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Sensitivity Analysis of Simulated Dissolved Oxygen in Bahr Hadus Drain, Egypt

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Abstract

Modeling is an essential tool in decision making in water quality assessment. Uncertainty in model parameters can have a profound impact on the results. Failure to accommodate parameter uncertainty undermines the ability to make informed decisions regarding water quality issues. In this paper, we illustrate the use of the Monte Carlo simulation method to propagate the uncertainty from model input to model output. The methodology is illustrated on a Streeter–Phelps prototype model, where basic uncertainty in aeration parameter, biochemical oxygen demand decay parameter, water temperature, and initial concentrations of dissolved oxygen and biochemical oxygen demand is considered. The effect of the basic input parameter uncertainty on the simulated dissolved oxygen in a stream at a specific point in time is assessed by assigning prescribed probability density functions to these parameters. The sensitivity of the simulated dissolved oxygen concentration with respect to the uncertainty in the basic input parameters is evaluated using the Pearson rank correlation coefficient. The proposed model is applied to Bahr-Hadus drain which carries irrigation return flows that contain loads of municipal wastewater from treatment plants, and untreated wastewater from villages.

Keywords: Water quality, Probability, Sensitivity, Monte Carlo, Simulation, modeling

Introduction

Water is the most valuable natural resource utilized by man for his essential needs. This is because only 2.7% of the total quantity of water on earth is freshwater, and 90% of freshwater is frozen in the North and South Poles in a form that is not available to human beings. Freshwater in the entire world rivers are about 48,000 km3, of which only 4,000 km3/yr are used (El-Shazli, 2004). Groundwater is estimated at 22 million km3. The survival of the human species depends on the proper use and management of this natural resource. Water quality, water pollution control and environmental protection are the main issues involved in water resources management. Currently, deteriorating water quality is a serious threat to countries with water scarcity. It does not only diminish the country's chance of sustainable development but it also threatens public health with spreading infectious diseases.

Egypt is among many countries faced with water scarcity by the year 2025 due to the rapidly increasing population (Engelman and Le Roy, 1993). Therefore, plans and strategies are made in a way that guarantees the proper management of existing water resources in order to ensure their sustainability through the years. This matter does not only include water conservation as a primary issue, but it also entails water quality, and pollution prevention as a major consideration. The problem here is that available data on water quality is always inadequate which causes deficiency in the modeling processes. Therefore, uncertainty analysis is encouraged since it allows the incorporation of parameter uncertainty in the model setting.

In Egypt, the water use per individual is around 859 m3/yr for the year 2000 compared to the minimum demand required per individual (1300 m3). Therefore, Egypt has opted to reuse part of its drainage water to compensate for the deficiency in supply. Drains either discharge to the Northern Lakes or get mixed with fresh water from canals for irrigation purposes. The drainage system is susceptible to pollution with untreated or partially treated wastewater carrying organic and inorganic materials that affect public health and lowers the amount of dissolved oxygen in the receiving streams (Abu-Zeid, 1997). Thus, it is deemed necessary to check the quality of the reused water in order to guarantee its compliance with allowable standards.

In 1980, a permanent network for routine monitoring of the drainage system was established in Egypt. The network has been upgraded over the years to provide reliable measurements on level gauges, electrical conductivity, velocity, temperature and salinity of water as shown in Figure 1. Later on, the growing concern over water quality in drainage water called for the measurement of other variables (heavy metals, organic matters and microbiology….etc). Samples were taken monthly at locations where low water quality conditions prevail.

