GEOSTATISTICAL MODELLING OF ENVIRONMENTAL VARIABLES AT MINE SITES

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Abstract: The mining activity is considered to be one of the biggest contaminators of the surrounding environment. To deal with this problem, new technologies for monitoring environmental attributes are being developed, in order to sample and record a large amount of variables related with specific features of the environment quality, in particular, river water, groundwater, air and soil.
In order to make use of the available information for prediction purposes, it is required to model the sub-systems in the mine site and compare the actual data with a baseline, prior to the beginning of the mining workings. Such models make use of geostatistics in order to estimate and simulate the values of variables in space and time, taking into account the independence between sub-systems and the physical laws that govern the behaviour of relevant variables, when pollutant sources and meteorological conditions can be identified. Hence, geostatistical techniques are to be adjusted to the specific characteristics of the environmental variables and objectives of environmental control.
The results of this research, referring to Neves Corvo Mine, in Portugal, are given in this paper, in what concerns the modelling of river water and air quality by stochastic spatio-temporal simulation, the integration of dispersion models with geostatistical estimation of groundwater quality, and the morphological simulation of soil contamination by particulate copper emissions.

1. Introduction

The monitoring programmes currently used for environmental control at mine sites provide a large amount of space-time data, referring to a variety of measured variables.

E.Y. Baafi and N.A. Schofield (eds.), Geostatistics Wollongong '96, Volume 2, 951-960.

In general, the data sets produced by these monitoring programmes are inarticulate, incomplete and statistically unbalanced. In fact, there is not a clear standard for monitoring environmental variables in the mining industry, which makes it difficult to take effective advantage of the results arising from the costly sampling procedures used to collect the basic information related to environment.

To approach this problem under a systemic view and produce reliable outputs to be visualised by a Geographic Information System (GIS), a Brite Euram project was launched - Environmental Simulation and Impact Assessment for the Mining Industry (Pereira, H.G., 1995). The achievements of this project related to geostatistics are given in this paper.

The first point addressed in this research is that the raw monitored variables are not directly inputted into the GIS, but are previously submitted to a Modelling Process that guarantees their representativeness in the spatial units concerned by the GIS, (Fig.1). Hence, the recorded variables, obtained by punctual sampling procedures, are extended to the ERU (Environmental Resource Unit), composed by the bias of geostatistical estimation/simulation techniques, associated with numerical/physical models, when appropriate. Therefore, geostatistical models are an interface between the raw monitored data and the visualisation/support decision tool (GIS). Moreover, the geostatistical models provide uncertainty levels to the monitored variables. In the case where estimation procedures are applied, the kriging variance (for measures expressed by a real number) or the proportion of samples in a given range around the limit that separates the two sub-populations of 1´s and 0´s (for measures expressed by an indicator variable) are the basis for uncertainty mapping. In the case where simulation is used for modelling the raw variables, uncertainty levels are given by counting the "favourable" outcomes in the set of equiprobable images that are simulated.

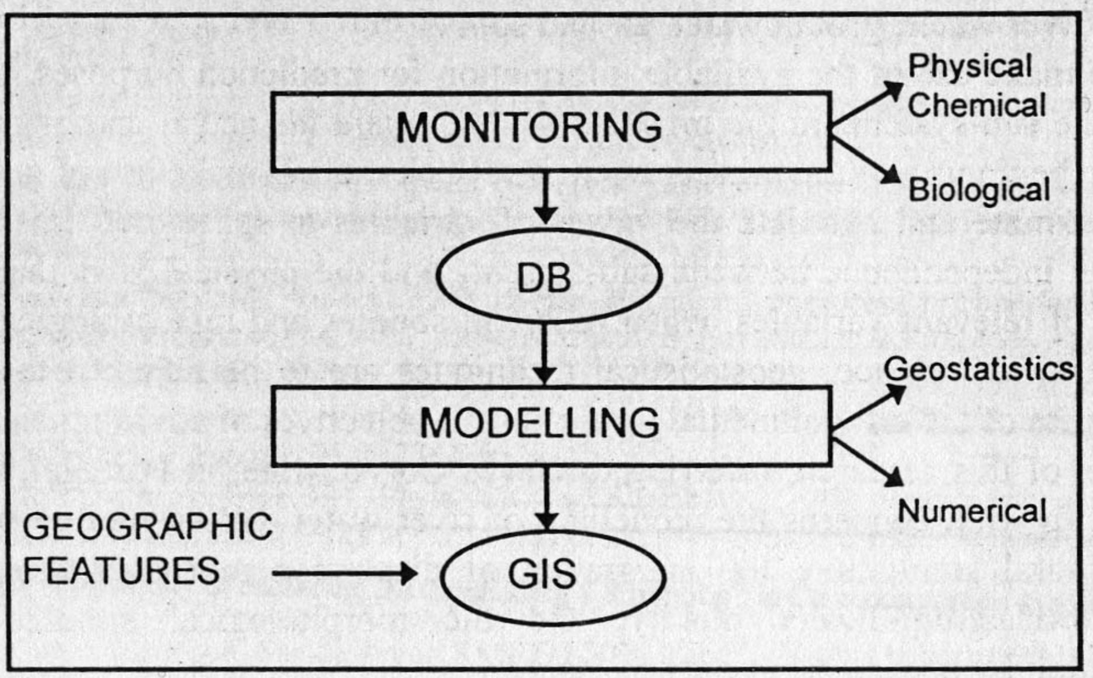

Fig.1 - General methodology.

