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Assessment of Groundwater Variability in Mbagathi River Catchment

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Abstract
Groundwater is increasingly an important source of water. Assessment of its variability spatially and temporally besides quality and quantity is not easy. Groundwater contains multiple range of chemical parameters. This contribution proposes a water quality index (WQI) to synthesize various groundwater quality parameters (Na^+, F^-, Cl^-, SO_4^{2-}, Ca^{2+}, Mg^{2+}, K^+ and NO_3^-) in Geographic Information Systems (GIS) based environment. The parameters are analyzed relative to the Kenya Standard (KS) East Africa Standard (EAS) 12:2018 standard in the Mbagathi river catchment, a metropolitan area, Southwest of Nairobi, Kenya. Prediction maps for three seasons (wet, moderate and dry) and a combination all three seasons were produced. Based on WQI classification, results showed 36% - 28% good, 58% - 61% fair, and 6%-11% poor. A noticeable declining groundwater quality trend from wet to dry seasons was observed. Groundwater quality deterioration was observed to be greater in areas with higher yield and water rest level. Groundwater is safe for drinking, barring the elevated fluoride content in some areas. Application of GIS was a valuable tool in exploration of groundwater characteristics. Maps generated can serve as first-hand information for groundwater development.
Keywords: groundwater, quality, kriging, semivariogram, variability
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1. Introduction

Groundwater changes in quantity and quality over space and time influenced by natural processes. These changes occur as surface water percolates and stays underground for a period of time (Nelson 2002). During this period, water is in reaction with the dissolved chemical elements occurring naturally in the geological formation (Li *et al* 2015). Groundwater varies in its spread and quality. It requires experience to predict groundwater variability. Computational models have been proposed as a means of obtaining groundwater level data. The models use simulation methods to predict the variability of groundwater. The models can also be used to derive aquifer hydrogeological properties (Peck *et al* 1988). Through multiple studies researchers have attempted to compare groundwater variability in quantity and quality around the same areas (Furkuor *et al* 2013). Knowledge in groundwater variability will enhance understanding in its exploration enabling informed decisions.

The census of 2019 in Kenya recorded a population of 47,564,296 people (Kenya National Bureau of Statistics (KNBS) 2019). Kenya's per capita freshwater is 412 cubic meters (m3) (World Bank (WB) 2020). This is a decline from 647 m3 per capita over a decade ago (Mogaka *et al* 2006). With increasing demand for water in the study area, groundwater resource is increasingly being exploited (Mulwa *et al* 2005). Variability of the groundwater has economic implications due to costs associated with its treatment and use. It is helpful to have prior knowledge of the groundwater variability so as to justify the investment in its exploitation. Such challenges and limitations necessitate investigation into the variability of the groundwater resource within the identified study area.

2. Study Area

Mbagathi river catchment area was selected due to its dependence of the groundwater for various uses. Understanding the variability of the groundwater would assist during its exploration. The catchment has an area covering 182km^2, between latitude -1.329452° and -1.452872°; and longitude 36.647828° and 36.790487°. Its population is 341,786 people. It has 111,408 households resulting to an average population density of 1878 persons/km^2 (KNBS 2019). It falls in the Athi Catchment Area which is one of the six drainage basins in Kenya. Climate in the study area is characterized by a bi-modal rainfall pattern. Short rains fall between October to December while the long rains fall between March to May. The rainfall gradient increases with altitude but its pattern is not uniform across the area. The temperatures vary with altitude ranging from 10ºC in Ngong Hills on the Northwest, to highs of about 31ºC towards Rongai to the South east of the study area.

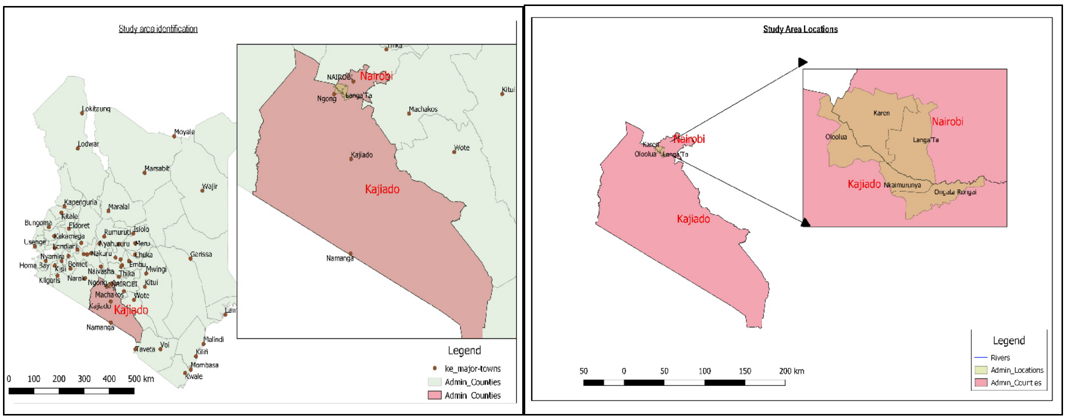


Figure 1: Mbagathi river catchment study area

Mbagathi River catchment area is located in the greater Nairobi City metropolitan area. It lies southwest of Nairobi County and north of Kajiado County. Surface water sources are inadequate to meet the water demand (Mulwa *et al* 2005). Groundwater is exploited as an alternative to cover the deficit in surface water supply. The groundwater is conveyed to the residents by piping. Water vending by water trucks, water kiosks and hart carts is done in the area

Faulting, volcanicity and tectonic movement are the factors that have contributed to volcanic activity in the study area. This has influenced the areas geological history and the geomorphological evolution (Saggerson 1991). The typical rock formations are tertiary volcanic rocks. These rocks include Ngong basalts, Ol Doinyo Narok agglomerate, Limuru quartz trachyte, Kerichwa valley tuff, Nairobi trachyte, Nairobi phonolite, Mbagathi trachyte, Kandizi phonolite and Ol Esayeti phonolite (Saggerson 1991). Kiserian-Matathia area is considered a water conservation zone to the east of Ngong hills. The water conserved is mainly determined by faulting affecting occurrence of groundwater in its distribution, flow and yield (Mulwa *et al* 2005).

