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Spatial Heterogeneity of the Nile Water Quality in Egypt

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Abstract

This paper aims to evaluate the water quality along the mainstream of the Nile in Egypt through modelling spatial distributions of water quality, using spatial statistical analysis. The study is based upon a sample frame of 78 sampling points collected in "February 2008" and located on the main waterway of the Nile and its delta (Rosetta and Damietta branches). Two water quality indices are calculated as general indicators of the overall water quality of the Nile, with special emphasis on drinking water quality. Exploratory spatial data analysis is carried out on the water quality indices, followed by plotting and modelling the experimental semi-variograms. Then, cross validation is executed in order to determine the best fitted models. Finally, surface maps are generated by performing spatial interpolation, using kriging technique. The generated surface maps of the two water quality indices show that water quality in Upper Egypt is excellent, in general, whereas water unfit for drinking is dominant in Middle and Lower Egypt. Therefore, intensive physical and chemical disinfection treatments are becoming pressing options for improving the quality of drinking water.

Keywords: The Nile, water quality, spatial modelling, semi-variogram, kriging.

1. Introduction

"Egypt gift of the Nile" said Herodot. The Nile constitutes the essential source of life in Egypt, it provides people with their fresh water needs. It is an essential factor of production and is vital for agriculture, transport, tourism and henceforth the socio-economic development of the country. However, the Nile has become, to a great extent, adversely affected by human activities. On the one hand, the population growth and the expansion of industrial, agricul-

tural, commercial and recreational activities that exploit natural resources, including water. On the other hand, industrial waste discharge, leakage of sewage by urban agglomeration and agricultural runoff contributes to the Nile contamination.

Therefore, the issue of Nile pollution should be on the top of the Government's environmental agenda. The protection of the aquatic environment requires regular water quality monitoring and effective pollution control in order to reduce the risk threatening the aquatic lives and people's health. Moreover, several quantitative research and statistical studies are needed to understand the intended problems, identify their limitations and, accordingly, propose realistic solutions.

To date, many studies try to make use of the spatial analysis methodology to model the spatial variations of the water quality indicators. The adopted method makes it possible to visualize the distribution of river water quality according to different land use and the interpolation of water quality at unsampled locations (Ouyang, Higman, Thompson, O'Toole, and Campbell 2001; Bordalo, Nilsumranchit, and Chalermwat 2001; French 2005; Sarangi, Madramootoo, and Enright 2006; Flipo, Jeannee, Poulin, Even, and Ledoux 2007; Rahman and Hossain 2008; Chang 2008)

Literature review reveals lack of studies that focus on water quality interpolation along the Nile through modelling the spatial variations of the water quality indicators. Therefore, this paper aims to fill this gap by mapping the water quality along the Nile, modelling the spatial variations and interpolating the water quality at unsampled locations. The software tool Geographic Information Systems (GIS) is used since the Nile has a geographical context. GIS is considered a powerful tool in managing water quality data, mapping and visualizing water quality spatial distributions (Elmahdi, Afify, and Abdin 2008; Hamad 2008).

Resorting to the interpolation techniques to illustrate the spatial variability is due to the difficulties of quantifying these variations at numerous locations. These difficulties are attributable to time constraints and impediments to access such locations. Thus, employing the interpolation technique help identify the locations with high concentration levels of pollutants. The generated surface maps, locating the spatial distribution of the water quality, will help decision makers adopt appropriate policies and undertake necessary measures not only to combat and prevent water pollution, but also to sustain this vital water resource, the Nile.

The remainder of the paper is organized to shed light on the study area and the available data. Section 3 provides the necessary back-ground of the applied methodology, taking into consideration the work-flow and the availability of reliable data as given in section 2. Results of the study are presented in section 4, and concluding discussion is given in section 5.

