# COMPARISON OF ANFIS AND ORDINARY KRIGING TO ASSESS HYDRAULIC HEAD DISTRIBUTION
### *The Orgeval Case Study*

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Keywords: ANFIS, Ordinary kriging, Hydraulic head, Orgeval.

Abstract: In this study, two methods are evaluated for assessing hydraulic head distribution in an aquifer unit. These methods consist in Ordinary Kriging (OK) and Adaptive Neuro Fuzzy based Inference System (ANFIS). Both methods are applied on the same case study: a part of the agricultural basin of the Orgeval located 70 km east of Paris, France. 68 samples were used to predict hydraulic head distribution on a 100 m square - grid. Cartesian coordinates of the samples were used as inputs of the ANFIS, which gives encouraging result. Both simulations have realistic pattern ($R^2 > 0.97$) even if OK performs slightly better than ANFIS at sampling site. Simulated hydraulic head distributions present discrepancies because the two methods capture different patterns. Combined use of the two approaches allow for improving the sampling location of the observation network.

## 1 INTRODUCTION

A hydrosystem is defined as a "part of space (where atmosphere overlap soil surface and subsurface) through which water flows. Physical and biogeochemical phenomena occur in all hydrosystem because of reactions due to water moving through a media" (Dacharry, 1993). Many earth scientists (hydrologists, geologists, biogeochemists,…) do interest in understanding the behaviour of such a complex system. Usually they first do experiments/observations in the field at specific locations and then try to distribute these observations/measurements in space and time using modelling techniques which are based on abstractions.

In this paper our focus is to distribute punctual hydraulic head measurements on a grid that covers a part of an experimental basin. One technique often used in earth sciences and especially in hydrogeology is kriging (Flipo et al., 2007a; Renard and Jeannée, 2008; Rivest et al., 2008). For a few years hydrologists started to apply fuzzy logic to transform an input signal – precipitation - to an output signal – discharge at the outlet of a catchment – with success (Kurtulus and Razack 2007). But only few hydrogeology studies used soft computing to solve their problem (Johannet et al., 2007; Kholghi and Hosseini, 2007). The goal of this work is to compare ordinary kriging (OK) and Adaptive Neuro Fuzzy based Inference System (ANFIS) in their ability to assess a hydraulic head distribution in a complex aquifer system.

## 2 EXPERIMENTAL SITE

With an area of 104 km$^2$, the Orgeval experimental basin (Figure 1) is located 70 km east from Paris



Kurtulus B., Flipo N., Goblet P., Vilain G., Tournebize J. and Tallec G. (2009).
COMPARISON OF ANFIS AND ORDINARY KRIGING TO ASSESS HYDRAULIC HEAD DISTRIBUTION - The Orgeval Case Study.
In *Proceedings of the International Joint Conference on Computational Intelligence*, pages 371-378
DOI: 10.5220/0002319903710378

