RESEARCH ARTICLE

Optimization of integrated water quality management for agricultural efficiency and environmental conservation

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Abstract The scarcity of water resources in Egypt has necessitated the use of various types of lower quality water. Agricultural drainage water is considered a strategic reserve for meeting increasing freshwater demands. In this study, a novel model series was applied to a drainage basin in the Nile Delta to optimize integrated water quality management for agriculture and the aquatic environment. The proposed model series includes a waste load allocation model, an export coefficient model, a stream water quality model, and a genetic algorithm. This model series offers an optimized solution for determining the required removal levels of total suspended solids (TSS), the chemical oxygen demand (COD) at point and non-point pollution sources, and the source flows that require treatment to meet a given water quality target. The model series was applied during the summer and winter to the El-Qalaa basin in the western delta of the Nile River. Increased pollutant removal and treated fractions at point and non-point sources reduced violations of the TSS standards from 732.6 to 238.9 mg/L in summer and from 543.1 to 380.9 mg/L in winter. Likewise, violations of the COD standards decreased from 112.4 mg/L to 0 (no violations) in summer and from 91.7 mg/L to no violations in winter. Thus, this model is recommended as a decision support tool for determining a desirable waste load allocation solution from a trade-off curve considering costs and the degree of compliance with water quality standards.

Keywords Waste load allocation · Agricultural drainage water · Export coefficient model · Water quality simulation · Optimization · Multi-objective

Introduction

Rapid population growth over the past few decades, particularly in the Middle East and North Africa, has caused severe water shortages. Billions of people lack access to safe water and adequate sanitation (WHO World Health Organization 2002). This is particularly because of recent increases in waste discharges that have polluted freshwater bodies (Mostafavi and Afshar 2011). Under these circumstances, resource management agencies are in need of a holistic approach to environmental management. One tool for implementing state water quality standards is the waste load allocation (WLA) process (US EPA 1992), which integrates management of point and non-point pollution sources and provides decision-making tools for attaining and maintaining water quality standards. Development of a WLA is based on a thorough understanding of site-specific relationships between pollution sources and water quality conditions (Yassuda et al. 2000).

Egypt is among the countries with the scarcest water resources (Khalil et al. 2010). The quality and quantity of agricultural drainage water (ADW) in the Nile Delta suggests that some of this water can be reused for irrigation (Khalil et al. 2010). At present, around 7 billion m³/year of ADW is directly recycled via controlled mixing with Nile water. This

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represents 40 % of the available ADW and can be increased to 9 billion m^3/year by 2017 (Talaat et al. 2002; DRI 2007). However, increasing pollution, particularly in the drainage system network, threatens the application of these reuse strategies (Shaban et al. 2010). Egyptian drains receive large quantities of partially treated or untreated domestic and industrial wastewater rich in biodegradable organic matter. This causes serious deterioration and consumes a large percentage of the dissolved oxygen (DO) present in the water (El-Sheikh et al. 2010). The amount of wastewater discharged into receiving drains far exceeds the natural ability of these water bodies to attenuate the pollution, violating water quality standards and making drainage water unsuitable for reuse (Abulnour et al. 2002). WLA for point and non-point sources of pollution may facilitate ADW use beyond current levels (US EPA 1992).

WLA determines the required pollutant removal from point and non-point sources to attain satisfactory water quality in a receiving water body. Traditional WLA models have been formulated to minimize the total treatment cost while satisfying water quality standards (Kerachian and Karamouz 2005). Moreover, in some previously proposed models, violations of the standards were considered the WLA model objective (Burn and Yuliant 2001; Yandamuri et al. 2006; Saadatpour and Afshar 2007). Recently, heuristic algorithms such as genetic algorithms (GA), simulated annealing, and ant colony algorithms have been employed to deal with multi-criteria problems (Yandamuri et al. 2006; Saadatpour and Afshar 2007). GA is a powerful optimization technique that has successfully been applied in water quality management (Karamouz et al. 2003). Ritzel et al. (1994) and Burn and Yuliant (2001) showed the effectiveness of GAs in developing a multi-objective model for WLA. In addition, Kerachian and Karamouz (2005) proposed a GA-based optimization model to address the dimensionality problem of the temporal WLA due to the large number of decision variables.

WLA includes prediction of point and non-point contributions to the total load in the stream. Many water quality models have been developed to estimate pollution loading into water bodies, including simple export coefficient models, regression models, and complex mechanistic models (Shrestha et al. 2008). Pollutant export coefficients, representing the rate of pollutant loading by land area, can be used to estimate loadings from non-point sources (Shrestha et al. 2008). In addition, a model of pollutant transport in the stream system is required for WLA. QUAL2E, and its enhanced versions, is a widely used water quality model (Brown and Barnwell 1987; Drolc and Konkan 1996; Park and Uchrin 1990; Park and Lee 1996; Pelletier and Chapra 2005; Kannel et al. 2007). Several attempts have been made to incorporate such simulation models into WLA models (Suresh and Mujumdar 1999; Mujumdar and Sasikumar 2002). Mujumdar and Vemula (2004) proposed a

simulation–optimization approach integrating a fuzzy WLA model with a water quality simulation model. However, further improvement in both point and non-point source estimation and pollutant transport simulation is necessary to apply these models to efficient agricultural practice and environmental conservation.

In this study, therefore, a multi-objective WLA model was proposed as an optimization method for water quality management and environmental conservation. An export coefficient model was integrated into a stream water quality model, QUAL2Kw, to estimate the spatial distribution of water quality constituents in the stream system based on point and non-point source contributions. That water quality simulation framework was incorporated within a multi-objective optimization model. The model was employed to (1) identify the qualitative and quantitative characteristics of point and non-point sources of pollution and (2) illustrate trade-offs between objectives, i.e., minimizing the cost of wastewater treatment and satisfying water quality standards for both reuse for irrigation and discharge into lakes. The model was applied during the summer and winter seasons to the El-Qalaa basin in the western delta of the Nile River. The proposed decision support tool can be used dynamically, allowing the results to be refined as additional water quality data become available.

Study area

The study area was a section of the El-Qalaa drain 10.41 km in length, with a drainage basin area of 140.7 km^2 located within the western delta of the Nile River (Fig. 1). The El-Qalaa drain is one of the most important drains in the western delta region, receiving approximately 70 % of Alexandria city wastewater, and is the primary pollutant source to Maryout Lake. The altitude of the study area is 2.44–6.1 m below mean sea level. The main source of fresh water to the basin is the Nile River. The target area is served by five secondary open drains that discharge water into the El-Qalaa drain (Fig. 1). The Agricultural, Zohra, and Amlak drains collect drainage water from the fields of three sub-basins through subsurface drains and discharge into the El-Qalaa drain. Effluent and overflow from the east wastewater treatment plant (EWTP) flow into the Somouha and Hydrodrome drains and then into the El-Qalaa drain.

Samples of the agricultural drainage water at point sources, sub-basin outlets, and monitoring stations were collected at fixed sampling sites every 2 weeks from April 2007 to January 2008. The samples were analyzed for pH, total dissolved solids (TDS), total suspended solids (TSS), DO, biochemical oxygen demand (BOD$_5$), total chemical oxygen demand (COD), nitrite nitrogen (NO$_2$–N), nitrate nitrogen (NO$_3$–N), and ammonia nitrogen (NH$_4$–N). Results for the ADW in the
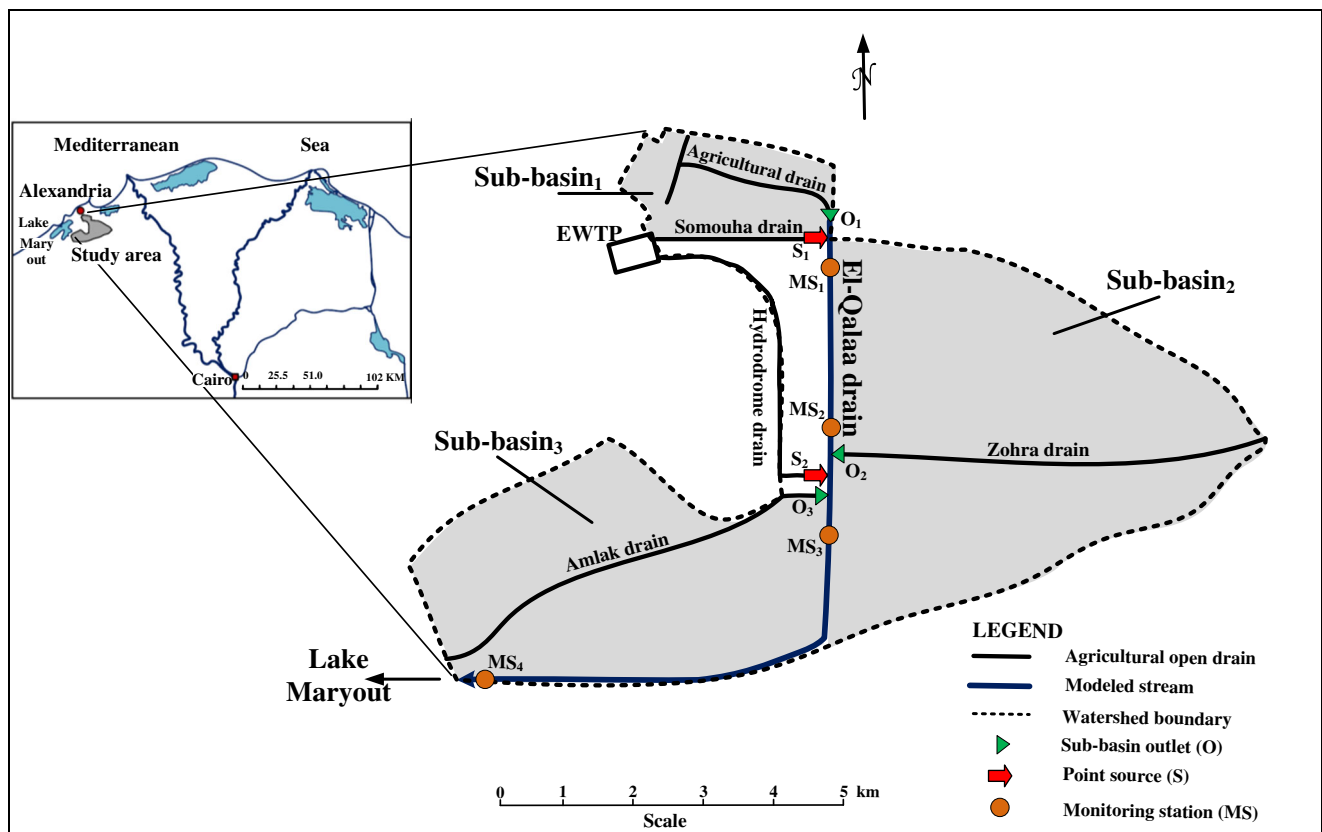
Fig. 1 Location of the study area (El-Qalaa drain, 140.7 km²) in the western delta of the Nile River, Egypt

