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Assessing Electrical Resistivity Tomography for Hydrofacies Detection Using a Sensitivity Dependent Probabilistic Method

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SUMMARY

Alluvial aquifers are generally composed of several facies with complex architectures and interconnections depending on the fluvial system. In this context, electrical resistivity tomography (ERT) may provide important information on the spatial distribution of hydrogeological parameters. However, ERT inversion introduces some bias in the resulting resistivity distribution due to regularization and resolution issues. In this study, we refine ERT inversions by incorporating prior information in order to improve the identification of facies through a probabilistic relationship derived from collocated measurements. We then analyze with synthetic cases the effect of spatially varying sensitivity on the probabilistic relationship. As expected, when sensitivity decreases, the distributions of resistivity for the different facies tend to be superimposed. A mean distribution thus overestimates the ability of surface ERT to discriminate hydrofacies in depth.

Introduction

Alluvial aquifers are generally composed of several facies (clay, loam, sand, gravel) with complex architectures and interconnections depending on the fluvial system. In this context, borehole logs and classical hydrogeological tests might not be sufficient to capture the complexity of the deposits and their influence on groundwater flow and solute transport. Geophysical methods can provide additional information on the spatial distribution of hydrogeological parameters. Among them, electrical resistivity tomography (ERT) is well-suited to study alluvial deposits. Indeed, the method has already been widely used to image deposits in alluvial aquifers and to improve the understanding of the depositional model (e.g., Bersezio et al., 2007; Doetsch et al., 2012).

For qualitative purposes, a simple interpretation of the tomograms may be sufficient. However, for a more quantitative integration of geophysical data into subsurface models, it is necessary to consider issues such as the choice and accuracy of the considered petrophysical relationship(s) (Irving and Singha, 2010), the spatially-dependent resolution of tomograms (e.g., Ruggeri et al., 2013) or the effect of regularization on the results (Caterina et al., 2014).

In this study, we use ERT to identify facies in an alluvial aquifer through a probabilistic relationship. First, ERT inversion is refined compared to traditional smoothness constraint inversion by incorporating detailed prior geostatistical and geological information. Then, the ability of ERT to identify facies is assessed using collocated borehole measurements and a probabilistic relationship is defined. Finally we analyze with synthetic cases the effect of spatially varying data sensitivity on this probabilistic relationship.

Methods

We used the program CRTOMO (Kemna, 2000) for ERT inversions. The objective function for the smoothness constraint solution is expressed as

$$\phi(\mathrm{m}) = \left\|\mathrm{W_d}(\mathrm{d} - \mathrm{f}(\mathrm{m}))\right\|^2 + \lambda \left\|\mathrm{W_m m}\right\|^2 \tag{1}$$

where W_d is the data weighting matrix, f is the non-linear operator mapping the logarithm of the conductivities of the model m to the data set d, W_m is the roughness matrix, and λ is the regularization parameter. We consider the incorporation of prior information through the geostatistical regularization

$$\phi(\mathrm{m}) = \left\|\mathrm{W_d}(\mathrm{d} - \mathrm{f}(\mathrm{m}))\right\|^2 + \lambda \left\|\mathrm{C}_{\mathbf{m}}^{-0.5}(\mathrm{m} - \mathrm{m_0})\right\|^2 \tag{2}$$

where C_m is the model parameter covariance matrix and m_0 is the prior model. The implementation of C_m (Caterina et al., 2014) enables the definition of non-stationarity by considering several zones with different correlation length in m_0 that are disconnected during inversion. To assess the quality of the inversion, we use the cumulative sensitivity matrix (Kemna, 2000)

$$\mathrm{S} = \mathrm{diag}\left\{\mathrm{J^T W_d^T W_d J}\right\} \tag{3}$$

where J is the Jacobian of the last iteration.

