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Knowledge and Perception of Water Quality Models

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Abstract: Water quality models are tools for simulating the movement of precipitation and pollutant from the surface through pipe and channel networks, storage, treatment units and finally to receiving waters (Brown and Barnwell, 1987). In the present study, an attempt is made to know the level of knowledge and perception on water quality models by potential users. In this context 113 potential users were selected to measure their ability to understand the fundamentals of water quality modeling. The association between knowledge and perception of the potential users with variables such as age, level of education and experience were determined by chi square test and it was found that results are highly associated with knowledge and perception.

Key words: Koggala lagoon, salt water intrusion, water quality, groyne.

Introduction

Mathematical models grow out of equations that determine how a system changes from one state to the next (differential equations) and/or how one variable depends on the value or state of other variables. Mathematical models can be divided into either numerical models or analytical models based on solution technique adopted (Zachary, 1989).

Numerical models are models that use some sort of numerical time stepping procedure to obtain the models behaviour over time. A generated table or graph represents the mathematical solution (William et al., 1992).

Analytical models are mathematical models that have a closed form solution i.e., the solution to the equation used to deserve changes in a system can be expressed as mathematical analytical function.

Statistical models include issues such as statistical characterization of numerical data, estimating the probabilities of future behaviour of a system based on past behaviour, extrapolation/interpolation of data based on some best fit, error estimates of observation, or model generated output or spectral analysis of data (Edelstein-Keshet, 1988).

Water quality modelling involves the prediction of water quality using mathematical simulation techniques. A typical water quality model consists of a collection of formulations representing mechanisms that determine position and momentum of pollutants in a water body (McCutcheon, 1989). The following are few examples of water quality models. There are several water quality simulation models which include Aquatic Ecosystems (AQUATOX); mixing zone model that can be used to assess water quality impacts from point source discharges at surface or sub-surface levels (CORMIX); an enhanced version of water quality analysis simulation program (WASP); and a river and stream quality model (QUAL 2K) which represents a modernized version of the QUAL2E model (Thomann and Muller, 1982).

River water quality model formulations include dissolved oxygen reaeration, alkalinity, carbonaceous deoxygenation, nitrogenous biochemical oxygen demand studies or other related parameters (Seng Lung and Larson, 1995).

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This paper describes a method of measuring water quality perceptions. Expert knowledge was captured and developed into a model, which characterizes the potentially hazardous processes inherent in the supply of drinking water. The methodology is based on the psychological framework of 'mental modelling' and compares differences in knowledge between water industry experts and lay people. Qualitative studies revealed striking differences between the two groups. These findings are being used to evaluate and improve communication between water companies and their customers about the risks associated with drinking water (Owen et al., 1999).

After identification of sensitive model parameters through sensitivity analysis and their estimation through laboratory and field studies, the field analysis results are predicted and compared by calibration and validation of the model (Les McNamara, 2004). The model study uses include examination and verification for implementation of environmental impact assessment evaluation (Himesh et al., 2000).

Water quality modelling for decision-making occurs at a disciplinary divide between science and management. Workers in science and management operate in fields that traditionally have different objectives, priorities and expectations (Peter, 1998). These differences can create barriers in the effective use of scientific models by watershed managers. This study reports on two methods used to overcome barriers that inhibit the successful use of models in watershed planning and decision-making. The first is the use of generic evaluation criteria that both scientists and managers may use to review water quality models from a decision-maker's perspective. Second is an activity in which water quality modelling is embedded into a water management organization's planning and management processes.

When considering ways of achieving water quality improvements, including reductions in nutrient loads to streams, watershed managers often turn to computer based mathematical models (Caminiti, 2002). Watershed simulation and prediction models are useful to scientists because they help them advance scientific knowledge by testing their understanding of processes in natural systems. For decision-makers, models hold the promise of allowing them to predict the environmental impact of human activities and evaluate or prioritize management interventions (Rizzoli and Young, 1997). Decision-makers expect that by undertaking simulation- and prediction-based scientific analysis of a decision-making problem, they will reduce the uncertainty associated with the decision-making process.