2. Data, study area and water quality indices

Although the Nile water quality is surely affected by the quality of water flowing from the upstream riparian countries, the current study only covers the Nile within the Egyptian territories. In Egypt, the Nile flows for a distance of about 1000 kilometers, starting from Aswan at $23^o58'24''N$ and $32^o53'54''E$ and ends into a large delta at where it flows into the Mediterranean Sea through Damietta branch at $31^o31'36''N$ and $31^o50'41''E$ and Rosetta branch at $31^o27'60''N$ and $30^o21'53''E$.

The Center of Environmental Monitoring and Studies of the Working Environment (CEMSWE) monitors the water quality of the Nile through 78 monitoring sampling points located along the Nile main stream and its two branches. At each sampling location, monthly random samples of water are taken, and their physical and chemical properties are measured and recorded to assess the water quality. These points are taken as the sample frame of the study where 13 points are located in Greater Cairo, 45 points in Upper Egypt and 20 points in Lower Egypt (3 on Rosetta branch and 17 on Damietta branch). Each available sampling point has been identified by its longitude and latitude. Figure 2 portrays the map of Egypt and the distribution of the sampling locations along the Nile. At data collection stage, the latest available were for 2008. Thus, the study uses February 2008 as the target period since it lies within the dry season and is characterized by low water flow and no rainfall. These environmental conditions increase the level of pollution due to the absence of runoff water that aids in pollutants sequestration (Elmahdi *et al.* 2008).