El-Qalaa were 7.2±0.1 for pH and 997.5±171.8, 618.4± 200.6, 0.4±0.1, 128.9±23.1, 231.3±57.8, 7.2±1.7, 2.1±0.5, and 13.8±2.4 mg/L for TDS, TSS, DO, BOD_5, COD, NO_2–N, NO_3–N, and NH_4–N, respectively. Thus, the ADW in this study is classified as medium-strength wastewater (Metcalf & Eddy Inc. 2003).

Materials and methods

Framework of the optimization method

A multi-objective optimization model was developed to provide a WLA approach for freshwater bodies. Non-point source contributions were predicted based on export coefficients. Estimated non-point source contributions and point source measurements were then integrated into a water quality simulator, QUAL2Kw, to estimate the spatial distributions of water quality constituents in the stream system. Qualitative and quantitative characteristics of the point and non-point sources of pollutants were identified to minimize the cost of wastewater treatment and satisfy water quality standards for reuse in irrigation and discharge into lakes. A GA-based optimization model was employed to address the multi-objective criteria of this WLA problem.

Waste load allocation model

Removal of TSS and COD and flow fractions subjected to treatment at the pollution sources were modeled to address three objectives. The first objective was to minimize the overall removal of TSS and COD and the treated flow volumes to minimize wastewater treatment costs. The second and third objectives were to minimize exceedances of irrigation water quality standards in the drain and water quality standards for discharge into lakes at the outfall. Table 1 presents the Egyptian water quality standards, Law 48/1982, for

Table 1 Irrigation water quality standard and water quality standard to discharge into lakes

Parameter	Irrigation water quality standards	Effluent licensed to discharge into lakes
pH	–	6–9
TDS	2,000	2,000
TSS	50	50
DO	>4	>4
BOD_5	60	40
COD	80	80
NO_3–N	50	50

discharge into lakes and irrigation water standards (MAB 1983). Exceedances were estimated by analyzing water quality indicator concentrations at several locations referred to as check points. The resulting WLA model minimizes three terms:

$$Z_1 = \sum_{i=1}^{n_s} \left[\sum_{j=1}^{n_p} X_{i,j} \right] T_i + \sum_{k=1}^{n_{sb}} \left[\sum_{k=1}^{n_l} \left(\sum_{j=1}^{n_p} X_{k,l,j} \right) T_{k,l} \right] \quad (1)$$

$$Z_2 = \sum_{m=1}^{n_c} \left[\sum_{j=1}^{n_p} w_j \left(V_{m,j} \right)^2 \right] \quad (2)$$

$$Z_3 = \sum_{j=1}^{n_p} w_j \left(V_{E,j} \right)^2 \quad (3)$$

Subjected to:

$$X_{i,j}, X_{k,l,j} \in X_{s,j} \quad (4)$$

$$V_{m,j} = \begin{cases} C_{m,j} - C_{IS,j} & \text{if} \left(C_{m,j} > C_{IS,j} \right) \\ 0 & \text{if} \left(C_{m,j} \leq C_{IS,j} \right) \end{cases} \quad (5)$$

$$V_{E,j} = \begin{cases} C_{E,j} - C_{LS,j} & \text{if} \left(C_{E,j} > C_{LS,j} \right) \\ 0 & \text{if} \left(C_{E,j} \leq C_{LS,j} \right) \end{cases} \quad (6)$$

where n_s is the number of point sources, n_p is the number of water quality indicators, $X_{i,j}$ is the removal (%) at point source i of indicator j, T_i is the treated flow (%) at point source i, n_{sb} is the number of sub-basins, n_l is the number of land use categories, $X_{k,l,j}$ is the removal (%) in sub-basin k for land use class l of indicator j, $T_{k,l}$ is the treated flow (%) in sub-basin k for land use class l, w_j is the weighting factor for indicator j (weights were derived in preliminary runs to equalize the effects of the water quality indicators), $V_{m,j}$ is the magnitude of exceedance of the irrigation standard at check point m for indicator j, $V_{E,j}$ is the magnitude of exceedance of the water quality standard for discharge into lakes at outfall E for indicator j, $X_{s,j}$ is the set of possible removal fractions available for indicator j, $C_{m,j}$ is the concentration at check point m of indicator j, $C_{IS,j}$ is the irrigation standard (IS) for indicator j, $C_{E,j}$ is the concentration at the outfall E of indicator j, and $C_{LS,j}$ is the standard for discharge into lakes (LS) for indicator j.

A combination of the ε-constraint method and GA was used to find an optimal solution for the various objectives. The ε-constraint method is a powerful technique for generating a non-dominated set when the objective functions and constraints are nonlinear. A multi-objective problem is transformed into a series of single-objective problems that can be solved using single-objective optimization methods such as GA. The ε-constraint method offers the advantage of better

control over search algorithms for non-dominated sets (Kerachian and Karamouz 2005).

This method for a minimization problem with n objectives can be summarized as follows:

Step 1. Solve n individual minimization problems to find the optimal solution for each individual objective.

Step 2. Compute the value of each of the objectives and determine the potential range of values for each of the n objectives.

Step 3. Select a single objective (ZO) to be minimized. Meanwhile the remaining $n-1$ objectives are transformed in the form of

$$Z_h \geq L_h, \qquad h = 1, 2, \ldots \ldots, 0-1, 0+1, \ldots n \quad (7)$$

Add these new $n-1$ constraints to the original set of constraints, where L_h represents the right-hand side values that will be varied.

Step 4. For each of the objectives and the associated range of potential values, select the desired level of resolution and divide the range into number of intervals determined by this level of resolution in order to find L_h.

Step 5. Solve the problem of step 3 for every combination of right-hand side values determined in step 4. These solutions form the approximation for the non-dominated surface (Karamouz et al. 2003; ReVelle and McGarity 1997).

The solution for the ε-constraint method was calculated using the GA (Karamouz et al. 2003; ReVelle and McGarity 1997; Fig. 2). Several generations were conducted per GA run until no further improvements (within a certain tolerance) were achieved in the objective functions for successive generations (Ng and Perera 2003; Saavedra et al. 2010). In this study, the algorithm operators were random population initialization, one-point crossover, and bit mutation.

