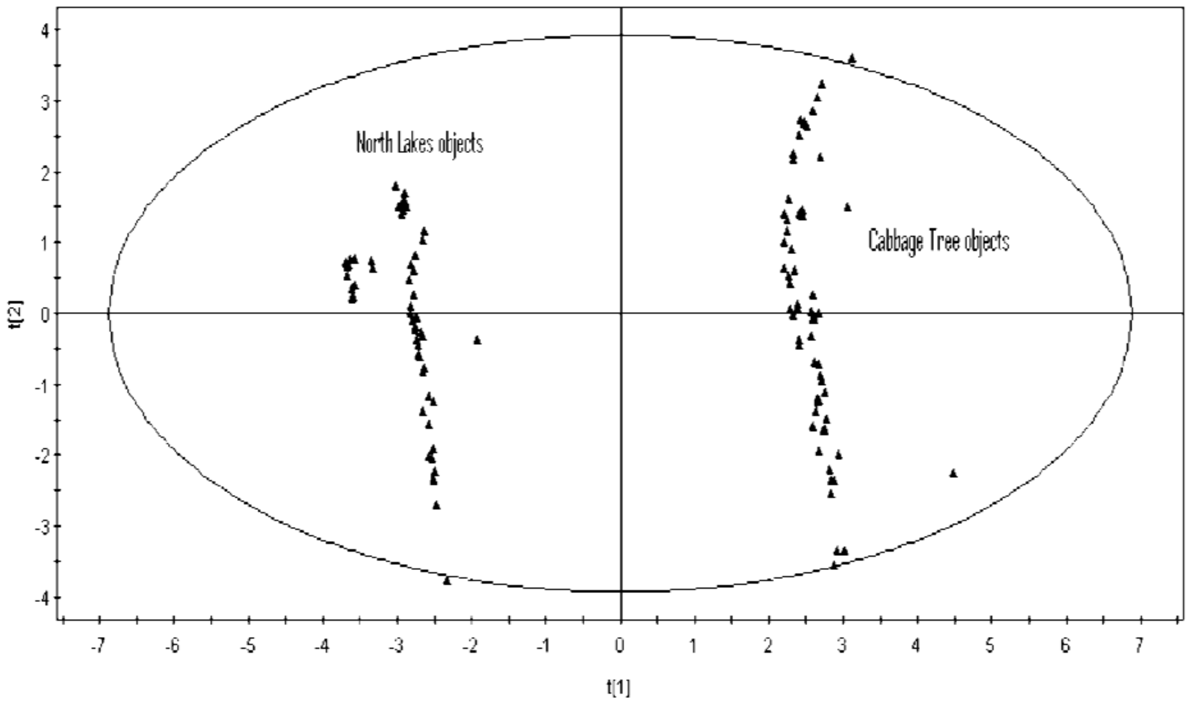


Figure 3: Loadings plot for the overall data from Cabbage Tree and North Lakes (Number of objects =117 and number of variables 18). t[1] and t[2] are Principal Components 1 and 2 and they explain 45% and 16% of the data variance respectively. Properties = land use characteristics of the catchments as described in Table 2.