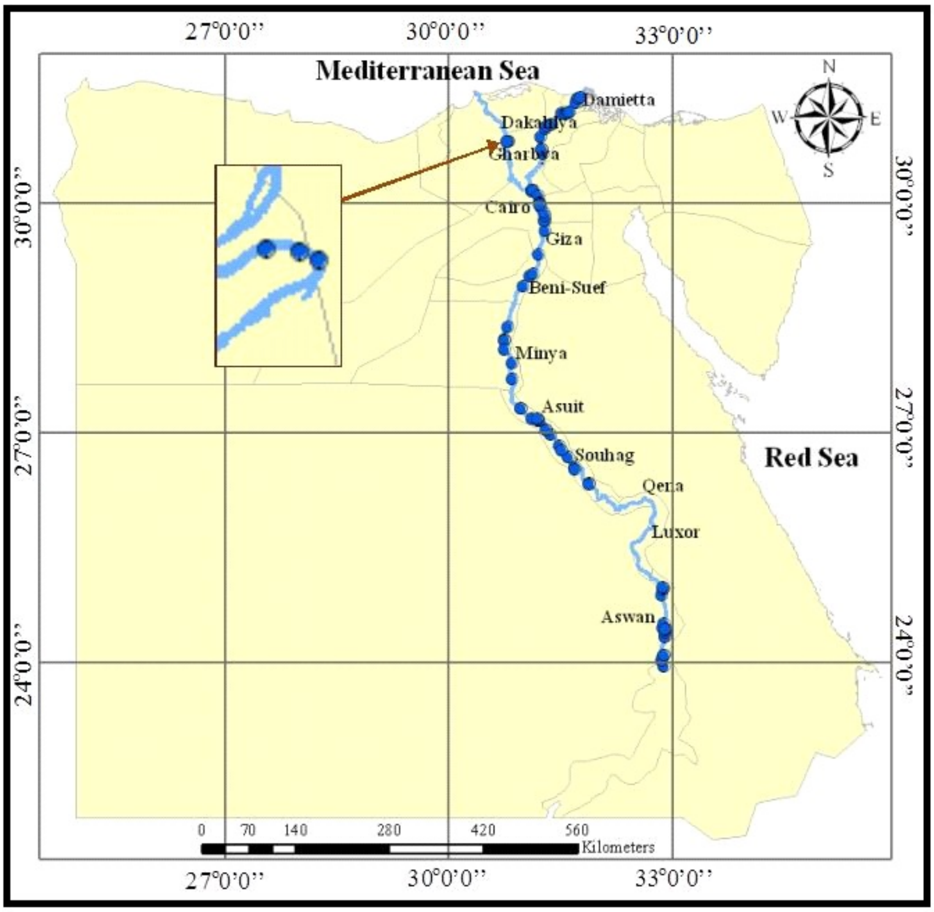

Figure 1: Map of the sampling points' distribution along the Nile

A water quality index (WQI) summarizes and streamlines complex water quality data into a single value that is easily conceivable. Once developed the WQI serves in examining trends, highlighting specific environmental conditions, planning water uses, as well as supporting decision making in assessing the worthiness of regulatory water quality program. In this research, the weighted water quality index (WWQI), proposed by Tiwari and Mishra (1985), is used to assess the overall water quality. Then, a drinking water quality index is developed to determine the suitability of water for this purpose. The WWQI determines the suitability of water to municipal uses, according to which, the water quality is rated excellent, good, poor, very poor and unfit when the value of the index lies between 0-25, 26-50, 51-75, 76-100 and >100, respectively. The WWQI is calculated as follows:

$$WWQI = \sum_{i=1}^{n} W_i Q_i, \tag{1}$$

where the subscript i denotes the i^{th} water quality variable included in the index and Q_i is the variable quality rating calculated using the following formula:

$$Q_i = \frac{V_i - I_i}{S_i - I_i} * 100, \tag{2}$$

where V_i is the variable observed value at a given sampling site, I_i is the ideal value of the variable and S_i is the recommended water quality standard of the variable according to the Egyptian Law no 48 for 1982. Yet, W_i is the variable unit weight that is inversely proportional to the recommended water quality standard of the corresponding variable, i.e. $W_i = K/S_i$ such that K is a constant equal to $\frac{1}{\sum_{i=1}^{n} 1/S_i}$ and $\sum_{i=1}^{n} W_i = 1$. While, n is the number of water quality variables included in the index.

The drinking water quality index (DWQI) determines the suitability of water for drinking use. It is the average of the variables' quality ratings (Q_i's), calculated by Equation 2, taking into account that simple physical treatment and disinfection are used in the water treatment plants, i.e. using more rigorous standards than those used in the WWQI [1]. The DWQI is calculated as follows (Donia and Farag 2010):

$$DWQI = \frac{\sum_{i=1}^{n} Q_i}{number\ of\ available\ indicators}, \tag{3}$$

A DWQI value below 100 indicates that water is suitable for drinking after simple physical treatment and disinfection. But a DWQI value greater than 100 indicates that water is unfit for drinking use and therefore intensive physical and chemical treatment and disinfection are required in the water treatment plant.[2]

3. Methodology

Spatial analysis is the evaluation of data properties and relations, taking into account the spatial locality of the considered phenomenon. Spatial statistics assumes that the measured value of a variable z at a given sampling location x within a certain region D, $z(x)$, can be expressed as:

$$z(x) = m(x) + \varepsilon(x) + \varepsilon', \tag{4}$$

where $m(x)$ is the deterministic component of the variable at location x, $\varepsilon(x)$ is the spatially correlated error and ε' is the spatially independent error (Fortin and Dale 2005). The

[1]It should be noted that one of the drawbacks of these indices is the use of simple summation of subsidiary quality ratings. However, the WWQI or the DWQI are widely used in the literature due to their simplicity.

[2]For more details on these indices and their construction, consult Abou-Ali and El-Ayouti (2012).

methodology starts with exploratory spatial data analysis (ESDA) to explore the properties of the data, to test the underlying assumptions and to help in identifying the suitable model, followed by the spatial interpolation. The remainder of this section is organized in a manner that details these two steps.

3.1. Exploratory Spatial Data Analysis

This section summarizes the ESDA applied in order to ensure the suitability of data to implement spatial statistical analysis. This is a common practice that entails four steps. The first step inspects the normality of the data distribution. If data prove not normally distributed, hence a normality transformation is required. The second step is to detect outliers by the semi-variogram cloud since their presence may affect the analysis.