Some examples of predictive models that are capable of modelling nonpoint sources of pollution, and have been used in SCA watersheds, include CMSS (Cuddy, 1994), ANSWERS (Armstrong et al., 1995), HSPF (AWT, 2000), IQQM (Young et al., 2000), Ann AGNPS (AWT, 2003). A brief overview of most of these models is found in Letcher et al. (1999).

This study reports the development of generic evaluation criteria that will enable SCA decision-makers to assess the utility of non-point source watershed models in the planning and decision-making process. A related activity is a pilot project in which a model will be integrated or 'embedded' into a planning process. Through the embedding activity, researchers and the SCA hope to be able to identify and overcome some of the institutional, technical and ideological barriers between science and management that inhibit the efficient and effective conversion of scientific knowledge into watershed management decisions and actions.

The access to, use of, and participation in decisions on improved water supply in the Volta basin of Ghana, is important since it is one of the first countries to introduce a community-based approach to rural water supply on a large scale. While 71 percent of the households interviewed have access to improved water, 43 percent of these continue to use unsafe sources as their main domestic water source. Our results indicate that quality perceptions and opportunity costs play an important role in households' choice of water source. The effect of prices and income levels on this choice differs according to the pricing system used (Stefanie Engel, 2005).

Given that supply characteristics such as the location and pricing system affect household decisions to use the improved source, households may try to influence these characteristics in their favour during the community decision-making process for the improved source. However, less than 40 percent of the households interviewed participated in decisions on location or technology participation.

The results indicate that quality perceptions play an important role in households' choice of water source. Specifically, households that consider the unimproved source to be of bad quality are significantly more likely to choose the improved source as their main water source. Differences in quality perceptions across households can be either due to actual quality differences or to differences in awareness. If the latter is the case, there is an important role for education and awareness building. More research is therefore needed on the underlying causes of the variation in quality perceptions (Stefanie Engel, 2005).

Hence, in connection with measuring of water quality available in various water sources like stream and river water and ground water models are very essential. In this connection and to know the awareness and understanding of various modelling basic concepts the study of knowledge and perception level identification (Hoef et al., 2006).

Storm water impoundments are one of many types of best management practices (BMP) designed and implemented to regulate water quantity and improve the quality of runoff from urban areas. Studies of water quality in urban impoundments have indicated that conventional designs are, however, not very effective at removing solids and associated pollutants. Accordingly, many urban impoundments are being re-designed to improve downstream water quality. However, few studies have systematically monitored and quantified post-design water quality improvements of urban impoundments. The changes in water quality performance of an urban impoundment (Columbia Lake) in Waterloo, Ontario resulted from redesign of the lake for the pre-design period (2003 and 2004) and the post-design period (2006 and 2007). To achieve this goal, four years of water quality data was collected at the inlet and outlet of Columbia Lake as part of the Laurel Creed Monitoring Programme. Water chemistry parameters included total Phosphorus (TP), soluble reactive phosphorus (SRP), suspended solids (SS), dissolved oxygen (DO), pH and total dissolved solids (TDS) (Han Yu Waterloo, 2006).

Multiple comparisons in Univariate Analysis of Variance indicated that the original model predictions were significantly different from the 83 measurements ($p = 0.021$ at 0.05 significant level), while no significant difference was observed between the adjusted model predictions and the measured outflow TP concentrations.

Based on the above literature studies the following objectives are necessary for our present study. They are listed below.

Objectives

(i) To measure the knowledge and the perceptional ability of the potential users.
(ii) To emphasize between the knowledge level and independent variables.
(iii) To study the association between level of perception/potential users and independent variables.

Methodology

Measures of Knowledge and Perception

The knowledge and perception levels of potential users of water quality models were measured by framing questionnaire on knowledge consisting of 10 questions (on basic ideas of water quality model like definitions, types and their applications) with multiple answers and for each answer are given scores to measure the knowledge levels of the users. Similarly the perception level was measured by framing 17 questions (on performance, aspects, accuracy, ease of data analysis, calibration, validation and prediction aspects of water quality modeling) and their scores were calculated.

Measurement of Independent Variables

Further knowledge and perception level grouped into three categories—low, medium and high based on mean and standard deviation scores—are given in Table 1.