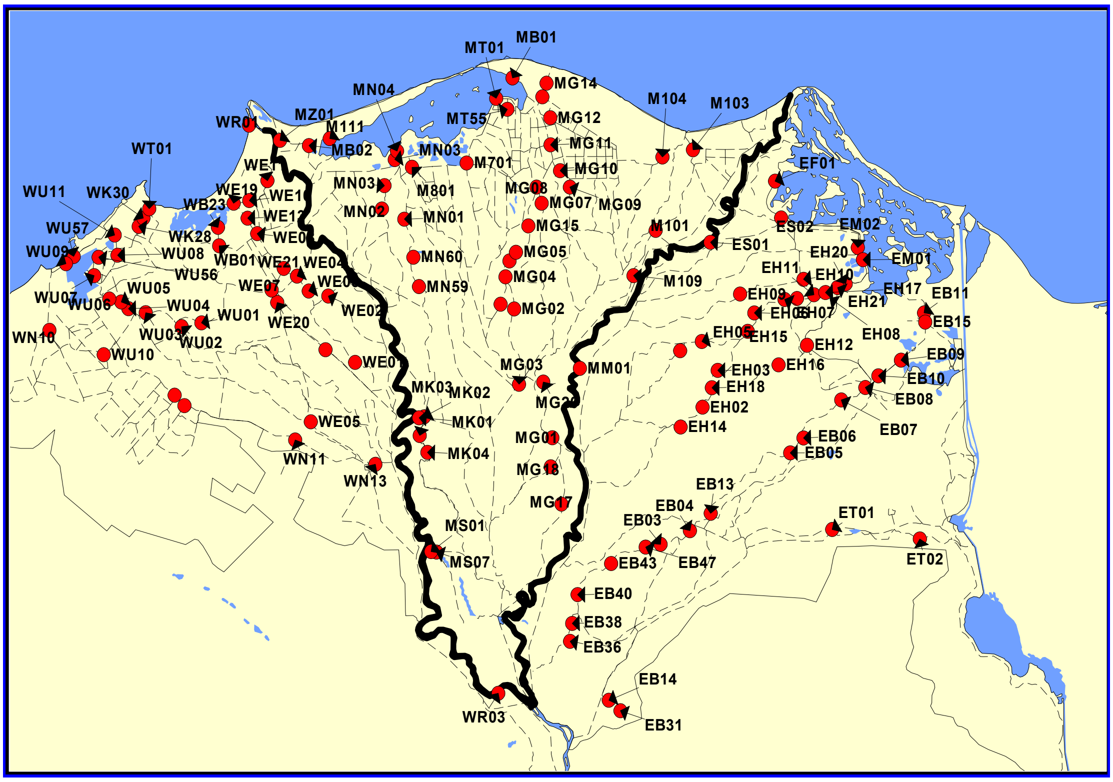


Figure 1. Monitoring sites in the drainage system in Nile Delta

Mathematical modeling is an indispensable tool to predict the possible impacts of pollution sources on water quality in streams. However, uncertainty related to input variables, model parameters, and model structure may render the results of mathematical models inaccurate. In this study we use the Monte Carlo simulation (MCS) method to incorporate the effects of model parameter uncertainty. This method involves random sampling from the distribution of inputs and carrying out successive model runs until a statistically significant distribution of the output(s) is obtained. A wide range of literature about the methodology and its applications is available in (Whitehead and Young, 1979; Rubenstein, 1981; Doll and Freeman, 1986; Sobol, 1994; Fishman, 1996; Kalos and Whilock, 1996). In this work, the uncertainty is propagated from the input to the output of a Streeter-Phelps prototype model.

Methodology

The dissolved oxygen variation in a stream is given by the Streeter-Phelps equation (Streeter and Phelps 1925), given by:

$$D(t)=D_0\exp(-K_a t)+\frac{L_0K_d}{K_a-K_d}[\exp(-K_d t)-\exp(-K_a t)] \qquad (1)$$

where D(t) and D_0 are the dissolved oxygen (D.O.) deficit at times t and 0, respectively; L_0 is the initial biochemical oxygen demand (BOD) concentration, K_a is the reaeration parameter, and K_d is the BOD decay parameter. The D.O. concentration is given by:

$$C(t) = C_s - D(t) \tag{2}$$

where C_s is the D.O. saturation concentration. The temperature dependence of the parameters K_a, K_d, and C_s is given by the following expressions:

$$C_s = 14.652 - 0.41022\,T + 0.007991\,T^2 - 0.000077774\,T^3 \tag{3}$$

$$K_a(T) = K_a(20)\,\theta_1^{(T-20)} \tag{4}$$

$$K_d(T) = K_d(20)\,\theta_2^{(T-20)} \tag{5}$$

where K(T) and K(20) is the reaction rate at temperatures T, and 20°C, respectively, and θ_1 and θ_2 are constants.

Application

The proposed model is applied to Bahr-Hadus drain which carries irrigation return flows that contain municipal wastewater from treatment plants, and untreated domestic wastewater from villages. These sources cause major pollution to drains which reflects onto the quality of fresh water in the streams fed by reused drainage water. Water quality of Bahr-Hadus is of special importance, as part of its water is diverted to the El-Salam canal to irrigate newly reclaimed land with blended drainage water. The drain is also reused unofficially due to a shortage in fresh irrigation water. The remainder is discharged into Lake Manzala as shown in Figure 2. Pumping stations like EH06, EH10, EH12 discharge their water into the drain. A branch of Bahr Hadus discharges its water into the main Hadus at EH17. There is a sampling program along the drain that monitors dissolved Oxygen (D.O.), biochemical oxygen demand (BOD), and Total Dissolved Solids (TDS) to indicate the influence of organic matter on the quality of water in a timely fashion.