The third step involves trend investigation. Trend consists of two components: a fixed global trend and a random short range variation (random error). The first, if existent, should be removed, to fulfil the sationarity assumptions, then the random error is modelled (Hamad 2008). As a result, the trend analysis 3-D plot is used to identify the global trend. Also, Dowd (2003) introduced the global D-statistic to test for constant spatial mean as follows:

$$D_G = \frac{1}{n}\sum_{i,j=1}^{n}\left[z\left(x_i\right) - z(x_j)\right], \tag{5}$$

where n is the total number of sampling locations. The null hypothesis tested is the stationarity of the spatial mean. The test statistic is the standardized global D-statistic ($\check{D_G} = \frac{D_G}{\sqrt{\mathsf{VAR}(D_G)}}$), which has asymptotically a standard normal distribution. The null hypothesis is not rejected with a confidence of (100-α)% if the value of the test statistic is within the confidence interval, otherwise it is rejected, where α is the significance level.

Finally, the presence of spatial dependence, one of the most important properties of spatial data sets, is checked. The spatial dependence structure must be taken into account through modelling the spatial variations using semi-variogram models (Haining 1990). The degree of spatial dependence can be estimated using spatial autocorrelation coefficients such as Moran's I, which is defined as follows (Fortin and Dale 2005):

$$I = \frac{1}{w}\frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}[z(x_i) - \overline{z}][z(x_j) - \overline{z}]}{\frac{1}{n}\sum_{i=1}^{n}[z(x_i) - \overline{z}]^2}, \tag{6}$$

where $z(x_i)$and $z(x_j)$ are the variable values at sampling location x_i and x_j, respectively and $\overline{z}$ is the sample mean of the variable. Yet, w_{ij} are the elements of the weight matrix such that $w_{ij} = \frac{1}{d_{ij}}$, where d_{ij} is the distance between $x_i$and x_j, and W is the sum of w_{ij}. Moran's I statistic ranges from -1 (negative correlation) to 1 (positive correlation). In this study, the geo-statistical analyst exploratory spatial data analysis toolbox of the Arc GIS 9.2 software is intensively used to apply the four main steps described above.

3.2. Spatial interpolation

The study applies the kriging interpolation technique, in which, the estimated value of the variable Z at a certain location x_o, $z^*(x_o)$, is a linear combination of the weighted average observations $z(x_i)$ at neighbouring locations x_i, $i = 1, 2, ..., m$ defined by: $z^*(x_o) = \sum_{i=1}^{m} w_i z(x_i)$. The weights w_i are based on the distance and the structure of spatial dependence between observations (Hamad 2008). In fact, kriging technique has many advantages, of which: *1)* it provides the best linear unbiased estimator for $Z(x_o)$; *2)* it incorporates the spatial variability to enhance the prediction efficiency; and *3)* it is accompanied with a measure of precision. Therefore, kriging has been considered the most suitable spatial interpolation technique to be used in this study.

Kriging is divided into two tasks: *1)* modelling the spatial structure of the data, using semi-variograms and *2)* interpolating the value of a certain variable at an unobserved location, where the weights assigned to the observations are determined on the basis of the fitted semi-variogram model. The semi-variogram is a function describing the spatial variability between the variable values at different locations within the study area. It is defined as $\gamma(h) = 1/2\ Var[Z(x) - Z(x+h)]$ and estimated using the following semi-variance function:

$$\widehat{\gamma}(h) = \frac{1}{2N(h)} \sum_{i=1}^{N(h)} \left[z(x_i) - z(x_i + h)\right]^2 \tag{7}$$

where $z(x_i)$ is the value of the variable Z at the sampling location x_i, and $N(h)$ is the number of pairs of sampling locations located at distance h from one another (Fortin and Dale 2005). Yet, h is the spatial lag size used to reduce the larger number of possible combinations. Trial and error approach is usually considered in the selection of the lag size and the number of lags (Johnston, Hoef, Krivoruchko, and Lucas 2001; Sarangi *et al.* 2006).

After computing the "experimental semi-variogram" from the sample data, a "theoretical semi-variogram" is modelled to fit this experimental semi-variogram, through estimating three parameters the sill, the range and the nugget. Since this study is limited to the longitudinal profile of the Nile, the semi-variograms are estimated and fitted in one direction only (i.e. isotropy is assumed). The best semi-variogram model and its parameters are evaluated using cross-validation method, by ignoring each data point, one at a time, and kriging the associated data value. Then, the differences between the interpolated and the observed values are summarized using cross-validation statistics, namely, the mean error (ME), the root mean squared error (RMSE), the mean standardized error (MStE) and the root mean squared standardized error (RMSStE) (Johnston *et al.* 2001).