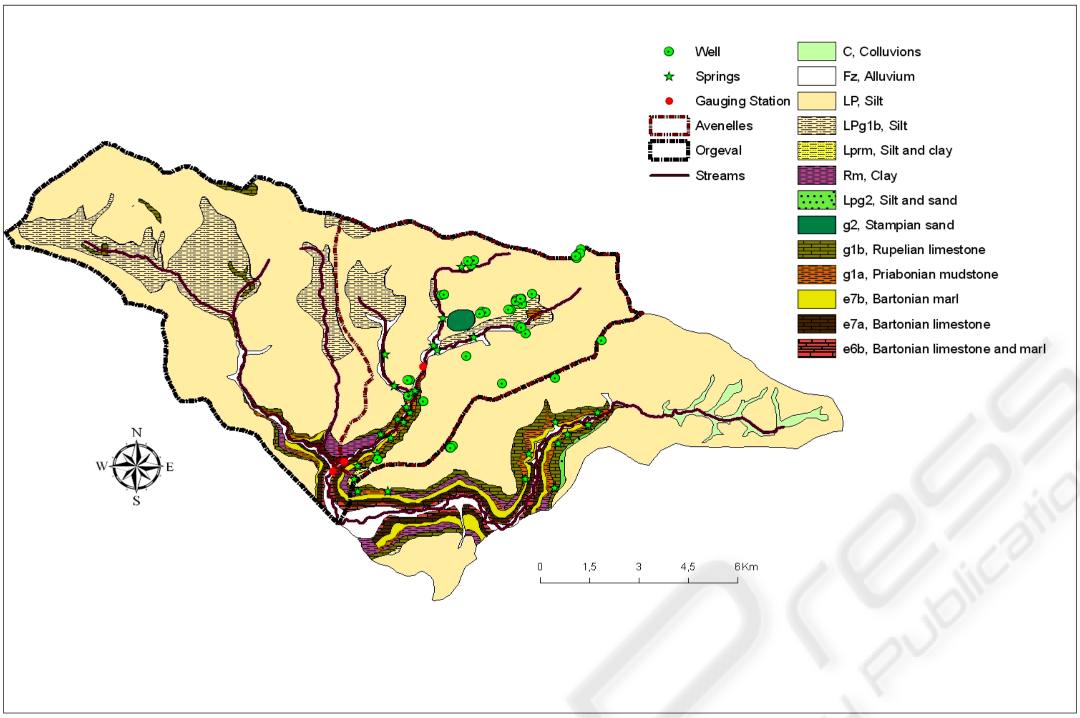


Figure 1: Geology of the Orgeval basin. Sampling points (wells and springs) and gauging stations.

(Anctil et al., 2009; Flipo et al., 2007b). Agriculture takes place on 80% of its surface while the remaining 20% are forested. The average annual air temperature is 9.7 ◦C. The annual mean rainfall is 706 mm, and the annual mean potential evaporation is 592 mm. The hydrological behaviour of the Orgeval basin is influenced by the aquifer system, which is composed of two main geological formations: the Oligocene (see Rupelian limestone, Fig. 1) and the Eocene (from Priabonian to Ypresian claystones, Fig. 1). These two aquifer units are separated by a clayey aquitard. Most of the basin is covered with table-land loess about 2-3m in thickness. These unconsolidated deposits are essentially composed of sand and loam lenses of low permeability but they seem to be more or less connected to the Rupelian limestone.

The basin is relatively flat with slopes increasing near the small valley at the river mouth (80% of the territory spans between 130 and 170 m above mean sea level).

In this work we will focus on hydraulic head distribution in the eastern part of the basin (Fig. 1).

## 3 DATA

The dataset is composed of two different types of data (Fig. 1). The first one consists in water levels in wells. The 61 wells were sampled on april 16, 2009 during a snapshot campaign. Our goal was to determine the hydraulic head distribution of the subsurface aquifer unit – silt connected to the rupelian limestone. Due to the complex geometry of the aquifer system at the outlet of the Avenelles basin and in the south-eastern part of the area of interest (Fig. 1), we needed to complete the wells dataset in this part of the domain of interest. To do so we used a digital elevation model (100 × 100 m) of the top of the Priabonian mudstone. The elevation of the limit between Priabonian mudstone and rupelian limestone was then implemented inside the dataset as a spring (Fig. 1). Finally the overall dataset is composed of 68 hydraulic heads.

## 4 INTERPOLATION METHODS

### 4.1 Ordinary Kriging

Geostatistics aims at providing quantitative descriptions of natural variables distributed in space and time (Chilès and Delfiner, 1999). Initially developed to address ore reserve evaluation issues in mining (Isaaks and Srivastava, 1989), it is now commonly applied to environmental sciences such as hydrogeology, air, water and soil pollution (Goovaerts, 1997).

Geostatistics is used to characterize the spatial structure of the variable of interest by means of a consistent probabilistic model. This spatial structure is characterized by the variogram, which describes how the variability between sampled concentrations increases with the distance between the samples. A variogram model is fitted to the experimental variogram for subsequent analysis.