Table 1: Measurements of independent variables

Category	*Criteria*
Low	$\bar{X} - \frac{1}{2}, SD$
Medium	$\bar{X} - \frac{1}{2}, SD$ to $\bar{X} + \frac{1}{2}, SD$
High	More than $\bar{X} + \frac{1}{2}, SD$

$\bar{X}$ = Mean values of total, SD = Standard deviation

Statistical Tool

In order to test association between the level of knowledge and perception of potential users with their age, level of education and experience Chi-square test was used. Chi-square is one of the most non-parametric statistical tests used most commonly in social and biological sciences (Macdonald, 1990).

Chi-square (χ^2) procedures measure the differences between observed (O) and expected (E) frequencies of nominal variables, in which subjects are grouped in categories or cells. There are two basic types of chi-square analysis, the goodness of fit test, used with a single nominal variable, and the test of independence, used with two nominal variables. Both types of chi-square use the same formula. The measure of the amount of discrepancy between the observed values and expected values, is always greater than zero, and is calculated with the following formula:

$$\chi^2 = \sum \frac{(O - E)^2}{E} \quad (1)$$

where the letter O represents the observed frequency—the actual count—in a given cell. The letter E represents the expected frequency—a theoretical count—for that cell. The more O differs from E, the larger χ^2 is. When χ^2 exceeds the appropriate critical value, it is declared significant.

The goodness of fit test is applied to a single nominal variable and determines whether the frequencies we observe in k categories fit what we might expect. Some call this procedure the Badness of Fit Test because a significant χ^2 value means that observed counts do not fit what we expect. The Goodness of Fit Test is applied with equal or proportional expected frequencies (EE, PE).

Testing the Chi Square Value

The computed value of χ^2 is compared to the appropriate critical value. The critical value is found in the Chi-square Table. Using α and df, locate the critical value from the table. For the Goodness of Fit Test, the degrees of freedom (df) equal the number of categories (k) minus one ($df = k - 1$). We determined (df) for the test of independence by the formula $df = (r - 1)(c - 1)$, where r is number of rows and c = number of columns in the contingency table.

Strength of Association

The chi-square test of independence tells you whether two nominal variables are related or not. It does not tell you how strong that relationship is. When you produce a significant chi-square (two variables are related), it is natural to wonder how strong the relationship is. Two procedures can provide such measures: the Contingency Coefficient (C) and Cramer's phi (ϕ_C).

Contingency Coefficient: The contingency coefficient (C) computes a "Pearson r" type correlation coefficient from a computed value. The formula is

$$C = \sqrt{\frac{\chi^2}{n + \chi^2}} \tag{1}$$

Cramer's phi (ϕ_C): While the contingency coefficient is popular, a better alternative to the measurement of association in a contingency table is Cramer's phi. The advantage of this procedure is that it ranges from 0 to 1 and is independent of the size of the table. Cramer's phi is defined as

$$\phi_c = \sqrt{\frac{\chi^2}{N(k-1)}} \tag{2}$$

Result and Discussions

Similarly, the independent variables such as age, level of education and experience of potential users were grouped into different categories as follows.

The responses of potential users of the water quality models collected through questionnaire and number of users and their percentage distributions are presented in the following tables.

The distribution of number of potential users according to the age is presented in Table 2.

Table 2: Age of potential users

Category of users	*Variable*		
	Age, in years	*No. of individuals*	*Percentage*
Young	< 30	76	67
Middle	30-50	33	29
Old	> 50	04	04

Table 2 indicates that maximum number of water model quality users is found in the age group of youngsters that is less than 30 years of age followed by middle age group.

The study of knowledge on water quality models and questionnaire results show that the number of potential users of the model is youngsters. It is because the youngsters have an exposure to the concerned subjects and they have working knowledge over those specifics. The percentage of the youth involvement in responding to the questionnaire is more because of the reason that they pursue higher studies like postgraduate and doctoral programme. Hence, the highest percentage is recorded.

As far as middle-aged group is concerned they have less awareness of water quality models. They do not have much exposure with the water quality models; moreover most of them may be employed and away from the mathematical model application fields. The old age people expressed their views very clearly that they have little knowledge on the models. It is because they did not have the awareness in their period about the water quality models.

