Optimizing a long-term groundwater monitoring network using geostatistical methods

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Abstract Groundwater long-term monitoring (LTM) is required to assess groundwater remediation and human health risk at sites with severe groundwater contamination. Groundwater LTM network optimization requires sampling at existing wells, data management, remediation, and risk reduction activities, costing millions of Euros. The study of monitoring network optimization was performed at a site in Eastern Germany using the geostatistical temporal spatial (GTS) algorithm in a 2.5D environment. The 2.5D environment assumes that there are multiple aquifers or hydrostratigraphic layers in the aquifer. An area of ~72 km^2 with 357 wells in the Tertiary aquifer and 462 wells in the Quaternary aquifer was selected. A dataset of the concentration of monochlorobenzine from October 2003 to December 2009 was obtained for optimizing the existing network. Local 3D geological and hydrogeological models were used to understand the spatial and temporal hydrogeological heterogeneity of the area. The optimal number and placement of wells in the existing network has been analysed for effective groundwater monitoring.

Key words groundwater long-term monitoring network optimization; multiple objectives approach; geostatistical methods

INTRODUCTION

Groundwater, a vital and essential resource, has a continuously increasing demand due to rapid population growth and extensive economic development in the whole world, and consequently, the rising water use *per capita* is putting pressure on available resources (Teixeira, 2008; Thakur *et al*., 2011a; Diwakar & Thakur, 2012). Groundwater is the major source of water supply in Germany. Approximately 75% of all water for public water supply in Germany is obtained from groundwater (BGR, 2011). Therefore, accurate quantification and quality evaluation of the available groundwater resources is a basic requirement for effective management, and consequently, groundwater monitoring is required. Groundwater monitoring consists of long-term standardized measurement, observation, evaluation of status and trends, and reporting of the groundwater conditions to meet monitoring programme objectives (Erechtchoukova *et al*., 2009; Thakur *et al*., 2011b). A typical groundwater monitoring program aims to prevent the potential danger to human health, assess the impact of anthropogenic substances via groundwater on aquatic ecosystems, document the state of groundwater pollution, and show the efficiency of water protection measures. This requires a complex infrastructure supporting the entire sampling, laboratory, and field-based analysis work, and the data processing activities. Consequently, the long-term groundwater quality monitoring constitutes a significant economic burden for many industrial and urban groundwater contaminating sites.

There are many research works carried out for the spatial optimization of groundwater quality monitoring networks (Loaiciga *et al*., 1988; Dhar & Datta, 2009), whereas few research works have focused on the multiobjective aspects of optimal spatiotemporal designs of groundwater quality sampling networks that explicitly involve both space and time (Herrera & Pinder, 2005; Nabi *et al*., 2011). Multiobjective groundwater long-term monitoring (LTM) is required to assess the performance of groundwater remediation and human health risk at sites with severe groundwater contamination. To ensure effective groundwater monitoring strategies in a 3D environment with a number of contaminants and in the time dimension, groundwater monitoring network optimization with multiobjectives is required to answer the following question, given an existing LTM network: what is the optimum number and placement of wells in that network? The aim of this work is to present the methodological aspects of the research to obtain the abovementioned multiple objectives for an existing groundwater monitoring network.

Tested datasets and study area

The study area, Bitterfeld/Wolfen, in the Federal State Saxony-Anhalt, measuring about 72 km^2, is a former chemical industrial site having significant groundwater contamination of about 200 million m^3 in volume in an area of about 25 km^2 (Wycisk *et al*., 2003). For the monitoring and remediation of this groundwater contamination, 436 wells in the Tertiary and 510 wells in the Quaternary aquifer constitute the groundwater monitoring network. In this study, an area of about 72 km^2, having a LTM network of 357 wells in the Tertiary and 462 wells in the Quaternary aquifer was selected. Although groundwater monitoring data from the existing LTM network are available from 1991 to 2009, a dataset of the concentration of monochlorobenzine (MCB) from October 2003 to December 2009 was used for the optimization of the monitoring network. A 3D geological model of 64 km^2 and a 3D hydrogeological model of 320 km^2, developed at the Department of Hydrogeology and Environmental Geology, Martin Luther University, Halle (Saale), Germany, were used to understand the spatial and temporal hydrogeological heterogeneity of the area (Wollmann, 2008; Gossel *et al*., 2009). The groundwater contaminants are heterogeneously distributed and have temporal variation in the flow direction.