There is inconsistency in the hydrogeology of the Mbagathi river catchment caused by the varied lithological conditions. Weathering and fractured nature of the geological formations affect the hydrogeology contributing to this inconsistency (Mulwa *et al* 2005). There are varied aquifers in the area. There are sands and sediment deposits interposed in tuff. Basalts, trachytes and turf rock strata with appreciable perviousness are also found in the area. The area also has connected rock formations such as basalts and turfs. Such connected rocks form aquifer that is fractured. Aquifers in fault zones have the highest groundwater yield. Basalt type of rocks influence at least 75% of the aquifer yields. Trachytes influence about 14% of aquifer yields. Weathered and jointed tuff influence about 6% of the aquifers (Mulwa *et al* 2005).

3. Data and Methods

Groundwater samples were collected from 36 borehole sites during wet, moderate and dry seasons according to weather patterns in the study area. The collection was done from already existing borehole sites which were operational at the time of the study. Polyethylene bottles were used to take samples. The bottles were stored in a cooler box at 20°C and safely transported to the lab for analysis. The bottles were labelled with preprinted stickers on site. Global Position Systems (GPS) coordinates were labelled on each sticker using Garmin eTrex® 10 handheld device. The coordinates were taken to World Geodetic System 1984 (WGS 84) coordinate system. The parameters selected were fluoride (F^-), chloride (Cl^-), calcium (Ca^{2+}), magnesium (Mg^{2+}), sodium (Na^+), potassium (K^+), sulphates (SO_4^{2-}) and nitrates (NO_3^-). Test procedures followed the KS EAS 12:2018, an East African Standard which specifies requirements, sampling & test methods for portable water intended for direct human consumption, domestic and industrial use.

Water Quality Index (WQI) was adopted to provide insight into the quality of the groundwater. The WQI characterized the influence of every parameter on the overall groundwater quality. KS EAS 12:2018 was the basis of calculation of the WQI. Development of WQI was in three steps. Each of the eight selected parameters (Na^+, F^-, Cl^-, SO_4^{2-}, Ca^{2+}, Mg^{2+}, K^+ and NO_3^-) was assigned a weight (w_i). This weighting of the parameters was based on the relative significance to the contribution of the parameter to drinking water quality. (Batabyal *et al* 2015) The weighting was scaled from 1 being lowest to 5 being highest as listed in Table2. Fluoride was the parameter with the highest weight at 5 because its mean from all samples was exceeding the specified limits according to KS EAS 12:2018 standard. The rest of the parameters were assigned weights based on their health and economic significance. Sulphate had the lowest rank since it had the least significance in the groundwater quality.
Relative weight (W_i) of the chemical parameter was computed using the following equation:

$$W_i = \frac{w_i}{\sum_{i=1}^{n} w_i} \quad (1)$$

W_i refers to relative weight
w_i refers to weight of each parameter
n refers to number of chemical parameters in the analysis (Batabyal *et al* 2015)
For each, relative weight (W_i) was computed as enumerated in table1 below

Table1: Relative weight of parameters

Chemical Parameters[a]	Kenyan Standard	Weight (w_i)	Relative weight
Fluoride	1.5	5	0.2381
Chloride	250	4	0.1905
Potassium	50	1	0.0476
Magnesium	100	3	0.1429
Calcium	250	3	0.1429
Sodium	200	2	0.0952
Nitrate	10	2	0.0952
Sulphate	400	1	0.0476
		$\sum wi$=21	$\sum Wi$ = 1.00

[a]chemical parameters in mg/l

In the third step, the quality rating was generated based on value of parameter concentration in every sample divided by the parameter respective value in the standard KS EAS 12:2018 and the result multiplied by 100.

$$q_i = \left(\frac{Ci}{Si}\right) * 100 \quad (2)$$

q_i refers to the quality rating
C_i refers to the parameter concentration in every sample in mg/l
S_i refers to the Kenyan drinking water standard for each parameter in mg/l

The subindex (SI) for every parameter was calculated by multiplying the quality rating with its relative weight. The WQI was then calculated by summation the individual subindices for every sample (Batabyal *et al* 2015). The formulae were

$$SI_i = q_i * W_i \quad (3)$$

$$\mathrm{WQI} = \sum SI_{\text{i-n}} \quad (4)$$

SI_i is the sub index of i[th] parameter;
W_i is relative weight of i[th] parameter;
q_i is the rating based on concentration of i[th] parameter, and n is the number of chemical parameters.

The WQI was categorized in five classes. Very Good 0<x<20, good 20<x<40, fair 40<x<60, poor 60<x<80 and very poor 80<x, where x is the class of water. The quality data was subjected to statistical analyses using Microsoft Excel 2016 software. Groundwater geochemistry was analyzed based on the concentration of the parameters selected. Correlation of the selected parameters was examined using IBM Statistical Packages for the Social Sciences (IBM SPSS) software. Correlation criterion as a statistical tool compares two variables to indicate if one variable can sufficiently predict the other by generating a correlation coefficient.

$$\text{Spearman coefficient, } \rho = 1 - \frac{6\sum d_i^2}{n\left(n^2-1\right)} \quad (5)$$

The coefficient is used to determine correlation between variables. The extent of correlation of dependent variable (x) being only influenced by an independent variable (y) and vice versa. The correlation coefficient (r) lies between -1 and +1. Coefficient correlation values +0.7 or higher is very strong positive, +0.4 to +0.69 strong positive, +0.3 to 0.39 moderate positive, +0.2 to 0.29 weak positive, +0.01 to +0.19 negligible. Conversely, -0.7 or higher is very strong negative, -0.4 to -0.69 strong negative, -0.3 to 0.39 moderate negative, -0.2 to -0.29 weak negative. -0.01 to -0.19 negligible.