The distribution of respondents according to their education level is presented in Table 3.

Table 3: Education level of respondents

Category	*Variable*		
	Education	*No. of individuals*	*Percentage*
Under graduate	B.E.	71	63
Master degree	M.E.	38	34
Doctoral degree	PhD	04	3.0

From Table 3, it is evident that more number of potential users of water quality models is engineering graduates followed by masters degree in engineering.

As far as the respondents details are concerned, the under graduate potential users of water quality models are more in number and in percentage. It is mainly because of the enthusiasm, drive and determination in the youth. They respond with positive spirit as they are in budding stage of learning water quality models and they naturally develop curiosity in that field. However, quite contradictorily as they grow more in knowledge the respondents of masters degree participate less in water quality models. Perhaps it is due to the shift in their vision or circumstantial fluctuations in their life. As the table shows, it is evident that the respondents of doctoral degree are very less. Perhaps it is also because their priorities and preferences might have undergone a change. Hence, their contribution to water quality models is less.

The distribution of potential users of water quality models according to their experience is presented in Table 4.

Table 4: Experiences of potential users

Experience in years	*No. of individuals*	*Percentage*
< 5	80	70
5-10	04	04
> 10	29	26

From Table 4, it is evident that, more number of potential users belong to less than 5 years of experience followed by more than 10 years of experience. The people with more professional experience around 10 or more years also have considerable knowledge. It is because as they grow in their professional experience, they might have got moderate knowledge on mathematical models.

As per Table 4, the people with little professional experience have more knowledge. It is simply because the fresh graduates or post graduates have tremendous knowledge about the models. The people with some professional experience around 5 or 10 years have more experience that is professional but knowledge on models not so significant. The table shows the actual conditions of various experiences of potential users.

Association between knowledge and perception of potential users of water quality models and their age, level of education and experience is considered. The associations between knowledge and age, level of education and experience of the potential users are presented in Table 5. Age, level of education and experience were studied using Chi-Square analysis and results are presented in Tables 5 and 6.

The final results were analyzed using ratings (different) by considering hypothesis:

H_0: Knowledge and age qualification and experience are independent; that is no relation.

H_i: Knowledge, age, qualification and experience are dependent; that is there is relation between each of the above.

Table 5: Association between knowledge and variables

Variables	$\aleph^2$
Age	2.058^{NS}
Level of education	3.023^{NS}
Experience	1.883^{NS}

NS: Non-significant

$\aleph^2 = 9.88$ at 5% degrees of freedom = 4

$\aleph^2 = 13.27$ at 1% degrees of freedom = 4

So reject H_0 because, $\aleph^2$ calculated > $\aleph^2$ from table

It is hypothesized that the level of knowledge of the potential users is independent of their age, level of education and experience. In order to test the above hypothesis chi square test is used and results are presented in Table 5. Result indicates that the hypothesis is non-significant. It means that there is association between the age, level of education and experience with the knowledge level of the potential users.

Similarly, association between level of perception of potential users, with their age, level of education and experience is presented in Table 6.

Table 6: Level of perception

Variables	$\aleph^2$
Age	0.611
Level of education	3.121
Experience	6.030

In this case also, the hypothesis is that the level of perception of the potential users is independent of their age, level of education and experience. The above statement is tested using chi-square test and results shown in Table 6. It was found that the test is non-significant. It means that there is an association between the age, level of education and experience with the perception level of the potential users.

There is a great disparity as far as the perception is concerned. The perception level of the respondents of a particular differs with the level of education. Similarly, the perception varies from level of education to their experience. This is mainly because of the lack of awareness and curiosity of water quality models. Even though there are perceptional differences, it is not significant. Hence, proper awareness is to be created in the minds of the people of all strata.

Conclusion

A study on water quality models was done to know the level of knowledge and perception of potential users. Samples of 113 users were selected at random for the study. The chi square test was used to measure the association between the level of knowledge and perception on water quality models by potential users with their age, level of education and number of years experience. The result indicates that there is an association between level of knowledge and perception of potential users with independent variables.

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