METHOD

Groundwater LTM network optimization

Optimizing an LTM network for multiple objectives needs the consideration of contaminant information, its physiochemical and toxicological properties, hydrogeochemical properties of the aquifer, and other associated information. In a polluted site, groundwater may contain various types of organic, inorganic, and metal contaminants. In the study area, as an organic contaminant, MCB was selected as a representative contaminant. The groundwater LTM network was optimized using MCB concentration at a particular depth in the monitoring well at a specific time along with other physicochemical and toxicological properties (Fig. 1).

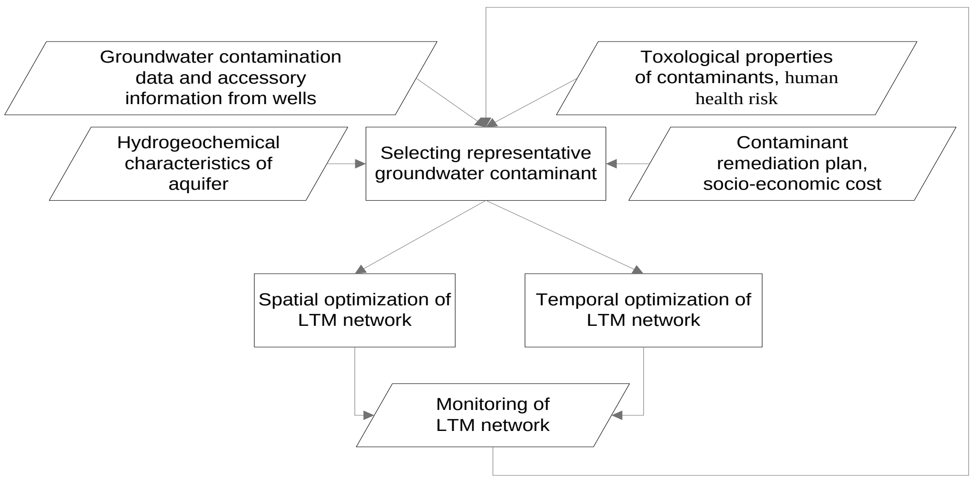

Fig. 1 Conceptual flowchart of groundwater monitoring network optimization.

Spatial optimization of LTM network

A geostatistical spatial optimization algorithm was used to predict redundant wells when the nearby wells offered the same information about underlying plume (Cameron & Hunter, 2002). In the geostatistical temporal spatial (GTS) concept, a well is considered redundant if its removal does not significantly change the interpolated map of the contaminant plume. Location-wise contaminant concentration data at a particular depth in the groundwater well on the monitoring date is prerequisite information required for the LTM network optimization. The investigation steps involved in locating redundant wells are shown in Fig. 2.