The interpolation technique, known as kriging, provides the ‘‘best’’, unbiased, linear estimate of a regionalized variable at unsampled locations, where ‘‘best’’ is defined in a least squares sense, as it aims to minimize the variance of estimation error (Chilès and Delfiner, 1999). As for the classical interpolations, the estimation by kriging of the concentration at any target cell is obtained by a linear combination of the available sample concentrations. The kriging differentiates only by the way of choosing the coefficients of this linear combination. Those coefficients are called kriging weights and depend on:

- the distances between the data and the target (like other classical interpolators),
- the distances between the original data themselves (data clustering),
- the spatial structure of the variable.

Exploratory data analysis, variogram fitting and kriging were performed using the Isatis software (Geovariances, 2008).

## 4.2 Adaptative Neuro Fuzzy Inference System

Fuzzy logic (FL) was first proposed by Zadeh (1965). It consists of three conceptual components: (1) a rule base which contains fuzzy if–then rules, (2) a database which defines the membership function and (3) an inference system which combines the fuzzy rules and produces the system result (Firat et al., 2006). The difficulty of FL is to determine membership function parameters and fuzzy rules. In order to overcome this deficiency, hybrid models (neuro-fuzzy) are generally used. It is well understood that FL and neural networks (NN) are complementary methodologies in the design and implementation of intelligent systems. Each approach has its merits and drawbacks. To take advantage of the merits and eliminate their drawbacks, integration of these methodologies has been proposed by researchers during the past few years (Cigizoglu, 2005; Özgür, 2006; Kurtulus et al., 2008).

Adaptive neuro-fuzzy inference system (ANFIS) is a neuro-fuzzy system developed by Roger Jang (1992). It combines a NN and a fuzzy system together. ANFIS uses a hybrid learning algorithm that combines the back-propagation gradient descent and least squares methods to create a fuzzy inference system whose membership functions are iteratively adjusted according to a given set of input and output data (Jang, 1993). For each iteration, the back propagation method involves minimization of an objective function using the steepest gradient descent approach in which the network weights and biases are adjusted by moving a small step in the direction of negative gradient. The iterations are repeated till a convergence criteria or a specified number of iterations is achieved. It has the advantage of allowing the extraction of fuzzy rules from numerical data and adaptively constructs a rule base. (Jang, 1997).

The architecture of the ANFIS systems is composed of five layers (Fig. 2). Each layer consists in different nodes described by node function. The output signal from nodes of a layer is the input signal of the next layer. Square nodes show parameter sets that are adjustable. These nodes are called adaptive nodes. Circle nodes represent parameter sets that are constant. These nodes are called fixed nodes. More details on ANN and ANFIS are available in Tagaki, 1985; ASCE, 2000; Pratihar, 2008; Zadeh, 2008.

The neuro fuzzy model were developed using the ANFIS procedures of MATLAB (Demuth and Beale, 2003). In this study, a code is written in Matlab 7.0 for ANFIS using appropriate functions to calculate the best performance of the methods.

The dataset is divided into 3 subsets for training, validation and test of the neuro-fuzzy model. Input data are XY coordinates of the springs and wells. Hydraulic head is the ANFIS output.

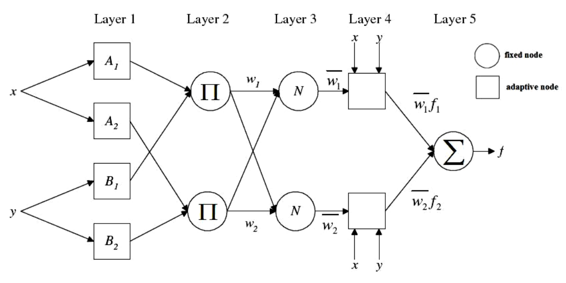


Figure 2: ANFIS architecture (x, y: inputs, A1 and B1: linguistic labels (low, medium, high, etc.), N: node, Layer1: generate of membership grades, Layer 2: Fuzzy rules Layer 3: ratio of the rules named firing strength, Layer 4: product of the normalized firing strength, Layer 5: fuzzy results transformed into a traditional output).

Before using the model to interpolate unknown outputs (hydraulics head), its actual predictive performance must be tested by comparing outputs estimated by the calibrated models with known outputs. At each phase (training, validation), the ANFIS performance is measured by the determination coefficient of goodness-of-fit $R^2$, and the root mean square error (RMSE).