The GIS environment used to perform spatial variability analysis in particular geostatistical wizard application in ArcGIS 10. The exploratory analysis sought to determine the variable temporal and spatial distribution. Fitting the theoretical semivariogram was applied with distribution of variables done using the histogram and Normal QQ plots. This aimed at determining whether the data was following a normal distribution. It was anticipated that the data would have a normal distribution. Log transformation of the data was done in the absence of normal distribution or to improve the normal data. These methods give indication as to the nature of distribution of a variable under consideration (Alexander *et al* 2017). If skewness of a parameter was observed to be more than $\pm$1 then log transformation was performed on the data in order to realize a log-normal distribution

(Oliver *et al* 2015). Mean, median and kurtosis statistics were examined form the data. Mean and median should to be close for a normal distribution (Gyamfi *et al* 2016). Kurtosis should be 3. From the data exploration, trends observed were analysed to determine presence of spatial variation (Gyamfi *et al* 2016).

Semivariogram is a measure of the relation of data points within a particular variable to each other with respect to distance. This measure was used to assess the spatial dependency of the selected variables. Kriging assisted in generating distribution pattern from the parameters, trend analysis and fitting of the theoretical semivariogram. Kriging is designed to specially generate the models based on spatial variability (Alexander et al, 2017). The general formula for kriging is formed as a weighted sum of the data:

$$Z(s_0) = \sum_{i=1}^{N} \lambda_i Z(s_i) \tag{6}$$

where:
$Z(s_i)$ = the measured value at the ith location
λ_i = an unknown weight for the measured value at the ith location
s_0 = the prediction location
N = the number of measured values (Alexander *et al* 2017)

As a method of interpolation of data, kriging is based on a statistical approach. It does weight based in specific values measured at the sampled locations (Alexander *et al* 2017). Kriging provides more than just predicted value of unsampled locations (Oliver *et al* 2015). The nugget and sill ratios of the semivariogram can be used to describe the spatial dependency. Nugget/Sill ratio of < 0.25, 0.25-0.75 and 0.75 were rated as having strong, moderate and weak spatial structure respectively. Different semivariogram models were compared to determine the model with the best spatial structure based on the nugget and sill ratio. The best fitting model selected based in the nugget/sill ratio is used in generating the prediction maps using ordinary kriging (Gyamfi *et al* 2016).

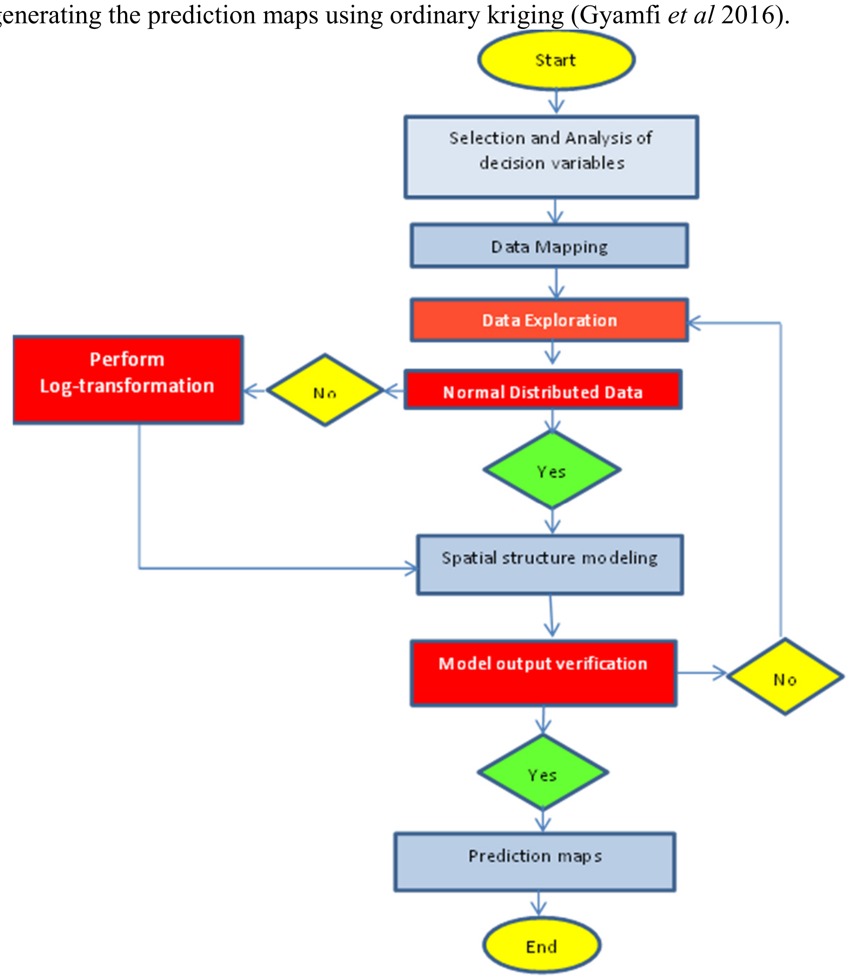


Figure 2: Flowchart of the data analysis, exploration and prediction maps

The data analysis, exploration and prediction maps were conceptually done by flowcharting the process as displayed in Figure 2. Geostatistical data must not follow a normal distribution. Other exploratory tools influencing the data such as the root mean square standard error and mean error should be taken into consideration (Oliver *et al* 2015). Kriging gives relevant analysis of errors associated with the estimated values for the unsampled locations

(Oliver *et al* 2015).