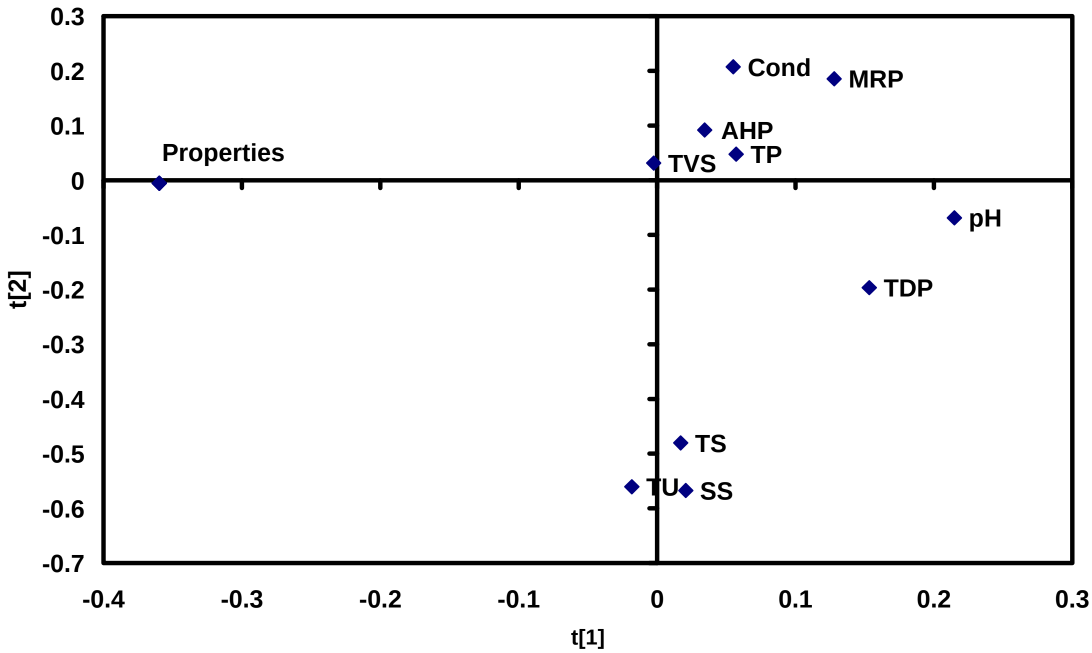


Figure 4: Cooman's plot from the models for Cabbage Tree (y-axis) and North Lakes (x-axis)

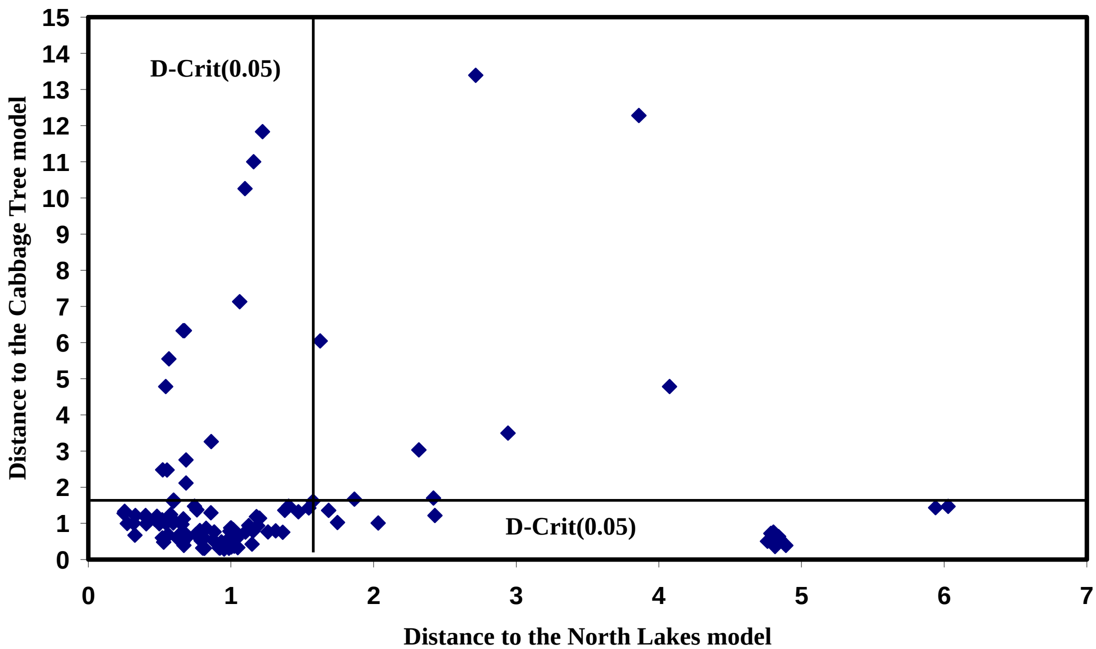


Figure 5: Plot of the PLS first latent variable u[1](Y-block) versus the PLS first latent variable t[1] (X-block) for the entire data.