It is recommended to normalize the data between slightly offset values such as 0.1 and 0.9. The dataset is normalized to be consistant with ANFIS's output that lies in the interval [0, 1]. It is also due to the fact that inputs and outputs usually have different unit and are then not homogoneous. The last reason is that membership functions are also included in the interval [0,1]. One way to scale input and output variables in interval [0.1, 0.9] is called pre-processing. In this work the preprocessing is done with a simple linear transformation. Let call $X$ the input vector with n coordinates ranging from $X_{min}$ to $X_{max}$. Each coordinate ($j$) of the transformed variable $Y$ is calculcated following the equation:

$$Y_j = \frac{1}{X_{\max} - X_{\min}} \left(0.8X_j + 0.1X_{\max} - 0.9X_{\min}\right) \qquad (1)$$

The selection of appropriate input parameters is a complex task. The first step is to determine the number of training and validation data. This selection was done iteratively in the following way:

- The area of interest is divided in for squares of equal size.
- If a square contains three points then two are selected for the training set and one for the validation set. Else the square is divided in four squares of equal size and so on.

Finally the dataset was split into two sets: 60 % of the data were assigned to the training set and the remaining to the validation and test set (20% each). Early stopping criteria provided by the validation datasets are used to prevent overtraining. Generalized bell curves were used as membership functions.

# 5 INTERPOLATION OF HYDRAULIC HEAD: RESULTS AND DISCUSSION

For each method (ANFIS and kriging) the hydraulic head distribution was calculated on a 100 m square grid.

## 5.1 Kriging

First of all the variographic clouds and the associated experimental variograms were calculated with different ranges (50 m, 100 m, 200 m and 1 km). They all reveal a clear linear structure (See Fig. 3 for a 250m range). The fitted variogram reveals a sill at 354.6 m$^2$ with a scale of 5000 m (Fig. 3). The fitted variogram was then used to krige the hydraulic head at each center of the 100 m scare grid. Figure 6a shows the result of the kriging.

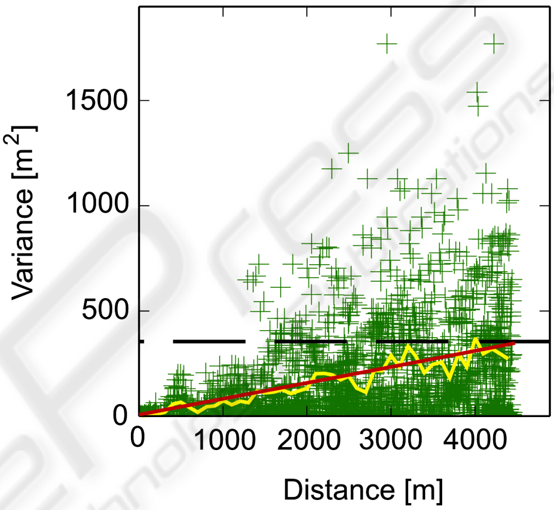


Figure 3: Variogram cloud (green crosses), experimental variogram (yellow line) and modeled variogram (red line).

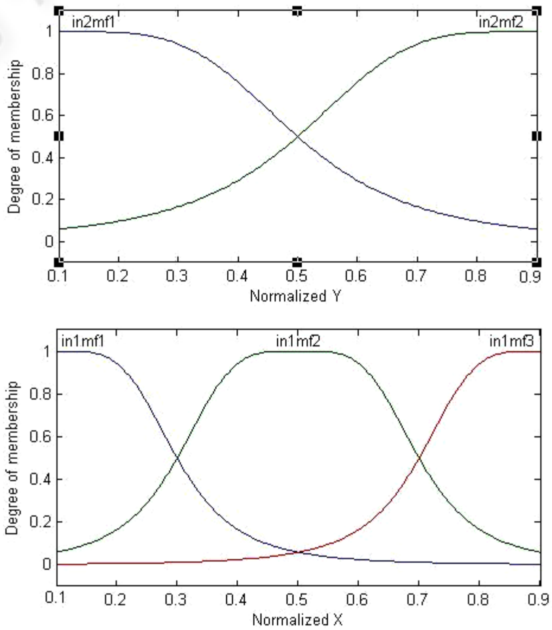


Figure 4: Membership functions (after 44 iterations).