2. Conceptual Model

A general conceptual model was designed to integrate, in a coherent framework, the different environmental impacts, resulting from a variety of sources. This model was developed for the Neves-Corvo mine, where the main sub-systems were identified and inter-related according to the sketch of Fig.2. Fig. 2a) focus on water contamination by the mine effluent and Fig.2b) focus on the flow of dust particles driven by the wind from the ore and concentrate stockpiles.

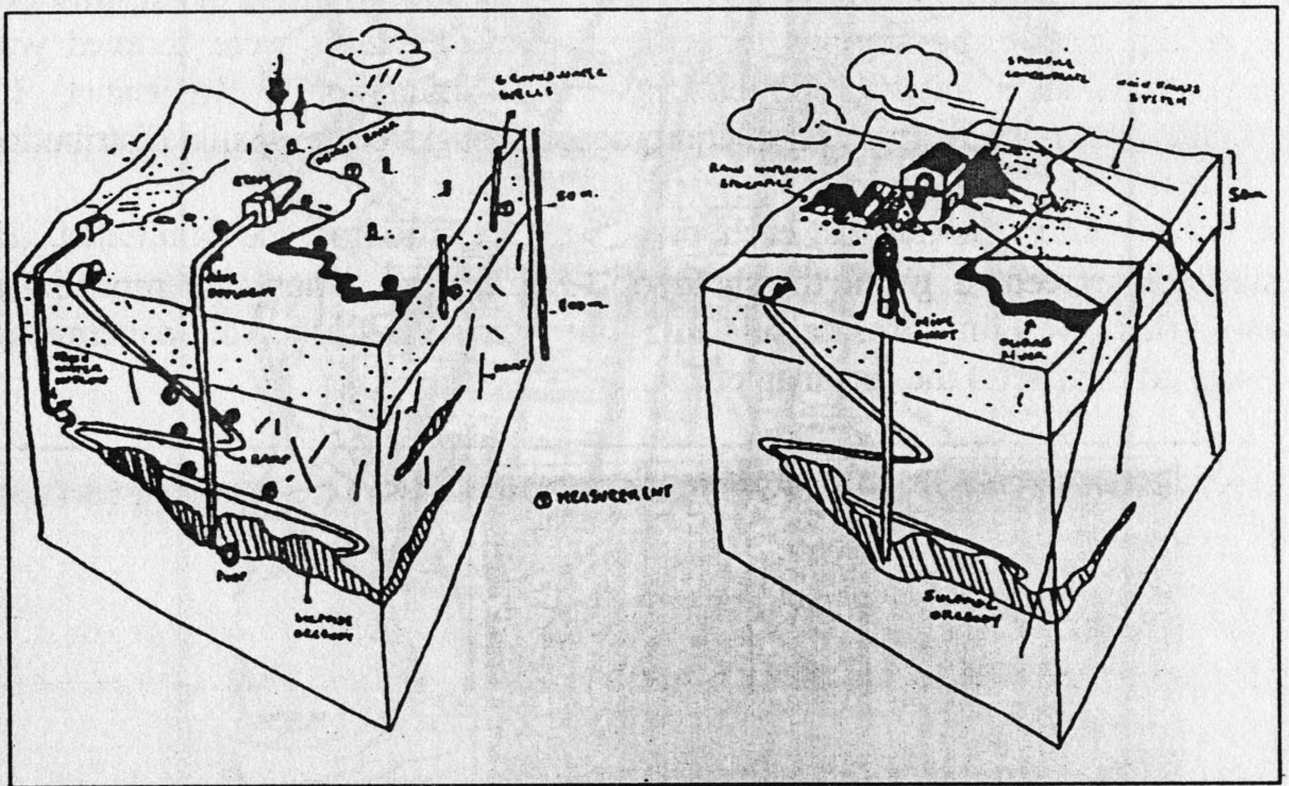

Fig. 2a) - Water sub-systems Fig.2b) - Flow of dust particles

Fig.2 - Sketch of the sub-systems inter-dependence in the surroundings of the Neves-Corvo mine.

In the area of influence of the mine there exist three aquatic sub-systems: the Oeiras river, which is affected by the mine water effluent discharge; the shallow aquifer, which is affected by superficial seepage and the deep aquifer, in contact with the mine workings. These sub-systems are interconnected by a set of faults, which are clearly identified by the geological survey of the mine. This set of faults are the main path relating the superficial deposition of dust particles in soils with the deep aquifer (Dias, M., 1996).

Three main contamination sources of the environmental system can be described as follows:

- Air pollution - The main air pollution source are the raw materials and concentrate stockpiles. The particulate emission and consequent deposition are the main responsible for the soil pollution;
- Ground water - Apart from direct contact of the aquifer with the mine water, there is contamination by superficial water, conveyed by the fault system;
- River - water - The mine water is pumped to the water treatment plant (ETAM), whose output is discharged into the river.