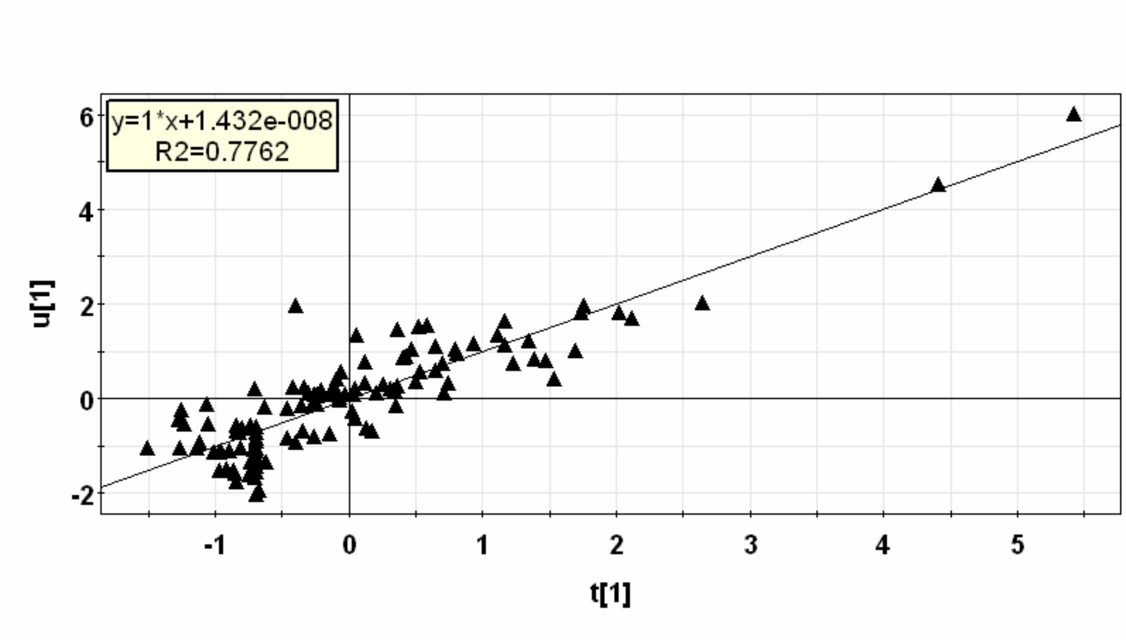


Table 1 Key indicator selection criteria

Group	Parameter	Justification for Selection
Solids	Total solids (TS)	Includes solids from both the particulate and dissolved compartments.
	Suspended solids (SS)	Solids inhibit light penetration and pollutant components attach to fine particulate matter.
	Total volatile solids (TVS)	Identifies the combustible material which is an indicator of organic matter.
	Dissolved volatile solids (DVS)	Identifies the fraction of combustible material associated with particle sizes less than 0.45 micron. This is an indicator of the organic matter in the dissolved fraction.
Phosphorus	Total phosphorus (TP)	Compounds stimulate biological activity.
	Total dissolved phosphorus (TDP)	Identifies the fraction associated with particle sizes less than 0.45 micron and determination of the amount readily available for biological uptake.
	Total molybdate reactive phosphorus (TMRP)	Potentially identifies the fraction in an orthophosphate form. Orthophosphate is the principal inorganic form of phosphorus and is found in rocks and soil.
	Total acid hydrolizable phosphorus (TAHP)	Potentially identifies the fraction in an inorganic form and allows determination of the organic content.
	Dissolved acid hydrolysable phosphorus (DAHP)	Potentially identifies the fraction in an inorganic form contained in particles with size less than 0.45 micron
Physical Characteristics	Conductivity (Cond)	Potential to provide information on dissolved solids.
	Turbidity (TU)	Potential to provide surrogate information on total and suspended solids concentrations.
Chemical Characteristics	pH	Potential for correlation with phosphorus reaction conditions and sediment precipitation rates.