## 5.2 Anfis

The best calibrated ANFIS model is obtained after 44 iterations. It contains 5 membership functions and 6 rules. Figure 4 shows the membership functions at the end of the learning phase.

## 5.3 Comparison of the Interpolation Methods

In this section observed and simulated data are compared. Table 1 summarizes statistics on observed and simulated data for each type of simulation: ANFIS and OK. Table 2 shows statistics on residuals at each cell of the grid containing a well or a spring. Root mean square errors (RMSE), Mean Error (ME), Mean Absolute Error (MAE) and coefficient of determination ($R^2$) were calculated for ANFIS and OK.

Table 1: Observed and simulated data statistics. SD: standard deviation.

| | Observed | ANFIS | Kriging |
|---|---|---|---|
| | | Values at sampling points | |
| Mean [m] | 139,49 | 139,47 | 139,33 |
| Min [m] | 102,00 | 107,73 | 102,42 |
| Max [m] | 179,85 | 181,03 | 179,47 |
| SD [m] | 20,05 | 19,91 | 19,90 |
| | | All Grid | |
| Mean [m] | - | 101,78 | 102,42 |
| Min [m] | - | 193,65 | 181,05 |
| Max [m] | - | 143,83 | 141,89 |
| SD [m] | - | 20,54 | 18,14 |

Table 2: Statistics of errors for ANFIS and OK.

| | ANFIS | OK |
|---|---|---|
| RMSE [m] | 3,30 | 0,77 |
| ME [m] | -0,03 | -0,16 |
| MAE [m] | 2,47 | 0,55 |
| $R^2$ | 0,97 | 0,99 |

Table 1 shows statistics of both series (observed and predicted hydraulics head). The minimum, maximum, average and standard deviation values are of the same magnitude for simulations (whatever the techniques) and for the observed values. Even if the two methods match properly the data (Fig. 5) with $R^2$ of 0.97 for ANFIS and 0.99 for OK, the comparison of performances (Table 2) indicates a slight advantage for kriging. Indeed RMSE for ANFIS and OK are 3.3 m and 0.8 m, respectively.

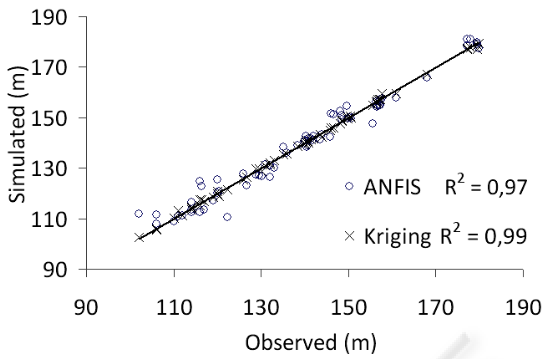


Figure 5: Observed vs simulated hydraulics heads.

After being compared with observations at each sample location, each method is used to interpolate the dataset at each cell center of a 100m grid (Fig. 6). It is then interesting to remark that the hydraulic head distributions have similarities and few differences far from sampling points. The Average values of the whole set is 102.4 m for ANFIS whereas OK calculates an average of 101.8 (Table 1). The standard deviation of the ANFIS interpolation increases (19.9 to 20.5 m) whereas the one of OK decreases (19.9 to 18.1).

Both simulations have realistic pattern except few details as local minima. Even if OK performs slightly better than ANFIS, the latter seems to be a valuable way of extrapolating hydraulics head but not a more efficient method than OK as stated by Kholghi & Hosseini (2008).

The fact that a few ANFIS estimates are far from the observed values (Fig. 5) may be due to the input variables (X and Y coordinates) of the ANFIS. Indeed these inputs do not have any physical meaning considering the hydraulic head distribution, which is partly driven by the river network. For further work one should test the euclidian distance to the river associated to only one coordinate (either X or Y) as input variables. The comparison of hydraulic head distributions calculated by OK and ANFIS (Fig. 6a & 6b) indicates that the two techniques capture the phenomenon in two different ways.