4. Results and Discussion

Borehole records data within the study area was obtained from the Water Resources Authority (WRA). This data provided the recorded borehole yield besides other pertinent information. The average yield stood at 8.6m3/hr based on the record of 140 boreholes obtained. This presents a relatively fair yield given that 57% of boreholes permit are for domestic use. It underlines the relative importance in provision of domestic water supply. Other permits have been granted for institutional, commercial and agricultural uses. The drilled depth of boreholes averaged 171m. The average drilled depth provides indication of the capital investment required to develop groundwater in the study area. The observed water rest level (WRL) averaged 57m. From the recorded borehole yield, a map of spatial variability was generated by geostatistical analysis in ArcGIS framework as indicated in Figure 3. Groundwater yield was observed to higher in the central parts of Matasia and Nkoroi. Higher yield was also observed to the eastern parts of Ongata Rongai. Most of the aquifer yield is fair. The low yield observed in the North and North east area is likely due to Karen area being a discharge zone. The rate of water abstraction is greater than the rate aquifers are replenished (Mulwa *et al* 2005).

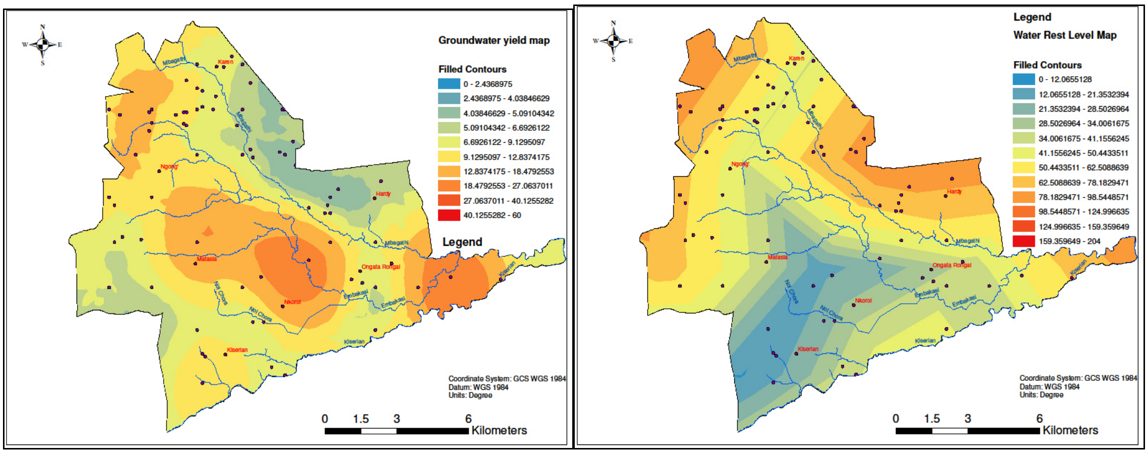


Figure 3: Groundwater yield and Water Rest Level map of the study area

The groundwater rest level map in Figure 3 indicates flow is generally from the Northwest part of Ngong, Northern part of Karen and Northeast part of Hardy resting predominantly to Southwest parts of Kiserian. This strongly agrees with the altitude of the area. This was however not consistent with the yield.

Table 2: Basic statistics for groundwater quality parameters

Parameters, mg/l		F^-	Mg^{2+}	Ca^{2+}	Cl^-	K^+	Na^+	SO_4^{2-}	NO_3^-
Wet	AM	1.6	29.0	53.1	106.1	15.7	16.9	8.2	0.8
	Max	3.3	99.1	163.4	243.7	25.3	43.7	28.4	2.5
	Min	0.7	2.4	12.3	36.9	6.6	6.7	2.2	0.2
Moderate	AM	1.7	25.1	46.6	102.0	15.6	18.3	8.0	0.7
	Max	3.3	94.5	116.2	211.0	24.0	49.0	30.0	2.4
	Min	0.6	0.7	11.4	38.0	5.0	6.5	1.0	0.2
Dry	AM	1.8	27.0	50.2	104.4	15.8	18.8	9.2	0.8
	Max	3.1	119.1	133.5	214.0	26.0	47.2	29.0	2.3
	Min	0.6	2.2	2.4	41.0	7.0	7.5	3.0	0.3
KS EAS 12:2018[a]		**1.5**	**100**	**150**	**250**	**50**	**200**	**400**	**45**
WHO Guidelines[a]		**1.5**	**100**	**250**	**250**	**-**	**200**	**-**	**45**

AM: Arithmetic Mean; Max: Maximum; Min: Minimum; [a]chemical parameters in mg/l

Basic statistics of parameters were summarized in Table 2 above. F^- was exceeding the permissible levels of KS EAS 12:2108 as per the Arithmetic Mean. F^- is typically the elevated parameter and most prevalent groundwater quality challenge in the study area. F^-, Ca^{2+} and Mg^{2+} had at least one sample exceeding the permissible levels as observed maximum test result. These combined parameters have the greatest impact on the groundwater. Ca^{2+} and Mg^{2+} contribute to water hardness. Hardness was not covered in the scope of this study. There is marginal variability is groundwater quality over the three seasons. This informed the basis of variability prediction.

The wet season showed higher levels of Ca^{2+}, Mg^{2+} and Cl^-. Ca^{2+} is the leading cation and F^- is the leading anion among the selected parameters. The concentration of the ions is largely influenced by the infiltration of water into the porous and permeable rocks during the rainy season (Mulwa *et al* 2005).

4.1 Exploration of Water Quality Index (WQI) data

The data used to compute WQI was examined to assess its distribution using geostatistical analysis.