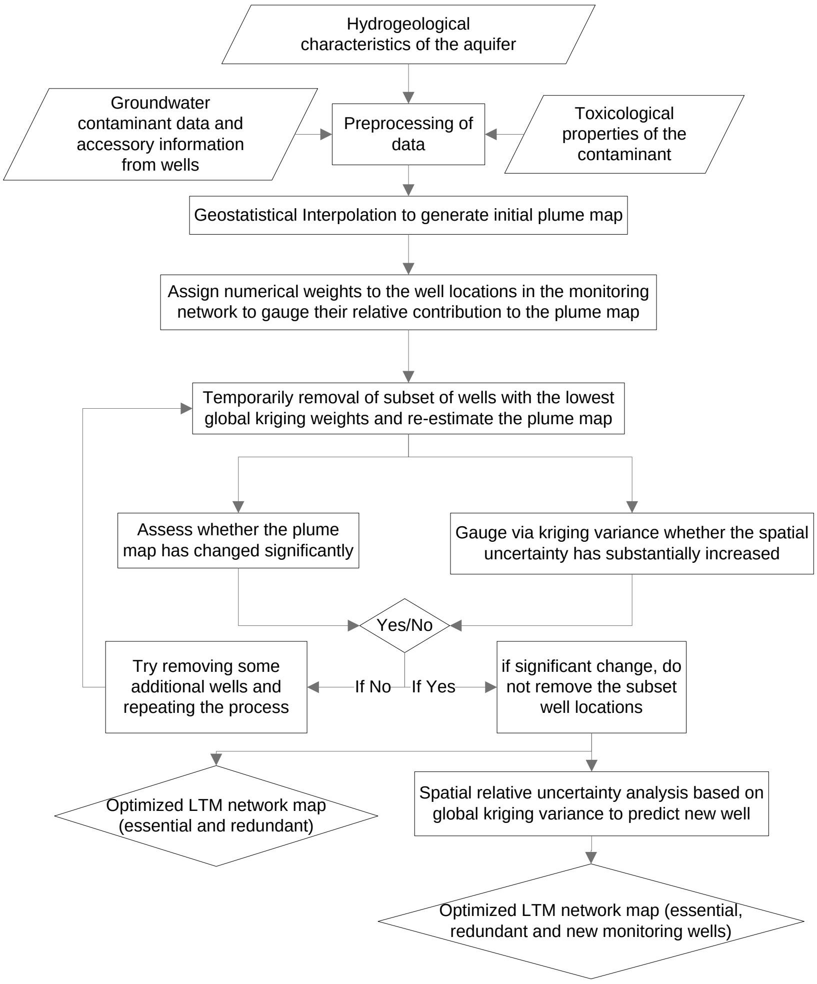

Fig. 2 Research steps to locate essential and redundant wells and to propose new wells in the existing monitoring network.

A contaminant concentration plume was generated, based on the input data of the concentration of MCB at a particular location of the well. The maximum contamination limit (MCL) of 100 μg/L for MCB, as per US EPA, was given as the indicator cut-off for the functioning of the statistical algorithm (US EPA, 2001). Some of the wells were sampled more often than others in the neighbourhood. To avoid giving more statistical weight to often-sampled well locations than others, each dataset was divided arbitrarily into a series of time slices (Cameron & Hunter, 2010). As an example, in a three-month time span, although a well is sampled frequently, its relative weight will be given by considering it as one-time sampled.

A plume map was created for the well locations in the monitoring network from the numerical weights of the wells based on global kriging. In this process, two intermediate computations are used: (i) the local kriging weights assigned to sampled locations can be accumulated and averaged to generate a "global" interpolation weight for each well (Isaaks & Srivastava, 1989) and (ii) the local kriging estimation variance indicates the relative uncertainty of the local block estimate, as compared to estimates at other blocks (Cameron & Hunter, 2002). Averaging all of the local kriging weights assigned to a given well forms global interpolation weights (λ^G) that can be used to estimate the well's overall contribution to the interpolated map, and they are given by

$$\lambda^G(x_i) = \frac{1}{N_B}\sum_{B=1}^{N_B} \lambda_i^B(x_i) \tag{1}$$

where N_B is the total number of estimated blocks and x_i is the location of the ith sampled well.

The global kriging weights give the relative rankings of well locations in terms of the independent spatial information that is provided. The wells having the lowest global kriging weights because of the smaller local kriging weights are spatially redundant wells. Then, from this monitoring network, the subsets of wells based on the lowest global kriging weights were removed temporarily. The subset of wells was removed from monitoring as long as the increase in global kriging variance was not more than 5% of the original value. The plume map was re-estimated. In the condition where the removal of the subset of wells does not change the plume map significantly with 95% confident level, the subset of wells was removed permanently. This process