After inversion, we compare the ERT results with borehole logs to compute the distribution of resistivity ρ for each facies A_i (gravel, sand or clay): $f(\rho|A_i)$. Using Bayes' rule, this can be used to compute the conditional probability of each facies $P(A_i|\rho)$

$$\mathrm{P}(\mathrm{A_i} \mid \rho) = \frac{f(\rho \mid \mathrm{A_i})\mathrm{P}(\mathrm{A_i})}{f(\rho)} = \frac{f(\rho \mid \mathrm{A_i})\mathrm{P}(\mathrm{A_i})}{\sum_{\mathrm{i}} f(\rho \mid \mathrm{A_i})\mathrm{P}(\mathrm{A_i})} \tag{4}$$

where $P(A_i)$ is the proportion of the facies deduced from boreholes.

Effect of regularization

We first test the ability of ERT to discriminate three facies (clay, sand and gravel) in the alluvial aquifer of the Meuse River on an experimental site of the University of Liege. The alluvial deposits are 10 to 12 m thick and lie on a Carboniferous shale bedrock. The position of the bedrock is known from borehole logs and seismic refraction surveying.

The ERT data were collected on 64 electrode profiles with 2m spacing using a dipole-dipole configuration ($n \leq 6$ and $a \leq 9$). The error on the data was assessed using reciprocal measurements. We derived a linear error model with an absolute error of 0.002 Ohm and a relative error of 0.26%. The inversion was stopped when the RMS of the error weighted data misfit reached 1 (the data are fitted within their error level).

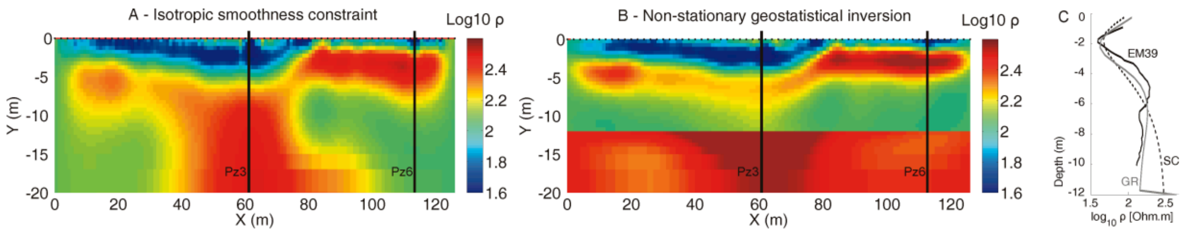

Figure 1 *Inversion of ERT data with (A) smoothness constraint and (B) non-stationary geostatistical inversion. (C) Comparison of resistivity distribution with electromagnetic logs in Pz3.*

The standard smoothness constraint inversion (Figure 1A) highlights important lateral resistivity variations in the deposits. However, the comparison with EM logs (Figure 1C), located in the middle of the profile, shows that this inversion fails to reproduce the decrease in resistivity between -5 and -10m. To improve this solution, we added independent information in the inversion process. From EM logs at the site, we deduced the correlation lengths of resistivity and computed the model parameter covariance matrix (equation 2). We also built a prior model taking into account the position of the bedrock. We obtain the solution of Figure 1B which better fits the resistivity distribution in Pz3.