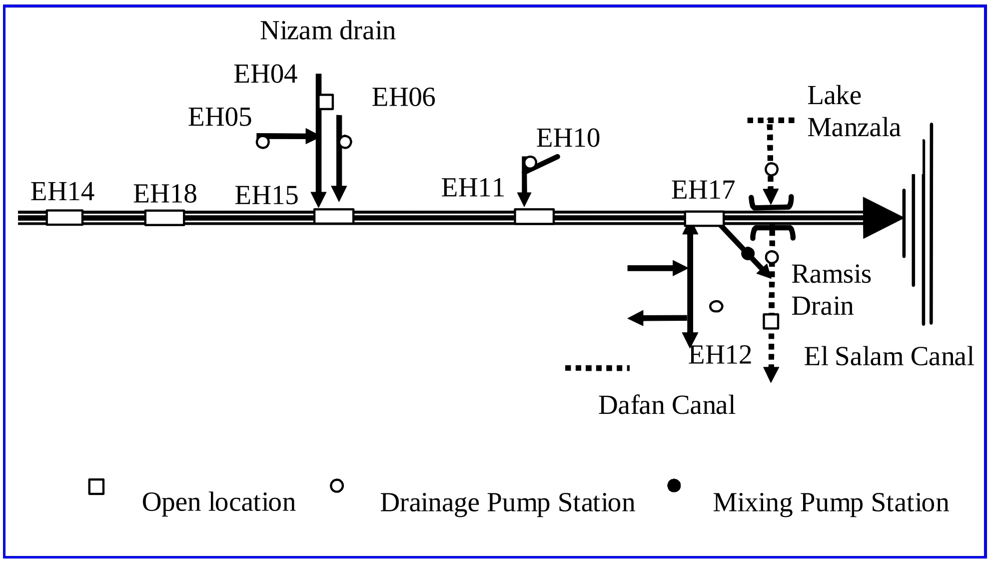


Figure 2. Layout of Bahr Hadus drainage system

To account for the input uncertainty, input variables were considered random variables with given probability distributions. Data on discharge, temperature, BOD, and D.O. were collected on monthly basis from1997 till 2004 at specific locations such as EH15, EH11 and EH17 (Figure 3). The data for stations EH15 and EH11 were used to determine the probability distribution for the parameters required for the model based on the empirical moments test and the Chi Squared test (

Table 1). (Gardiner, 1983; El-Beshry and Ali, 2007). The data were found to fit either a normal (N) or a lognormal distribution (L).

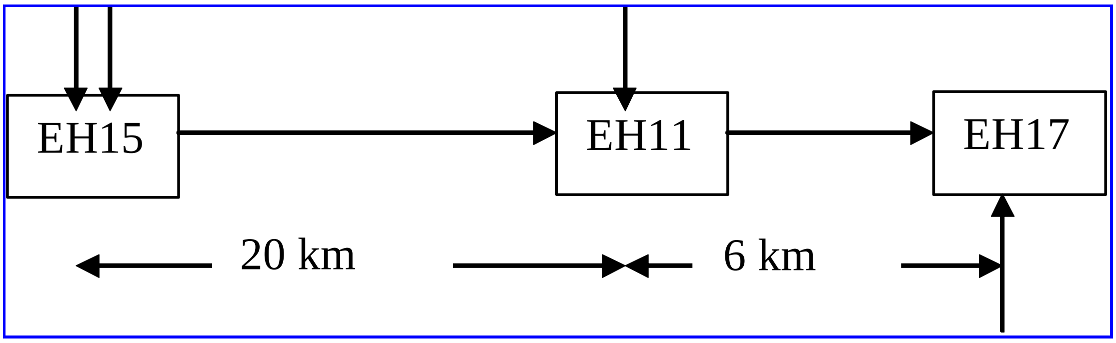


Figure 3. Simplified schematic of the reach of interest to this work

Table 1. Probability distribution of parameters for EH15 and EH11

Parameter	Units	Distribution
	EH 15	
$K_d(20)$	day^{-1}	**N(0.331,0.1)**
$K_a(20)$	day^{-1}	**N(0.69,0.2)**
L_0	mg/l	**N(3.98159,0.722805)**
D_0	mg/l	**N(0.748897,0.684001)**
T	^oC	**L(23.0373,5.3969)**
	EH 11	
$K_d(20)$	day^{-1}	**N(0.331,0.1)**
$K_a(20)$	day^{-1}	**N(0.69,0.2)**
L_0	mg/l	**N(3.7959,0.934069)**
D_0	mg/l	**N(0.919501,0.498213)**
T	**^oC**	**L(22.5369,5.2286)**

Results

We are interested in the dissolved oxygen level at EH17. Due to the uncertainty in the input variables, the dissolved oxygen level is not a single value, but rather a probability distribution. Five hundred thousand (500,000) Monte Carlo simulations were carried out using the distributions in Table 1.The histogram of the simulated dissolved oxygen level is demonstrated in Figure 4. The quantile-quantile (QQ) plot indicates that the dissolved oxygen almost coincides with the line which indicates normality in figure5.