3. Case Study

3.1 ATMOSPHERIC DEPOSITION

The flow of Cu particles from the source (stockpiles) to the deposition in the soil is driven by meteorological conditions (wind direction and velocity). The atmospheric sub-system concerned by this flow is described by a Gaussian Plume dispersion model, based on 19 lichens update monitoring stations (Pereira, M.J., *et al*, 1995). In order to account for the spatial variability of the pollutant concentration, the results of the model at the monitoring stations for different time horizons were coupled with a stochastic simulation method (Probability Field Simulation - Srivastava, 1992, Froidevaux, 1993), producing a set of equiprobable images of the spatial distribution of the pollutant in the soil (Pereira, M.J., *et al*, 1996).
In the set of simulated images, each pixel was classified as "contaminated" if its concentration exceeds a given threshold of 1.8 μ.mol.g^{-1}. Then, the probability of exceeding this given limit was calculated by the relative frequency of "contaminated" outcomes, giving rise to the risk map of Fig.3.

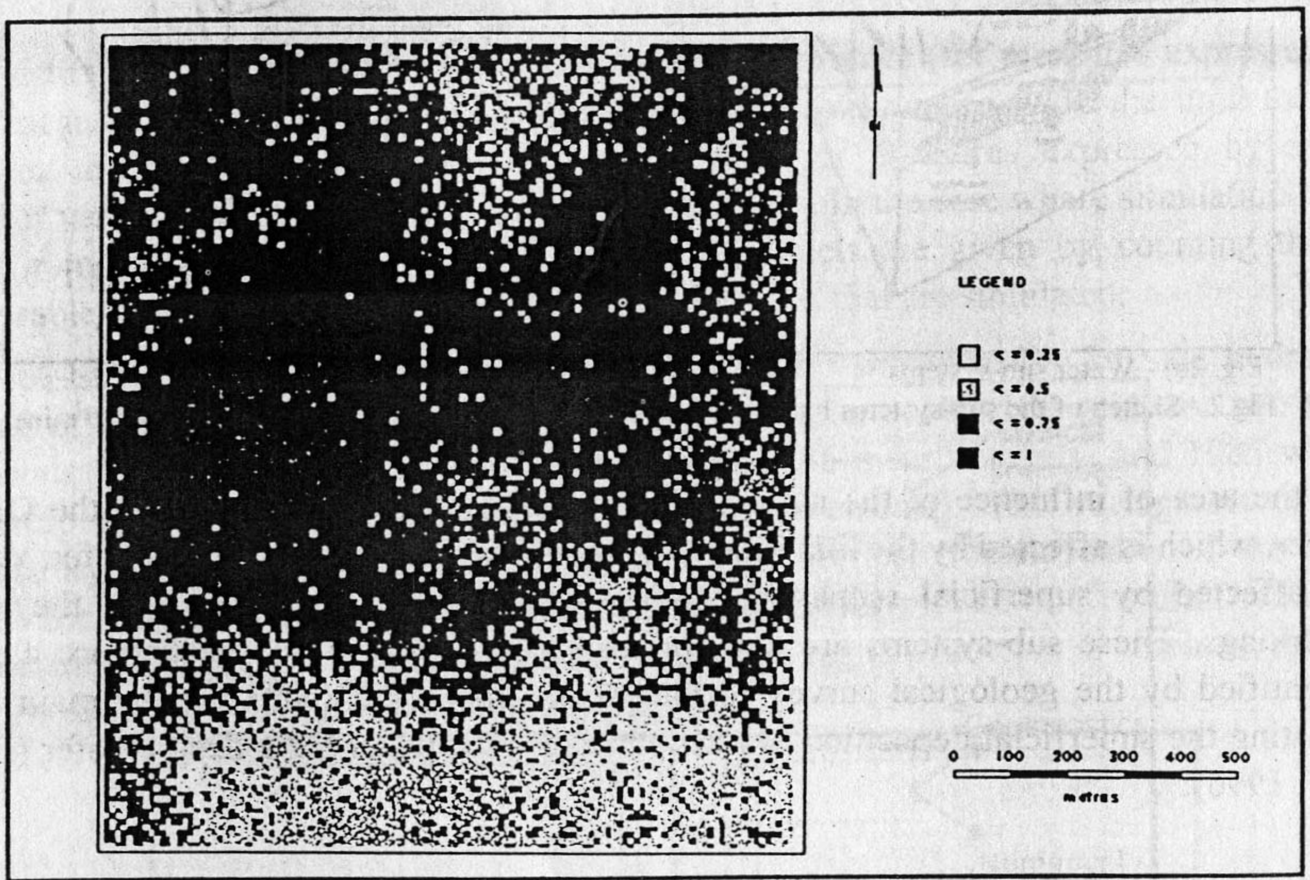

Fig.3 - Probability of exceeding the threshold of 1.8 μ.mol.g^{-1} in Cu concentration in soil.

3.2 RISK OF AQUIFER CONTAMINATION

Once established the deposition model of particulate Cu in soil, the next step of the methodology is to assess the impact of this pollutant on the aquifer, through the set of faults identified by geology. In fact, the geological model of the area indicates that the very low permeability of the lithological formations (schists and grawakes) occurring in the surroundings of the mine, prevents significant seepage.