Table 3: Statistics of Normal and Log-Normal data

Season	Statistic	Normal	Log-Transformed
Wet	Mean	44.18	3.76
	Median	43.68	3.78
	Skewness	0.25	-0.45
	Kurtosis	2.87	3.34
Moderate	Mean	44.19	3.76
	Median	43.48	3.77
	Skewness	0.38	-0.43
	Kurtosis	3.45	3.6
Dry	Mean	46.64	3.8
	Median	44.56	3.8
	Skewness	0.98	0.068
	Kurtosis	4.57	3.28

The mean, median and skewness were tabulated in Table 3 using the results from the ArcGIS geostatistical analysis. Under normal distribution, the mean and median should be close to equal, skewness should lie between -1 and 1 (Gyamfi et al, 2016), kurtosis should be 3. Skewness was 0.25, 0.38 and 0.98 for wet, moderate and dry seasons respectively. This was within acceptable range. The mean and median were not equal for all the seasons.

Them mean was closest to median for wet season but difference increased from moderate to dry seasons. Kurtosis was below 3 for wet season but above 3 for moderate and dry seasons. Log transformation was performed to determine if mean, median and kurtosis would comparatively improve. Mean and median improved and were equal in all seasons after log transformation to 3.8.

Kurtosis improved for dry seasons upon log transformation from 4.57 to 3.28 becoming less leptokurtic. The marginal improvement in kurtosis was insignificant. Kurtosis however marginally deteriorated for wet and moderate seasons.

In wet season, kurtosis moved from being less platykurtic to being more leptokurtic from 2.87 to 3.34. In the moderate season, kurtosis increase from 3.45.to 3.6 becoming more leptokurtic. The log transformed data for all seasons was observed to be leptokurtic having relatively thick edges.

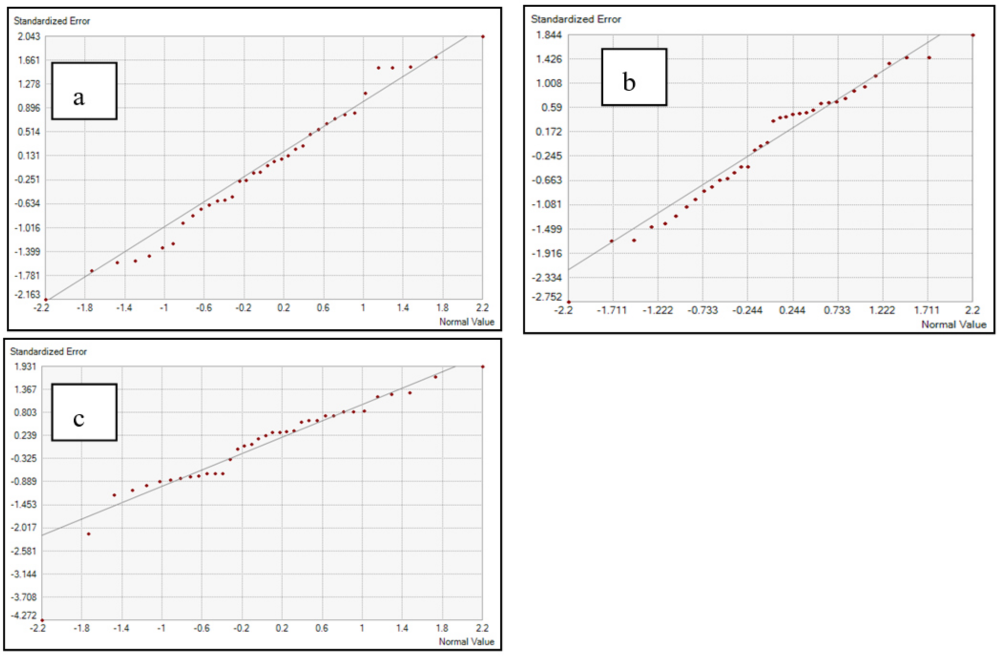


Figure 4: Fitted Normal QQ Plots for (a) Wet - normal distribution (b) Moderate season - normal distribution and (c) Dry season - Log-normal distribution

The normal QQ plots for the normal and log-normal transformed data was explored for best fit in Figure 4. Wet and moderate seasons presented best of fit under normal data while dry season best fit was the log-normal transformed.

The data was subjected to ordinary kriging to find the best fit model. Semivariogram models used were stable, Gaussian, exponential, J-Bessel and spherical.

Table 4: Summary of Normal data Semivariogram model comparison

Season	Statistic	Stable	J-Bessel	Gaussian	Exponential	Spherical
Wet	RMMSE	1.06	1.03	1.06	1.05	1.04
	ME	-0.07	-0.01	-0.07	-0.06	-0.07
	Nugget	40.11	41.90	40.11	9.36	23.61
	Sill	95.19	67.95	95.19	132.05	106.05
	Nugget/Sill ratio	0.42	0.62	0.42	0.07	0.22
Moderate	RMMSE	1.05	1.02	1.05	1.05	1.04
	ME	-0.05	-0.09	-0.04	-0.04	-0.06
	Nugget	26.00	24.72	26.00	0.00	8.74
	Sill	90.00	62.50	90.23	121.10	101.18
	Nugget/Sill ratio	0.29	0.40	0.29	0.00	0.09

RMSSE: root mean square standardized error; ME: mean error

The model predictions result in Table 4 showed the best fit model for wet season was the Exponential with nugget/sill ratio of 0. This also applied to moderate season with a nugget/sill ratio of 0.07.

Table 5: Summary of Log-Normal Semivariogram model comparison

Season	Statistic	Stable	J-Bessel	Gaussian	Exponential	Spherical
Dry	RMMSE	1.15	1.29	1.14	1.22	1.18
	ME	-0.02	-0.38	0.31	-0.19	0.19
	Nugget	0.00	0.01	0.04	0.02	0.03
	Sill	0.08	0.05	0.04	0.06	0.04
	Nugget/Sill ratio	0.00	0.19	1.09	0.34	0.71

RMSSE: root mean square standardized error; ME: mean error

The best fit model for dry season was the Stable after Log-transformation with a nugget/sill ratio of 0 as shown in Table 5 above.