In the kriging family, ordinary kriging is the most commonly type used. This study uses ordinary kriging, which assumes the model $Z(x) = \mu + \varepsilon(x)$, where $\varepsilon(x) \sim (0, \Sigma)$, μ is an unknown constant mean and $Z(x)$ is weakly stationary. The optimal weights w_i, $i = 1, 2, \ldots, m$, that will yield the best linear unbiased estimate for the value of the variable of interest at one or more unsampled locations, can be obtained by minimizing the kriging variance $\sigma_E^2 = V[Z^*(x_o) - Z(x_o)]$, subject to the unbiasedness condition $\sum_{i=1}^{m} w_i = 1$. The estimated weights are then substituted in $z^*(x_o) = \sum_{i=1}^{m} w_i z(x_i)$ in order to obtain the interpolated value $z^*(x_o)$.

In brief, after computing the experimental semi-variogram, different semi-variogram models are fitted to the experimental semi-variogram to select the best fit model and its parameters, using cross-validation techniques. Finally, interpolating the variable values at unsampled locations and generating surfaces illustrating the spatial distributions of the variable under study can be performed, using kriging interpolation technique. Also, ArcGIS geo-statistical toolbox has been used for spatial interpolation, using the ordinary kriging module, for the two water quality indices: WWQI and DWQI, taken one by one.

4. Results

4.1. Exploratory Spatial Data Analysis

Following the four stage of ESDA previously described. Starting with testing the normality assumption through the inspection of the normal Q-Q plots indicate that the two WQIs are not normally distributed. Applying a log transformation to the WQIs ensures the normality of the variables.

Second, the 3-D trend analysis plots indicate that the WWQI and the DWQI decrease from Upper Egypt to Middle Egypt and Lower Egypt. However, the results of the D-statistic test support the stationarity of the WWQI (D = 1.83, p-value = 0.27) and the DWQI (D = 1.9, p-value = 0.23). Accordingly, there is no need to remove the first order polynomial trend. Thus, it can be concluded that the WQIs are stationary and it is better to use ordinary kriging assuming constant trend to interpolate their quality levels along the Nile.

Third, scrutinizing the semi-variogram clouds of the WQIs reveals the presence of outliers. However, these outliers have no significant effect on the degree of spatial dependence measured by Moran's I with a value of about 0.5 and a p-value < 0.001. Hence, no need to delete them from further analysis. Moran's I statistics indicate the significant presence of positive moderate spatial autocorrelation i.e. near locations are more related than distant locations.

4.2. Spatial interpolation

By trial and error, the lag size is set to 20 km and the number of lags is chosen in a manner that the distance of significant autocorrelation becomes clearly visible. Figure 2 illustrates both the experimental and the theoretical best fitted semi-variogram model for each variable, assuming constant trend. Generally, each semi-variogram starts low at closer distances and elevates as the distance widen. The spatial analysis results indicate that the best theoretical models (based on the root mean square errors) which fit the experimental semi-variograms are the Gaussian models for both WQIs given by:

$$\gamma\left(h\right) = \begin{cases} C_o + C_1\left[1 - \exp\left(-3\frac{h^2}{a^2}\right)\right] & for\ 0 < h < a \\ C_o + C_1 & for\ h \geq a \end{cases}, \tag{8}$$

where C_o, C_1, a indicate the nugget, the sill and the range, respectively and h is the lag size.