The less sampling points, the more different are the estimates. Kriging is really sensitive to the variogram that depends on the number of sampling points. In the Avenelles basin there are only 68 sampling points. The fitted variogram might entail considerable uncertainty. Using this variogram for OK leads to biased results (Pardo-Iguizquiza et al., 2009). To our knowledge ANFIS was used only once by Kholghi & Hosseini (2008). This is not enough to draw conclusion.

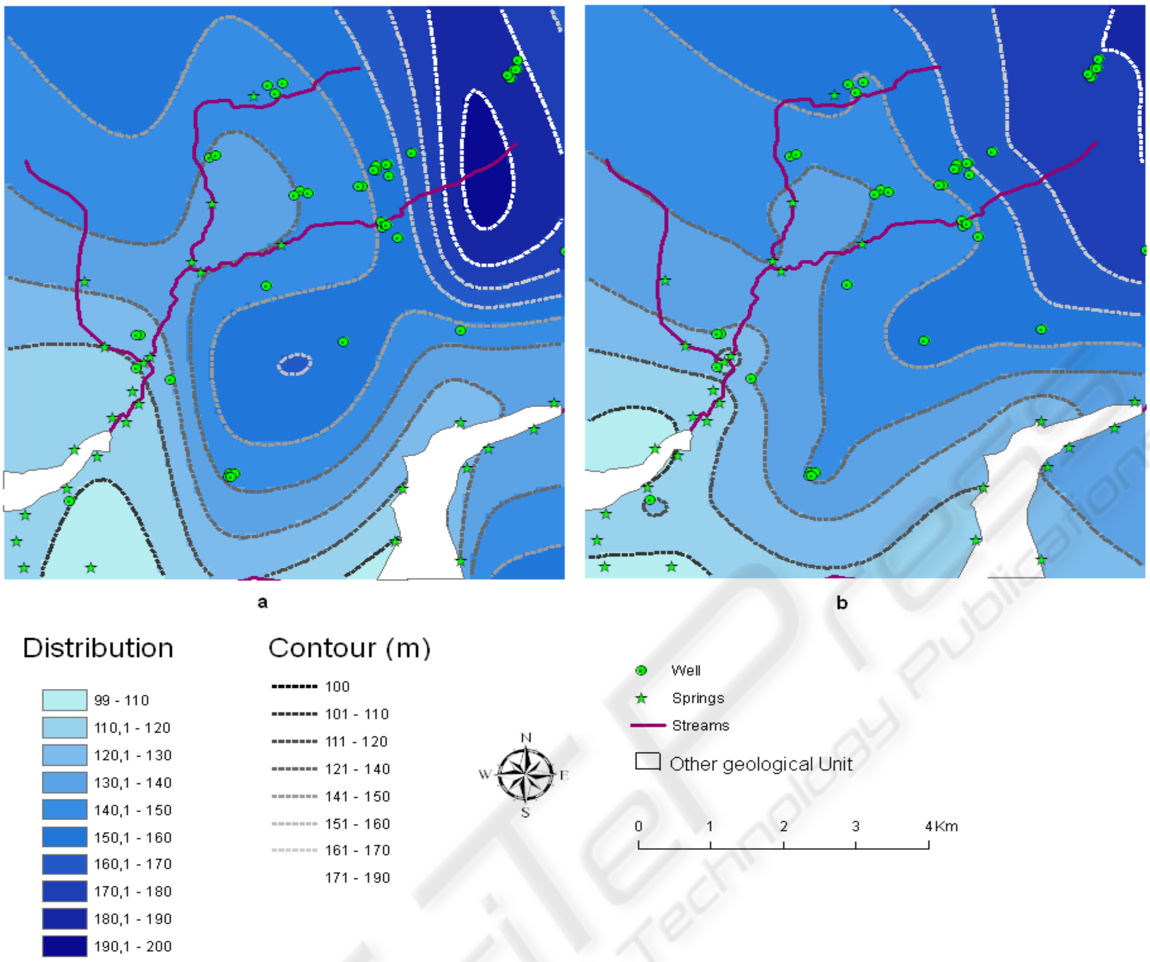


Figure 6: (a) Kriging interpolation and (b) ANFIS interpolation.