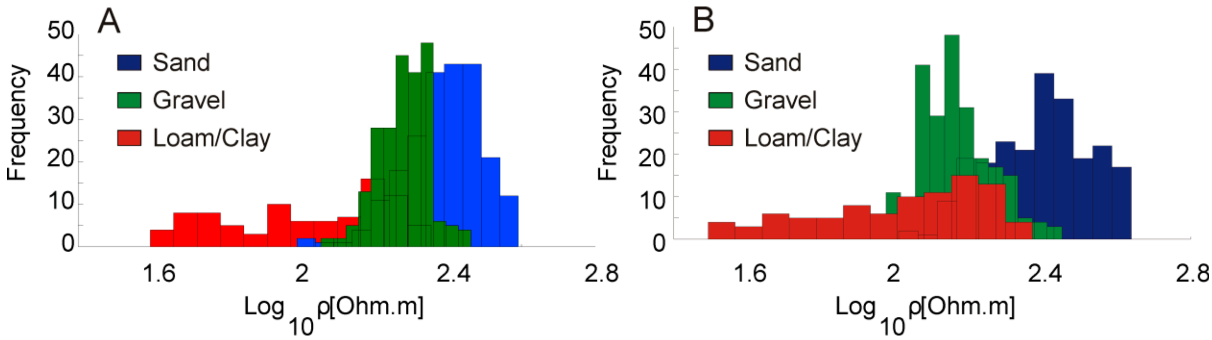

Figure 2 *Resistivity distribution of each facies obtained by comparison of ERT results with borehole logs. (A) The smoothness constraint inversion is not able to discriminate precisely sand and gravel because their mode is relatively close whereas (B) the geostatistical inversion identifies them better.*

In total 12 ERT profiles were considered and compared to the facies observed in 20 boreholes at the site. The proportion of clay, gravel and sand are respectively 18%, 42% and 40%. The ERT resistivity distribution was computed for each facies and each inversion method. We see in Figure 2 that the geostatistical inversion is able to better discriminate the sand and gravel facies. The smaller resistivity of gravel is attributed to its higher water content and the absence of fine sediments.

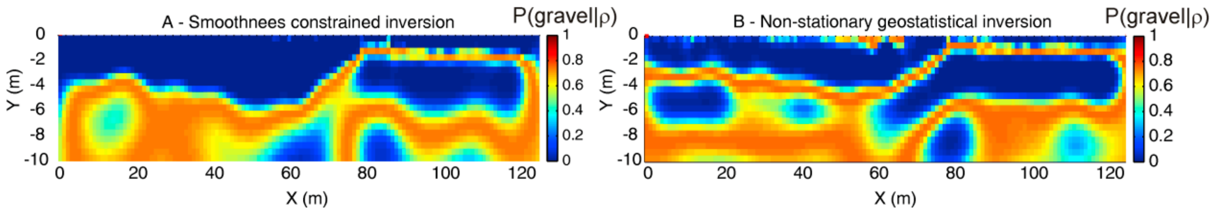

Figure 3 *Probability maps of gravel obtained using equation 4 for the smoothness constraint solution (A) and the geostatistical solution (B).*

Through Bayes' rule (equation 4), we computed the probability of gravel according to the resistivity distribution (Figure 3). Due to the smoothing effect, the smoothness constraint solution (Figure 3A) tends to overestimate the probability of gravel below -5m. The differences are only due to the incorporation of prior information which enables us to better estimate the resistivity distribution.

Effect of sensitivity

The probability maps in Figure 3 were computed without considering the spatial variations in resolution and sensitivity of the ERT data. Indeed, it is well-known that the sensitivity of ERT surface-array data decreases rapidly when we move away from the electrodes, i.e. at the sides of the section and at depth (Figure 4). However, the effect on the probability distribution is difficult to see in the field due to a lack of data.

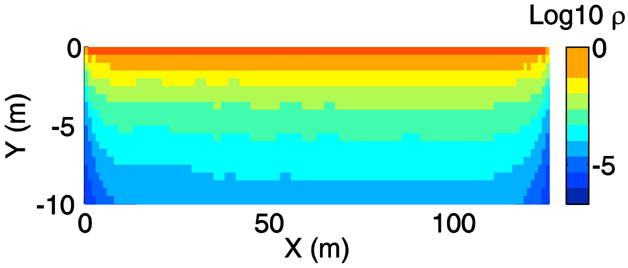

Figure 4 *The cumulative sensitivity distribution displays the well-known decrease with depth because the electrodes are located at the surface.*

To overcome this limitation, we have simulated 96 synthetic models with gravel (140 Ohm.m) and clay (100 Ohm.m) anomalies in a sand background (250 Ohm.m). We simulated the resistance data (same dipole-dipole configuration and noise level as the field data) and inverted all data sets with the smoothness constraint inversion.