Hence, the preferential paths for the flow of superficial water into the aquifer is the above mentioned fault system (Fig.4).

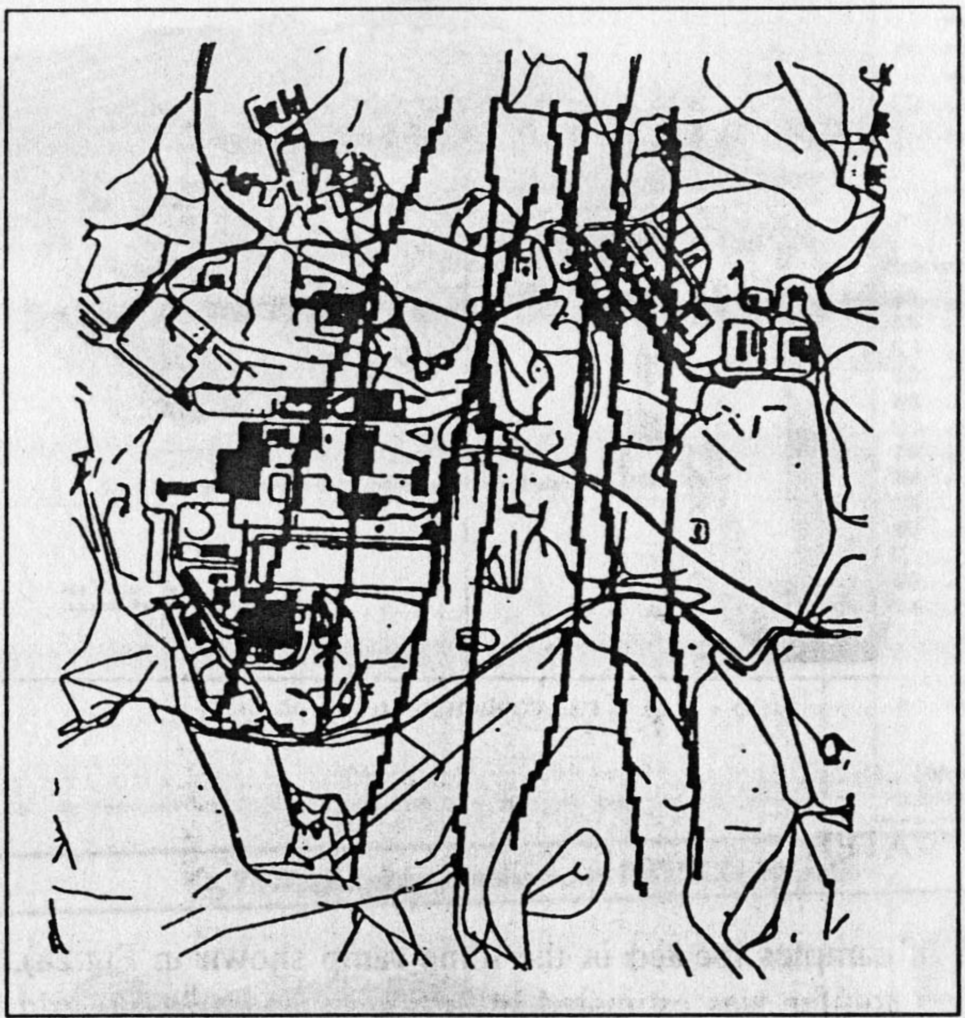

Fig.4 - Fault system in grid format and mine infra-structures.

Now, the contamination risk of each pixel can be calculated in the GIS, by composing the probability map given in Fig.3, with a structural distance to the fault system depicted in fig.4, according to the expression:

$$I_{i,j} = d_{ij} \cdot C_{ij}$$

where

$\mathbf{I_{i,j}}$	is the probability of aquifer contamination for the pixel **i, j**,
$\mathbf{d_{ij}}$	is the structural distance from pixel **i, j** to the nearest faults,
$\mathbf{C_{ij}}$	is the probability of the Cu concentration to exceed the threshold.

The Structural distance $d_{i,j}$ was derived from the digital terrain model by using the hydrological function of the GIS (ARC/INFO) that provide the direction of rain water flow. Those distances were standardised in the [0, 1] interval, through the Gower distance (Gower and Ross, 1969). Hence, $I_{i,j}$ can be viewed as the product of two

independent probabilities: the probability of flow to the nearest fault (d_{ij}) and the probability of the Cu concentration to exceed the given threshold (C_{ij}).
The risk of aquifer contamination is depicted in Fig5, a map produced by the GIS where scenarios of remediation can be assessed .