The decision variables were the percent removal of TSS and COD and the flows subjected to treatment at the sources. The upper and lower boundaries of the percent removal were set to the removal amounts possible for each indicator. The treated flows were defined as the percentage of the flows at the sources that were subjected to treatment. The upper boundary was set to 100 %, assuming that all of the source flows would be entirely treated. Conversely, the lower boundary was set to 0 %, indicating no treatment. The removal and treated flow fractions at the point sources are relatively easy to implement and control. However, the control and implementation for the non-point sources is difficult. In the Nile Delta, drainage water is collected by artificial drainage network. The bleeding between the drainage water from different land use categories occurred later after dumping in open systems such as the El-Qalaa drain and its branches. Thus, the
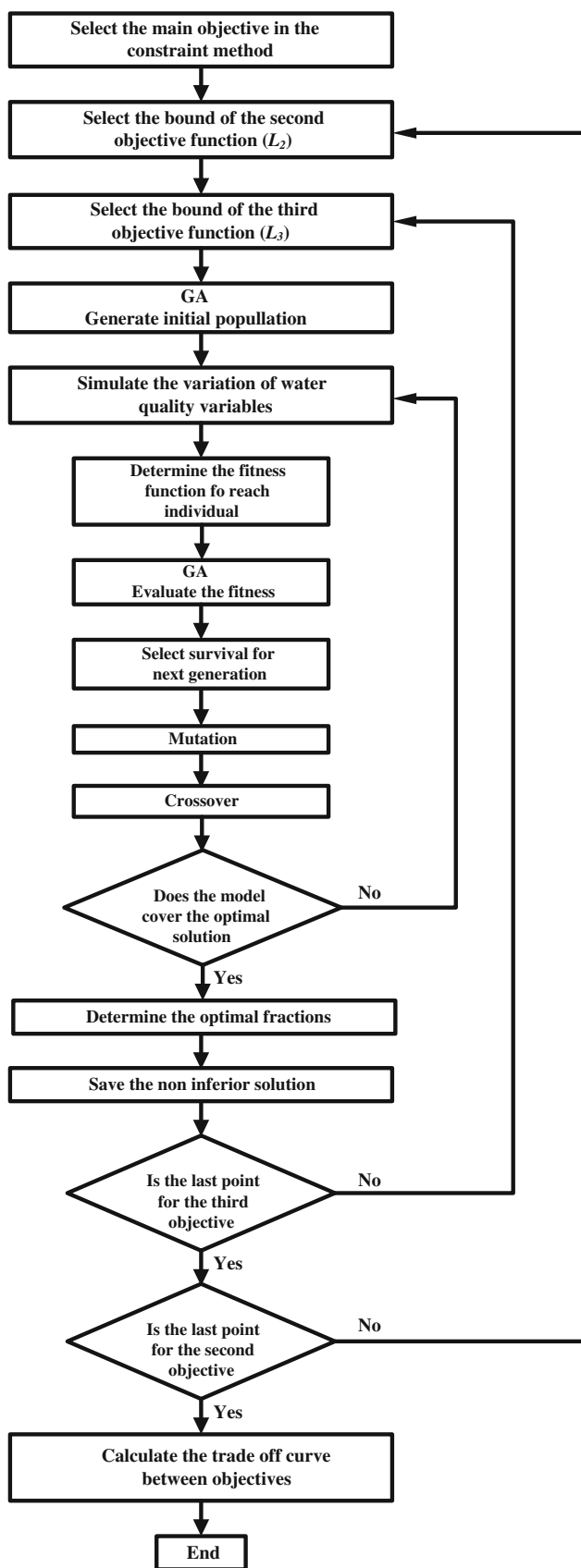
Fig. 2 Flowchart of the combination of the ε-constraint method and the GA minimizing a problem with n objectives

quantity of the treated flow from non-point sources could be controlled by collecting this drainage water before discharge into the open-stream systems. To control the removal rate, techno-economic biological reactors with small footprints such as down-flow hanging sponge (Fleifle et al. 2013) are required.

Minimization of pollutant removal and treated flows at the sources was the main objective of this study. TSS and COD concentrations in the ADW were the primary pollution indicators for evaluating exceedances of water quality standards for irrigation and discharge into lakes. Initial tests indicated that 50 generations were sufficient for each step of the WLA model to obtain optimal or near-optimal solutions because variations in the function for the primary objective were very small for additional generations. The model controlled for the effects of population size, probability of crossover, and probability of mutation. A larger population in each generation does not improve the fitness of the optimal solution, but can reduce the number of generations required to obtain it. Decreasing the probability of crossover can increase the number of generations required to obtain the optimal solution. A population size of 100, probability of crossover of 0.85, and probability of mutation of 0.005 produced the best results for the main objective function.

The ε-constraint method provided trade-off curves between the selected objectives. Three potential solutions for the decision-making process were presented (MV, MF, and MP). The MV solution refers to minimum standard violations, which represents the optimal solution along the trade-off curve that minimizes exceedances of irrigation and lake discharge water quality standards, objectives 2 and 3. In contrast, the MF solution—minimum total removal and treated flow fractions—provides the optimal solution for minimizing the percent removal of TSS and COD and the treated flows at the sources (objective 1) regardless of exceedances of the standards. The MP solution is a midpoint solution.

Water quality simulation

The water quality simulation estimates the spatial distribution of water quality constituents in the stream system based on point and non-point source contributions and includes a pollutant export coefficient model (ECM) and a model of pollutant transport in the stream system. The total loads and the percentages of loads from different land uses were estimated using the ECM at the sub-basin outlets. Pollutant transport, sub-basin non-point and point source discharges, and transformation processes in the stream were estimated using QUAL2Kw (Pelletier et al. 2006). Measured data in summer (April–September 2007) were used for calibration, while measured data in winter (October 2007–January 2008) were used for verification.

Export coefficient model

The ECM assumes that the pollutant load exported from a watershed equals the sum of the losses from individual land uses, including agricultural, urban, rural, and barren lands (Johnes 1996). This empirical model can be expressed as

$$L_{i,j} = \sum_{k=1}^{n_{lu}} E_{k,i} A_{k,j} + P_{i,j} \qquad (8)$$

where $L_{i,j}$ is the average load of pollutant i at the outlet of sub-basin j (ton/month), n_{lu} is the number of land use categories, $E_{k,i}$ is the export coefficient of land use category k for pollutant i (ton ha^{-1} month^{-1}), $A_{k,j}$ is the area of land use category k in sub-basin j (ha), and $P_{i,j}$ is the load of pollutant i at the outlet of sub-basin j from precipitation (ton/month).

However, concentrations rather than loads are required to integrate the ECM with the stream quality simulator. Thus, the ECM equation must be modified as follows:

$$C_{i,j} = \frac{\sum_{k=1}^{n_{lu}} E_{k,i} A_{k,j} + P_{i,j}}{Q_j \times 2.592} \qquad (9)$$

where $C_{i,j}$ is the concentration of pollutant i at the outlet of sub-basin j (mg/L) and Q_j is the discharge at the outlet of sub-basin j (m^3/s).

Export coefficients are usually derived from literature sources and the results of field experiments to determine the rate at which pollutants are lost from each identifiable source to the surface drainage network (Johnes 1996). Generally, the export coefficients associated with rural homes and livestock can be determined from the literature because these coefficients do not vary significantly. However, export coefficients for other land use types have generally been obtained under specific conditions that reflect regional features and therefore are not sufficiently accurate when used for other catchments. Thus, in the present study, monthly monitoring of pollutant exports from small catchments with a predominant land use was conducted to establish pollutant loads specific to the study area. The mean values for these data were then used to determine the export coefficients for summer and winter. We assumed that export coefficients for the same land use category were valid within sub-basins. This is a reasonable assumption as the entire region has similar wastewater treatment technologies, topographic characteristics, soil properties, climatic conditions, and land management practices.

The proportions of major land uses in each sub-basin were determined through supervised maximum likelihood classification. An Enhanced Thematic Mapper Plus (ETM+) image acquired on 17 July 2007 was used for the classification. The image was acquired during the growing season under clear atmospheric conditions from the Landsat archive of the United States Geological Survey (http://glovis.usgs. gov; http://edcsns17.cr.usgs.gov). All visible and infrared bands (other than the thermal infrared band) were included in the analysis.

We applied contrast stretching to the selected image for visual interpretation. Prior to image classification, land use features were categorized into five broad types: barren land, agricultural land, urban land, rural land, and free water bodies. These five types were identified based on visual interpretation of the satellite imagery and verified with field inspection. Barren land refers to non-cultivated land or bare land. Agricultural land refers to areas cultivated with field crops, forage crops, vegetables, or fruit trees. Urban areas include cities in the study area, typically served by wastewater treatment plants. In contrast, rural areas include villages and small communities that frequently do not have wastewater treatment facilities. Free water bodies include open irrigation and drainage canals, shallow water bodies, and small lakes. We used ERDAS IMAGINE 9.2 (Leica Geosystems 2008) software for supervised classification of the Landsat image. Training samples were selected for each of the predetermined land use types by delimiting polygons around representative sites. Using the pixels enclosed by these polygons, we derived spectral signatures for the respective land cover types in the satellite images. A spectral signature is considered to be satisfactory when confusion among the land cover types to be mapped is minimal (Gao and Liu 2010). Once the spectral signature was deemed satisfactory, it was entered into the classification process. The supervised maximum likelihood method was used for classification. Supervised classification outputs a thematic raster layer (the classified image) and a distance file. Both the thematic layer and the distance file were used to generate a land use map for the study area.

A classification accuracy assessment was performed using 91 ground truth points that were randomly located to represent the different land use classifications. The reference data and classification results were compared and statistically analyzed using error matrices.