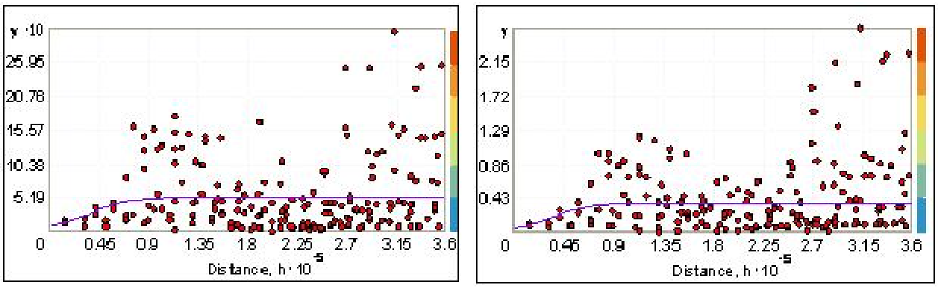

Figure 2: Best fitted semi-variogram model assuming constant trend

Table 1 illustrates the best fitted semi-variogram model parameters. It also illustrates a measure for the degree of spatial dependence given by the share of the variability due to spatial dependence (sill) to the total variability (sill + nugget). Examining Table 1, it is found that both the WWQI and the DWQI exhibit strong spatial dependence between the sampling points along the Nile up to a distance of 87 and 81 km., respectively. The cross validation statistics (Table 2) indicate that the selected semi-variogram models and the associated parameters are reasonable. They have the smallest RMSE, the MStE are closer to zero and the RMSStE are closer to one.[3]

Variable	Model	Number of lags	Nugget C_o	Sill C_1	Range a	$\frac{Sill}{Sill+Nugget}$
WWQI	Gaussian	18	0.09	0.42	87 km.	0.82
DWQI	Gaussian	18	0.06	0.29	81 km.	0.83

Table 1: Best semi-variogram model assuming constant trend

Variable	ME	RMSE	MStE	RMSStE
WWQI	-2.265	50.86	-0.088	0.9452
DWQI	-3.792	114.8	-0.058	1.001

Table 2: Cross validation statistics of ordinary kriging assuming constant trend

The generated WWQI map depicted in Figure 3 shows excellent water quality at Upper Egypt, except at Asuit where good and poor water qualities are noticed. Also, it shows that the water quality varies between excellent and good at Middle Egypt. Noticeably, the water is of poor quality at Beni-Suef. Generally, Lower Egypt suffers from poor water quality, especially at El-Sarw Drainage. Indeed, the water quality is very poor in Rosetta Branch, especially in Kafr El-Zayat. The contour map of prediction errors (Figure 3) indicates that the prediction errors of the points located in Middle and Lower Egypt are considerably large relatively to those sited in Upper Egypt. Moreover, it shows that the prediction standard errors are relatively smaller around the sampling points than in areas without sampling points.

The DWQI map (Figure 4) represents the spatial distribution of the drinking water quality. The water of the Nile is of good quality for drinking in Upper Egypt, except in Asuit. Poor drinking water qualities are depicted from the map in Greater Cairo and Lower Egypt. An interesting point is that the DWQI is above 100 at all the drinking water intakes along the Nile in Middle and Lower Egypt, indicating poor drinking water qualities. The contour map of prediction errors (Figure 4) shows that the prediction errors are large, in general. However, the prediction errors of the points located in Middle and Lower Egypt are larger compared with those sited in Upper Egypt. This result is due to the presence of extreme outliers. Moreover, the prediction errors, as expected, are larger in Luxor, Qena and Rosetta branch due to the shortage of sampling points.

Figure 5 illustrates the percentage contribution of each polluting variable to the drinking water quality index, which could help in determining the cause of water pollution. The figure

[3]This model is the best fitted model as compared to all other semi-variogram models.