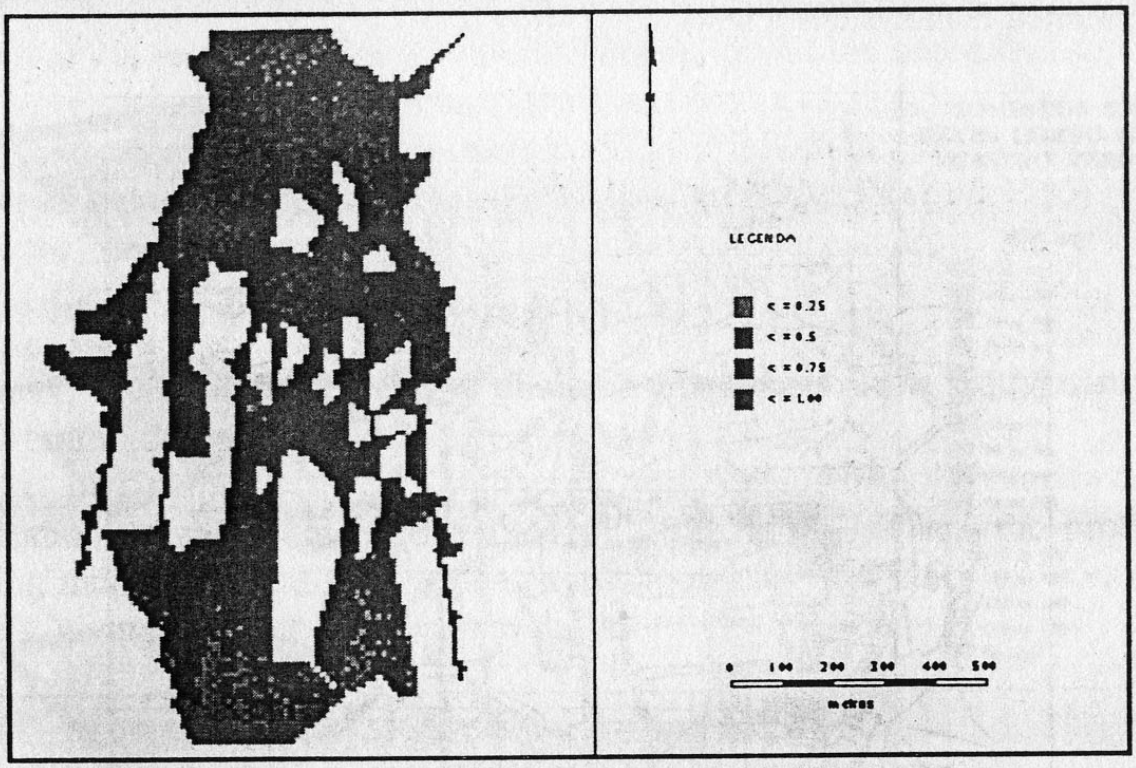

Fig.5 - Map of risk contamination (probability).

3.3 GROUNDWATER

Based on a set of samples located in the mine ramp shown in Fig.2a), the hydraulic head of the deep aquifer was estimated by kriging, in a 100x100 grid, for two time periods: 1982, which corresponds to the baseline (86 measurements) and 1985 which corresponds to the mine development (33 measurements). The variograms of the variable, as shown in Fig.3 for 1982 and 1985, reflect the alteration of the flow regimen: In the first period a non-stationary behaviour reflects the natural hydraulic gradient, (Fig.6a), while in the second period a less regular function is obtained, related to the disturbances caused by pumping (Fig. 6b)).

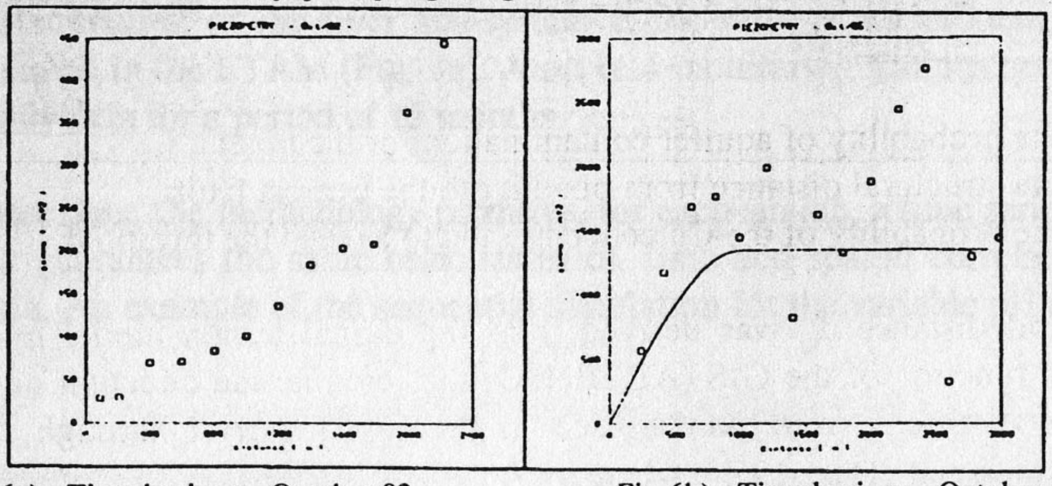

Fig. 6a) - Time horizon - October 82. Fig.6b) - Time horizon - October 85.
Fig. 6 - 2D variograms of piezometric levels, computed before and after the mining works.

The integration of the kriged results into the GIS gives rise to Fig. 7 and Fig.8, which show the estimated hydraulic heads of the aquifer around the mine site for the period 1982 and 1985, respectively. From the baseline of 1982, the 1985 situation is characterised by two depression cones caused by the development of the mine.