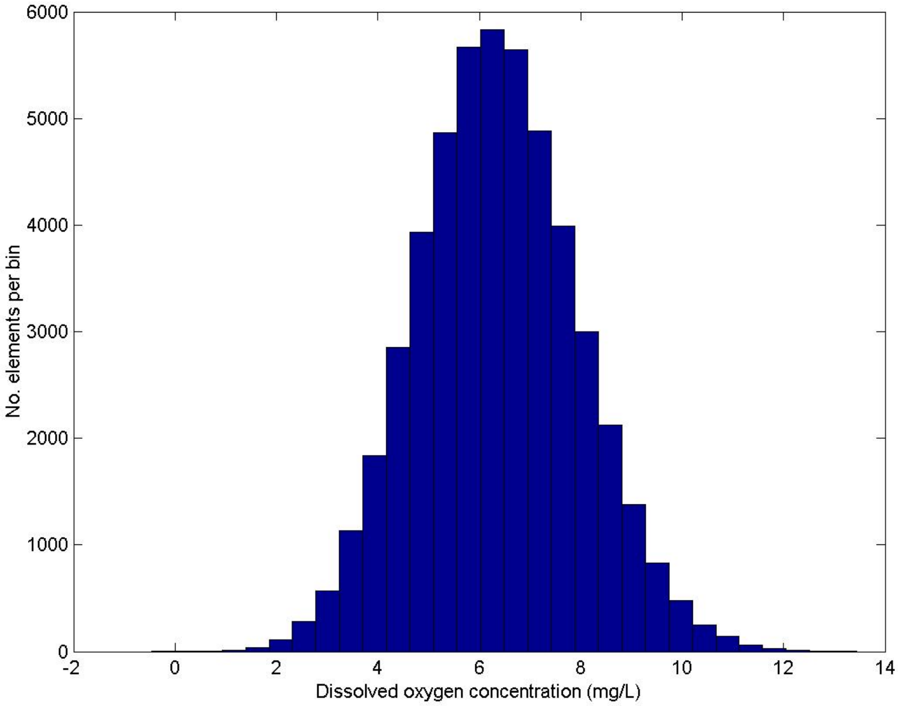


Figure 4. Histogram of D.O. at EH17