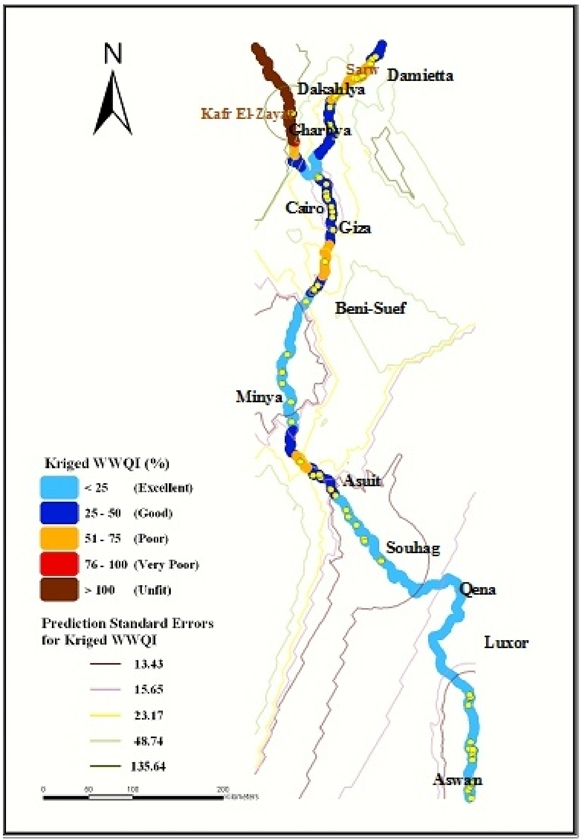

Figure 3: Surface generation of the WWQI and contour map of the prediction standard errors for kriged WWQI

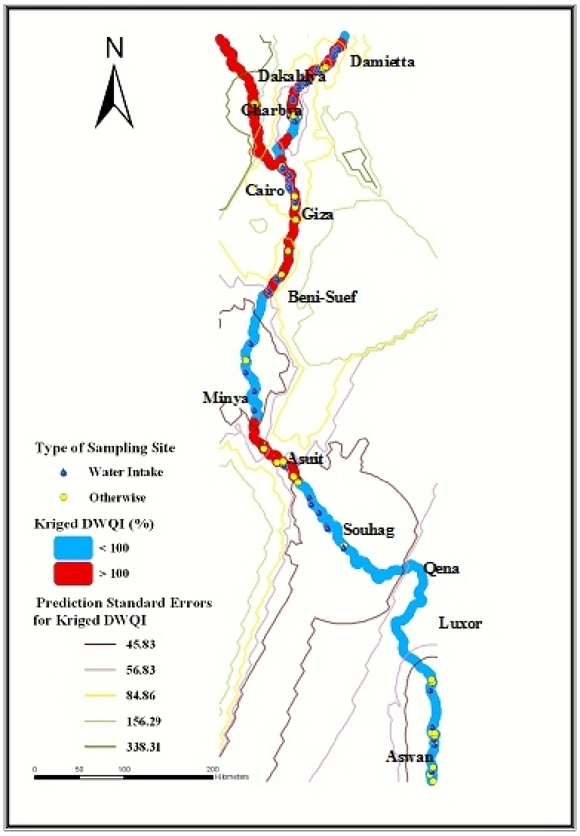

Figure 4: Surface generation of the DWQI and contour map of the prediction standard errors for kriged DWQI

shows that the unfit water for drinking use dominant in Asuit are attributed to the high levels of Ammonia (NH_4). As well as, the poor drinking water quality in Beni-Suef and Greater Cairo are due to the high levels of heavy metals (Mn + Fe). Additionally, the figure indicates that the high prevalence of biological oxygen demand (BOD) has a great effect on the water quality. This means that the organic waste is problematic in Aswan, Sohag, Menya and Gharbeya. A major type of organic waste is human waste, which usually involves significant human pathogens creating a health hazard (Rahman and Hossain 2008).

5. Discussion

The Nile pollution becomes a pressing national issue in Egypt. This is due to the accelerated population growth and economic activities, which impose a heavy burden on the viability of the Nile water quality. Accordingly, this study aims to assess the Nile water quality in Egypt at "February 2008" using spatial statistical analysis. In fact, spatial interpolation techniques facilitate the identification of highly polluted areas. This in turn will aid decision makers in adopting appropriate policies to combat and prevent the Nile water pollution.