Table 2 Land use characteristics at Cabbage Tree Creek tributary and North Lake Development

Land Use	Classification	Area (ha)		Portion of Catchment (%)	
		Cabbage Tree Creek	North Lakes	Cabbage Tree Creek	North Lakes Development
Function	Residential Allotments	15	20	35	28
	Commercial/ Industrial Allotments	10	-	24	-
	Road Reserve	7	15	17	21
	Forest	5	18	12	26
	Park	5	8	12	11
	Agriculture	-	10	-	14
Surface cover	Pervious Area	29	57	69	80
	Impervious Area	13	14	31	20

Table 3 Summary of catchment discharge quality characteristics

Parameter	Flow Condition	Indicator	Monitoring Station Location: Cabbage Tree Creek Tributary	Monitoring Station Location: North Lakes Development
Concentration Range (mg/L)	High Flow	Total Solids	150 – 500	200 – 500
		Suspended Solids	100 – 400	50 – 200
		Total Phosphorus	0.3 – 0.8	0 – 0.1
		Dissolved Phosphorus	0.1 – 0.3	0 - 0.02
	Low Flow	Total Solids	100 – 300	200 – 400
		Suspended Solids	50 – 200	50 – 100
		Total Phosphorus	0.2 – 0.3	0 – 0.1
		Dissolved Phosphorus	0 – 0.1	0 – 0.03
	Base Flow	Total Solids	400 – 800	200 – 700
		Suspended Solids	5 – 20	0 – 20
		Total Phosphorus	0.2 – 0.3	0 – 0.2
		Dissolved Phosphorus	0 – 0.2	0 – 0.1
Median Concentration (mg/L)	All Flows	Total Solids	320	325
		Suspended Solids	130	13
		Total Phosphorus	0.3	0.1
		Dissolved Phosphorus	0.13	0.02
Load (kg/ha/annum)	All Flows	Total Solids	1787	828
		Suspended Solids	771	133
		Total Phosphorus	1.42	0.157
		Dissolved Phosphorus	0.62	0.056

Table 4 Potential surrogate indicators for solids and phosphorus

Substance	Key indicator	Potential surrogate indicator	Comment on surrogate indicator
Sediment	Suspended Solids	Turbidity	Interference to light transmission by suspended particles.
	Dissolved Solids	Conductivity	Dissolved particles are charged colloids and inorganic salts.
	Total Solids	Turbidity	Interference to light transmission by solid particles.
		Conductivity	Colloidal particles are charged.
Phosphorus	Total Phosphorus	Turbidity	Interference to light transmission by particles with phosphorus attached.
		Conductivity	Phosphorus attached to charged colloidal particles.
		Suspended Solids	Suspended particles provide phosphorus attachment sites.
		Total Solids	Solids provide phosphorus attachment sites.
	Particulate Phosphorus	Turbidity	Interference to light transmission by suspended particles with phosphorus attached.
		Suspended Solids	Suspended particles include a proportion of particulate phosphorus.
	Dissolved Phosphorus	Conductivity	Phosphorus attachment to dissolved charged particles.
		Dissolved Solids	Dissolved solids provide sites for phosphorus attachment.