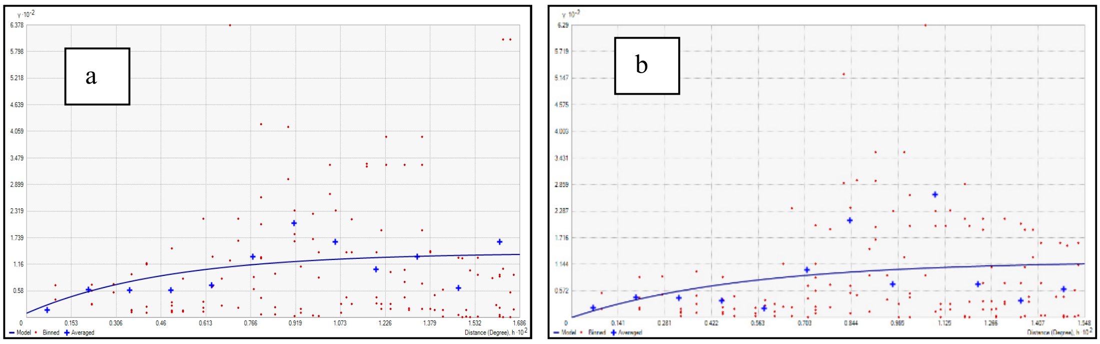


Figure 5: Exponential Semivariogram for (a) Wet and (b) Moderate season based on Normal data

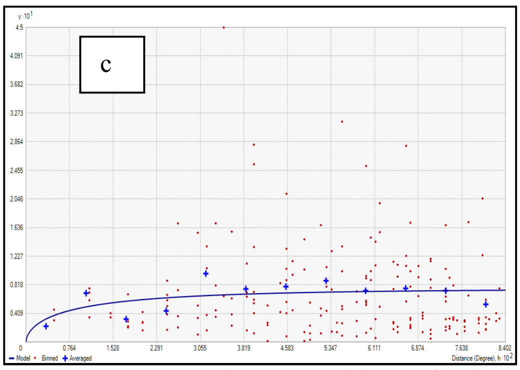


Figure 6: Stable Semivariogram (c) Dry season based on Log-Normal Data

The nugget/sill ratio indicated a strong spatial structure dependency in all the seasons as displayed in Figure 5 for wet and moderate season and Figure 6 for the dry season.

4.2 Correlation

It was anticipated that the nugget/sill ratio will be strong. This is because the groundwater quality parameters have an existing relationship. The relationship within the groundwater parameters is however complex. It is not easy to judge which parameters are more depended on others using the nugget/sill ratio. The nugget/sill ratio is generated from the data that has been indexed. It was therefore necessary to undertake further analysis to determine spatial dependency between parameters. The data from the sampling stations for Na^+, F^-, Cl^-, SO_4^{2-}, Ca^{2+}, Mg^{2+}, K^+ and $NO_3^-$was correlated using the SPSS. Spearman rho correlation coefficient was generated to determine nature of linear relationship among the parameters.

Table 6: Spearman rho correlation for wet Season

	Na^+	F^-	Cl^-	SO_4^{2-}	Ca^{2+}	Mg^{2+}	K^+	NO_3^-	WQI
Na^+	1	0.34	0.70**	0.92	0.37	0.26	0.37	0.35	0.53
F^-		1	0.64**	0.29	0.61**	0.95**	0.52	-0.21	0.62
Cl^-			1	0.98	0.22	-0.01	0.37	0.17	0.04
SO_4^{2-}				1	0.26	0.45	0.63	0.85**	0.57
Ca^{2+}					1	0.00	0.31	-0.01	0.02
Mg^{2+}						1	0.84**	0.07	0.01
K^+							1	0.59	0.87**
NO_3^-								1	0.52
WQI									1

**. Correlation is significant at the 0.01 level (2-tailed).

Table 6 shows in the wet season, parameters largely exhibited moderate, strong and very strong positive relationship. Cl^- to Na^+, Ca^{2+}, Mg^{2+}, and F^- had strong to very strong correlation. F^- had a moderately strong correlation with Na^+, Ca^{2+}, K^+ and NO_3^-. Weak negative relationship existed between Mg^{2+} to F^- and NO_3^-; F^- to NO_3^-.

Table 7: Spearman rho correlation for moderate Season

	Na^+	F^-	Cl^-	SO_4^{2-}	Ca^{2+}	Mg^{2+}	K^+	NO_3^-	WQI
Na^+	1	0.338	0.7	0.916	0.367	0.26	0.366	0.347	0.526
F^-		1	0.642	0.285	0.61**	0.954	0.522	0.209	0.71
Cl^-			1	0.984**	0.221	0.01	0.366	-0.17	0.039
SO_4^{2-}				1	-0.26	0.451	0.626**	0.852	0.57
Ca^{2+}					1	0	0.308	-0.009	0.024
Mg^{2+}						1	0.836	0.069	0.005
K^+							1	0.59	0.873
NO_3^-								1	0.52
WQI									1

**. Correlation is significant at the 0.01 level (2-tailed).

During the moderate season, table 7 indicates Cl^- to Na^+ F^-, Ca^{2+}, Mg^{2+} and K^+ had strong to very strong correlation. F^- had a moderately strong correlation with Na^+, Ca^{2+}, K^+ and NO_3^-. Weak negative relationship existed between Ca^{2+} to NO_3^-; and Cl^- to NO_3^-.

