THE USE OF GROUND-PENETRATING RADAR DATA IN THE DEVELOPMENT OF FACIES-BASED HYDROGEOLOGIC MODELS

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1. INTRODUCTION

One of the main challenges in the development of hydrogeologic models is acquiring the data required to accurately represent the properties of the heterogeneous subsurface region of interest. We are developing new ways of using ground penetrating radar (GPR), a high resolution geophysical technique, to obtain the information required to develop accurate hydrogeologic models. Given the advances in data acquisition and processing over the past decade, it is now possible to obtain well-focused radar images of the top few tens of meters of the earth. Captured within these radar images is information about the large-scale structure or architecture of the subsurface at the scale of meters to tens of meters, and information about the smaller scale spatial variability down to the limits of the resolution of the radar measurement. We have adopted a facies-based approach to developing hydrogeologic models with GPR data. This approach utilizes the links between radar facies, lithofacies and hydrofacies.

2. RADAR FACIES

The question we ask: How best to use the information captured in a radar image to develop a hydrogeologic model? We could build our model using, as a starting point, the large-scale architecture seen in the image. This assumes that the large-scale architecture seen in the radar image is also the large-scale architecture relevant to the movement of fluids in the subsurface. This approach has been formalized into a concept referred to as radar facies analysis, first applied in the early 90's in the work of Baker (1991), Beres and Haeni (1991), and Jol and Smith (1991).

Radar facies are defined by Baker (1991) as “groups of radar reflections whose parameters (configuration, amplitude, continuity, frequency, interval velocity, attenuation, dispersion) differ from adjacent groups. Radar facies are distinguished by the types of reflection boundaries, configuration of the reflection pattern within the unit and the external form or shape of the unit.” The concept of radar facies analysis has been used extensively in some areas to aid in the development of hydrogeologic models of the subsurface. A ten-year effort, involving 30 km of data collection, has been undertaken in the Netherlands to compile the characteristic radar signatures of most of the sedimentary environments suitable for GPR surveys (van Overmeeren, 1998). A significant effort has also been made to use GPR for the investigation of fluvial deposits in the Rhine valley, Switzerland (Huggenberger, 1993; Beres et. al., 1995; Beres et. al., 1999). There have been some studies illustrating ways of using a subsurface model of radar facies to generate hydrogeologic models (e.g. Rauber et. al., 1998; Langsholt et. al., 1998; Regli et al., 2002) but all methods, to date, have neglected uncertainty in the interpretation of radar facies from the radar image.

3. DESCRIPTION OF METHODOLOGY

Our approach, described in Moysey et al. (2003) is based on the use of neural networks as the framework for classification of the radar facies. Neural networks have been used for the classification of lithology from geophysical well logs (Mukerji et al., 2001; Avseth, 2000), for facies recognition in seismic data (Caers and Ma, 2002), and are commonly used in the fields of image analysis and artificial intelligence (Bishop, 1995). The particular design and method of calibration to be used for the neural network will result in the interpretation of the output to be a vector of facies probabilities at each location in the radar data. These facies probabilities can either be retained for further geostatistical analysis, used as soft constraints in inverse problems or can be used to classify the image to produce a single “best estimate” radar facies map. There are a number of possible definitions of “best”, the choice of which will depend on the application. One example would be to use a decision rule that minimizes the probability of facies misclassification, i.e.
maximum likelihood classification. The ability to incorporate estimates of uncertainty is a key part of the methodology we are developing for the classification and identification of radar facies.

The key to a successful classification system for radar facies is defining the set of classification features that can be used to discriminate between the various facies. Pattern-based approaches to interpretation of radar facies have been common in the literature (e.g., Beres and Haeni, 1991; Beres et al., 1999; Regli et al., 2002). These studies have relied on patterns related to characteristics like reflection amplitude, continuity, configuration, and external form (i.e., the shape of a radar facies unit) to help discriminate between different radar facies in an image (van Overmeeren, 1998). When these characteristics occur in a unique repeatable pattern within a given radar facies, we refer to the pattern as defining a ‘radar texture’. Moysey et al. (2006) explored how different measures of a radar image, such as windows of the raw data, instantaneous attributes, and local spatial covariance, impact classification accuracy. These authors found that extracting textural information from the GPR image using spatial covariance gave the best classification results.

One of the characteristics of a radar facies that we have investigated in some detail, is the correlation structure of the reflections in the radar image. Geostatistical analysis of radar reflection images has yielded high quality variograms that were used to determine the correlation length of radar reflections for a variety of depositional environments (Tercier et al., 2000). We suggest that the correlation structure can therefore be a useful characteristic of a radar facies. Some studies further suggest that this correlation structure is representative of the spatial distribution of the subsurface property (at many sites, water content or water-filled porosity) that controls the location of the reflections in the radar image (Knight et al., 2007). This would then provide further information about spatial heterogeneity at a site below the scale of the facies.

The classification of radar data in terms of radar facies can be done in a way that is either supervised or unsupervised. In the supervised case, a manual interpretation of a section of the radar data is completed, a set number of radar facies defined, the neural network is trained to recognize the radar facies, and the output is constrained to include only those facies. Alternatively in unsupervised classification, there is no training needed as classification is based on segmenting the data into regions based a given set of distance criteria using tools like k-means clustering or self-organizing maps.

When core data are available from a site, there is an opportunity to produce a facies map in terms of lithofacies or hydrofacies. In this case, we can use a manual interpretation to link radar facies to lithofacies and then to hydrofacies. At some sites, this might be relatively straightforward, but at other sites the transform to lithofacies from the radar facies could involve a high level of uncertainty. An alternate approach is to train the neural network directly to classify the radar data in terms of lithofacies, using the core data in the training.

