Application of a combined geostatistical and optimization model for the optimal groundwater quality monitoring network design

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INTRODUCTION

Monitoring networks provide essential information for water resources management and water quality, especially in areas with significant groundwater exploitation due to extensive agricultural use. In this work, a simulation-optimization framework is developed based on the geostatistical method Kriging and the use of Artificial Neural Networks (ANN).

Based on existing groundwater quality mapping, the proposed optimization tool will determine a cost-effective observation wells network that contributes crucial information to the water authorities. The elimination of wells that add little or no beneficial information to the groundwater level and quality mapping of the area can be performed by using estimations of uncertainty and statistical error metrics without affecting the assessment of the groundwater quality. Given the high maintenance cost of groundwater monitoring networks, the proposed tool could be used by water regulators in the decision-making process to obtain an efficient network design.

METHODOLOGY

The first step is to perform the mapping of the area based on information at the existing 43 observation well locations, using the **geospatial analysis method Kriging**. The method is described by the equation

$$\hat{z}(s_0) \sum_{\{i:s_j \in S_0\}} \lambda_i z_i(s_i)$$

where

$\hat{z}(s_0)$ is the estimated value

λ_i Is the weighted Kriging factor

$z_i(s_i)$ Is the measured value

The calculation of the weights λi is based on the theoretical semi-variogram which is selected depending on how wellit fits to the experimental dat. In the present analysis the selected theoretical semi-variograms for each period are *Matérn* for the 2008 and 2009 wet periods and *Spartan* for the 2009 dry period.

Depending on the selected semi-variograms the quality mapping of the area for each of the aforementioned periods is conducted. **The estimation of the quality values on the locations of the observation wells are used in order to calculate statistical error metrics (e.g. mean absolute error) and evaluate the accuracy of the estimation** .

In the second step of the analysis, Artificial Intelligence will be used to approximate the results of human reasoning by organizing and manipulating factual and heuristic knowledge. In particular, **a Artificial Neural Networks (ANN) will be developed which is a simplified "computational model" of the biological neural network systems, having the ability to adapt, learn, generalize and organize data**.

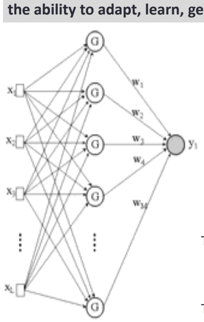

Fig.1 – RBFN typology

- A **Radial Basis Function Network** is used as the approximation model, with **inputs** equal to the number of design variables and a **single output.**
- The **hidden layer** uses a number of nodes (the so called **centers** c_i) smaller than the number of the available training patterns, in order to obtain better generalization.
- In order to have a **local approximation model**, only the best fitted individuals are used to retrain in each generation the approximation model, which **evolves with the population.**
- For the training process the direct learning approach is adopted.

The nonlinear activation function G is chosen to be the **Gaussian radial basis function**

$$G(u,\sigma) = \exp\left(-u^2/\sigma^2\right)$$

The corresponding output $y(x)$ for a x_i, $i = 1, L$ input, is:

$$y(x) = \sum_{i=1}^{M} w_i \cdot G(x, c_i) = \sum_{i=1}^{M} w_i \cdot G(\|x - c_i\|)$$

CASE STUDY: MIRES BASIN, GREECE

- Intense agricultural activity
- Geropotamos river is crossing the area
- Groundwater level and concentration of NO_3 obtained from 43 observation wells for 3 different hydrological periods(Wet 2008 & 2009 and dry 2009)

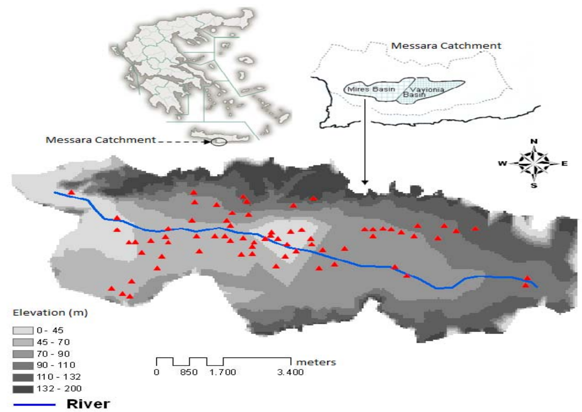

Fig.2 – Location of the observation wells in Mires Basin

RESULTS

The following figure compares the three most accurate theoretical semi-variogram models for the 2009 dry period. Both error and visual comparison result to the selection of the *Spartan* (SP) model instead of the *Matérn* (M) and the Spherical (SPH).

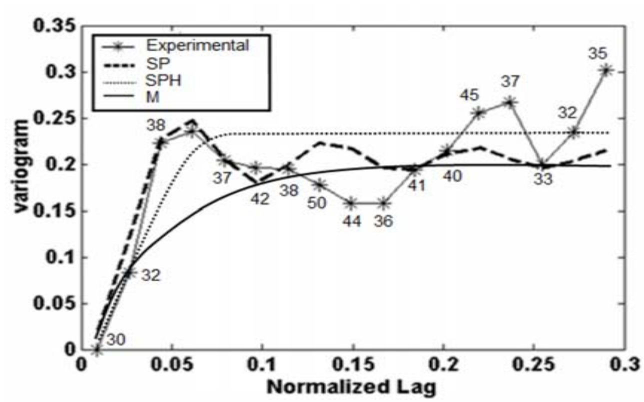

Fig.3– Plot of the experimental and three theoretical semi-variograms

The estimation of groundwater levels in the study area and the uncertainty of them using the Kriging methodology based on the *Spartan* model is showed in the heat-maps below.

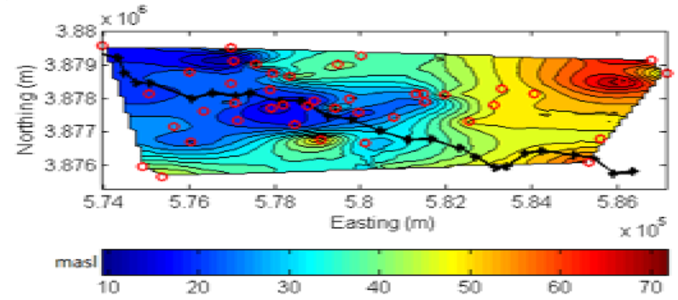

Fig.4– Estimation map of groundwater level

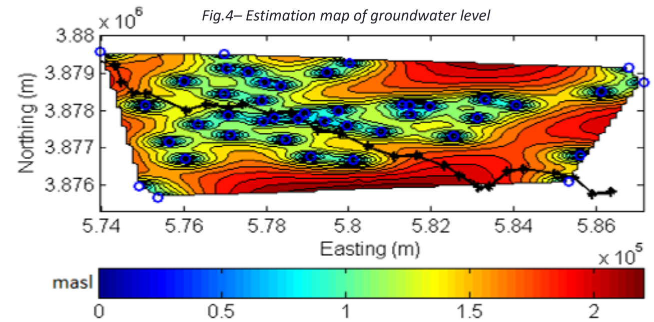

Fig.5– Uncertainty map of groundwater level estimation

CONCLUSIONS

- In areas where the network density is high, at least one observation well can be excluded from the estimation process without significantly affecting the result.
- Preliminary results has shown that a removal of up to 10 monitoring locations does not affect the estimated groundwater level spatial variability.
- The reposition of 4-6 observation wells can improve the overall estimation and minimize the uncertainty.
- Changing the position of some wells can improve the process but lacks of cost effectiveness.

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