Table 8: Spearman rho correlation for dry Season

	Na^+	F^-	Cl^-	SO_4^{2-}	Ca^{2+}	Mg^{2+}	K^+	NO_3^-	WQI
Na^+	1	0.848	0.384	0.678	0.535	0.912	0.664**	0.858	0.988
F^-		1	0.714**	0.716**	0.458	0.842	0.727	-0.018	0.590**
Cl^-			1	0.181	0.065	0.255	0.362	0.917	0.042
SO_4^{2-}				1	-0.129	-0.130	0.510**	0.817**	0.145
Ca^{2+}					1	0.000	0.398	0.384	0.007
Mg^{2+}						1	0.555**	0.220	0.001
K^+							1	0.909**	0.952
NO_3^-								1	0.005
WQI									1

** Correlation is significant at the 0.01 level (2-tailed).

The dry season exhibited strong to very strong correlation Cl^- to F^-, SO_4^{2-}, Ca^{2+}, Mg^{2+}, and K^+ from Table 8. Na^+ had strong relationship with F^- had a moderately strong correlation with Na^+, Ca^{2+}, K^+ and NO_3^-. Weak negative relationship existed between Mg^{2+} to F^- and NO_3^-; F^- to NO_3^-.

4.3 Temporal Variability based on WQI

There was no sample station that presented very good groundwater quality. The increase in the poor quality is noted from the wet to dry seasons. 6% of the sampled stations recorded poor quality in wet season. Poor quality increased to 8% in moderate and dry season. The dry season recorded very poor-quality water at 3%.

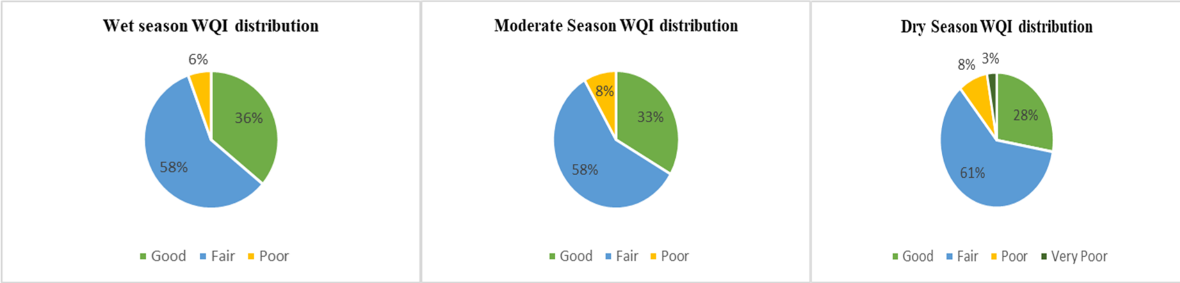


Figure 7: WQI Sample stations distribution

The WQI distribution and quality of groundwater samples was presented in Figure 7. The WQI indicated that groundwater samples deteriorated from the wet to dry seasons. The wet season exhibited 36% good quality, which was highest compared to 33% and 28% for moderate and dry seasons respectively. The fair groundwater quality remained the same at 58% for both the wet and moderate season but increased marginally to 61% in the dry season. The increase in the dry season can be attributed to the decline in good quality in the same season.

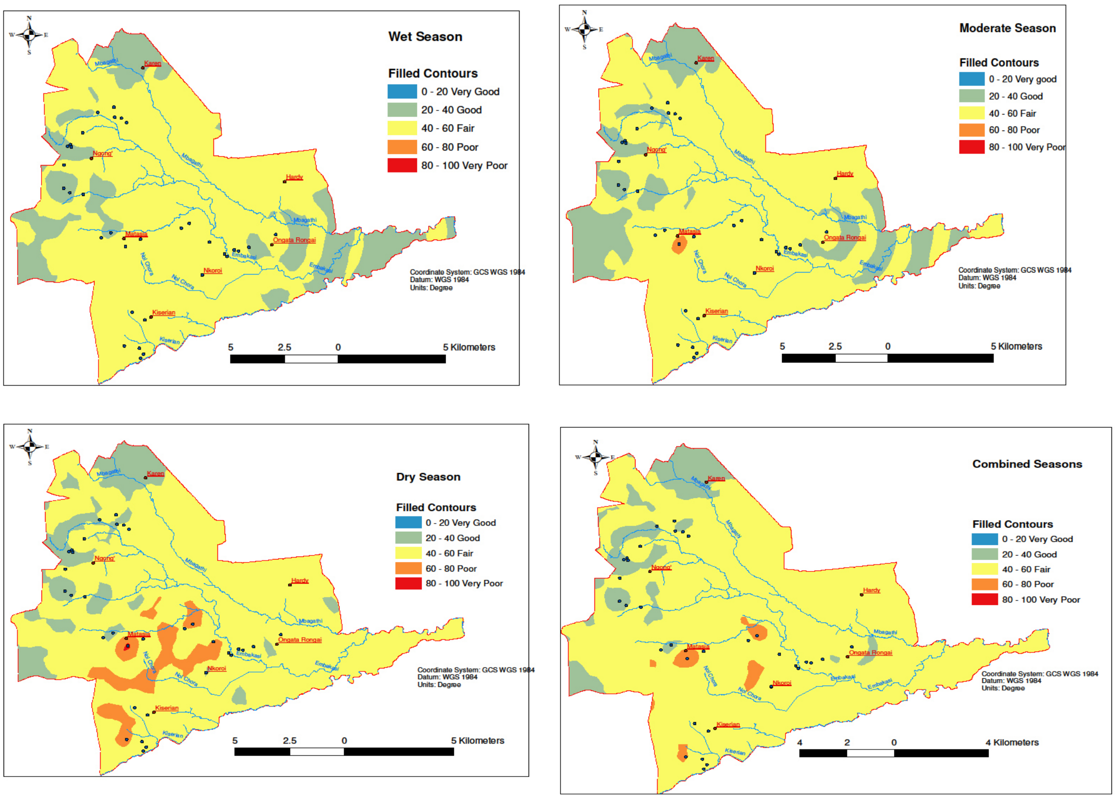
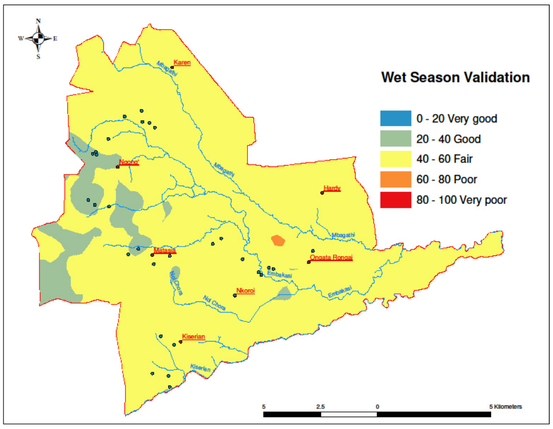