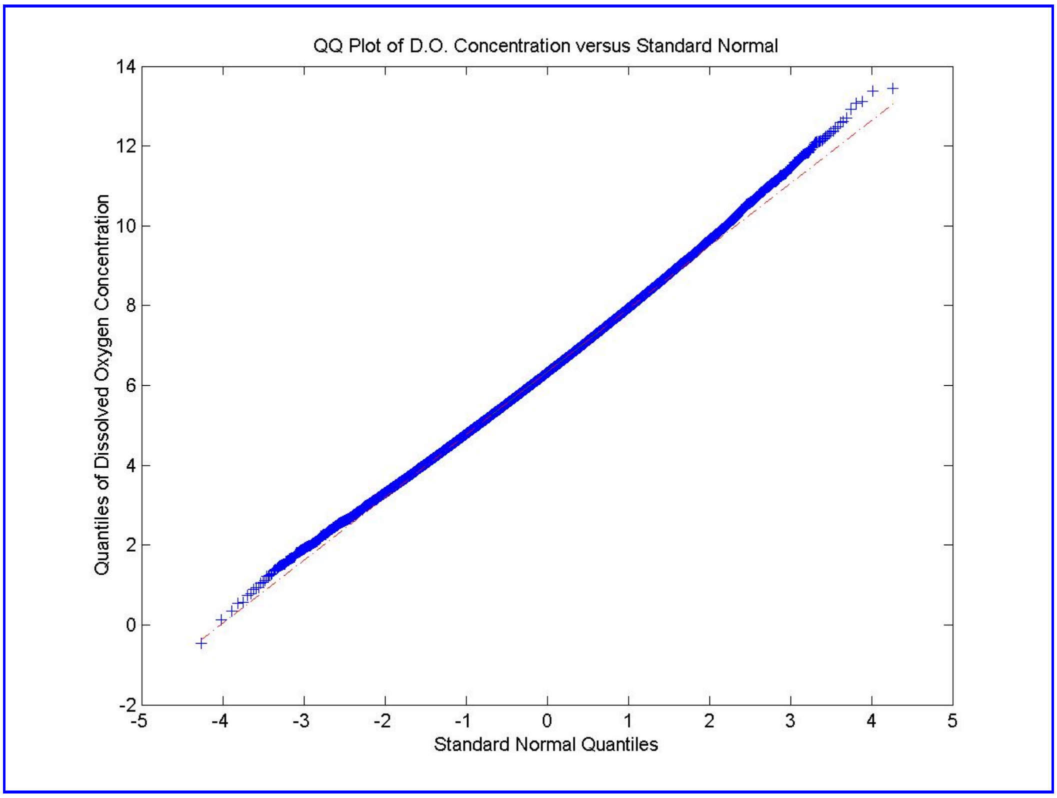
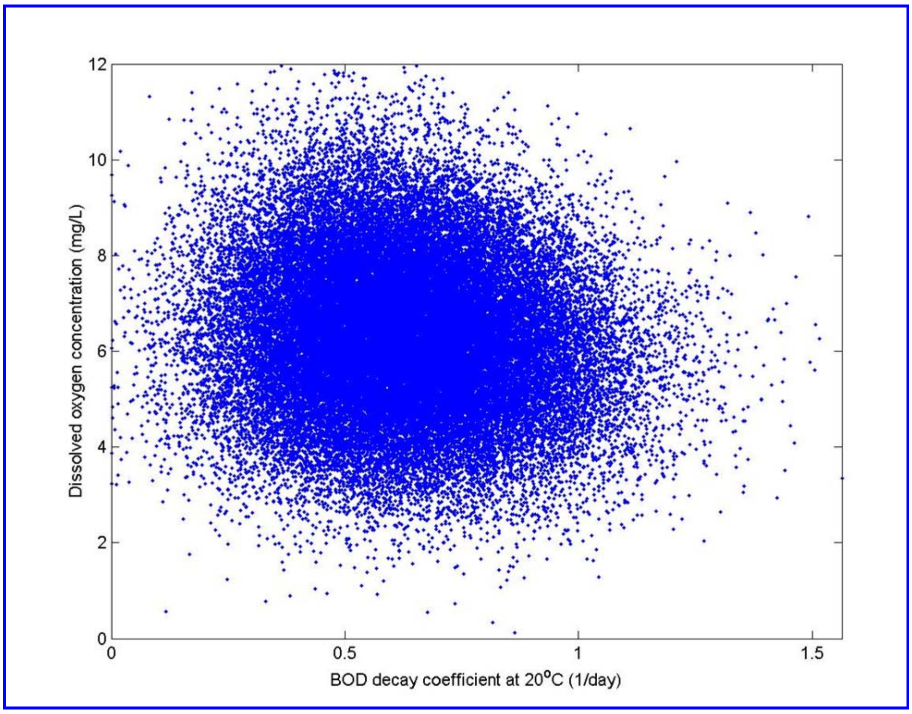