Table 5 Surrogate indicator relationships

Data Set	Indicator	Surrogate Indicator	Equation	Coefficient of Determination	Standard Error of Estimate	Number of data points
Cabbage Tree Creek	Suspended Solids	Turbidity	SS(mg/L)=1.06 Turb (NTU)	0.83	47.39	46
North Lakes	Suspended Solids	Turbidity	SS(mg/L)=0.55 Turb (NTU)	0.93	28.20	38
All Data	Suspended Solids	Turbidity	SS(mg/L)=0.72Turb (NTU)	0.74	50.46	84
Cabbage Tree Creek	Dissolved Solids	Conductivity	TDS(mg/L)=0.56 Cond (μs/cm)	0.90	55.19	38
North Lakes	Dissolved Solids	Conductivity	TDS(mg/L)=0.65 Cond (μs/cm)	0.77	52.10	38
All Data	Dissolved Solids	Conductivity	DS(mg/L)=0.60Cond (μs/cm)	0.86	56.33	76
Cabbage Tree Creek	Total Particulate Phosphorus	Suspended Solids	TPP(mg/L)=0.0011 SS (mg/L)	0.59	0.09	49
North Lakes	Total Particulate Phosphorus	Suspended Solids	TPP(mg/L)=0.0005 SS (mg/L)	0.52	0.01	36
Cabbage Tree Creek	Total Dissolved Phosphorus	Dissolved Solids	TDP(mg/L)=0.0006 DS (mg/L)	0.55	0.16	49
North Lakes	Total Dissolved Phosphorus	Dissolved Solids	TDP(mg/L)=0.00008 DS (mg/L)	0.46	0.01	36

Table 6 Recommended surrogate relationships for phosphorus and solids

Indicator	Surrogate Indicator	Catchment	Equation	Applicable Range	Comments
Total Dissolved Phosphorus (TDP)	Dissolved Solids (DS)	Cabbage Tree Creek Tributary	TDP(mg/L)= 0.0006 x DS(mg/L)	0 to 500mg/L DS 0 to 0.4mg/L TDP	Applicable to Wetland at Cabbage Tree Creek Confluence
Total Particulate Phosphorus (TPP)	Suspended Solids (SS)	Cabbage Tree Creek Tributary	TPP(mg/L)= 0.0011 x SS(mg/L)	0 to 400mg/L SS 0 to 0.4mg/L TPP	Applicable to Wetland at Cabbage Tree Creek Confluence
Total Dissolved Phosphorus (TDP)	Dissolved Solids (DS)	North Lakes	TDP(mg/L) = 0.00008 x DS(mg/L)	0 to 600mg/L DS 0 to 0.05mg/L TDP	Applicable to Creek Waterways
Total Particulate Phosphorus (TPP)	Suspended Solids (SS)	North Lakes	TPP(mg/L) = 0.0005 x SS(mg/L)	0 to 160mg/L SS 0 to 0.08mg/L TPP	Applicable to Creek Waterways
Suspended Solids (SS)	Turbidity (Tu)	Cabbage Tree and North Lakes	SS (mg/L) = 0.72 x Turb. (NTU)	0 to 400 mg/L SS or up to 600 NTU	Generic relationship applicable to minor freshwater streams in the study area
Dissolved Solids (DS)	Conductivity (Cond)	Cabbage Tree and North Lakes	DS (mg/L) = 0.60 x Cond. (μS/cm)	0 to 600 mg/L DS or up to 1000μS/cm	Generic relationship applicable to minor freshwater streams in the study area

Table 7: Ranking information on the samples

Rank	Sample	Net outranking flow	Catchment
1	A1	0.0709	NL
2	A2	0.0703	NL
3	A12	0.0702	NL
4	A4	0.0692	NL
5	A11	0.0691	NL
6	A6	0.0688	NL
7	A8	0.0671	NL
8	A7	0.0669	NL
9	A3	0.0642	NL
10	A9	0.0635	NL
110	A93	-0.0432	CT
111	A116	-0.0481	CT
112	A35	-0.0487	NL
113	A115	-0.0529	CT
114	A82	-0.0559	CT
115	A44	-0.0.568	NL
116	A57	-0.0662	NL
117	A83	-0.0951	CT
118	A56	-0.1471	NL
119	A52	-0.1943	NL

CT = Cabbage Tree; NL = North Lakes