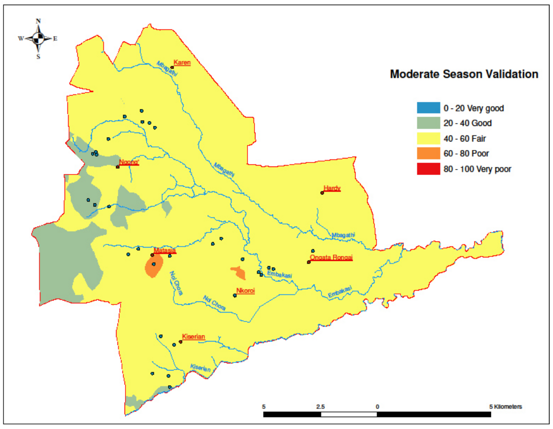
Figure 8: Temporal variability of sampled stations

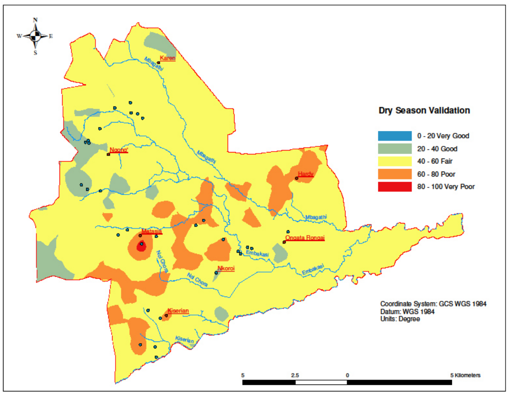
The WQI temporal variability was mapped as shown in Figure 8. During wet season, the prevalence of the 58% fair quality was mainly in the south, central and eastern parts. This represented the Matasia, Kiserian and Nkoroi areas. Central and Southern parts had the highest recorded yield and highest water rest level. Quality deteriorated marginally in the moderate season. Good quality in the south east dropped marginally increasing the poor quality in the central parts of Matasia. In the dry season there was an increase in poor and very poor-quality totaling to 11% of the sampled sites within the central to the southern parts. Good quality water was largely recorded in the North and West during the dry season.

4.4 Model Validation

The WQI kriging model was evaluated for credibility. Four sampling stations used in the calculation of WQI were randomly removed from data for the three seasons. RMSSE and ME was used to evaluate the model performance.







Season	Statistic	Stable	Exponential
Wet	RMMSE	1.02	1.00
	ME	-0.08	-0.07
Moderate	RMMSE	0.98	0.97
	ME	-0.06	-0.05
Dry	RMMSE	1.07	1.00
	ME	-0.06	-0.04

Figure 9: Model validation output

The validation model gave a fair result of RMSSE between 0.98 – 1.02 for stable and exponential semivariogram as displayed in Figure 9. ME was between -0.04 to -0.08. Both cases the model was within the expected range of RMSSE and ME. The results demonstrated that the model can reasonably estimate the groundwater quality using the sampling stations data.

5 Conclusions and Recommendations

Groundwater is an important source of water within the Mbagathi river catchment (Mulwa et al, 2005). With dwindling surface water sources, groundwater is drastically increasing in importance. Increased utilization of groundwater sources continues with little monitoring of quality and quantity. To harness the groundwater for various uses, understanding of the of the quality and quantity is vital for sustainable exploration of this important resource. 57% of the boreholes have a good yield of 8.3m3/hr able to cater for domestic purposes. The yield largely follows the rivers drainage regime in the basin. Groundwater yield is more available along the central and south east. Higher yield in the area largely follows the river regime in the drain basin. Variability of ground water exists with respect to seasons. Water quality deteriorates with decrease in rainfall.

Use of WQI and Geostatistical tools in a GIS framework enables synthesis of different groundwater quantity and quality parameters into an understandable format. Using the WQI it was possible to delineate variability. Spatial variability was observed with the Northwest and Southwest parts of Ngong, Matasia and Ongata Rongai respectively recording good and fair quality. Parts with low yield and poor quality can be highlighted for further investigations. The decline of 5% in groundwater quality from wet to dry seasons in sample stations indicates the temporal variability of the groundwater. The central parts of Matasia and Kiserian are seen to harbor the greatest decline in quality. These same parts have relatively high yield and water rest levels. It is likely that the deterioration in quality can be associated with the flow of groundwater beneath the earth surfaces. Groundwater in the study area can be termed as 36% - 28% good, 58% - 61% fair, and 6%-11% poor for drinking based on its hydrochemistry barring the elevated fluoride content in some areas. A noticeable declining groundwater quality trend is observed from wet to dry seasons. Elevated groundwater quality deterioration in areas with higher yield and water rest level was also observed. Additional biological and physiochemical parameters can be added to the analysis and with longer periods of sampling to generate more models.

The best fit semivariogram was the exponential and stable models. There is observed strong spatial dependency for all the three seasons. Using correlation analysis there was strong to very strong similarities. Despite the successful use of these geostatistical tools to predict the variability of groundwater, more sampling stations and longer periods of monitoring would enhance the prediction. Using the maps generated, at 95% confidence level, quality within a given area can be estimated. This shall enhance understanding of prevailing groundwater condition.

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