Figure 5. QQ plot of dissolved oxygen at EH17

The sensitivity of the simulated dissolved oxygen with respect to the uncertainty in the input random variables is estimated using the Pearson rank correlation coefficients. At point EH17, the random variables whose uncertainty affect the probabilistic dissolved oxygen are shown below. For instance, the sensitivity of the dissolved oxygen is highest to the basic uncertainty in oxygen deficit, i.e., if the initial dissolved oxygen deficit were to increase, then the dissolved oxygen deficit at the simulation time increases, which would decrease the dissolved oxygen concentration; resulting in the negative rank correlation coefficient and the inverse relation shown in Figure 6.

The initial BOD load indicates a Pearson rank correlation coefficient that is neutral. illustrates a constant dissolved oxygen concentration with an increase in the initial BOD load. This could be attributed to discrepancy in measurements.



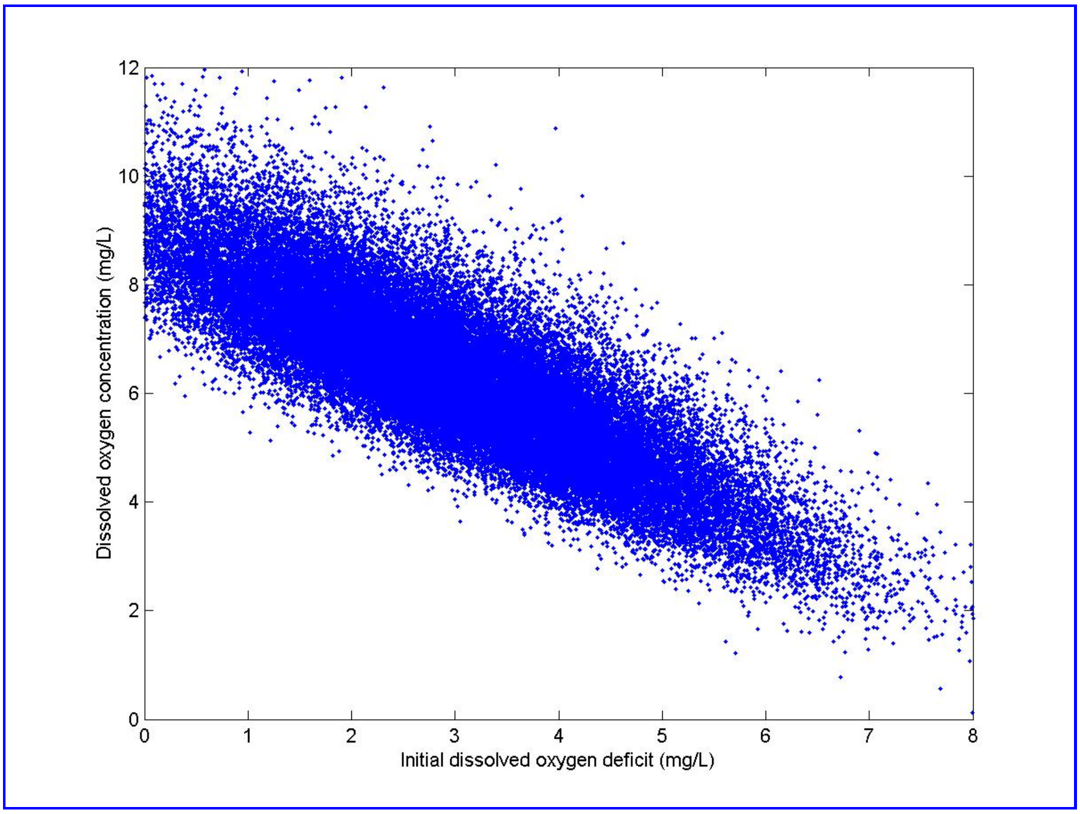


Figure 6. Scatter plot of simulated dissolved oxygen concentration versus initial oxygen deficit

Figure 8 indicates that the dissolved oxygen concentration decreases with an increase in BOD decay coefficient because the organic waste is biodegraded especially at the beginning of the process where oxygen is being used up. With time the oxygen concentration picks up when the natural conditions of the stream are restored.

The sign on the spearman rank correlation for the re-aeration coefficient is positive at the beginning which indicates that the dissolved oxygen concentration increases with an increase in aeration coefficient right after waste disposal. At EH17, there is an inclination towards a mild negative correlation coefficient all the way through the decay process which maybe due to a discrepancy in data (Figure 9).

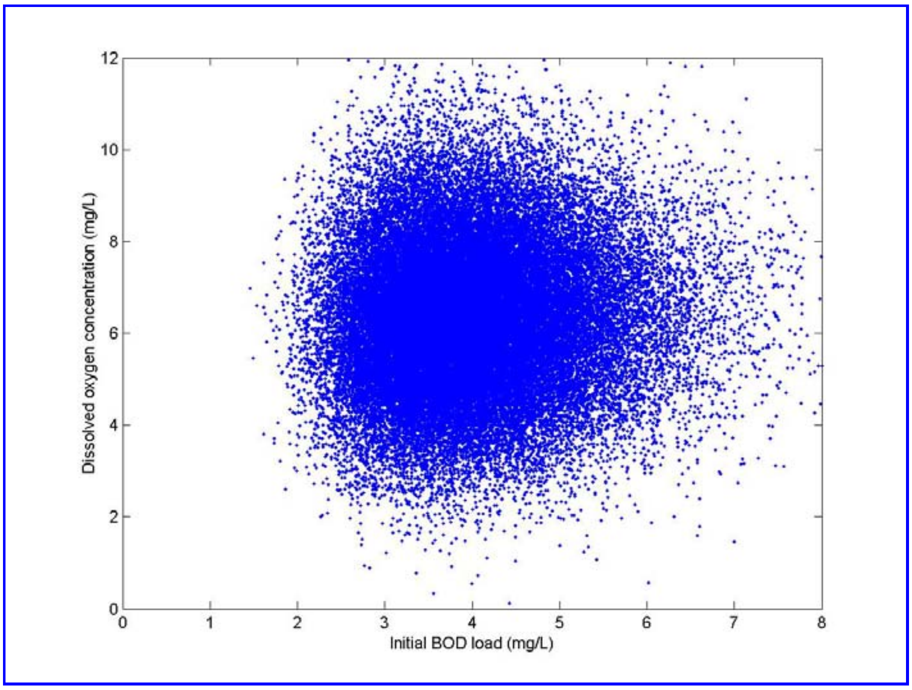


Figure 7. Scatter plot of simulated dissolved oxygen concentration versus initial BOD concentration