Stream water quality model

We used the stream water quality model QUAL2Kw (Pelletier et al. 2006). For auto-calibration, the model uses a GA to maximize the goodness of fit of the model results compared with measured data by adjusting a large number of parameters. Fitness is determined as the reciprocal of the weighted average of the normalized root mean squared error (RMSE) of the difference between the model predictions and the observed

Fig. 3 System segmentation with
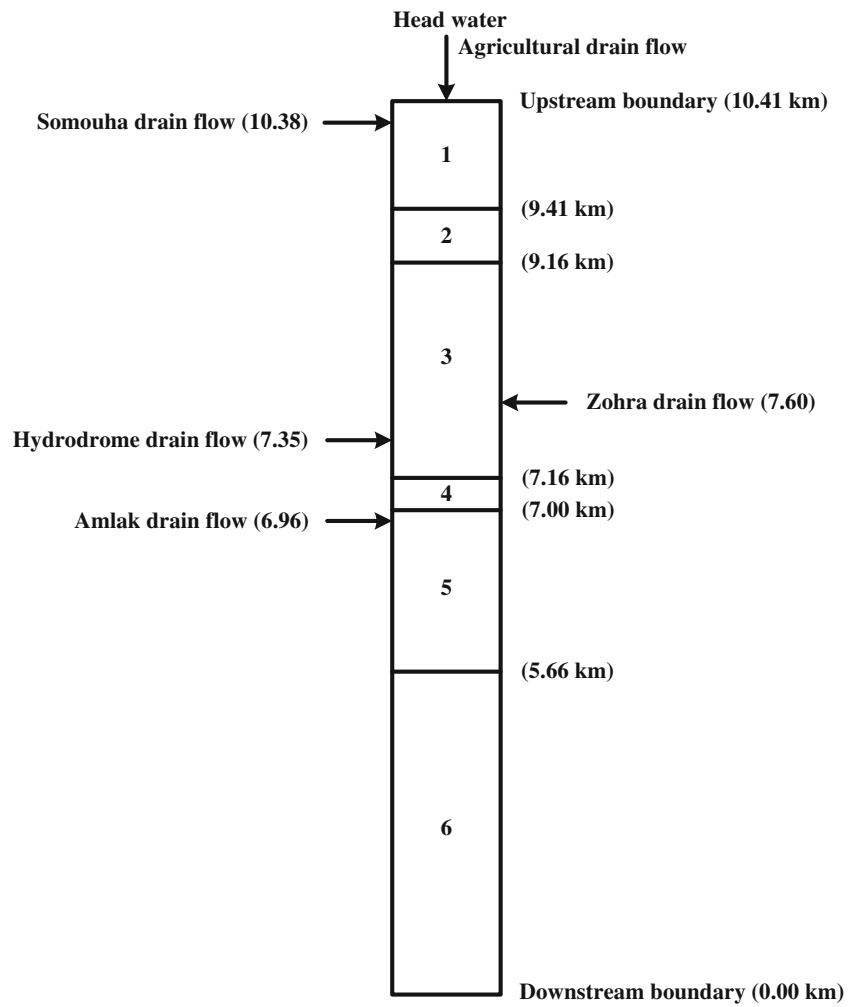the location of pollutant sources
along El-Qalaa drain

Head water

Agricultural drain flow

Upstream boundary (10.41 km)

Somouha drain flow (10.38) →

1

(9.41 km)

2

(9.16 km)

3

← **Zohra drain flow (7.60)**

Hydrodrome drain flow (7.35) →

(7.16 km)

4

(7.00 km)

Amlak drain flow (6.96) →

5

(5.66 km)

6

Downstream boundary (0.00 km)

Fig. 4 Land use map resulting
from the supervised classification

**Agricultural
sub basin**

**Zohra
sub basin**

**Amlak
sub basin**

Land use types

- ■ **Agricultural land**
- ■ **Urban land**
- ■ **Rural land**
- ■ **Free water bodies**
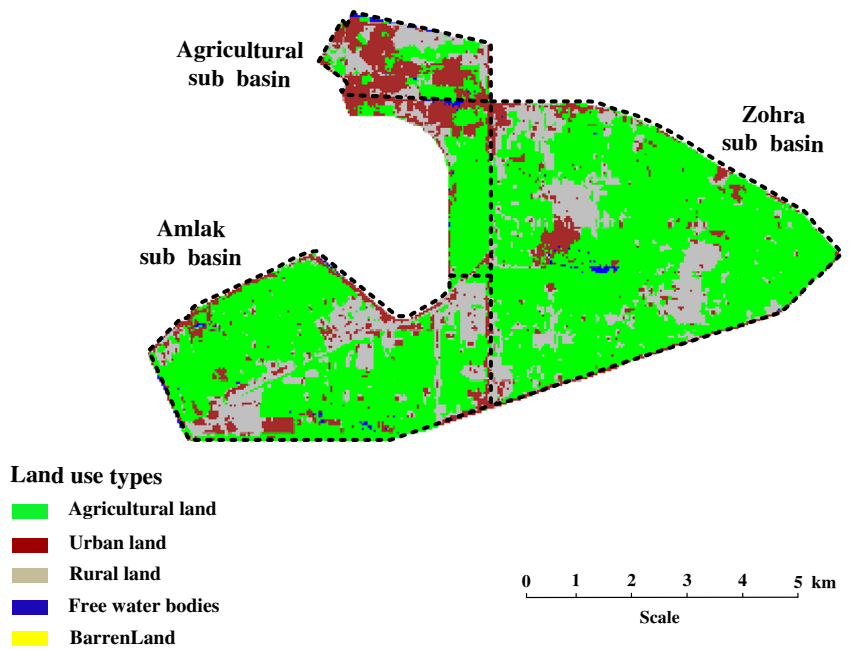- ■ **BarrenLand**

0 1 2 3 4 5 km

Scale

Table 2 Error matrix and total classification accuracy for the classified image

LULC classes	Reference data					Classification accuracy	
	Agriculture	Urban	Rural	Water bodies	Barren	Production accuracy (%)	Use accuracy (%)
Agriculture	49	1	3	0	0	96.08	92.45
Urban	1	14	0	0	0	93.33	93.33
Rural	1	0	17	2	0	85.00	85.00
Water bodies	0	0	0	3	0	60.00	100.00
Barren	0	0	0	0	0	100.00	100.00
Total accuracy (%)						90.52	

data for water quality constituents. The GA maximizes the fitness function $f(x)$ as follows:

$$f(x) = \left[\sum_{i=1}^{n} w_i\right]\left[\sum_{i=1}^{n}\frac{1}{w_i}\left[\frac{\left(\sum_{i=1}^{n} Q_{i,j/m}\right)}{\sqrt{\left[\sum_{j=1}^{m}\left(P_{i,j}-O_{i,j}\right)^2/m\right]}}\right]\right] \quad (10)$$

where w_i is a weighting factor, n is the number of different state variables included in the reciprocal of the weighted normalized RMSE, $O_{i,j}$ are observed values, $P_{i,j}$ are predicted values, and m is the number of pairs of predicted and observed values. A detailed description of the auto-calibration method can be found in Pelletier et al. (2006).

The El-Qalaa drain was discretized into six reaches with various lengths. Figure 3 shows the system segmentation along the El-Qalaa drain along with the locations of point sources of pollution and the lengths of each reach. The stream geometries were used to determine hydraulic characteristics. Manning's equation was used to determine hydraulic characteristics, water velocity, and depth of the stream. The El-Qalaa drain is a natural stream which is almost clean and has a straight alignment. Thus, a Manning roughness coefficient of 0.025 was used for all reaches (Chow et al. 1988).

The water quality input parameters included in the model were flow rate, pH, TDS, TSS, DO, BOD$_5$, NH$_4$–N, NO$_3$+ NO$_2$–N, and COD. Phytoplankton and pathogens were not measured and these inputs were left blank. Based on the available data provided by the Drainage Research Institute (DRI 2007), algae and bottom sediment oxygen demand coverage were assumed to be 40 and 100 %, respectively. The sediment/hyporheic zone thickness was assumed to be 10 cm.

The ranges for model rate parameters required by QUAL2Kw were obtained from various sources, including US EPA (1985), the QUAL2Kw user manual (Pelletier and Chapra 2005), and documentation for the enhanced stream water quality models QUAL2E and QUAL2E-UNCAS (Brown and Barnwell 1987). The re-aeration rate was internally calculated based on the scheme developed by Covar

(1976). An exponential model was chosen for oxygen inhibition for BOD oxidation, nitrification, denitrification, phytorespiration, and bottom algae respiration. Wind effects were considered negligible. The other parameters were set to their defaults in QUAL2Kw.

Data measured in the summer were used for calibration. The calculation step was set to 11.25 min to avoid instability in the model. The integration solution was carried out using Euler's method (Newton–Raphson method for pH modeling). The goodness-of-fit evaluation was performed with the QUAL2Kw default weighting values for various parameters. The model was run until the system parameters were appropriately adjusted and reasonable agreement between model results and field measurements was achieved. The model was run for a population size of 100 with 100 generations of evolution, in accordance with Pelletier et al. (2006). To test the ability of the calibrated model to predict water quality under various conditions, the model was run using a completely different data set for the winter season, without changing the calibrated parameters.

Results and discussion

Estimating pollutant loadings

The generated land use map for the El-Qalaa drain is shown in Fig. 4, with the spatial distribution of the land use categories.