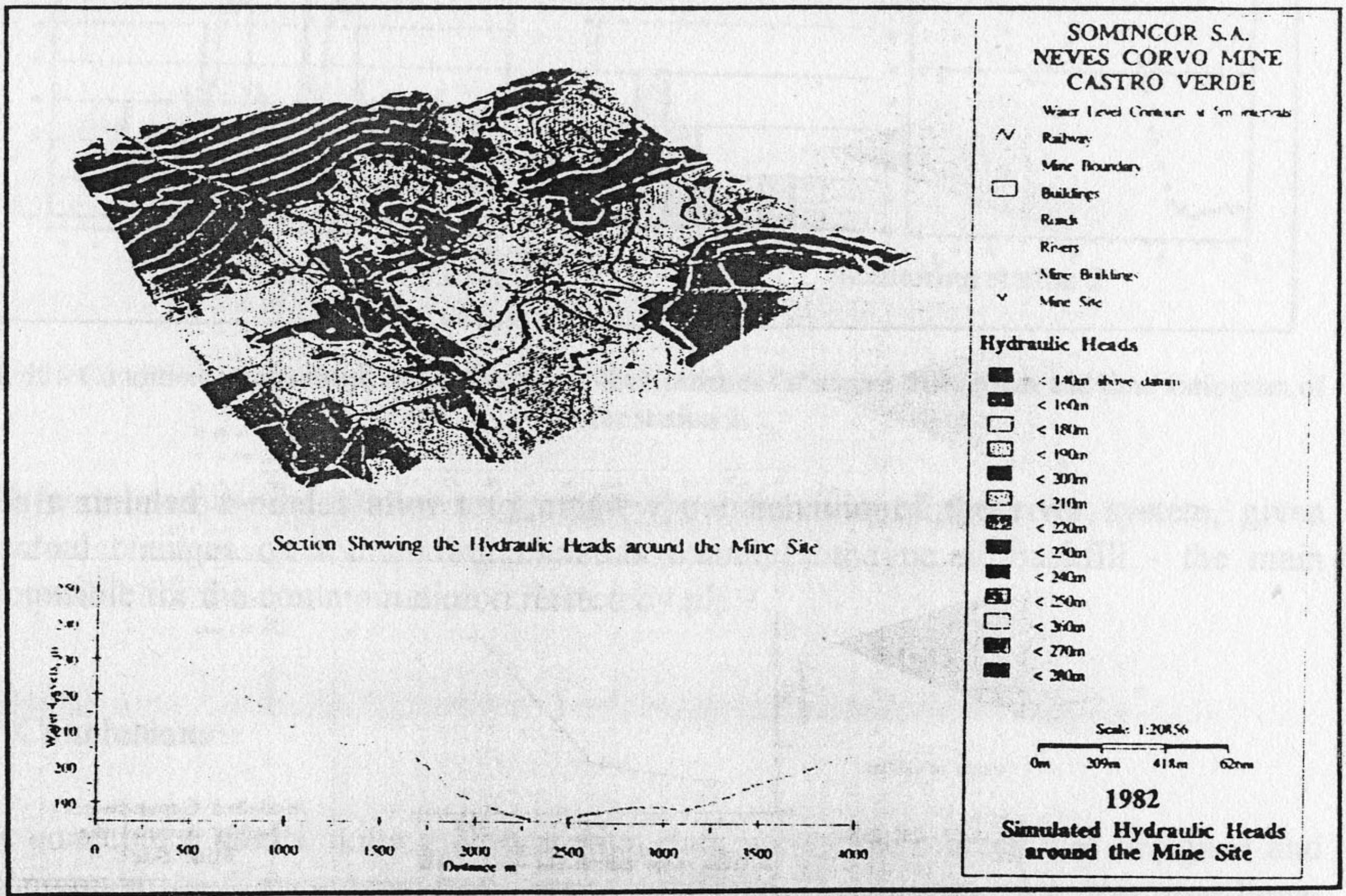

Fig.7 - Kriged hydraulic heads for 1982 (GIS output).