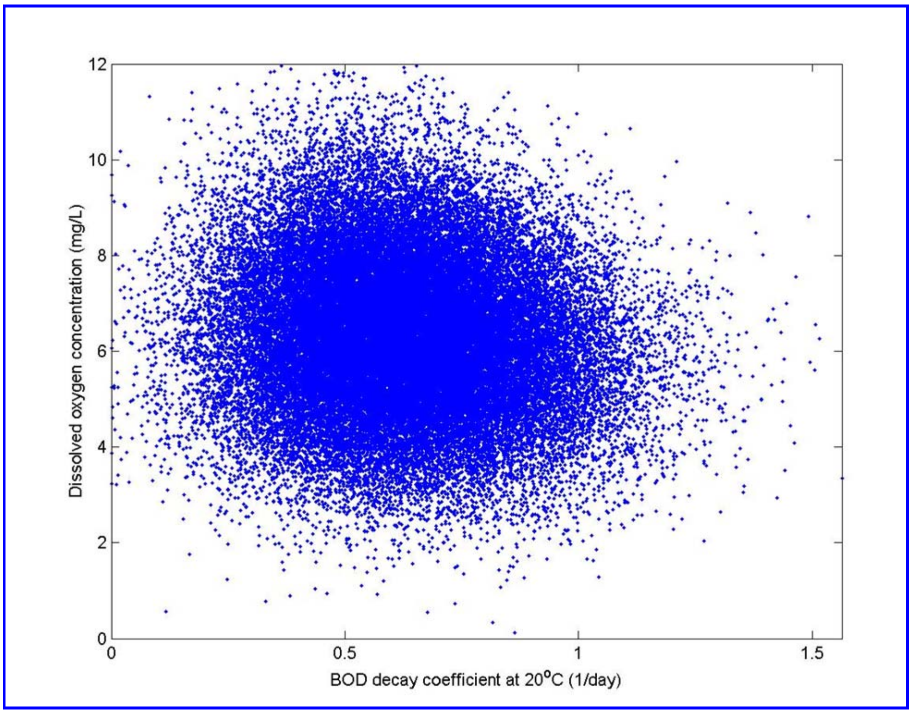


Figure 8. Scatter plot of simulated dissolved oxygen concentration with the BOD decay coefficient

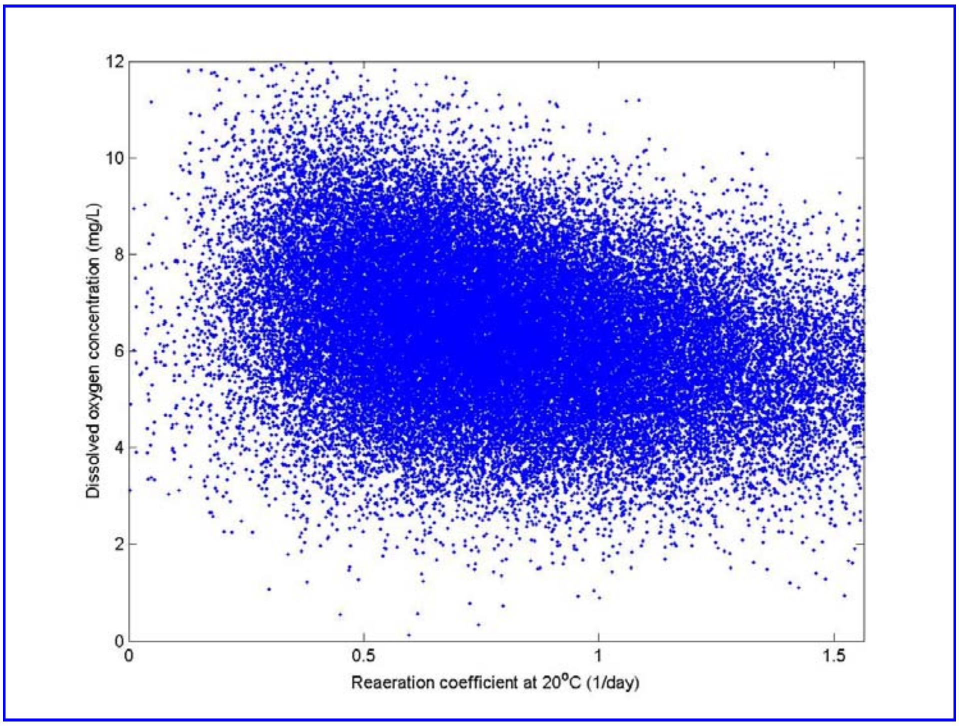


Figure 9. Scatter plot of simulated dissolved oxygen concentration with the reaeration coefficient

Figure 10 indicates that the simulated dissolved oxygen concentration is most sensitive to the basic uncertainty in the initial oxygen deficit and then to the BOD decay coefficient in the decay process. Temperature follows in its sensitivity and the aeration coefficient has a minor effect and the initial BOD load has the least sensitivity of all.