Table 3 Area of each land use class for each sub-basin resulting from the classified image

Sub-basin	Area (ha)			
	Urban	Rural	Agriculture	Free water bodies
Agricultural	1,376.2	806.1	744.3	13.4
Zohra	164.6	443.6	1,849.9	7.2
Amlak	455.2	900.9	2,931.6	13.1

Table 4 Average values of the export coefficients (ton ha^{-1} month^{-1}) estimated for major land use categories for the summer and winter seasons

Land use		Pollutants					
		TDS	TSS	BOD$_5$	COD	NH$_4$–N	NO$_2$+NO$_3$–N
Summer season	Urban	2.65	3.78	18.33×10^{-2}	19.52×10^{-2}	9.52×10^{-3}	7.62×10^{-3}
	Rural	3.62	0.72	6.78×10^{-2}	24.16×10^{-2}	5.47×10^{-3}	1.43×10^{-3}
	Agricultural	0.19	0.28	0.57×10^{-2}	0.60×10^{-2}	1.43×10^{-3}	2.86×10^{-3}
Winter season	Urban	4.41	4.98	18.33×10^{-2}	19.52×10^{-2}	7.14×10^{-3}	10.47×10^{-3}
	Rural	2.27	0.82	5.69×10^{-2}	21.28×10^{-2}	2.38×10^{-3}	1.43×10^{-3}
	Agricultural	0.19	1.76	0.57×10^{-2}	0.60×10^{-2}	1.67×10^{-3}	1.19×10^{-3}

The classifications were compared with the reference data to assess classification accuracy and an error matrix was generated (Table 2). The classification accuracy was approximately 90.5 %, and each land use classification had the highest classification accuracy. In the Zohra and Amlak sub-basins, agricultural land was the largest class, representing 75 and 68.2 % (1,849.9 and 2,931.6 ha), respectively (Table 3). In the Agricultural sub-basin, urban land was the largest class,
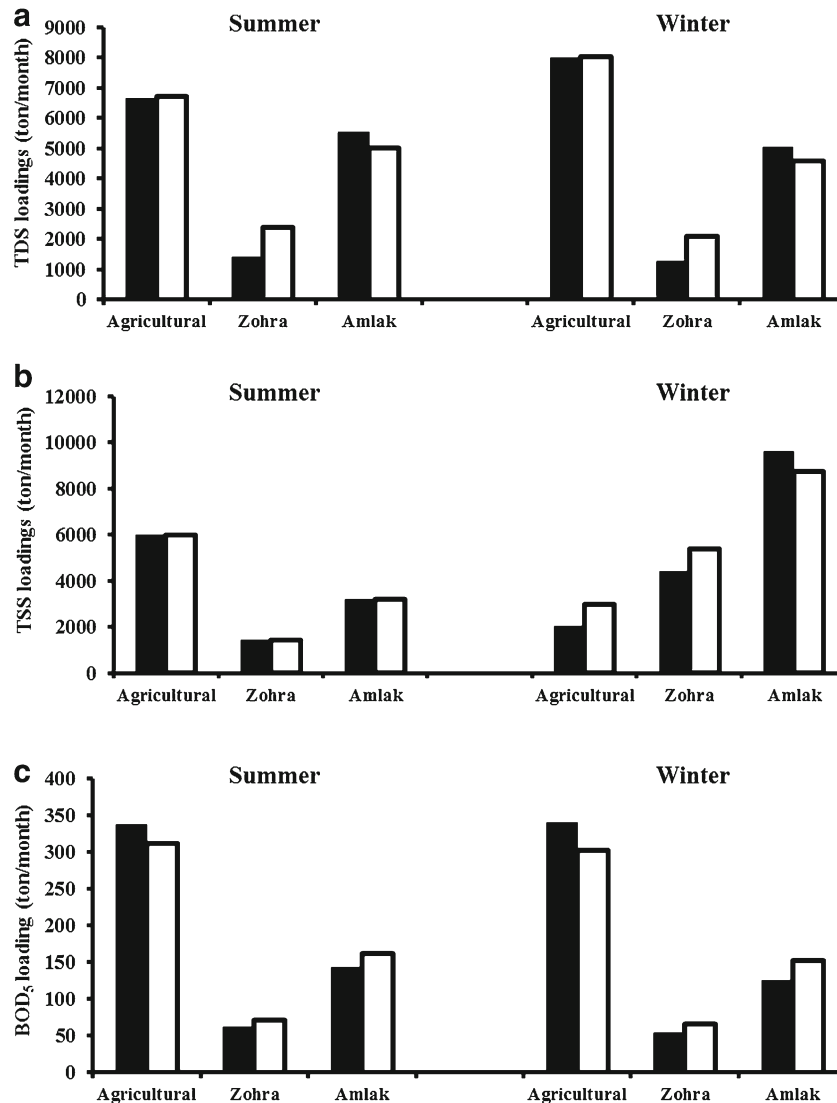

Fig. 5 Observed and estimated loadings at the outlet of the Agricultural, Zohra, and Amlak sub-basins in the summer and winter seasons. **a** TDS loadings. **b** TSS loadings. **c** BOD$_5$ loadings. **d** COD loadings. **e** NH$_4$–N loadings. **f** NO$_2$+NO$_3$–N loadings

d

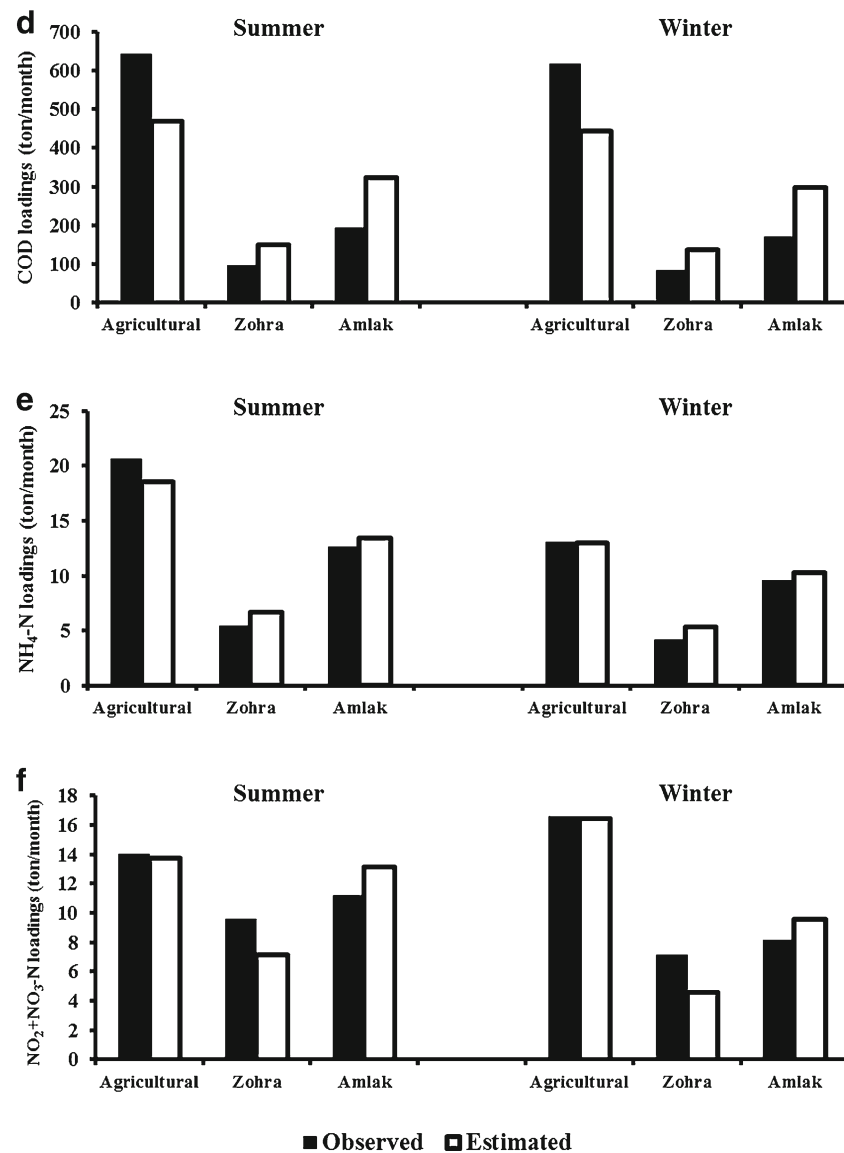**e**

f

■ Observed □ Estimated

Fig. 5 (continued)

representing 46.8 % (1,376.2 ha). The free water bodies class was the smallest of the land use categories among all sub-basins, and the barren class was not detected in any sub-basin.

Based on measurements of pollutant exports from small catchments with a predominant land use, export coefficients for summer and winter were estimated (Table 4). The load exported from precipitation was negligible. The pollutant export coefficients and land use classification results were then input into the ECM. The ECM was validated by comparing the estimated with the measured loads at the outlets of the three sub-basins (Fig. 5). The observed and the estimated loads were compared using relative root mean square error (RRE). The RREs for TDS, TSS, BOD_5, COD, NH_4–N, and NO_2+NO_3–N loads were 12.3, 0.1, 7.1, 23.7, 9.6, and 40.3 % for the summer (April–September 2007) and 7.8, 12.4, 9.6, 23.9, 8.8, and 17.9 % for the winter (October 2007–January

2008), respectively. Although the estimated loads had some-what high RREs in some cases, overall, the ECM was in reasonable agreement with both summer and winter measurements.

Overall, the highest percent loads of TSS (58.7 %), NH_4–N (49.5 %), and NO_2+NO_3–N (56.5 %) were from urban land. Agriculture land was the next largest source of these pollutants, contributing 29.9, 26.3, and 33.9 %, respectively. Rural land had the smallest contributions of 11.4, 24.2, and 9.6 %, respectively. Rural land use represented about 27.4, 17.8, and 20.9 % of the areas of the Agricultural, Zohra, and Amlak sub-basins, respectively. These areas contributed the largest COD load (53.6 %) because they lack access to adequate wastewater treatment. The second largest source of COD was urban land (42.9 %). Agricultural land contributed an almost negligible COD (3.5 %) compared to rural and urban lands. For

TDS and BOD$_5$, urban land was the dominant source (48.7 and 68.9 %, respectively), while rural land was the second highest source (44.2 and 25.2 %). The contribution of agriculture land to TDS and BOD$_5$ was lowest at 7.1 and 5.9 %, respectively.