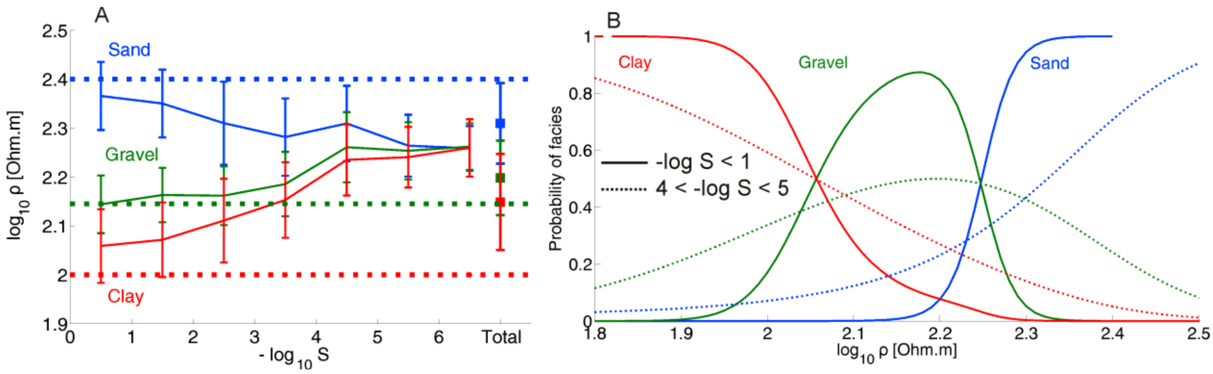

Figure 5 *(A) Mean resistivity and double standard deviation interval according to the sensitivity for the different facies. The dotted lines represent the resistivity values used for forward modelling. (B) Conditional probability of facies for two different values of sensitivity.*

After inversion, we calculated the resistivity distribution for each facies according to the opposite of the logarithm of the sensitivity values classified in bins of 1 unit (e.g., $0 < -\log_{10} S < 1$). Figure 5A illustrates the results. We see that the standard deviations of the distributions are rather similar for the facies and independent of the depth, which means that the standard deviation is mainly related to the inversion process and regularization. In contrast, the means of the distributions are well separated for high sensitivities, whereas for low sensitivities they fall upon the same value, meaning that ERT is not informative regarding the true resistivity distribution anymore.

Using Bayes' rule, we computed the conditional probability at two different levels of sensitivity (Figure 5B). The solid lines correspond to high sensitivity, and show that the distributions are well-identified and the intermediate facies (gravel) may be detected with a probability close to 90%. For low sensitivities (dotted lines), the distributions are superimposed and it is difficult to discriminate the facies. The maximum possible probability for gravel is around 50%. Only extreme values can be interpreted with confidence.

Conclusions

Our results confirm that electrical resistivity tomography is a suitable tool to image lateral and vertical heterogeneity in alluvial deposits. However, for a more thorough integration of geophysical results in hydrogeological models, it is necessary to quantify the uncertainty related to the predictions.

We have used a probabilistic approach to analyze how surface ERT results were affected by the inversion procedure (regularization) and the sensitivity pattern. The results show that incorporating independent prior information is crucial to obtaining an ERT resistivity distribution closer to the true distribution. The use of a prior model based on seismic and borehole data, along with a geostatistical constraint, enabled to refine the resulting image.

We investigated the role of sensitivity using synthetic simulations. They highlight that for high sensitivities, ERT is able to discriminate easily between different facies. However, when sensitivity decreases, the distributions of resistivity for the different facies tend to be superimposed, yielding a poor discrimination of facies. A mean distribution, as generally calculated for field cases, thus overestimates the ability of surface ERT to discriminate hydrofacies in depth, whereas it is underestimated near the surface.

Acknowledgement

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