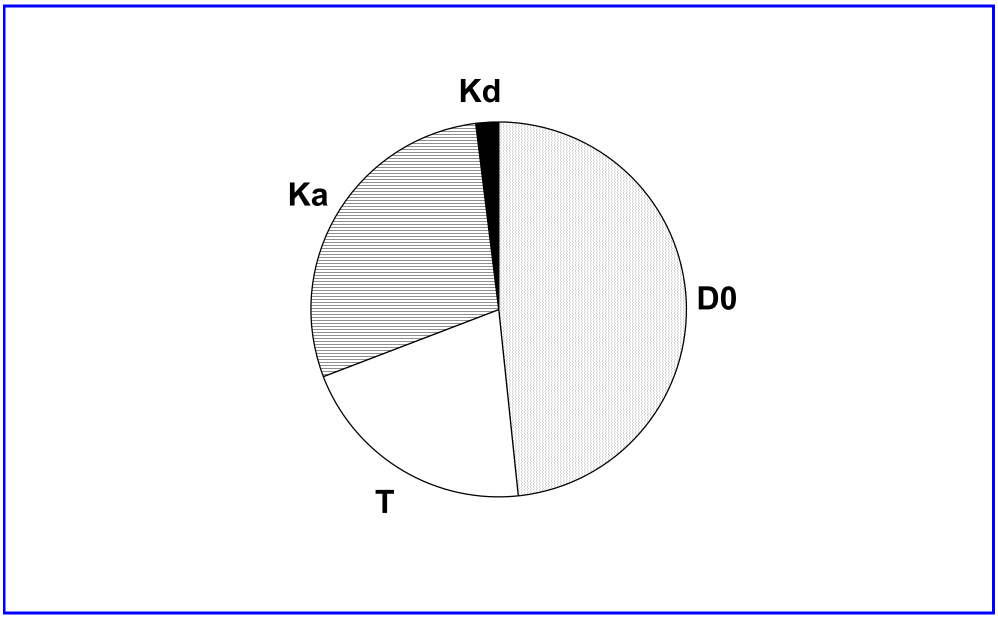


Figure 10. Percent Contribution to Variance by Random Variables

Conclusions

Modeling is an essential tool that is commonly used to simulate water quality parameters in streams. It is also utilized to predict the status of these parameters under different circumstances for decision making purposes. The problem here is that available data on water quality is always inadequate which causes deficiency in modeling processes and their expected results. Thus, failure to accommodate parameter uncertainty undermines the ability to make informed decisions regarding water quality issues.

The assessment of uncertainty relevant to modeling surface water quality on Bahr Hadus drain was illustrated. A simulation method, the Monte Carlo simulation, was used to propagate uncertainty from the input to the output. The simplicity of the used Streeter-Phelps model allowed the execution of a large number of simulations. This provides for a more robust assessment of uncertainty, it also encourages applying it to other surface water quality models, whether analytical or numerical.

In this study, uncertainty analysis was applied to Bahr Hadus drain using data collected from 1997 to 2004 over a 3 year period. Probability distribution functions for the temperature, initial DO and initial BOD have been estimated based on the empirical moments test and the Chi Squared test to be input into the proposed model. Other probability distribution functions for Kd, Ka were estimated from the literature. The simulated dissolved oxygen was predicted by the model using the probability distribution of the input variables. This was done by the Monte Carlo simulation method which is based on repeated random sampling from the probability distribution of the input parameters, running the mathematical model, obtaining the results, then estimating the statistics of the resulting ensemble of model output. The methodology was illustrated on a Streeter–Phelps prototype model, where basic uncertainty in aeration parameter, biochemical oxygen demand decay parameter, water temperature, and initial concentrations of dissolved oxygen and biochemical oxygen demand is considered. Sensitivity information of the dissolved oxygen to these input variables was presented. In general, the results showed that the effect of probability density of the input variables was not appreciable, however, the simulated dissolved oxygen concentration seemed to be most sensitive to the basic uncertainty to the initial oxygen deficit and then to the BOD decay coefficient. The sensitivity to temperature came next, and the sensitivity to the reaeration coefficient preceded the initial BOD load in its importance. At point EH17, the sign of the Spearman rank correlation coefficient showed no sensitivity to the initial BOD load and was opposite to what is expected for the reaeration coefficient. This was attributed to a discrepancy in measurements. This discrepancy proves the necessity in incorporating uncertainty in the modeling process.

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تحليل الحساسية فى حساب الاكسجين المذاب فى مصرف بحر حادوس

منار البشري
وحدة جودة المياه – وزارة الري والموارد المائية - مصر

تعد النماذج الرياضية احد الوسائل الضرورية المستخدمة فى اتخاذ القرارات الخاصة بحالة نوعية المياه. كما تؤثر عوامل عدم الثقة فى متغيرات النموذج الرياضى على نتائج النموذج بشكل كبير. لذا فان الفشل فى ادراج عوامل عدم الثقة لهذه المتغيرات يقلل من قدرته على اعطاء نتائج صحيحة يعتد بها فى اتخاذ القرارات المطلوبة. تعرض هذه الورقة العلمية طريقةلادراج عدم الثقة المسماة ببرنامج محاكاة مونت كارلو فى المتغيرات المدخلة على النموذج الرياضى ستريتر-فيلبس الخاص بحساب الاكسجين المذاب فى المياه وهو العامل الدال على مدى صحة المياه. وتقوم هذه المنظومة بحساب مدى تاثير عدم الثقة فى مدخلات النوذج الرياضى على نتائجه. وقد تم تطبيقهاعلى مصرف بحر حادوس الذى يتلقى تصرفات محملة بالمواد العضوية القادمة من محطات معالجة الصرف الصحى من القرى المحيطة بالمصرف. وبالتالى استخدمت المنظومة المقترحة فى حساب تركيز الاكسجين المذاب فى المصرف تبعا لعدم الثقة فى المتغيرات المدخلة للبرنامج و التى تضم معامل التهوية و معامل تحلل الاكسجين الحيوى الممتص و التركيز الاولى للاكسجين المذاب فى المياه و كذلك التركيز الاولى للاكسجين الحيوى الممتص. كما تم دراسة مدى حساسية حساب الاكسجين المذاب لمعاملات عدم الثقة المقترنة بمدخلات النموذج.