Water quality simulation of the El-Qalaa drain

The results for the calibration parameters for the El-Qalaa drain are shown in Table 5. The model calibration and verification results were in good agreement with the measured data,

with some exceptions. The RMSEs between the simulated and observed values for pH, TDS, TSS, DO, BOD$_5$, COD, NO$_2$+ NO$_3$–N, and NH$_4$–N were 0.07, 76.5, 156.9, 0.02, 34.8, 44.8, 8.8, and 5.2 mg/L, respectively, for the summer simulation (April–September 2007). For the winter simulation (October 2007–January 2008), these values were 0.11, 146.7, 258.9, 0.15, 43.8, 51, 7.3, and 3.9 mg/L, respectively.

The El-Qalaa water did not meet the water quality standards for irrigation or for discharge into lakes for TSS, DO, BOD$_5$, and COD (Figs. 6 and 7). However, along the drain and at its end, TDS and NO$_3$–N concentrations were below

Table 5 Calibration parameters of the El-Qalaa drain water quality modelling for 2007

Parameter	Value	Units	Auto-calibration	Min. value	Max. value
Stoichiometry					
Carbon	40	g C	No	30	50
Nitrogen	7.2	g N	No	3	9
Phosphorus	1	g P	No	0.4	2
Dry weight	100	g D	No	100	100
Chlorophyll	1	g A	No	0.4	2
ISS settling velocity	0.86	m/day	Yes	0	2
O$_2$ re-aeration model	Internal		No		
Slow CBOD hydrolysis rate	2.6	day^{-1}	Yes	0.04	4.2
Slow CBOD oxidation rate	2.92	day^{-1}	Yes	0.04	4.2
Fast CBOD oxidation rate	0.18	day^{-1}	Yes	0.02	4.2
Organic N hydrolysis	0.04	day^{-1}	Yes	0.02	0.4
Organic N settling velocity	0.07	m/day	Yes	0.001	0.1
Ammonium nitrification	0.13	day^{-1}	Yes	0	10
Nitrate denitrification	0.18	day^{-1}	Yes	0	2
Sed. denitrification transfer coeff.	0.02	m/day	Yes	0	1
Detritus dissolution rate	3.73	day^{-1}	Yes	0	5
Detritus settling velocity	3.67	m/day	Yes	0	5
COD decay rate	0.006	day^{-1}	Yes	0	0.8
COD settling velocity	0.21	m/day	Yes	0	1
Bottom algae					
Growth model	Zero-order				
Max growth rate	244.13	mg A/m^2/ady	Yes	0	500
First-order model carrying capacity	1762.91	mg A/m^2	Yes	500	2,000
Respiration rate	0.34	day^{-1}	Yes	0.05	0.5
Excretion rate	0.5	day^{-1}	Yes	0	0.5
Death rate	0.4	day^{-1}	Yes	0	0.5
External nitrogen half-sat. constant	86	µg N/L	Yes	10	300
Inorganic carbon half-sat. constant	9.12E-05	mol/L	Yes	0.0000013	0.00013
Light model	Half-saturation				
Light constant	52.84	Ly/day	Yes	1	100
Ammonia preference	17.08	µg N/L	Yes	1	100
Subsistence quota for nitrogen	0.38	mg N/mg A	Yes	0.072	7.2
Maximum uptake rate for nitrogen	236.38	mg N/mg A/day	Yes	1	500
Internal nitrogen half–sat. ratio	2.33		Yes	1.05	5

Fig. 6 Calibrated results of water quality in the El-Qalaa drain for the summer season, April–September 2007


Observed, ▬ Simulated
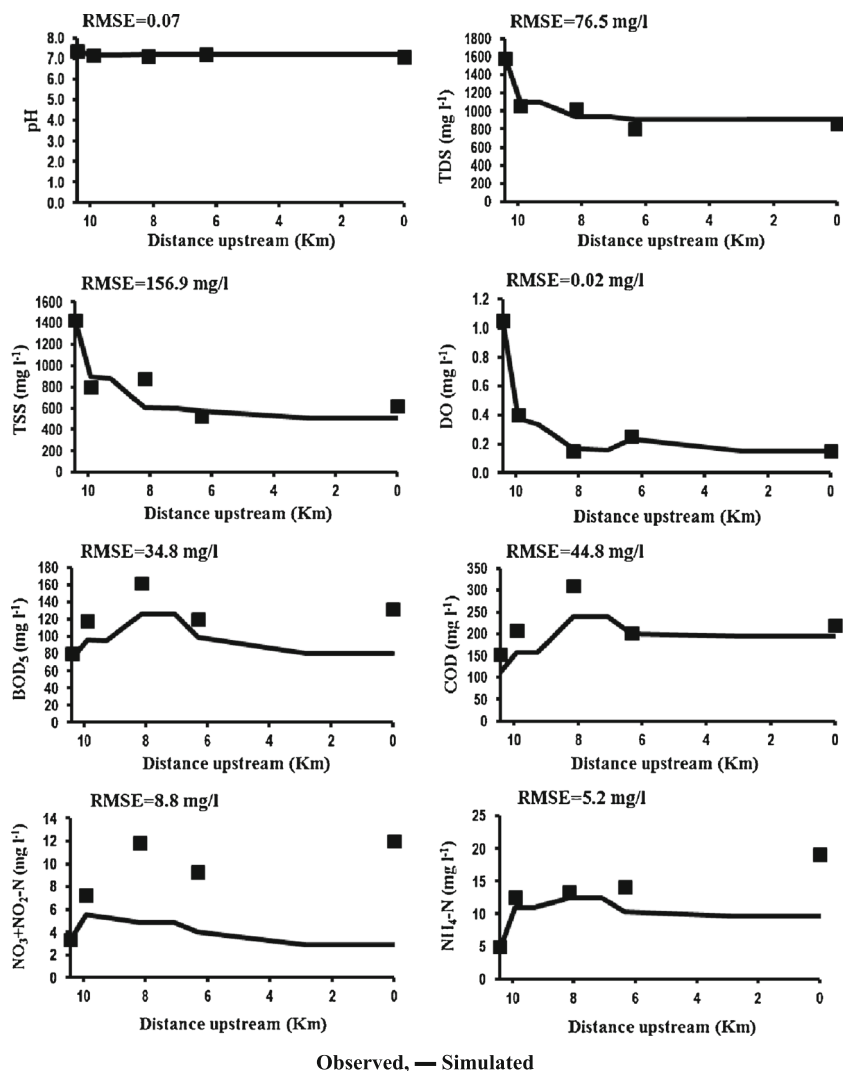
2,000 and 50 mg/L, respectively, satisfying the water quality standards. In addition, pH was within the water quality limitations. Thus, suspended and organic material concentrations are critical management issues for the El-Qalaa drain because of substantial violations of TSS, DO, BOD_5, and COD water quality standards.

At the head of the El-Qalaa, TSS concentrations were very high compared to the standards because urban land is the dominant land use (46.8 %) within the Agricultural sub-basin and urban lands were the largest source of TSS. TSS concentrations then decreased due to their relatively low concentrations in the discharges from the other sub-basins and point sources. BOD_5 and COD peaks were observed between kilometers 7.6 and 10 of the drain due to the input of organic pollutants from the Somouha and Hydrodrome drains receiving the influent and overflow of the EWTP. This influent consumes a large amount of the DO in the water course, and a subsequent oxygen depression was observed within this section of the drain.

The water quality profiles for the summer and winter seasons show some differences, likely due to changes in meteorological variables such air temperature and precipitation. Moreover, there is a significant change in crops between the two seasons. Rice, maize, and cotton are the main crops in summer, while wheat, beans, and berseem are dominant in winter. This difference in crops, coupled with associated changes in the quantities of irrigation water, types and quantities of fertilizers, and agricultural practices, results in more agricultural wastewater in the summer compared to the winter with different characteristics.

The El-Qalaa drain and its branches receive domestic and industrial wastewaters in addition to the agricultural drainage water. The major portion of the industrial and domestic wastewaters is collected first to the EWTP and then the effluent and the overflow of the plant are discharged to the El-Qalaa. A significant portion of these wastewaters is unofficially directly discharged to the El-Qalaa and its branches. The industrial and domestic wastewaters were

Fig. 7 Verification results of water quality simulation in the El-Qalaa drain for the winter season, October 2007–January 2008