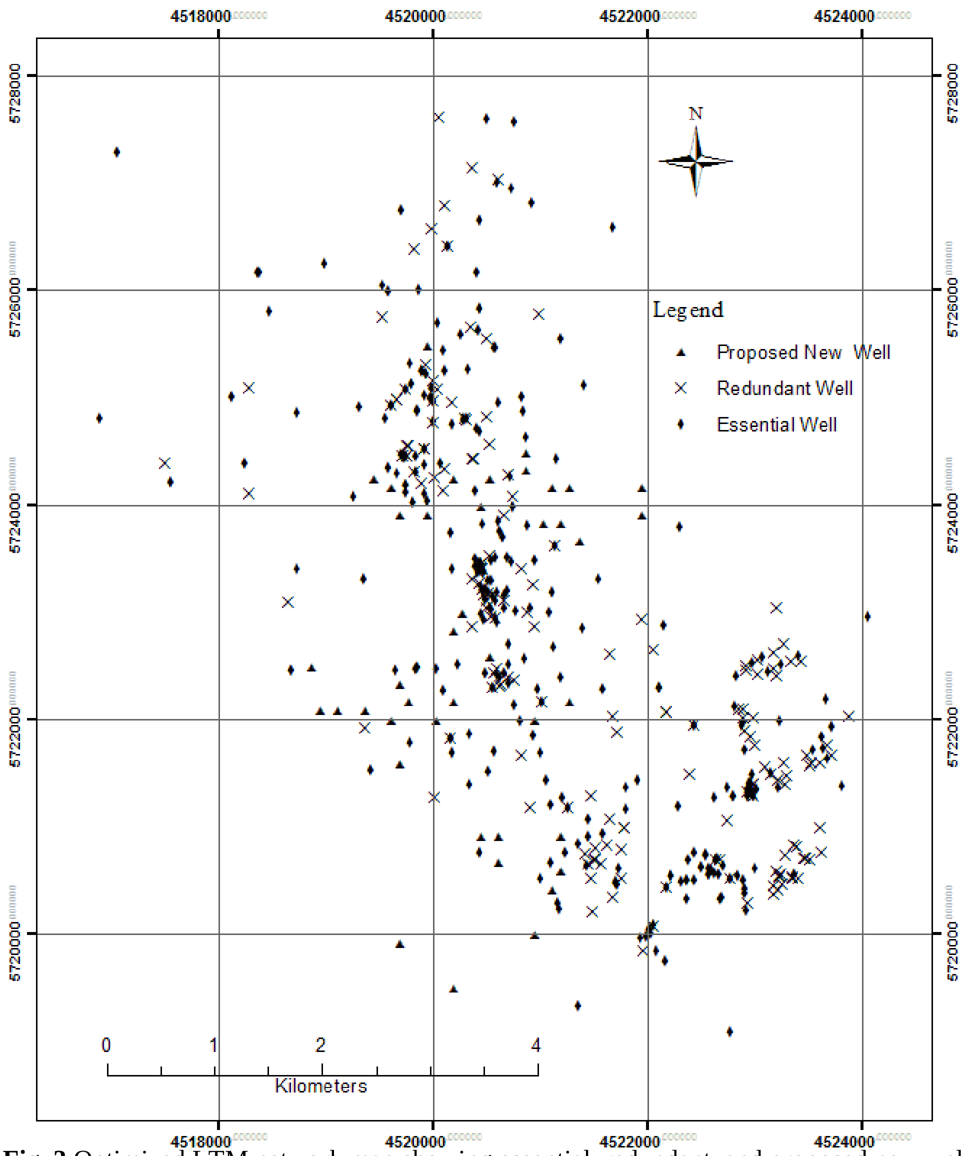

Fig. 3 Optimized LTM network map showing essential, redundant, and proposed new wells.

was repeated until the removal of a subset of wells changed the plume map. In the condition where the removal of a subset of wells significantly changed the plume, the subset of wells was not removed from the monitoring network.

The spatial relative uncertainty for the installation of new monitoring wells in the existing LTM network is based on the local kriging variance and is given by the global kriging variance (kv^G), as defined below:

$$kv^G = \frac{1}{N_B}\sum_{B=1}^{N_B} kv^B(x_B) \tag{2}$$

where x_B denotes the location of the *B*th block and $kv^B(x_B)$ is the local kriging variance of the *B*th block.

RESULT AND DISCUSSION

The optimization of the groundwater LTM network according to the GTS method described above was done for both aquifers separately. In the Tertiary aquifer, 357 wells are monitored, however, the optimization result based on the abovementioned method suggests that the monitoring of only 256 wells is required. At the same time, among the 462 wells in the Quaternary aquifer, the optimized monitoring network suggests that 292 wells be monitored at the suggested temporal interval. By removal of these wells at the existing location in the monitoring network the global kriging variance was not increased by more than 5% of the original value. However, after removing these wells from the monitoring network, the local kriging variance was increased at other locations. Furthermore, the spatial uncertainties analysis, in terms of the global kriging variance, also suggests that 22 and 41 new monitoring wells should be installed in the Tertiary and Quaternary aquifers, respectively. The spatial distribution of redundant, essential, and proposed new wells in the Quaternary aquifer is depicted in Fig. 3.

The original and the optimized LTM network datasets produced similar numerical kriging weights of the wells, which lead to the conclusion that a reduction in the number of observation points does not compromise the quality and resolution of the collected samples if the network distribution is properly designed.

CONCLUSION

It must be noted that the list of spatially redundant wells for a single contaminant were proposed for removal, strictly on the basis of the above geostatistical analysis with GTS. Before such a recommendation is implemented, the specific well locations would need to be optimized by considering major contaminants, examined by hydrogeologists and experts familiar with the site and by appropriate regulators, to ensure that valuable information other than the concentration data used here is not lost. Other than a change in cost estimates, the optimization algorithm would in no way be damaged or altered if someone decided for other reasons that one or more wells tagged as redundant should be kept on the monitoring list and not be removed. Furthermore, the proposed new monitoring wells can be installed in order to improve the understanding of the LTM network.

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