At this point, it is not possible to determine the best interpolation technique but one can use them to improve measurement network based on discrepancies between the two estimates (Fig. 7). The discrepancy map indicates in black and deep blue the area where sampling should be achieved in order to understand which method do perform best for the Orgeval aquifer unit.

## 6 CONCLUSIONS AND PERSPECTIVES

This paper focuses on the comparison of Adaptive Neuro-Fuzzy Interface System (ANFIS) and Ordinary Kriging (OK) to interpolate hydraulics head in the Avenelles aquifer system. Both methods provide satisfactory estimates even if they catch two different representation of the phenomenon. On the one hand, X and Y coordinates were used as input variables of the ANFIS and may be improved by using the distance to the river instead of one of them. On the other hand kriging gives results entailed with a large uncertainty far from sampling points. It is not possible to determine which method performs best but the combined use of both methods may help to improve the observation network.

The next step of this work will be to obtain a consistent hydraulic head distribution in the basin. This consistent field will then be used as a reference to apply inverse methods on the basin which will allow to determine physical parameter distribution in the experimental site.

Finally ANFIS could be a possible alternative method to kriging in the case of discontinuities or in highly heterogeneous media. For instance, the building of the heterogeneous structure of an aquifer system is still a research topic for hydrogeologist, geomorphologists and other earth science researchers.

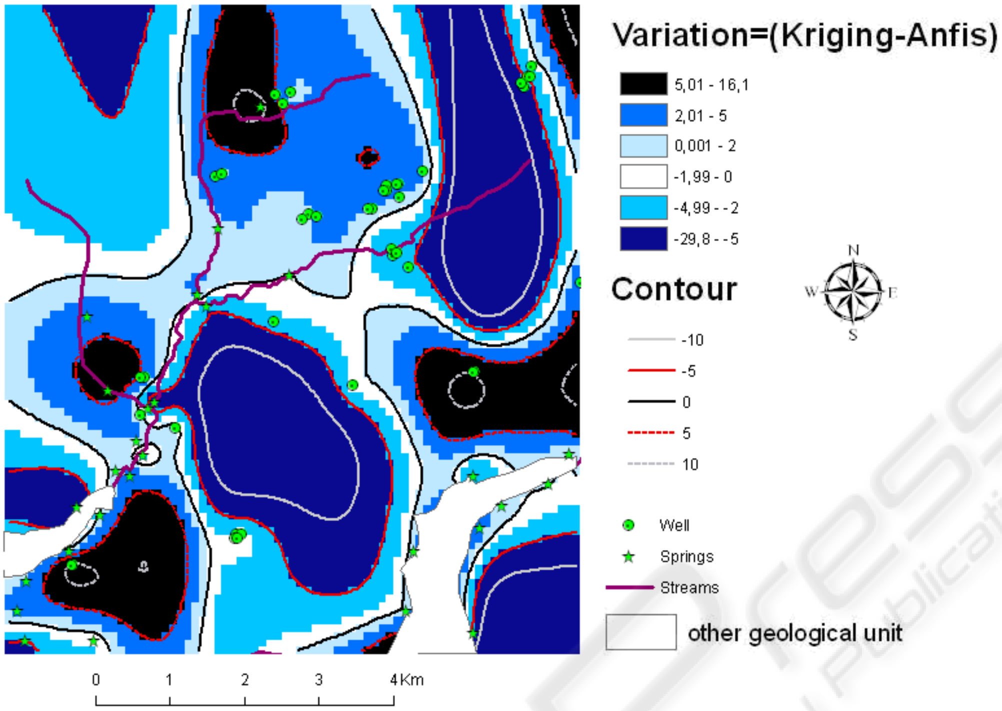


Figure 7: Difference between OK and ANFIS estimates.


## ACKNOWLEDGEMENTS

This work was funded by the ANR Carnot Institut, the PIREN Seine research program, and the FIRE (Federation Ile de France de Recherche en Environnement). It is also a contribution to the GIS Oracle that maintains the experimental basin of the Orgeval. We kindly thank the BRGM for providing the DEM of the top of the aquifer system.


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