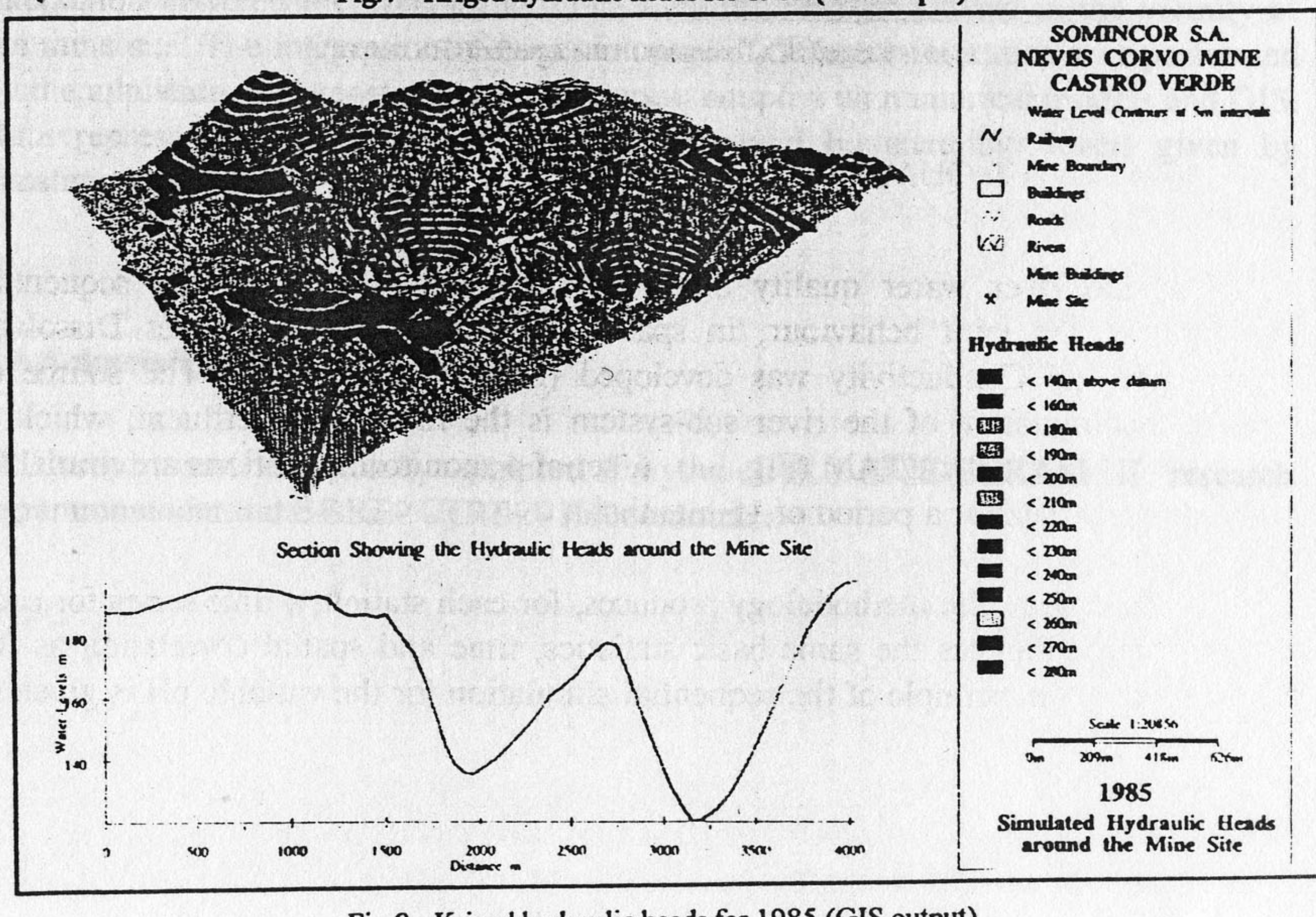

Fig.8 - Kriged hydraulic heads for 1985 (GIS output).

Regarding groundwater quality, it is given in Fig.9 an example of a GIS output obtained by kriging the $SO_4^{=}$ content for three sections in space and three periods in time. This figure depicts the increase in acidity caused by the mine workings.