■ Observed , — Simulated
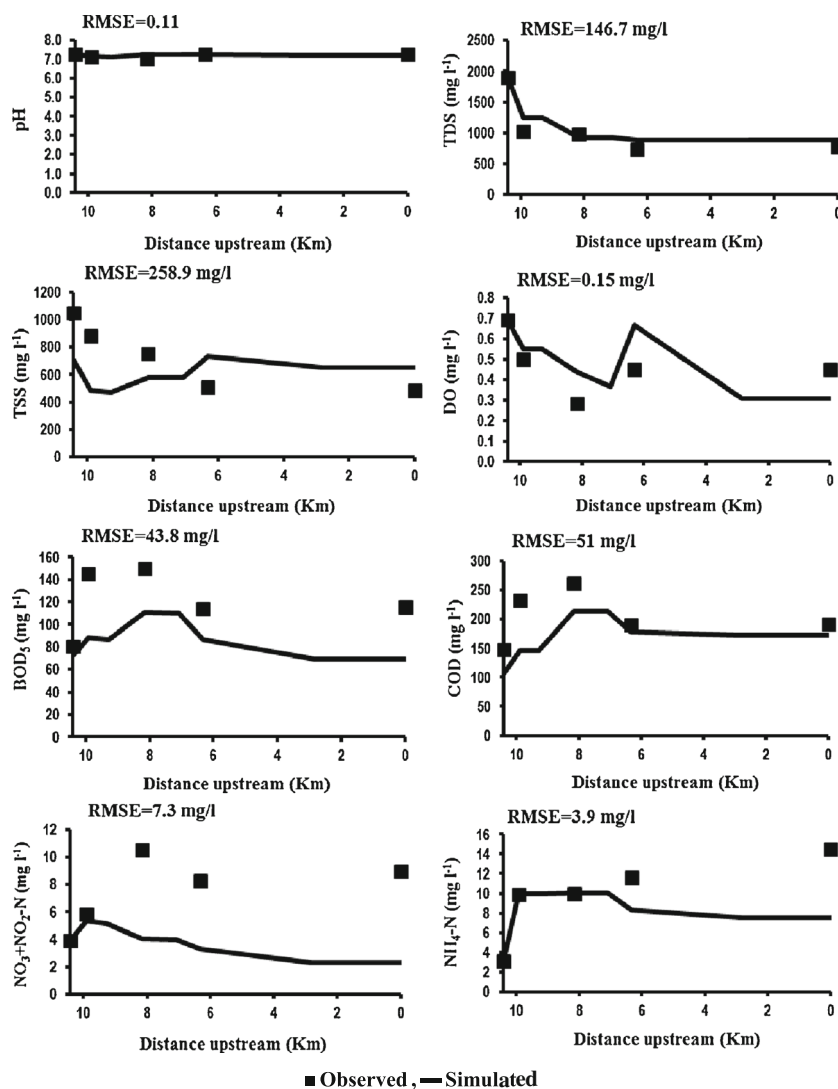
not quantified and completely identified. Some input variables such as algae coverage and sediment oxygen demand were not monitored. This limitation in the data and the monitoring results in low accuracy in the verification simulation using the same calibrated parameters. Despite some errors in the water quality framework results, the modeling results were acceptable for achieving modest management goals for such a data-limited condition. Greater accuracy could be achieved through frequent monitoring; monitoring additional input variables such algae coverage, sediment oxygen demand, and organic nitrogen; and using more sophisticated 2D or 3D stream models.

The combination of the water quality simulation model (QUAL2Kw) and the ECM increased the understanding of the source apportionment of water pollutants. This water quality framework helped decision makers to achieve their goals in an economic way by deciding the required removal for the root causes of pollution.

Optimized solutions for water quality management

The proposed multi-objective WLA optimization model examines solutions that vary from minimizing violations with correspondingly large treatment costs to those that result in greater violations and lower costs. Figure 8a, b exhibits the trade-off curves for the objectives for summer and winter, respectively. Violations of both irrigation and lake discharge standards were inversely proportional to the removal of TSS and COD among the sources and the flows subjected to treatment. By increasing the pollutants removed and treated flows, exceedances of the water quality standards for TSS and COD in the El-Qalaa drain decreased from 845 to 223 mg/L in summer and from 634.9 to 343.4 mg/L in winter, a reduction of 73.6 and 45.9 % for summer and winter, respectively. The difference in the decrease was due to changes in the meteorological conditions and crop patterns between the seasons. Pollutant concentrations in the agricultural wastewaters were

Fig. 8 Trade-off curves between the total removal and treated flow fractions at point and non-point sources, deviation from irrigation standards along the drain, and deviation from standard to discharge into lakes at the drain end for the summer (**a**) and winter seasons (**b**)
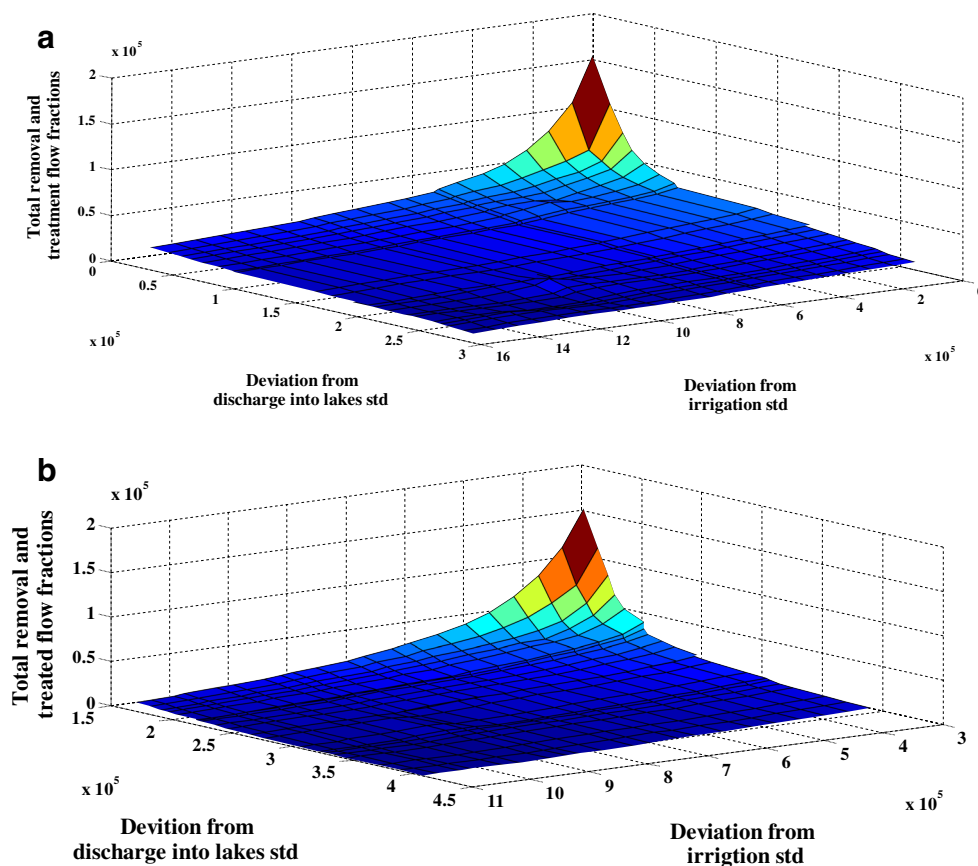
noticeably higher in winter, particularly for TSS (export coefficient of agricultural land for TSS increased from 0.28 ton ha^{-1} month^{-1} in summer to 1.76 ton ha^{-1} month^{-1} in winter).

The trade-off curves can assist decision makers in selecting the most favorable solution, based on their priorities. The MV, MP, and MF solutions (as potential solutions for decision making) are summarized in Table 6 for each season. The required quantities to be treated for the MV, MP, and MF solutions were 7.23, 2.71, and 0.84 m^3/s, respectively, for the summer season, which were 0.69, 0.42, 0.01, 0.21, 0.01, 0.19, 1.06, and 4.64 m^3/s from the urban land discharge of the Agricultural sub-basin, the rural land discharge of the Agricultural sub-basin, the urban land discharge of the Zohra sub-basin, the rural land discharge of the Zohra sub-basin, the urban land discharge of the Amlak sub-basin, the rural land discharge of the Amlak sub-basin, Somouha drain discharge, and Hydrodrome drain discharge, respectively, for the MV solution; 0.49, 0.41, 0.01, 0.01, 0.01, 0.01, 0.89, and 0.89 m^3/s for the MP solution; and 0.16, 0.06, 0.01, 0.05, 0.001, 0.04, 0.29, and 0.25 m^3/s for the MF solution. Similarly, the required quantities to be treated for the MV, MP, and MF solutions were 7.68, 5.04, and 1.70 m^3/s, respectively, for the summer season, which were 0.71, 0.37, 0.04, 0.04, 0.17, 0.42, 1.31, and 4.61 m^3/s from the urban land discharge of the Agricultural sub-basin, the rural land

discharge of the Agricultural sub-basin, the urban land discharge of the Zohra sub-basin, the rural land discharge of the Zohra sub-basin, the urban land discharge of the Amlak sub-basin, the rural land discharge of the Amlak sub-basin, Somouha drain discharge, and Hydrodrome drain discharge, respectively, for the MV solution; 0.003, 0.01, 0.003, 0.04, 0.03, 0.06, 0.67, and 4.22 m^3/s for the MP solution; and 0.02, 0.02, 0.002, 0.05, 0.01, 0.06, 0.74, and 0.79 m^3/s for the MF solution. The required removal fractions for TSS and COD for each source for these solutions are dedicated in Table 6. Overall, the MV solution required the highest treated quantities and removal fractions which minimize the exceedances of the water quality standards. In contrast, the MF solution required the minimum treated quantities and removal fractions. The MP solution was presented as a midpoint solution. The treatment of the drainage water from both Somouha and Hydrodrome drains was essential to meet the water quality standards. Figure 9a, b presents the water quality profiles for TSS and COD for the summer season, respectively, along the El-Qalaa drain for each of these three solutions. Likewise, Fig. 10a, b presents these profiles for the winter season. The average exceedances of the water quality standards for the MV and MF solutions were 238.9 and 732.6 mg/L for TSS, respectively, and 0 and 112.4 mg/L for COD, respectively, in summer. In winter, the average exceedances for the MV and MF solutions were 380.9 and 543.1 mg/L for TSS and 0 and