4. Application to Data Acquired at the Borden Groundwater Research Site

The field site used for the development and testing of our methodology is the Borden groundwater research site in Ontario, Canada. Over the past eight years Allen-King and co-workers have used measurements of sedimentological and hydrogeologic properties to define the relationship between litho- and hydrofacies at the Borden site. This makes this an ideal location for the collection of radar data and comparison of the radar images with the subsurface distribution of litho- and hydro-facies.

Radar data were collected under contract to David Redman (University of Waterloo) along 34 lines. Each line was 20 m long; half of the lines were oriented east-west, and half were oriented north-south. 450 MHz data were acquired along all the lines, for a total of seventeen 450 MHz radar sections in each direction. These sections extend to a depth of ~ 3 m, and have vertical resolution on the order of 5-10 cm. 200 MHz data were acquired along every-other line giving a total of nine 200 MHz radar sections in each direction. In June 2005 12 good-quality cores were taken in the upper 1.5 m at locations selected to correspond to regions of high quality radar data. The core data were corrected for compaction that occurred in all the cores above the water table, using a linear correction. (The water table was at ~3 ft.). The cores were mapped identifying in the cores the following facies which are generally ~5-15 cm thick: Soil, Faint Plane Laminated (FPL), Distinct Plane Laminated (DPL), Massive Coarse-Grained (MCG), Massive Fine-Grained (MFG), Fine-Grained Planar Cross-Stratified (FPXS), Low-Angle Planar Cross-Stratified (LPXS), High-Angle Planar Cross-Stratified (HPXS), Deformed Sand (DS), Cross-Stratified Sand (XSS), Complexly Cross-Stratified Sand (CPXS), Laminated Silt (ZM).

We first completed a manual interpretation of the data sets to determine whether we could observe a relationship between radar facies and lithofacies. Working initially with the detailed core mapping, we found
no consistent relationships found between mapped facies in the cores and what was seen in the radar data; the scale of the mapping produced a level of variability that was not captured in the radar data. In addition, there were difficulties encountered in identifying facies in cores with varying orientation. We also encountered challenges working with the radar data. There was not an accurate estimate of electromagnetic wave velocity at the site, so the depths to features in the radar data were uncertain, leading to considerable leeway in matching the cores to the radar data.

The core mapping was repeated by examining groups of ~3 to 4 proximal cores and identifying larger-scale facies packages (on the order of 10’s of cm thickness) that could be seen in all the cores. As an aid to developing an understanding of the correspondence between the radar facies and lithofacies, we used the visualization software GeoProbe. The radar data were compiled to form two data cubes for the east-west and north-south profiles. A data cube for the north-south profiles is given in Figure 1, with the core data displayed along the radar lines. We identify four main radar facies in these sections which correspond generally to core facies packages and which are separated by three radar horizons (shown as colored surfaces). A group of several prominent horizontal reflections above the uppermost horizon in the image corresponds to soil mapped in the cores. Between the upper and middle horizon, we observe a second radar facies characterized by dipping reflections, which are coincident with faint plane laminated (FPL) and cross-stratified (HPXS, LPXS) lithofacies. A third radar facies is found at intermediate depths comprised of sub-horizontal, weakly-continuous reflections, corresponding in depth to a grouping of fine-grained massive and laminated lithofacies (MFG, DPL, ZM). Below the deepest horizon, a fourth radar facies is observed in patches of very low energy with complex and discontinuous reflections; the few deep cores identify this region as deformed sand (DS) and interbedded massive units (MFG, MCG).

Figure 1. Data cube from Borden showing cores and interpreted facies horizons.

Supervised interpretation of the radar data for each profile orientation was completed using the algorithms previously developed and described in Moysey et al. (2003) to produce a map of facies classifications. A neural network was trained using a small portion of the data (<2%) by choosing regions from one profile which typify the four radar facies outlined above; the trained network was then used to classify the 16 remaining profiles in the data cube. A representative classified profile is shown in Figure 2 superimposed with the original data and horizon interpretations from GeoProbe. The resulting facies classifications are in good agreement with both the core data and identified horizons. The first two radar facies corresponding to the soil layer and cross-stratified units are particularly well-identified. Less continuous classification of the deeper half of the image, which shows a patching of radar facies 3 and 4 may reflect the lateral variation observed in the cores and radar data at these depths.
5. SUMMARY AND CONCLUSIONS

The supervised classification detected radar facies that appear to be well correlated with lithofacies packages of relatively distinct texture and structure. Previous work has demonstrated that the lithofacies mapped for this study exhibit distinct permeability modes in this aquifer, and further, that lithofacies with similar texture and structure exhibit similar permeability distributions. These combined observations suggest that the radar facies identified here are also likely to exhibit distinct permeability modes. Through correlation to lithofacies, the radar facies identify regions of distinct permeability that can improve spatial information for groundwater flow and transport modeling.

Others (Ritzi and Allen-King, 2007) have shown that the permeability semivariogram can be reproduced from knowledge of the hierarchical spatial structure of the lithofacies within the aquifer (as captured by the transition probabilities among units), lithofacies dimensions and permeability modes. Of all of these properties, the most challenging information for hydrogeologists to obtain is a reasonable description of the spatial distribution of lithofacies, particularly in the horizontal (lateral) dimension. Whereas cores can provide highly detailed data sets (as in this study), we are limited in our ability to characterize the continuity of units in the subsurface particularly in the lateral dimension - the one most important to groundwater flow. Hence, through correlation to lithofacies, radar facies identification has the potential to reduce uncertainty in hydrologic models through spatial constraint of lithofacies packages with relatively distinct texture, structure and permeability distribution.

6. REFERENCES