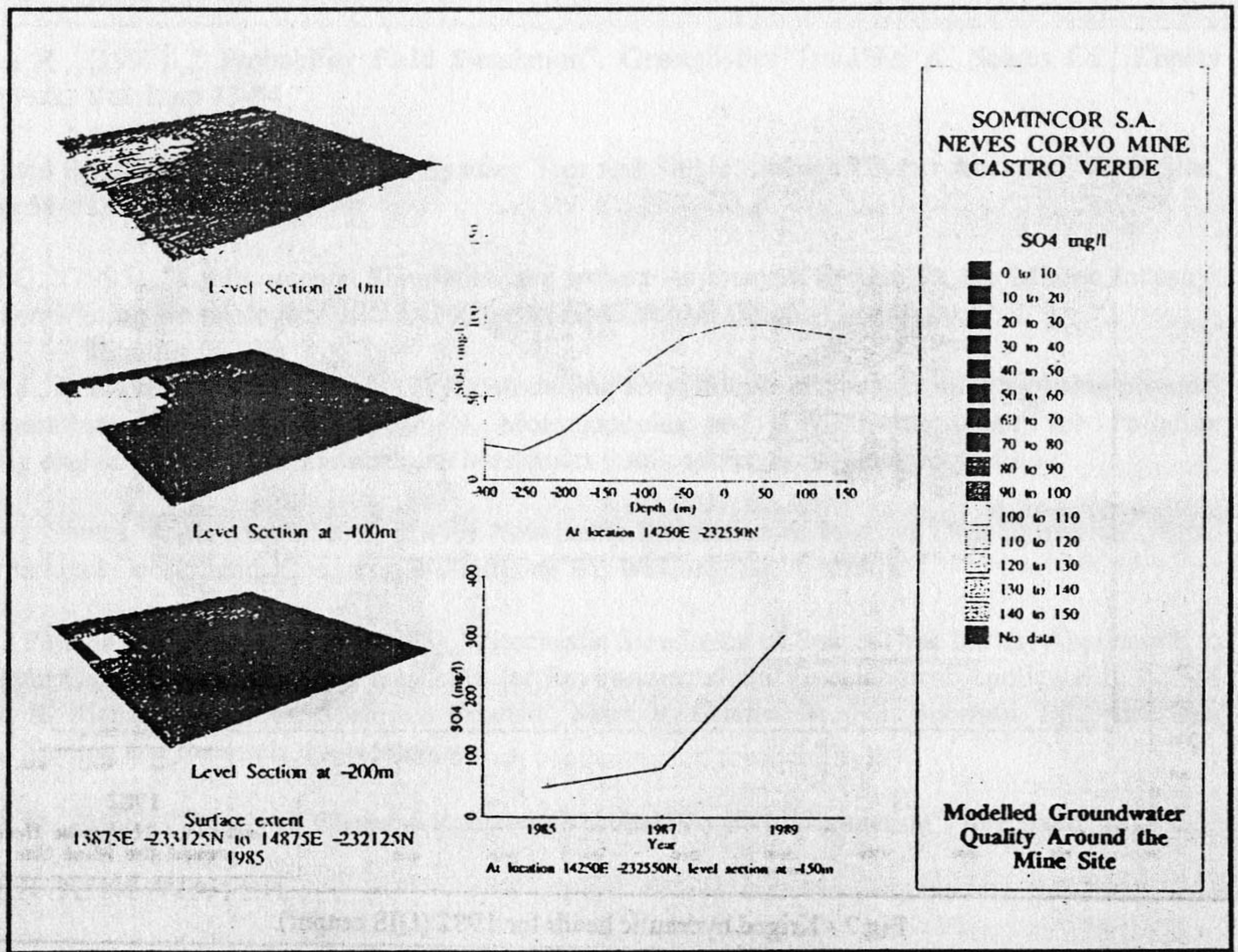

Fig.9 - Kriged $SO_4^{=}$ content in the aquifer (GIS output).

3.4 RIVER WATER QUALITY

Regarding the river water quality assessment, a methodology for the sequential simulation of the joint behaviour, in space and time, of the variables Dissolved Oxygen, pH and Conductivity was developed (Soares *et al*, 1995). The source of possible contamination of the river sub-system is the mine water effluent, which is previously treated in the ETAM (Fig. 3a). A set of 4 monitoring stations are available, providing daily data for a period of 15 months.

Based on these data, the methodology produces, for each station, a time series for each variable that guarantees the same basic statistics, time and spatial correlation as the historical data. An example of the sequential simulation for the variable pH is given in Fig. 10.

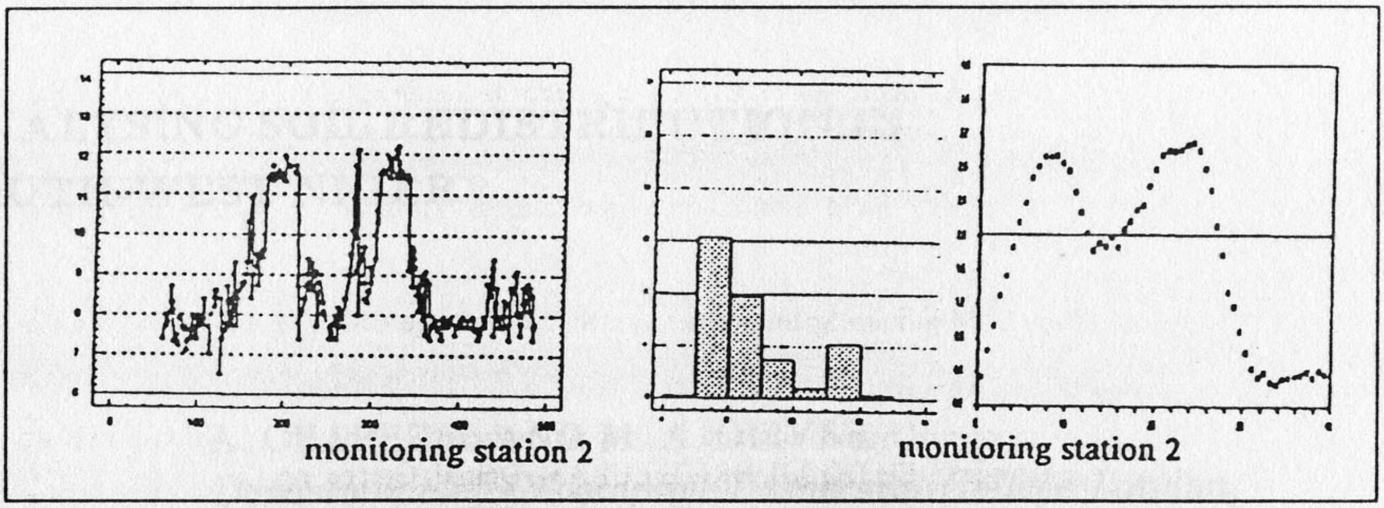

Fig. 10 - Conditional Sequential simulation of pH time series for station 2. Histogram and time variogram of pH for station 2.

This simulated model allows to preview the behaviour of the river system, given eventual changes on the mining methods namely the type of backfill - the main responsible for the contamination reflected by pH.

4. Conclusions

A conceptual model linking environmental data with their sources was designed and components of the geosystem were established, accounting for the non-linear interaction between the orebody and other natural resources located in the vicinity of the mine site. The integration of large volumes of different information was performed by the application of geostatistical techniques, coupled with numerical models and GIS. Data representativeness in the GIS was improved by uncertainty levels given by geostatistics models.

5. Acknowledgements

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6. References

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