Table 6 Minimum standard violation (MV), middle point (MP), and minimum total removal and treated flow fractions (MF) solutions for the summer and winter seasons

Source	Decided fraction (%)	Summer season			Winter season		
		MV	MP	MF	MV	MP	MF
Agricultural sub-basin	Treated flow fraction from urban land	91.15	64.92	20.44	94.23	0.42	2.53
	Treated flow fraction from rural land	94.27	91.39	12.40	83.89	2.32	5.44
	TSS removal fraction for urban discharge	2.96	3.34	70.95	18.41	23.17	95.22
	TSS removal fraction for rural discharge	12.04	84.32	85.54	6.21	6.36	88.32
	COD removal fraction for urban discharge	41.70	88.73	99.85	16.94	61.13	81.50
	COD removal fraction for rural discharge	64.35	99.33	97.03	99.66	77.40	79.41
Zohra sub-basin	Treated flow fraction from urban land	7.04	8.32	7.71	42.91	3.32	2.50
	Treated flow fraction from rural land	87.31	3.67	20.79	14.34	16.01	21.15
	TSS removal fraction for urban discharge	42.38	74.73	98.42	76.03	65.47	95.17
	TSS removal fraction for rural discharge	53.85	53.15	98.31	24.11	44.51	79.50
	COD removal fraction for urban discharge	20.25	93.23	88.00	5.57	89.42	93.57
	COD removal fraction for rural discharge	98.87	98.78	98.52	7.47	99.10	94.69
Amlak sub-basin	Treated flow fraction from urban land	5.67	2.22	0.25	68.67	11.39	3.16
	Treated flow fraction from rural land	38.13	0.97	7.21	84.65	12.42	12.24
	TSS removal fraction for urban discharge	16.98	53.05	45.06	29.00	66.44	88.11
	TSS removal fraction for rural discharge	92.07	97.19	98.43	11.94	66.38	81.93
	COD removal fraction for urban discharge	58.18	98.18	57.73	72.47	98.37	88.47
	COD removal fraction for rural discharge	93.47	3.90	89.55	84.81	84.69	43.55
Somouha drain	Treated flow fraction	75.94	64.17	20.61	94.30	48.31	53.32
	TSS removal fraction	2.14	69.93	78.75	1.76	90.29	56.72
	COD removal fraction	18.71	82.50	92.47	8.52	45.96	46.76
Hydrodrome drain	Treated flow fraction	99.67	19.11	5.38	98.97	90.62	17.05
	TSS removal fraction	5.41	9.39	82.28	9.43	21.68	73.30
	COD removal fraction	16.81	11.04	87.23	5.11	51.32	86.74

91.7 mg/L for COD, respectively. As can be seen in Figs. 9a and 10a, exceedances of the standards for TSS are unavoidable because of the high TSS concentrations in the headwaters and significant contributions from agricultural wastewater along the drain.

Decision makers can select a desirable WLA solution from the trade-off curves produced by the multi-objective optimization model based on their treatment budget and degree of exceedance of the water quality standards. This approach can be extended to other drainage basins throughout the Nile Delta region and to other basins with similar agricultural characteristics. Improvements in water quality measurements can be used to refine model input data, improve model recommendations, and utilize the methodology in a dynamic way.

Conclusions

- A multi-objective optimization model integrating several component models was developed to provide waste load allocation alternatives for a freshwater system.

- This approach provides optimal treatment strategies for achieving competing wastewater treatment, wastewater reuse, and environmental objectives.
- The water quality framework was calibrated and verified using data obtained in 2007–2008 for the El-Qalaa drain in the Nile Basin, Egypt. A larger data set is necessary to refine the general approach used here. Nevertheless, the framework represented the field data satisfactorily and can be used to support future WLA decisions.
- The results show that the El-Qalaa drain water did not meet the water quality standards for irrigation and lake discharge for TSS, DO, BOD$_5$, and COD. Thus, suspended and organic material concentrations are critical considerations for El-Qalaa drain water quality management.
- The model provides trade-off curves among the selected objectives, with increases in pollutant removal and treated flow fractions at point and non-point sources leading to decreases in exceedances of the water quality standards. These trade-off curves can assist decision makers in selecting the most favorable solution based on their priorities.

Fig. 9 Water quality profiles for the summer season along the El-Qalaa drain resulting from minimum standard violation (*MV*), middle point (*MP*), and minimum total removal and treated flow fraction (*MF*) solutions for the summer season for TSS concentration (**a**) and COD concentration (**b**)
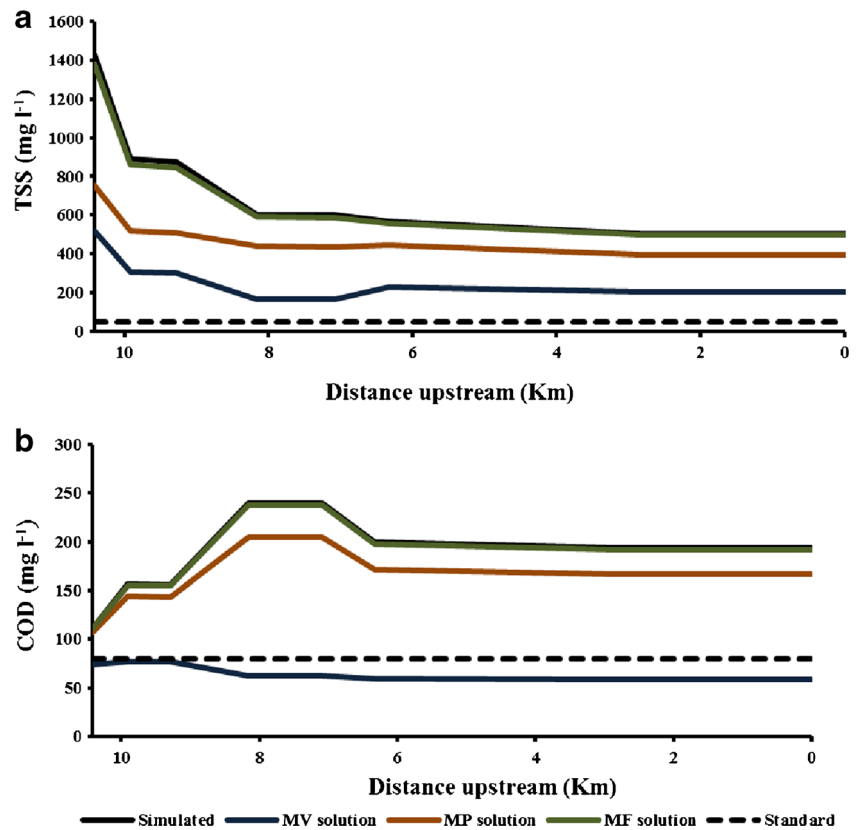
- This approach can be extended to other drainage basins throughout the Nile Delta region with similar

characteristics and to other regions through collection of area-specific land use and water quality data.

Fig. 10 Water quality profiles for the summer season along the El-Qalaa drain resulting from minimum standard violation (*MV*), middle point (*MP*), and minimum total removal and treated flow fraction (*MF*) solutions for the winter season for TSS concentration (**a**) and COD concentration (**b**)
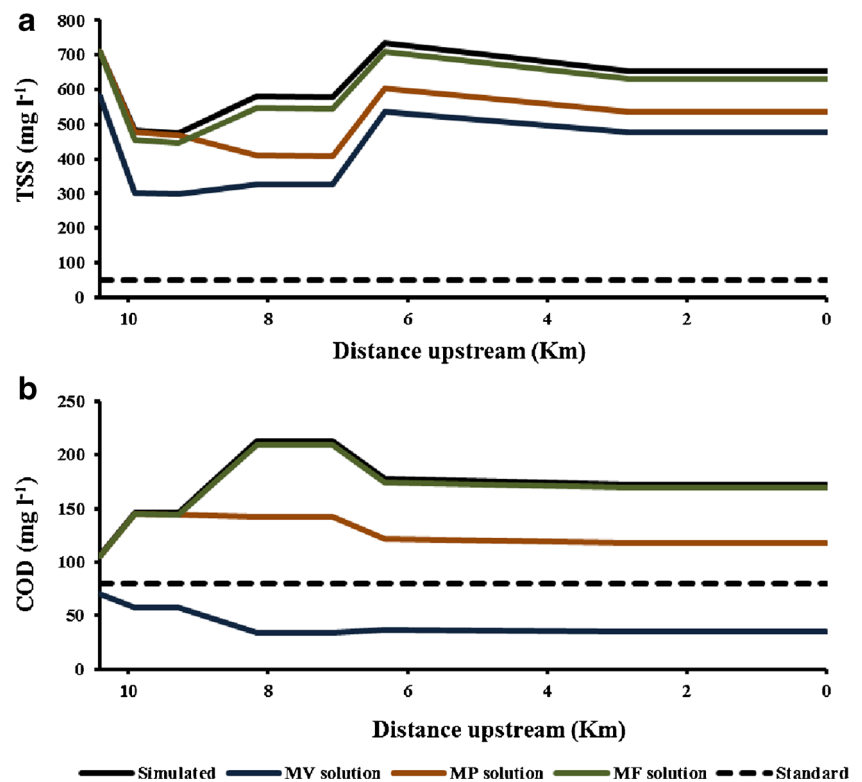
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