SPATIAL DISTRIBUTION OF GROUNDWATER GEOCHEMISTRY IN WARIYAPOLA AREA

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Introduction

In Sri Lanka groundwater resources are widely used for domestic, commercial, industrial and irrigation purposes. About 80 percent of the rural domestic water supply needs are met from groundwater. In this study groundwater geochemistry of Wariyapola area is analyzed.

Wariyapola is located in North western part of Sri Lanka which covers area about 150,000 ha. The topography of the area is generally a flat with few inselburgs which do not rise more than 360m height. The climate is tropical climate and the region has been derived in to semi-dry zone of Sri Lanka. Also the area consists of Precambrian metamorphic rocks and Jurassic and Miocene sedimentary formations. As groundwater flows, sediments are dissolved, and it may later be found in high concentrations in the water. Therefore, groundwater in this area show high concentrations of cations and anions. (eg: F^-, NO_3^{2-}, Cl^-, Na^+, K^+, Zn^{+2}, Fe^{+2} etc). Excessive concentrations of some of these cations or anions causes various health problems and affect that to drinkability of water. The objectives of this study is to analyze the spatial distribution of groundwater geochemistry, from which it is possible to identify the suitable groundwater locations.

Secondary data collected by the third author (Gunatilake 1987) were used for the analysis. Data has been collected from 157 wells in and around Wariyapola area. Well locations have been selected randomly. Measured concentrations of the geochemical parameters were used to identify the spatial distribution.

Methodology

Geostatistical methods are one of the most advanced techniques for interpolation of groundwater geochemistry. Kriging method was used for predicting spatial distribution of each of groundwater geochemical parameters. (Mehrjardi et.al.2008). First the outlying observations were identified by extreme variogram cloud values, and they were removed. Data were normalized using logarithm base 10. Then the data set was divided into 2 parts such that one third of the data set was taken as testing sample and other part was taken for the analysis. Spatial variation of the each geochemical parameter was analyzed through a function called variogram. Since a large spatial trend in the data across the area was identified, the stationary assumption was violated. Therefore, detrending was performed by fitting a regression model using weighted least squares, and experimental variogram was fitted by using the residuals of weighted least squares. Basic assumptions of residuals were checked. For selecting a suitable model (e.g. spherical, exponential, Gaussian) on experimental variogram, least SSE value was used. The model parameters (e.g. range, nugget and sill) are then used in the kriging procedure. Ordinary kriging was used for constant trend models and universal kriging was used for polynomial trend models. Validation and cross- validations were done to check the model validation. Finally the values were back transformed to the original scale and GIS map of groundwater was prepared. Geostatistical analysis were carried out mainly using the R package "gstat" version 0.9-69 (http://www.gstat.org/). To obtain the R codes Roger and Edzer (2008) was referred.

Results and Discussion

An exploratory data analysis of each geochemical parameters was performed. The Kendall correlation coefficients of each pair-wise parameters were calculated to identify the relationship among parameters. Total hardness with Ca was highly correlated (0.83, $P<0.001$) and total hardness with conductivity and conductivity with Ca were moderatively correlated (0.46, $P<0.001$ and 0.46, $P<0.001$). Most of the other pairs had low correlation values. The data with high skewness were normalized using logarithmic method. It was also noted high standard deviations for Fe, Zn, Total Hardness and Cl. The trend surface was fitted for each parameter using polynormial regression. The suitable trend models were selected with minimum SSE and maximum R^2 values. Semi-variograms were drawn using residuals of the trend models. Model parameters were calculated with minimum SSE values, and these values are used to determine the models for geochemical parameters. Cl and PH have exponential models, and spherical model was the most preferable model to describe the spatial correlation for Ca, Co, Fe, NO_2 and NO_3. Other parameters have Gaussian model (Table 1 – Appendix).

Then the nugget, sill and range values were calculated. Total hardness, Fe and NO_3 have higher values for effective range. The ratio of nugget variance to sill expressed in percentages can be regarded as a criterion for classifying the spatial dependence of groundwater quality parameters(Table 1. Appendix).