After exploring data properties and resorting to ordinary kriging to spatially interpolate the

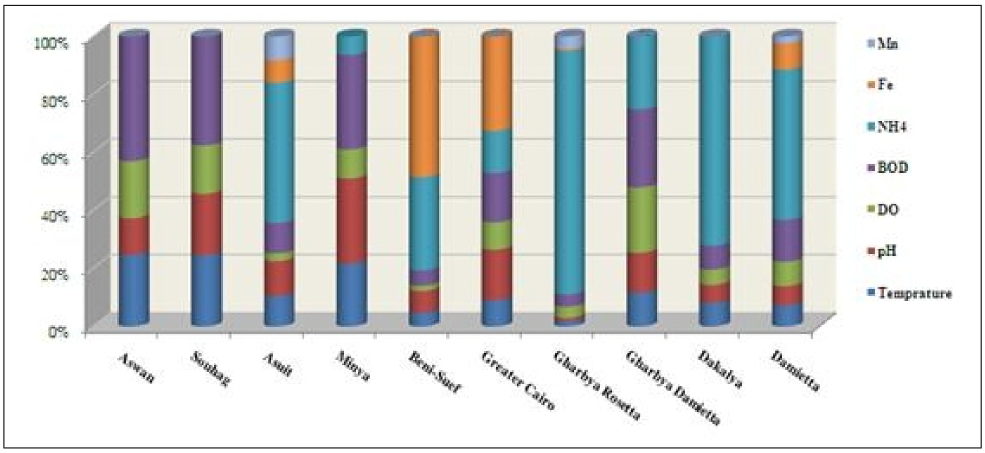

Figure 5: Surface generation of the DWQI and contour map of the prediction standard errors for kriged WWQI

water quality along the Nile in Egypt, cross-validation technique proved that the Gaussian models are the best fitted semi-variogram models describing the spatial variability of both indices, WWQI and DWQI. Spatial interpolation is performed on the bases of these models and surfaces are generated to map the spatial distribution of the water quality.

It can be concluded from the results of the study, in conjunction with the findings of other relevant studies and information, that:

- Upper Egypt has excellent water quality, except Asuit which is characterized by water quality varying between good and poor. Poor water quality in Asuit is attributed to agriculture discharges and fertilizers factories situated on its river banks (CEMSWE 2008);

- Water quality varies between poor and good in Middle Egypt and along Damietta branch. Very poor water quality is observed at the Rosetta branch due to accumulated industrial discharges into the river. These discharges originate from the industrial complex of pesticides and fertilizers located at Kafr El-Zayat and some factories located in Greater Cairo. Besides agricultural discharges stemming from the agricultural drainages in Beni-Suef (CEMSWE 2008);

- Excluding Asuit, good water suitable for drinking after applying simple physical treatments and disinfection in the water intake plants is situated at Upper Egypt;

- Unfit water for drinking, dominant at Asuit and along Rosetta and Damietta branches, is attributed to the high levels of Ammonia (NH_4) originating from the agricultural drainages and the wastes of the pesticides and fertilizers factories. The poor drinking water quality at Beni-Suef and Greater Cairo is due to high levels of heavy metals (Mn + Fe)(CEMSWE 2008). Therefore, simple physical and chemical treatment with disinfection is not adequate and intensive physical and chemical treatments with disinfection are the most suitable options for the water intake plants in these areas. Moreover, strict water quality standards should be imposed on drains and wastewater discharges; and

- The BOD has a significant negative effect on water quality in Aswan, Sohag, Menya and Gharbeya. This can be attributed to the bad municipal sewage network covering those governorates (CEMSWE 2008). These high BOD levels reduce the ability of water to sustain aquatic life, inducing negative impact on the ecosystem and fisheries.

In light of the results and the experience and knowledge acquired during field practice, the following recommendations may be useful for future research:

- The sampling points should be increased to enhance the accuracy of estimation in areas with few or without sampling points;
- Taking the direction of the water flow into account would produce better results since, in a river system, sampling site Y is only affected by upstream sampling site X; and
- Carrying out further studies which highlight seasonal distribution and spatio-temporal analysis and emphasize the concept of the dynamic transport of pollutants loadings.

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