If this ratio is less than 25%, then the variable has strong spatial dependence; if the ratio between 25% and 75%, the variable has moderate spatial dependence and greater than 75%, the variable shows weak spatial dependence. According to this criterion Ca, Co, Zn, Cl and NO_2 have strong spatial structure, Co, conductivity and total hardness have moderate spatial structure and Fe, F and NO_3 have weak spatial structure.

Kriging procedure was used to predict the values for parameters for blocks (Total area is divided into 1500 blocks). Root mean square error (RMSE) of each geochemical parameter were small, and mean error (ME) of each parameter is almost zero. The contour maps of groundwater geochemical parameters were prepared using GIS. As an example the contour map for Ca is shown in Fig.1. (Appendix). These contour maps can be used to identify the suitable groundwater locations.

Conclusions

Suitable probability models were identified for geochemical parameters. Based on these models it was noted that Ca, Co, Zn, Cl, NO2, Co, conductivity and total hardness have spatial dependence, and Fe, F, and NO_3 have weak spatial dependence. Finally to identify the suitable groundwater locations the contour maps can be used in practical situations.

Correlation among parameters are affecting to the spatial distribution of ground water. Therefore, for further studies co-kriging method can be used to identify the highly correlated variables.

References

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Gunatilake J (1987). Geochemistry of Groundwater around Wariyapola area with special reference to nitrates. B.Sc.(special) in geology research report.

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Appendix

Table 1. Suitable model for variogram according to SSE

Parameter	Trend	Spherical	Guassian	Exponential	Model	$C_0/(C_0+C)$
Ca	Const.	4.83E-08	7.35E-08	5.58E-08	Spherical	0.23
K	Third	7.32E-10	7.28E-10	7.86E-10	Gaussian	0.33
Co	Third	1.41E-07	9.45E-08	1.53E-07	Spherical	0.06
TH	First	2.87E-10	2.73E-10	5.41E-10	Gaussian	0.75
Fe	First	1.86E-07	2.34E-07	1.87E-07	Spherical	0.93
Zn	Const.	6.52E-08	6.15E-08	8.61E-08	Gaussian	0
F	Second	9.19E-09	9.18E-09	1.00E-08	Gaussian	0.78
Cl	First	1.40E-08	1.47E-08	1.33E-08	Exponential	0
NO2	Second	3.29E-09	3.32E-09	4.64E-09	Spherical	0
NO3	Const.	4.29E-06	1.70E-05	5.30E-05	Spherical	0.91
COND	Const.	1.21E-08	1.18E-08	1.22E-08	Gaussian	0.75
PH	Third	0.001212	0.001206	0.001192	Exponential	0.53

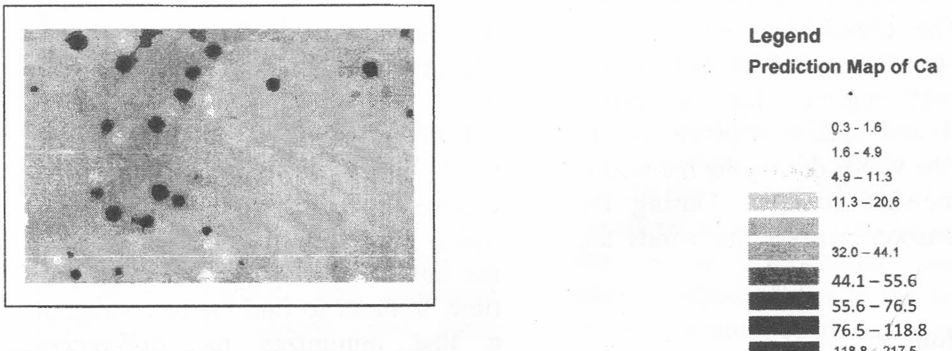

Fig. 1. Spatial distribution of Ca